IMPLEMENTATION OF FUZZY INFERENCE SYSTEM (FIS) FOR CARDIOVASCULAR DISEASES PREDICTION

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ABSTRACT

Abstract- Cardiovascular diseases (CVDs) continue to be a leading cause of mortality worldwide. Early and accurate prediction of CVDs risk is crucial for effective prevention and management. This study presents the implementation of a Fuzzy Inference System (FIS) for predicting suseptibility cardiovascular diseases. The implementation of FIS for the prediction of cardiovascular disease is by determining the membership function for risk factors that influence the susceptibility of the disease. The FIS developed in this study integrates five risk factors, including age, systolic blood pressure, diastolic blood pressure, blood sugar and cholesterol and one output parameter CVDs prediction. The FIS method used Mamdani with 162 rules. Real-world patient data diagnosed with cardiovascular disease is used to train and validate the FIS. Validity testing produces 100% valid data. Testing is carried out using patient data. The method used to validate the results of the FIS implementation is by distributing questionnaires to several paramedics.. These findings provide insights into further refinements of CVD risk modeling and potential applications in clinical practice.

KEYWORDS

Fuzzy Inference System, Membership Function, Mamdani FIS, Prediction, cardiovascular

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INTRODUCTION

Cardiovascular diseases (CVDs) persist as a leading cause of global mortality, imposing a substantial burden on both society and healthcare systems. In the quest to address this challenge, early and accurate prediction of cardiovascular disease risk has become a paramount focus in the prevention and management of these conditions.

Estimated 17.3 million people died from CVDs in 2008, this represents 30% of all death globally. Of these cases of death, an estimated 13.5 million occur due to CVDs. More than 80% of deaths from CVDs occur in this country lower middle income and there is a balance between men and women. Prevention program CVDs in developing countries is not comparable to developed countries, the result Death rates in developing countries are higher than developed countries. Risk of death Patients with CVDs can decrease with a combination of drugs and appropriate treatment (WHO, 2013). Certainty in assessing an individual's CVD risk can provide a robust foundation for timely interventions, lifestyle modifications, and effective clinical management.(Faris et al., 2023; Liu et al., 2022; Naseer et al., 2020; Ravi, 2022; Sivagowry S, 2015a)

The early identification of cardiovascular diseases (CVDs) will affect healing and costs incurred. Initial identification can be done by looking at the risk factors of cardiovascular diseases (CVDs). Early identification of cardiovascular diseases opens up opportunities for using digital/computing technology and methods. Data mining and machine learning are growing fast in their applications in healthcare. The application of data mining and machine learning for early identification of cardiovascular diseases (CVDs) has been widely implemented. Various methods such as KNN, SVM, decision tree, neural network and others have been used. The prediction and classification are two functions that are widely used for the identification of cardiovascular diseases (CVDs). Predictions are related to rates of susceptibility to CVDs while classification corresponds to labels related to status on CVDs. Prediction and classification of CVDs are mostly carried out using fuzzy logic and artificial neural networks.((Harjai & Khatri, 2019; Nguyen et al., 2021; Olsson & Nordlöf, 2015)

.Fuzzy Inference System (FIS) enables automatic judgment and reasoning in a way that is logically consistent with the way humans' reason. Based on the premise that experience is better represented by linguistic means, fuzzy logic is a very precise tool for expressing domain knowledge without requiring a strong mathematical background. As a result, fuzzy systems are increasingly being used for modelling systems in various domains (including health care) and have repeatedly proven their efficiency (references). Many systems were designed to introduce a health care infrastructure that supports the safety of human health depending on new emerging technologies. Many studies agree that the use of FIS as both the main and second part of the expert system produces accurate results (references). More than just a system that follows the consulting system paradigm, diagnostic monitors must pay attention to the fact that the human body is a dynamic system that exhibits very complex behaviors. (Espitia et al., 2019; Feng et al., 2021; Husein & Simarmata, 2019; Rizvi et al., 2020; Sivagowry S, 2015b)

Prediction is the process of making an educated guess or estimation about a future event or outcome based on available data, patterns, and knowledge. It involves using information from the past and present to anticipate what may happen in the future. Predictions can be made in various fields, including science, technology, finance, weather forecasting, sports, and healthcare. Predictive modeling and analysis often play a significant role in making predictions. This involves using statistical algorithms, machine learning techniques, and data analysis to identify patterns, relationships, and trends in data that can be used to forecast future events. For example, in healthcare, predictive modeling can be used to predict disease outbreaks, patient outcomes, or the effectiveness of treatment plans. The accuracy of predictions can vary widely depending on the quality and quantity of data, the complexity of the problem, and the methods used for analysis. Predictions are essential for decision-making, risk assessment, and planning in many domains, helping individuals and organizations make informed choices and prepare for future scenarios.(Antar et al., 2021; Dehdar Karsidani et al., 2022; Gowda & Chaithra, 2020)

The cardiovascular disease prediction models using fuzzy inference system (FIS) have been widely implemented. The FIS was used to predict heart disease risk which is divided into state of health, mild, severe and very severe. The input parameters used are age, BMI, blood pressure and gender with 27 rules (Yunda et al., 2015). The FIS method used by Mamdani with number of input 5 (cp, exang, slope, ca, thal), number of output severity and number of rules 63. The model used defuzzification method is centroid (Sivagowry and Durairaj, 2015). The FIS was used to predict CVDs on six input parameters like age, systolic blood pressure (BP), cholesterol, diabetes, chest pain and electrocardiography (ECG) and one output diagnosis of heart disease (DHD) with the number of rules 729 (Naseer et al., 2022). The FIS cardiovascular disease prediction model with input variables used the symptoms of heart disease, including chest pain, blood pressure, cholesterol, blood sugar, ECG, maximum heart rate, exercise, old peak, gender, thallium, and age. The output variable is the variable that will be used as a diagnosis based on the input variable. The output variable was an integer value between 0 and 4. The rule base is the central part of the fuzzy inference system. The rule base used which consists of 44 rules. (Dehdar Karsidani et al., 2022; Faris et al., 2023; Mobispc et al., 2022)

RESEARCH METHOD

This study aims to implementation of fuzzy inference system (fis) for cardiovascular diseases prediction. The FIS developed in this study integrates several risk factors, including age, systolic and diastolic blood pressure, blood sugar and cholesterol levels to assess a person's risk of susceptibility to cardiovascular diseases. For more details, the model architecture can be seen in Fig. 1:

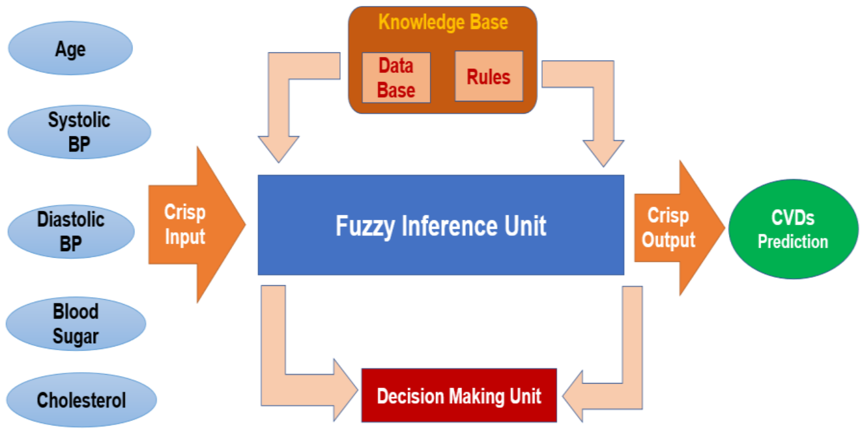

Figure 1 Fuzzy Inference System (FIS)

The research dataset comes from PKU Muhammadiyah Surakarta patient data. The sample for training used 20 data with 5 input parameters, namely age, systolic blood pressure, diastolic blood pressure, blood sugar and cholesterol. The input data is then processed according to the membership function of each parameter. The fuzzification process also involves 162 rules. The decission making process involves data and rules which then enter the defuzzification process to produce predictive values. The membership function shown in figure 2 and 3 below:

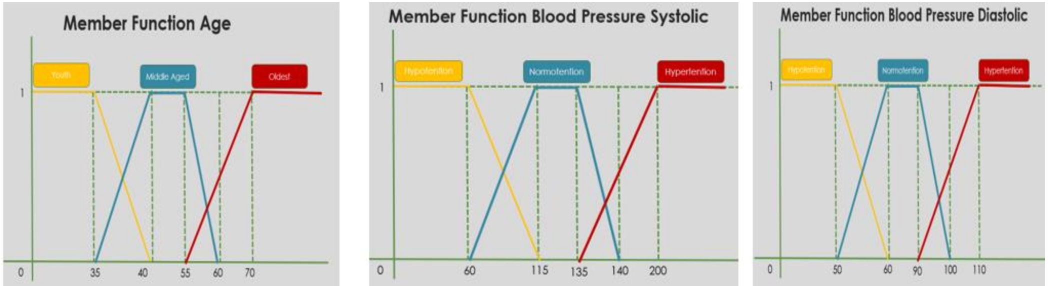

Figure 2 Membership Function Age and Blood Pressure

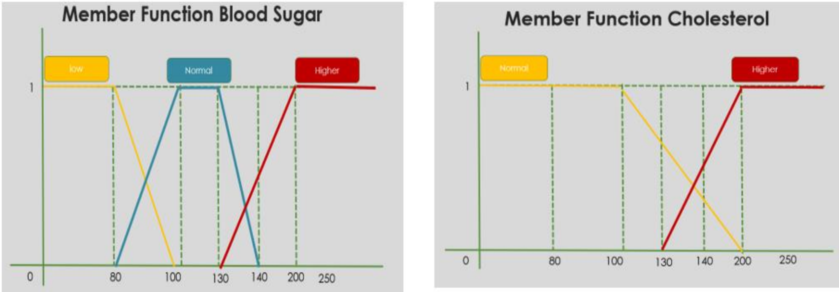

Figure 3 Membership Function Blood Sugar and Cholesterol

This model was developed using Mamdani method with 243 rules. The rules is made by input parameters and output parameter, for list of rules shown below:

R1: IF **Age** is **Youth** AND **Systolic** is **Normotension** AND **Diastolic** is **Normotension** AND **Blood Sugar** is **Normal** AND **Cholesterol** is **Normal** THEN **Susceptibility Lower**

R2: IF **Age** is **Middle Age** AND **Systolic** is **Normotension** AND **Diastolic** is **Normotension** AND **Blood Sugar** is **Normal** AND **Cholesterol** is **Normal** THEN **Susceptibility Lower**

R3: IF **Age** is **Middle Age** AND **Systolic** is **Hypertension** AND **Diastolic** is **Normotension** AND **Blood Sugar** is **Higher** AND **Cholesterol** is **Normal** THEN **Susceptibility Medium**

R3: IF **Age** is **Middle Age** AND **Systolic** is **Normotension** AND **Diastolic** is **Hypertension** AND **Blood Sugar** is **Normal** AND **Cholesterol** is **Higher** THEN **Susceptibility Medium**

R162: IF **Age** is **Old** AND **Systolic** is **Normotension** AND **Diastolic** is **Hypertension** AND **Blood Sugar** is **Higher** AND **Cholesterol** is **Higher** THEN **Susceptibility Higher**

R162: IF **Age** is **Old** AND **Systolic** is **Hypertensionn** AND **Diastolic** is **Hypertension** AND **Blood Sugar** is **Higher** AND **Cholesterol** is **Higher** THEN **Susceptibility Higher**

Final processing by defuzzification to produce value of CVDs susceptibility prediction. There are 3 state, namely lower, medium and higher. The membersHip function of output parameter shown in figure 4 below.

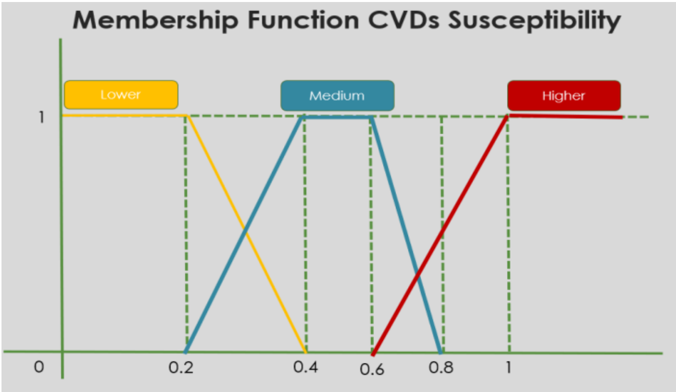

Figure 4 Membership Function Output Parameter/Prediction

RESULT AND DISCUSSION

The developing FIS model used MATLAB software. The result of membership function shown in figure 5 below:

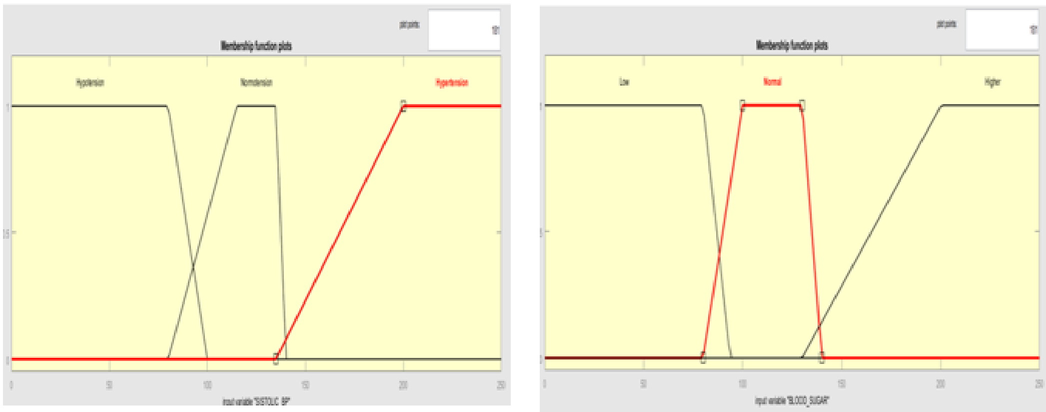

Figure 5 Membership Function

The results of the implementation of the Mamdani FIS model with 5 input parameters and 1 output are shown in Figure 6 below.

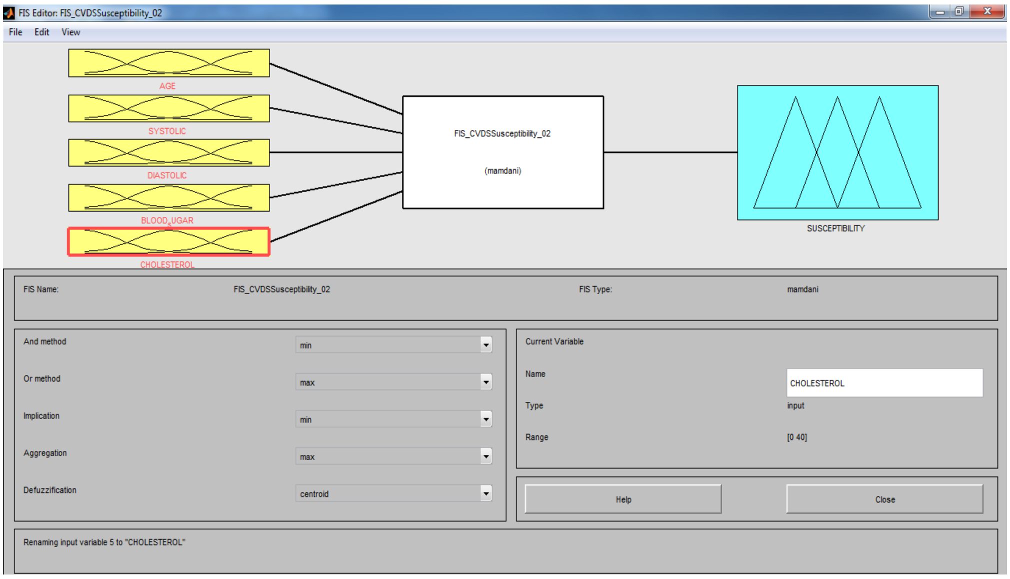

Figure 6 The Mamdani FIS Model

The input data with five parameters was processed according to the membership function which is then associated with the available rules. The fuzzification process in this model is shown in Figure 7 below.

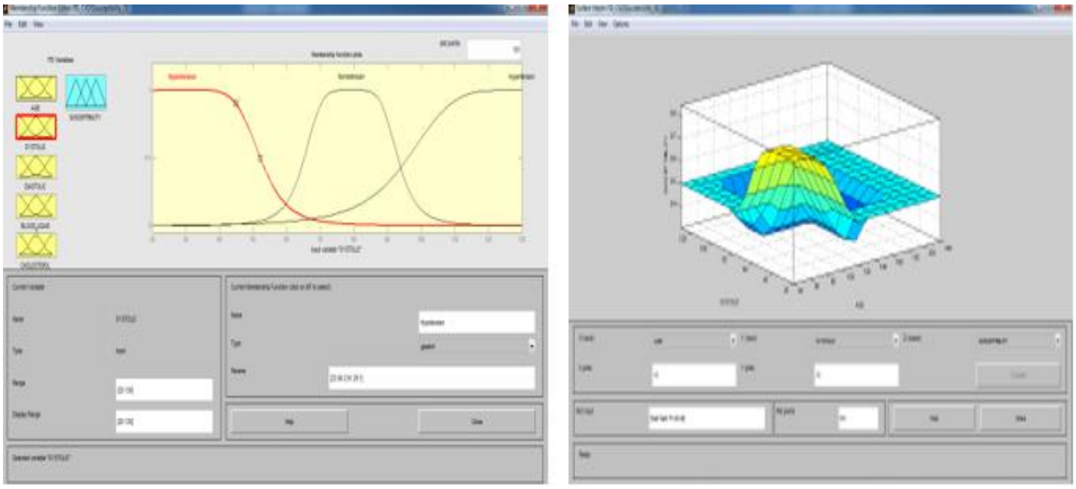

Figure 7 Fuzzification Processing

The fuzzification process in the Mamdani Method is also frequent known as the Max-Min Method. Using MIN in the implication function, and MAX on composition between functions implication. The input of the defuzzification process is a fuzzy set is obtained from the composition of fuzzy rules, while the resulting output is a number in the domain of the fuzzy set. The defuzzification used is Centroid Method (Composite Moment), a crisp solution is obtained by taking the center point fuzzy regions. The final process in output parameter shown in figure 8 below.

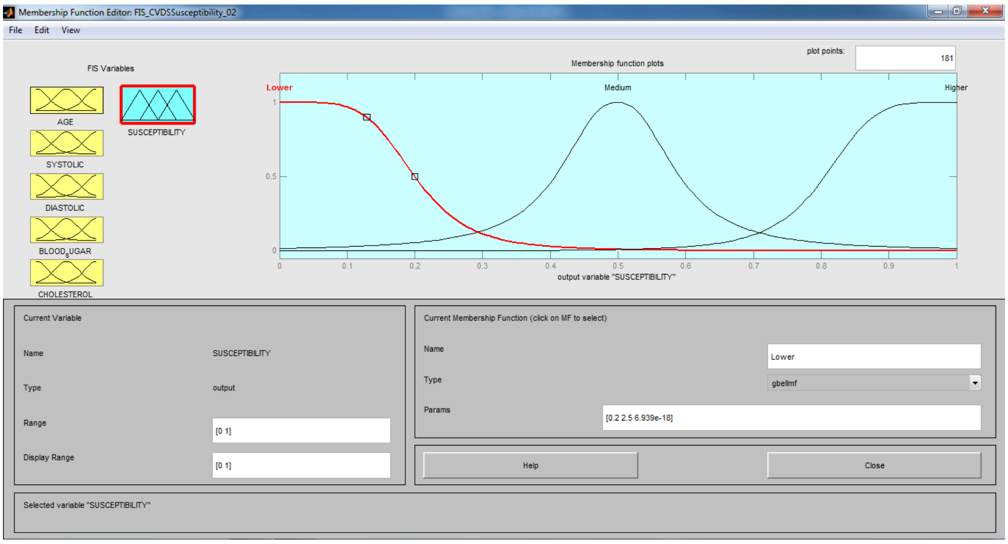

Figure 8 Membership Function of Output Parameter

The results of processing the Mamdani FIS model with 20 patient data as training data obtained results as shown in table 1 below:

Tabel 1. The Result of Mamdani FIS Model

ID	BLOOD SUGAR	CHOLES TEROL	SYSTOLIC	DIASTOLIC	AGE	LABEL	FIS OUTPUT
D01	140	150	120	80	19	0	0.1306
D02	130	120	150	110	19	0	0.0079
D03	120	160	170	90	18	0	0.0427
D04	100	175	100	80	19	0	0.2932
D05	125	135	120	90	18	0	0.2061
D06	130	100	120	120	21	0	0.1005
D07	120	135	105	90	18	0	0.1624
D08	115	140	120	90	18	0	0.2506
D09	90	150	145	90	19	0	0.0837
D10	100	120	120	80	40	0	0.0301
D11	119	100	120	80	54	1	0.9800
D12	98	275	130	58	58	1	0.8376
D13	120	100	111	76	56	1	0.7811
D14	111	100	120	80	76	1	0.8120
D15	143	263	135	88	49	1	0.9992
D16	100	200	120	90	58	1	0.9972
D17	123	125	111	80	53	1	0.6873
D18	110	115	162	74	63	1	0.8853
D19	122	130	120	80	71	1	0.8765
D20	112	200	145	75	67	1	0.9021

From the table for testing the results of the process, the RMSE value (root mean square error) is used. From the calculation, the RMSE value is 0.03536. If we round up the FIS results, we can immediately calculate that the model accuracy is 100%.

CONCLUSION

The FIS developed used Mamdani method. There are five risk factors, including age, systolic blood pressure, diastolic blood pressure, blood sugar and cholesterol and one output parameter CVDs prediction. The FIS method used Mamdani with 162 rules. Real-world patient data diagnosed with cardiovascular disease is used to train and validate the FIS. Validity testing produces 100% valid data and value RMSE small.

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