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Food Menu Recommendation System for Cholesterol and Diabetes Patients using Fuzzy Logic

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Abstract

The number of people with high cholesterol and diabetes continues to increase due to unhealthy eating habits. Choosing appropriate foods is difficult because nutritional values vary and individual health conditions differ. This study suggests a food menu recommendation system that uses fuzzy logic. It aims to help patients with cholesterol and diabetes make better dietary choices. The system processes LDL, HDL, triglycerides, fasting blood glucose, and HbA1c through fuzzification, inference rules, and defuzzification. Experimental testing shows that the system consistently classifies health risk levels into normal and high-risk categories and successfully integrates 571 food items to generate personalised recommendations. The results demonstrate that fuzzy logic effectively handles uncertainty in medical parameters and provides relevant dietary advice based on individual health profiles. The proposed system demonstrates that integrating lipid profile parameters and glycemic indicators within a single fuzzy inference framework enables more comprehensive and consistent dietary recommendations for patients with overlapping metabolic conditions.

Keywords: *Artificial intelligence; Cholesterol; Diabetes; Food recommendation system; Fuzzy logic.*

1. Introduction

In medical decision-making, patient health conditions often involve uncertainty and various risk levels instead of clear boundaries. Clinical measures such as cholesterol levels and blood glucose values may overlap, which makes strict threshold-based classifications less useful. This issue is particularly evident in dietary recommendation systems, where individual health conditions cannot always be accurately represented by fixed rules.

Fuzzy logic is often used in medical decision support systems because it can handle unclear and uncertain data. By modeling linguistic variables and membership functions, fuzzy logic allows for smoother classification of health risks, which reflects real clinical reasoning. Previous studies indicate that fuzzy-based approaches offer more flexible and realistic assessments compared to traditional rule-based or deterministic methods, especially in nutrition and chronic disease management.

Patients with both diabetes and dyslipidemia commonly face similar metabolic risks that need careful dietary management. However, dietary recommendations tend to be general or concentrate on just one condition.This can lead to confusing or poor food choices. Strict dietary rules might not accurately reflect gradual changes in clinical measures like cholesterol and blood glucose levels. We need a decision-support method that is more adaptable. It should handle uncertainty and consider multiple health indicators when planning diets.

Most current food recommendation systems tend to address either diabetes or cholesterol separately and usually rely on a narrow set of health indicators. This creates a gap in dietary recommendations for patients with overlapping metabolic conditions. Therefore, this study addresses this issue by developing a fuzzy logic-based food recommendation system that simultaneously considers lipid profile parameters (LDL, HDL, triglycerides) and glycemic indicators (fasting blood glucose and HbA1c) to support more personalised dietary decision-making [1], [2].

2. Literature Review

Dietary management is essential for controlling chronic metabolic diseases like diabetes and dyslipidemia. Several studies have suggested decision support systems to help patients choose suitable food menus based on nutritional content and health conditions[13]. Traditional methods often depend on strict threshold values or fixed rules, which may not accurately reflect the uncertainty and gradual changes in clinical parameters like blood glucose and cholesterol levels.

Fuzzy logic is often used in healthcare decision support systems. It can handle unclear and uncertain data using language variables. Earlier studies have shown that fuzzy-based systems effectively support dietary recommendations for diabetic patients by considering blood glucose levels and nutritional needs.Other studies have focused on cholesterol management by utilising lipid profile indicators to classify cardiovascular risk levels and generate appropriate food recommendations [6], [12].

However, most existing diet recommendation systems address diabetes or cholesterol independently and rely on a limited number of health indicators. Such approaches may be insufficient for patients with overlapping metabolic disorders, where glycemic control and lipid abnormalities interact simultaneously. In addition, many existing systems apply rigid decision rules that are less capable of handling uncertainty in clinical data [7]. Therefore, an integrated approach that simultaneously considers glycemic and lipid parameters within a single fuzzy inference framework is required. This study addresses a gap in research by proposing a food menu recommendation system that uses fuzzy logic. It combines cholesterol and diabetes indicators to provide better and more flexible dietary suggestions.It combines cholesterol and diabetes indicators to offer better and more flexible dietary suggestions.

3. Research methodology

3.1. Research stages

This research uses the **fuzzy logic** method, which consists of three main stages: **fuzzification, inference, and defuzzification**.

3.2. Research steps

1. **Fuzzification**: Converting input data (such as health numbers) into fuzzy sets.
2. **Inference**: Processing the data using logic rules (IF-THEN) to make a decision.
3. **Defuzzification**: Turning the fuzzy results back into a clear output or recommendation.

3.3. Fuzzy logic and membership functions

The LDL variable is modeled into several fuzzy sets that follow clinical classifications: optimal, near optimal, borderline high, high, and very high.Triglycerides are also modeled into several fuzzy sets, namely normal, borderline high, high, and very high. Meanwhile, HDL is modeled into three fuzzy sets, namely normal, moderate and high[4], [14].The division of these fuzzy sets aims to represent clinical conditions commonly used in evaluating patient lipid profiles, so that the system can provide results that are relevant to actual medical conditions[5], [2]. At the fuzzification stage, input data in the form of cholesterol levels (LDL, HDL, triglycerides) for cholesterol patients [6] and fasting blood glucose levels (fasting glucose) and HbA1c for diabetes patients[1] will be translated into fuzzy categories.

Table 1: Cholesterol Classification

Parameter	Category	Value
LDL	Normal	< 100 mg/dL
	Moderate	130–159 mg/dL
	High	160–189 mg/dL
	Very High	≥ 190 mg/dL
Triglycerides	Normal	< 150 mg/dL
	Moderate	150–199 mg/dL
	High	200–499 mg/dL
	Very High	≥ 500 mg/dL
HDL	Low	< 40 mg/dL
	Normal	40–59 mg/dL
	High	≥ 60 mg/dL

Table 2: Diabetes Classification

Parameter	Category	Value
Fasting Glucose	Normal	< 100 mg/dL
	Prediabetes	100–125 mg/dL
	Diabetes	≥ 126 mg/dL
HbA1c	Normal	< 5.7%
	Prediabetes	5.7–6.4%
	Diabetes	≥ 6.5%

With these categories, the input data will be translated into fuzzy sets that describe the patient's condition within the context of diabetes risk.

3.4. Inference rules

The inference process uses a set of IF-THEN rules to check how cholesterol and diabetes impact one another. These rules reflect expert knowledge and clinical thinking for assessing patient health. The results from this process determine the overall risk level. This information serves as the foundation for creating dietary recommendations. To simplify this stage, clinical lipid categories have been grouped into normal, moderate, and high levels[11], [15]. The specific IF–THEN rules used in the inference process are detailed in Table 1.

Table 3: Inference rules for cholesterol calculation

Rule	LDL (mg/dL)	Triglycerides (mg/dL)	HDL (mg/dL)	Output (Risk Level)	Description
R1	< 130	< 150	≥ 60	Normal	Good lipid profile; high HDL provides a protective effect
R2	< 130	< 150	40 – 59	Normal	Still within safe limits; dietary habits should be maintained
R3	< 130	150 – 199	≥ 60	At Risk	Triglycerides are increasing, but HDL remains protective
R4	130 – 159	< 150	≥ 60	At Risk	LDL begins to increase but is still offset by high HDL
R5	130 – 159	150 – 199	40 – 59	At Risk	Risk increases due to two moderately elevated indicators
R6	130 – 159	150 – 199	< 40	High	Low HDL worsens the lipid condition
R7	≥ 160	< 150	≥ 60	High	High LDL becomes the primary risk factor
R8	< 130	≥ 200	≥ 60	High	High triglycerides significantly increase risk
R9	≥ 160	150 – 199	40 – 59	High	LDL is dominant; HDL is not sufficiently protective
R10	130 – 159	≥ 200	40 – 59	High	Triglycerides are dominant; HDL is not protective enough
R11	≥ 160	≥ 200	40 – 59	High	Combination of high LDL and high triglycerides
R12	≥ 160	≥ 200	< 40	Critical Level (Highest Risk)	Worst-case condition: high LDL and triglycerides with low HDL

3.5. Defuzzification

After the inference rules are applied, the fuzzy results will be converted into crisp values or concrete numbers using the defuzzification method. At this stage, the system uses the centroid method to calculate the weighted average of all existing fuzzy results. The resulting value is a risk score that can be used to determine the patient's health status[7].

Cholesterol: The system provides a risk value based on a combination of LDL, triglyceride, and HDL parameters. If all parameters are at a good level, the patient's cholesterol risk will be low. Conversely, if one of the parameters is high, the patient's cholesterol risk will increase[2].

Diabetes: The system provides a diabetes risk score based on a combination of fasting blood glucose and HbA1c. If fasting blood glucose and HbA1c levels are within normal ranges, the patient's diabetes risk will be low. However, if blood glucose or HbA1c levels are high, the risk of diabetes will increase[1].

3.6. System implementation

The system processes user-input health parameters using a fuzzy inference system to determine cholesterol and diabetes risk levels. The output is classified into categories such as Normal, Borderline High, or High, accompanied by general dietary recommendations. In addition, the system integrates the results of the patient's condition analysis with a food database to provide suitable menu suggestions. These suggestions are displayed based on the results of the food nutrition analysis that has been processed previously.

3.7. System testing

During system testing, users input LDL, triglyceride, and HDL values. For testing purposes, sample inputs of LDL 90 mg/dL, triglycerides 90 mg/dL, and HDL 86 mg/dL were used. The fuzzy inference system classified the cholesterol status as normal because LDL and triglycerides were in the low category and HDL was in the high category. These consistent results should give the team confidence in the system's accuracy. Based on these results, the system recommended maintaining healthy dietary habits and displayed appropriate food recommendations.

4. Results and discussion

4.1. System testing

The test results show that the fuzzy logic system can reliably classify health risk levels for cholesterol and diabetes. The system clearly distinguishes between normal conditions and high-risk ones by taking various clinical factors into account. One of the main benefits of this approach is its ability to provide personalized dietary recommendations. Unlike general dietary guidelines, the system's suggestions are based on the health profile of each person. This makes them more appropriate for the user's situation. The system creates food menu suggestions. These are organized into low, moderate, and high suitability levels based on the user’s health condition.

4.1.1. System testing for diabetes cases

Fig. 1: Output of fuzzy inference showing high-risk diabetes classification based on fasting glucose and HbA1c values.

System testing for diabetes cases involved entering fasting blood glucose and HbA1c values into the fuzzy inference system. The input data went through fuzzification, rule-based inference, and defuzzification stages to identify the diabetes risk level.
In one test, the user reported a fasting glucose level of 110 mg/dL and an HbA1c of 10%. The fuzzy inference results showed that the system recognized the user's condition as diabetes and rated it as high risk. This classification mainly relied on the HbA1c value, which fell into the high category and indicated poor long-term blood glucose control.
Next, the system offered recommendations for the user. It suggested avoiding high-sugar foods, cutting down on simple carbohydrates, and discussing other treatment options with medical professionals that fit the user's health needs.

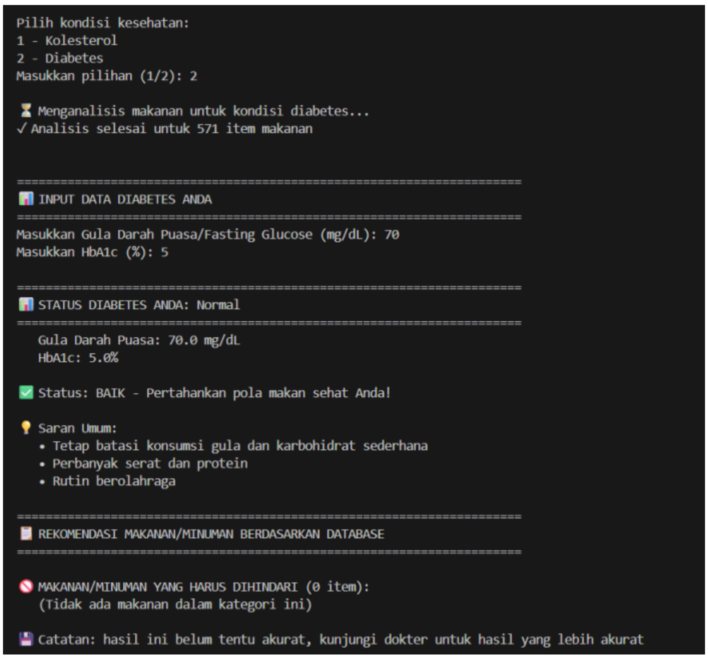

Fig. 2: Output of fuzzy inference showing normal diabetes classification based on safe glucose and HbA1c values.

In another scenario, when the user entered a fasting glucose value of 70 mg/dL and HbA1c of 4%, the system classified the condition as Normal. For this case, the system recommended maintaining a healthy diet, limiting excessive sugar consumption, and adopting an active lifestyle. These results demonstrate that the fuzzy logic system is capable of distinguishing between normal and high-risk diabetes conditions based on combined health parameters.

4.1.2. System testing for cholesterol cases

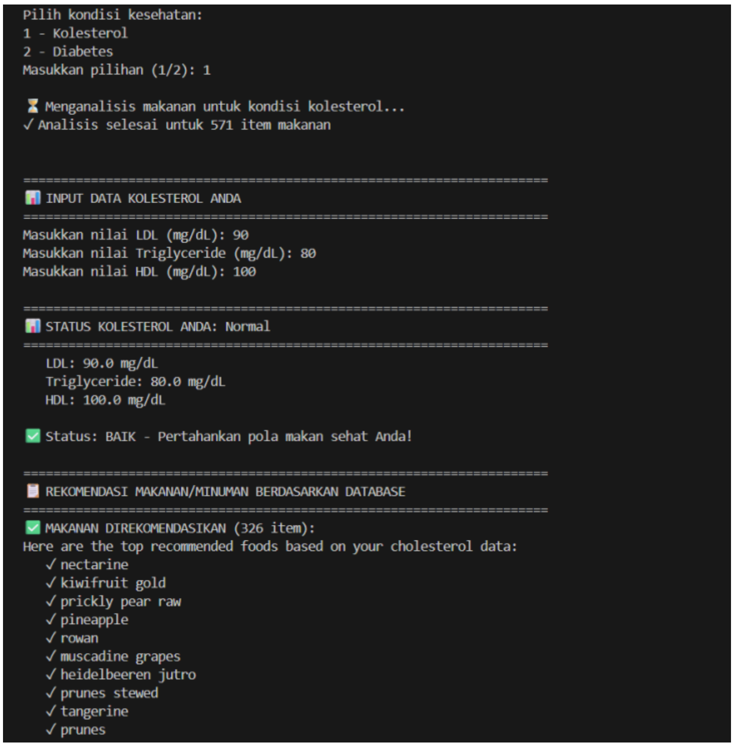

Fig. 3: Output of fuzzy inference showing cholesterol classification based on LDL, triglycerides, and HDL values.

Cholesterol testing used LDL, triglyceride, and HDL values as the main input factors.These values were sorted into fuzzy sets according to recognized clinical categories.
In one test case, the LDL was 90 mg/dL, triglycerides were 80 mg/dL, and HDL was 100 mg/dL. The fuzzy inference results classified the cholesterol status as "good."
This classification occurred because the LDL value was close to the optimal range and the HDL value was high, which offers protection. Therefore, even though the risk was not considered high, dietary control was still advised. The system recommended cutting back on high-fat and high-cholesterol foods while choosing healthier options to improve lipid profiles.
These results show that the fuzzy logic system can effectively combine multiple lipid indicators at once and provide classifications that match clinical interpretations. These values were sorted into fuzzy sets according to recognized clinical categories.

4.2. Food recommendation results

After determining the user's health status, the system integrated the fuzzy analysis results with a food database to generate personalised food recommendations.
For high-risk diabetes, a high-risk system prioritises foods with low sugar content and higher fibre content. Conversely, for users classified as normal, the system did not impose strict dietary restrictions but still encouraged balanced nutritional intake[8].
For cholesterol cases, the system recommended lower-fat, lower-cholesterol foods for users classified as borderline or high risk. These recommendations were personalised because they were directly derived from the fuzzy evaluation of each user's health condition[9], [14].
However, in several testing scenarios, limitations were observed in mapping foods to the "foods to avoid" category, with the number of items classified as restricted remaining limited or empty. This indicates that further refinement of food classification rules and nutritional thresholds is required.

4.3. Discussion

Based on the testing results, the fuzzy–logic–based food recommendation system consistently classified health risks for both cholesterol and diabetes cases. The use of fuzzy logic enables the system to handle uncertainty in medical data and to produce more flexible decision-making than rigid threshold-based approaches [10].
The main strength of this system is its ability to provide personalized dietary recommendations by taking multiple health factors into account at once. This method offers more specific guidance based on the individual's health condition, rather than general dietary advice[10], [15].
However, the system still has limitations, especially in connecting health risk results to restricted food categories. In addition, the recommendations generated by the system should be considered as supportive guidance rather than a substitute for professional medical diagnosis. Future work may focus on improving food classification rules. It will also involve validating the system with medical professionals or nutrition experts.

5. Conclusion

By using fuzzy logic, this food recommendation system makes it easier for people to track and understand their cholesterol and diabetes risk levels.By looking at specific markers like LDL, HDL, blood glucose, and HbA1c, it can offer dietary advice tailored to each person. Our testing shows that the system is great at spotting the difference between "normal" and "high-risk" cases and suggesting the right next steps. While this AI provides much more personalized support than generic health tips, it's meant to be a helpful guide rather than a replacement for a doctor's professional diagnosis.

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