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Fuzzy rules-based prediction of heart conditions system

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ABSTRACT

Heart disease is known as the deadliest disease in the world which mostly focus on coronary diseases, cerebrovascular diseases, and ischemic heart disease. The treatment for the diseases is highly costly, and not only that, the monitoring system or devices that are in the market are low in accuracy and not satisfying. This work proposed to develop a prediction system for heart conditions using fuzzy system that is based on essential risk factors: age, gender, body mass index (BMI), blood pressure level (systolic), cholesterol level, heart rate, smoking habit, alcohol intake, eating habit and exercise. The specific fuzzy rules are created and produced in the output category of low, medium, and high risks. The proposed system was later evaluated by comparing the machine learning performance metrics such as accuracy, specificity, sensitivity and F1 score. It is found that the accuracy, sensitivity, specificity and F1 score are calculated as 88.2%, 78.8%, 21.2%, and 80.9%, respectively, which demonstrates a reliable percentage score. It is believed that this work has the potential to be an alternative method in providing as a dependable and cheap means of predicting heart disease.

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1. INTRODUCTION

A report published by the World Health Organization in June 2021 revealed that an estimated 17.9 million people has died from cardiovascular or heart diseases in 2019, representing 32% of all global deaths. Moreover, 85% of these deaths were caused by heart attack and stroke. The increment in the number of deaths is due to some risk factors that increase the probability of causing cardiovascular disease such as age, family genetic of cardiovascular infection, sexual orientation, elevated cholesterol, hypertension, diabetes, obesity, and smoking [1], [2]. Avoiding the risk factors could diminishes the probability of premature heart attack and strokes, which could be achieved through better healthy eating habits, regular physical exercises, and avoiding tobacco. It is also important to check and control the risk factors of heart diseases and stroke such as hypertension that could elevate the cholesterol, glucose and blood sugar level. Clinically, the early analysis and prediction of heart disease is an essential level prior to the development of prevention model. Thus, it could provides more safety measures to decrease the number of deaths in high-risk groups [3].

A precise analytic study on heart disease has indicated that contrast from one person to another is dependent on age, sexual orientation, weight and numerous other factors. The variety and multitude of these factors require tons of time and energy concentration on clinician's part for settling on effective choices. This has caused researchers to develop clinical decision support systems based on previous treatments, clinical records, statistics, and information in the database [4]. Taking into consideration of several machine learning and fuzzy rules-based methods and technologies could assist in heart diseases data analysis and information extraction.

Since coronary angiography (CA) is an expensive and defensive procedure which requiring innovation and significant level of technical insight, it is not feasible to be utilized for screening a larger size population [5]–[7]. Hence, non-defensive methods for coronary angiography become essential. In addition, instead of having a specific treatment, most people would prefer prediction systems developed by researchers, such as decision tree (DT), neuro-fuzzy, association rule mining and genetic algorithm [8]. However, the accuracy of the system is still in argument as a poor measure due to the usage of a smaller number of features. Meanwhile, in Almustafa [9] it is reported that the accuracy rates for heart disease predictions by K-nearest neighbour (KNN), Naive Bayes (NB), DT J48, and JRip classifiers, is within the range of 97% and 99%. A number of researchers have also studied on fuzzy inference system for application to the the prediction of heart conditions [10]–[15]. Thus, fuzzy rules holds great potential for healthcare industry to enable health systems to systematically use data and analytics for identifying inefficiencies and best practices which would improve care services and reduce the costs. A balanced comparison needs to be made between fuzzy rules and the model prediction systems. The system practically would provide the users with health condition information based on several setup database. The relationship of the database finally would be able to provide prediction which would later benefit users to take the early precautions. Even though there is a lot of digital and analogue data available within the healthcare systems, the effective analysis tools are still lacking for finding the hidden relationships and trends in the data for some types of heart disease conditions. Thus, this work aims to develop a prediction system for heart diseases diagnosis by using the fuzzy rules that would implement the relationship between medical dataset from outsources and would later to compare the accuracy level with that of the model prediction systems.

2. METHOD

2.1. Development of fuzzy prediction system

In fuzzy, inference engine act as a control unit and defuzzification work as the output. There are five functional blocks for the development of fuzzy interference system (FIS) as shown in Figure 1. Fuzzy rule base consists of fuzzy if-then rules. Meanwhile, inference engine applies logical rules to the information base to conclude and summarize new data. Fuzzification is used to discover on which inputs and outputs belong to each of the correct fuzzy sets. Finally, the defuzzification that is the inverse of fuzzification roles acts to change over the fuzzy amounts into crisp amounts.

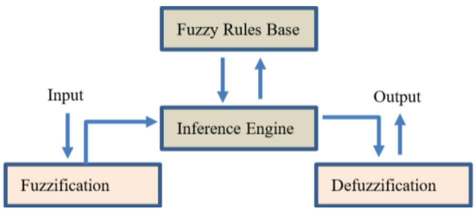

Figure 1. Block diagram of fuzzy logic

The input to the system is the risk factors that have been clarified as age, gender, body mass index (BMI), blood pressure (systolic), cholesterol, heart rate, smoking habit, alcohol intake, eating habit and exercise. The range of each risk factors is determined as below, following [16]–[24]:

– Age: young(<30), middle(35-45), old(40-60), very old(70>) [16].
– Gender: male(0), female(1) [17].
– BMI: normal(18.5-24.9), overweight(25.0-29.9), obesity (30) [18].
– Blood Pressure (Systolic): low(40-90), medium(90-120), high(120-140), very high (140>) [19].
– Cholesterol: low(<3), high(3-3.8), very high(3.8>) [20].
– Heart Rate: low(<60), medium(60-100), high(100>) [21].
– Smoking Habit: no(0), yes(1) [22].
– Alcohol Intake: no(0), yes(1) [23].
– Eating Habit: healthy diet(0), non-healthy diet(1) [24].
– Exercise: walking(0), gardening(1), cycling(2), swimming(3), running(4) [24].

Figure 2 shows the fuzzy inference system using Mamdani FIS. Every membership input constitutes a risk factor while each input is included in different membership functions within specified characterized range values. These ranges are setup with reference to the research articles by previous researchers before finalized for the system. In the prediction system, it takes 10 inputs and 1 output with some membership functions for each of the input and output settings. The output would be low, medium, or high-risk factors settings. The boundary of each category is structured based on the ten previously studied risk factors. These observations indicate that the heart conditions prediction or classifications using this fuzzy rule is comparatively easier. Since the rules depend on the foredetermined rules, the process of prediction system is based on fuzzy logic. If these standards are distorted, the outcomes may not be tolerable at all. For example, if a patient's age is 25, gender is male, BMI is 20, blood pressure is 45, and has no smoking, no alcohol intake, is eating healthy diet with characteristic exercise type walking, then the patient has the low risk of getting heart disease. Another example for the OR function could be, if the patient's age is 85 or gender is female or blood pressure is 130, has no smoking or no alcohol intake, and is eating healthy diet with exercise type running, then most probably the patient has the medium risk of getting heart disease.

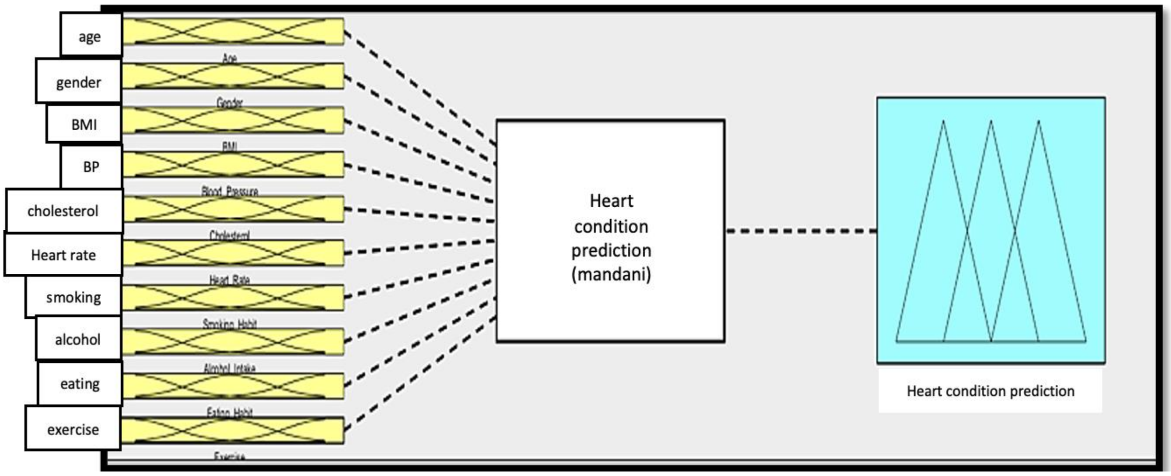

Figure 2. Main surface of fuzzy system for heart condition detection

2.2. Evaluation of the prediction system

To evaluate the performance of proposed system with models such as ensemble, neural network, and support vector machines (SVM), three elements of specificity, sensitivity, and accuracy need to be calculated. The datasets used for this project were separated into two sets, of which, training data is 60% and testing data is 40%. In the testing stage, the test dataset applied to the proposed framework for finding the prediction of heart conditions of the patients are assessed for accuracy estimates. From the confusion matrix Figure 3, the model's exactness, accuracy review and F1 score can be computed. The values are calculated based on the best model trained in machine learning. From all the considered risk factors, a numbers of fuzzy rules are produced and evaluated by finding the most suitable model that fits using the train dataset. The model performance is then be measured in the testing part that is yielded from the confusion matrix. Below are the definitions of each computed parameter. Accuracy is defined as the proportion of the records that the model accurately classified over the complete value of records [25]. It can be expressed as (1).

$$\text{Accuracy} = \frac{TP+TN}{TP+TN+FP+FN} \tag{1}$$

TP represents true positive, TN is true negative, FP is false positive, and FN is false negative. Precision is the proportion of the positives that are accurately recognized by the model over absolute sure records and can be expressed as (2).

$$\text{Precision} = \frac{TP}{TP+FP} \tag{2}$$

Sensitivity is the capacity of a test to accurately recognize the true positives. For example, individuals or patients who have the infection and model distinguished. Sensitivity is shown as (3).

$$\text{Sensitivity} = \frac{TP}{TP+FN} \quad (3)$$

Specificity could be defined as the capacity of a test to accurately distinguish the true negatives which the individuals or patients who does not have the illness and model recognized. The equation of specificity is shown as (4).

$$\text{Specificity} = \frac{TN}{TN+FP} \quad (4)$$

F1 score is a weighted normal of the accuracy and review or responsiveness, with a best possible score at 1 and most obviously poor score at 0. The equation is shown as in (5).

$$\text{F1} = \frac{2\times(\text{Recall}\times\text{Precision})}{\text{Recall}+\text{Precision}} \quad (5)$$

3. RESULTS AND DISCUSSION

The performance of the proposed model has been assessed by utilizing a dataset created in MATLAB R2022a. From the total of 384 data (100%), 40% of the information has been used for testing and 60% of the data has been applied for training. Table 1 shows the 13 examples of rules out of the 384 rules accumulated from the fuzzy.

Table 1. Configuration of fuzzy set in the proposed prediction system

No	Fuzzy rules	Output
1	If age is 25, gender is male, BMI is 20, blood pressure is 45, cholesterol is 5.18, heart rate is 60, no smoking, no alcohol intake, eating healthy diet, exercise type is walking	Low risk
2	If age is 22, gender is female, BMI is 19.5, blood pressure is 45, cholesterol is 5.18, heart rate is 60, no smoking, no alcohol intake, eating healthy diet, exercise type is walking	Low risk
3	If age is 18, gender is male, BMI is 26, blood pressure is 95, cholesterol is 5.18, heart rate is 60, no smoking, no alcohol intake, eating healthy diet, exercise type is walking	High risk
4	If age is 23, gender is female, BMI is 25.3, blood pressure is 90, cholesterol is 5.18, heart rate is 60, no smoking, no alcohol intake, eating healthy diet, exercise type is walking	High risk
5	If age is 29 gender is male, BMI is 30, blood pressure is 145, cholesterol is 5.18, heart rate is 60, smoking, having alcohol intake, not eating healthy diet, exercise type is walking	High risk
6	If age is 21, gender is female, BMI is 30, blood pressure is 43, cholesterol is 5.18, heart rate is 60, smoking, having alcohol intake, not eating healthy diet, exercise type is walking	High risk
7	If age is 35, gender is male, BMI is 19, blood pressure is 43, cholesterol is 5.18, heart rate is 60, no smoking, no alcohol intake, eating healthy diet, exercise type is gardening	Low risk
8	If age is 36, gender is female, BMI is 23, blood pressure is 50, cholesterol is 5.18, heart rate is 55, no smoking, no alcohol intake, eating healthy diet, exercise type is gardening	Low risk
9	If age is 38, gender is male, BMI is 20, blood pressure is 95, cholesterol is 5.18, heart rate is 75, smoking, having alcohol intake, eating healthy diet, exercise type is gardening	High risk
10	If age is 40, gender is female, BMI is 22, blood pressure is 102, cholesterol is 5.18, heart rate is 60, smoking, having alcohol intake, eating healthy diet, exercise type is gardening	High risk
11	If age is 45, gender is male, BMI is 23, blood pressure is 145, cholesterol is 6.0, heart rate is 60, no smoking, no alcohol intake, eating healthy diet, exercise type is gardening	High risk
12	If age is 37, gender is female, BMI is 24, blood pressure is 150, cholesterol is 5.18, heart rate is 60, no smoking, no alcohol intake, eating healthy diet, exercise type is gardening	High risk
13	If age is 45, gender is male, BMI is 24, blood pressure is 85, cholesterol is 5.18, heart rate is 60, no smoking, no alcohol intake, eating healthy diet, exercise type is gardening	Low risk

The performance of the proposed prediction system was evaluated with several models to find the specificity, sensitivity, and accuracy. Figure 3 shows the confusion matrix of the ensemble model obtained utilizing this machine learning based approach on the test dataset. To summarize, the accuracy, sensitivity, specificity, false negative rate (FNR), false positive rate (FPR), precision and F1 score for the model used to evaluate the performance of the proposed system are 88.2%, 78.8%, 21.2%, 93.2%, 6.8%, 83.2% and 80.9%, respectively. Based on the results, a total of 31 models are being tested on the dataset. In this prediction system, ensemble classification model has the highest accuracy which is 88.2%, compared with other model types such as, Naïve Bayes, SVM, KNN, Kernel and few more has lower accuracy. Ensemble model has shown the best result during training due to the combination of multiple other models in the prediction process. The validation confusion matrix of ensemble model is shown in Table 2. This confusion matrix demonstrates on how the selected classifier performed in each class. Good classifiers have a dominantly diagonal confusion matrix since all the predicted labels match the actual label.

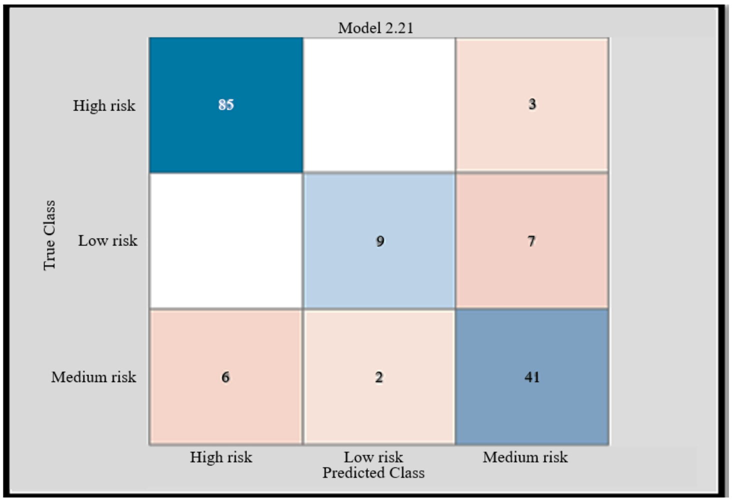

Figure 3. Confusion matric of ensemble model

Table 2. Validation confusion matrix of ensemble model

Parameter		Predicted values		
		High risk	Low risk	Medium risk
Actual values	High Risk	**85 (cell 1)**	0 (cell 2)	3 (cell 3)
	Low Risk	0 (cell 4)	**9 (cell 5)**	7 (cell 6)
	Medium Risk	6 (cell 7)	2 (cell 8)	**41 (cell 9)**

Here, 85 observations have been classified as high risk correctly while six medium risk have been wrongly classified as high risk. Besides, nine of the low-risk classes have been correctly classified as low risk, while two medium risk have been wrongly classified as low risk. 41 medium risk class have been correctly classified has medium risk, seven low risk have been wrongly classified as medium risk and three more of high risk have been wrongly classified as medium risk. The overall classification result achieved at 88.2% accuracy level can be considered as a good performance when compared to the 384 rules made in fuzzy. Even though there is no redundancy n the 384 rules, the misclassification factors might happen due to their similarities in terms of the rules made. In future, the fuzzy rule is expected to precisely control the boundary between low, medium, and high risks to ensure that the classification performance achieved by the designed models can be achieved with higher accuracy.

4. CONCLUSION

This work focuses on the development of prediction system of heart condition using fuzzy-rule. Moreover, this work would help in the investigation of many physiological parameters that used as risk factors for the prediction of heart conditions. Therefore, the risk factors have been carefully chosen from some previous study that has been made. In addition, this proposed system specified the fuzzy set to be correlated with the physiological parameter. The fuzzy set has been defined by developing fuzzy logic controller for classification of heart conditions. Besides, this proposed system has been validated by assessing the accuracy using machine learning. Finally, the highest accuracy (88.9%), was achieved by the ensemble model. Lastly from the results obtained, the performance analysis has been conducted in terms of accuracy, sensitivity, specificity, FNR, FPR, precision and F1 score. The proposed project of Fuzzy rule-based prediction system will reduce medical practitioner’s load during consultation and simplify other problems related with hospital consultations. In future, this system is recommended to be tested in clinics, medical centers or hospitals with doctors and medical expert’s advisory committee consultation.

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