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An Intelligent Food Recommendation System for Dine-in Customers with Non-Communicable Diseases History

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Abstract

The rising prevalence of diet-related diseases necessitates a focus on individual food selection to enhance nutrition intake and promote overall health. This study introduces a novel food recommender system utilizing artificial intelligence, specifically a genetic algorithm (GA), to intelligently match diverse nutritional needs with available food items. The research incorporates machine learning methodologies, such as collaborative and content-based filtering, to develop a recommendation model. Data from a commercial restaurant, Nutrisurvey, and the Indonesian food composition list inform the nutritional analysis of five menu items. Consumer variability, considering factors like sex, body mass index, medical histories, and physical activity, are integrated into the GA framework for personalized food pattern matching. The presented results demonstrate the efficacy of the proposed model in offering tailored food recommendations for consumers with non-communicable diseases (NCDs), such as diabetes, hypertension, and cardiovascular disease. The multi-objective GA technique employed in the system ensures a balance between nutritional adequacy and individual preferences. The presented GA-based approach holds promise for promoting healthier food choices tailored to individual needs, contributing to the broader goal of fostering a sustainable and personalized food system.

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1. Introduction

It is widely recognized that the intake of food lacking in nutritional value has a profound impact on the prevalence of diseases related to diet and lifestyle (Marshall, Jimenez-Pazmino, Metoyer, & Chawla, 2022). The absence of regular physical exertion, combined with the adoption of detrimental dietary habits, has precipitated a surge in health afflictions such as diabetes, cardiovascular diseases, cerebrovascular incidents, diverse forms of cancer, excessive weight, and obesity (Gonçalves, Coelho, Martinez, & Monteiro, 2021). In light of the escalating prevalence of individuals afflicted with diet-associated illness, it becomes imperative to ascertain that consumers are receiving sufficient nutritional intake (Marshall et al., 2022). In regards of sufficient nutrition intake with the aim to increase human health, individual food selection is an integral part in achieving a healthy and also sustainable food system (Rampalli, Blake, Frongillo, & Montoya, 2023).

The individual selection of food is characterized as a decision-making sequence in which individuals contemplate, procure, arrange, allocate, and consume foodstuffs and beverages (Rampalli et al., 2023). The choices that individuals make regarding which specific foods to select, how to do so, and the reasons behind these selections, are limited by the availability and accessibility of food within their local environments (Constantinides et al., 2021), food preferences and also by their knowledge regarding the nutritional content of various types of food (Schreiber, Bucher, Collins, & Dohle, 2020). Research results show that the properties of food, specifically its nutritious composition, are the factor that has received the most extensive scrutiny in relation to food selection and the development of meal planning recommendation algorithms (Symmank et al., 2017; Yang et al., 2017). The significance of food nutrition is paramount as it facilitates growth, enhances the functionality of bodily organs, and offers a shield against the potential risk of diseases (Adriyendi & Melia, 2021). Elsweiler et al. (2017) in their research, scrutinized the inability of consumers to accurately differentiate between recipes that contain a significantly higher or lower nutritional content, therefore proposed a food recommendation system which incorporated recipe metadata, including quantities of sugar, sodium, fat, and saturated fat (Elsweiler, Trattner, & Harvey, 2017). The individual's health status is also factored into the development of personalized dietary systems, providing recommendations for users with dietary/health constraint labels along with nutrition information (Agapito et al., 2018).

A multitude of technological methodologies have been adopted by researchers with the objective of steering consumers towards healthier food choices. These methodologies include, but are not limited to, classification models, recommendation systems, and a variety of other digital interfaces or applications, which have demonstrated significant efficacy (Marshall et al., 2022). Technologies pertaining to food selection which utilize and employ machine learning methodologies may possess the potential to facilitate consumers in distinguishing the healthy options at their disposal and in comprehending what they should ideally be eating (Marshall et al., 2022). With the goal to furnish users with high-quality suggestions pertaining to specific items, recommendation models are used to represent machine learning methodologies, employing strategies such as collaborative filtering and content-based filtering (Marshall et al., 2022).

The composition of one's diet is of utmost significance to their health, as it should ladequately fulfill the caloric requirements, food portions, variety of food items, nutritional content, and overall nutritional value (Adriyendi & Melia, 2021). In short, food nutrition composition needs to be optimal. A variety of methods can be employed to address the issue of food composition, such as linear

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programming and meta-heuristic methods (Fauziyah & Mahmudy, 2018). Meta-heuristic approaches offer solutions that are near-optimal, exhibit high performance, and provide flexibility, all within a reasonable computational timeframe (Dib, Moalic, Manier, & Caminada, 2017). Several renowned metaheuristic algorithms that are based on population include the Genetic Algorithm (GA), Particle Swarm Optimization (PSO), Ant Colony Optimization (ACO), Spotted Hyena Optimizer (SHO), Emperor Penguin Optimizer (EPO), and Seagull Optimization (SOA) (Katoch, Chauhan, & Kumar, 2021).

The Genetic Algorithm, a widely utilized computational strategy for optimization issues, has been suggested by numerous scholars for addressing food-related challenges. These studies include the creation of combined menus for cholesterol prevention, the determination of food composition for individuals with diabetes mellitus and high blood pressure, and the influence of balanced nutritional practices on one's nutritional status (Adriyendi & Melia, 2021). One of the superior features of GA is Elitism. Elitism is a strategy employed to preserve the superior individuals possessing the highest fitness values, thereby preventing any potential harm caused by genetic procedures and ensuring their survival into subsequent generations. Chromosomes with favorable fitness values are more likely to be chosen. Following multiple generational processes, the genetic algorithm will reveal the most advantageous chromosomes, which are anticipated to provide a solution that is optimal or near-optimal for the given problem. Elitism can solve probability of information loss and improve performance (Katoch et al., 2021). In contrast to the previously discussed meta-heuristic algorithms, which are impeded by the absence of elitism, the necessity for parameter sharing, and significant computational complexity, GA does not exhibit these constraints. (Katoch et al., 2021). GA will be selected as the algorithm used to optimize food nutrition compositions in this study based on the explanation above.

The objective of this study is to develop a system for food selection that leverages artificial intelligence, considering the variety of available food items and the diverse nutritional needs of consumers. The system employs a GA to intelligently select food. The daily consumption of food is tailored to match the caloric and nutritional value required by individuals under specific circumstances (i.e. healthy and sick people), whilst the food nutrition compositions will be transformed into mathematical models. Chromosomes have been designed to house a set of genes, each representing the nutritional composition of a food item. The prototype to be developed will empower consumers with the ability to freely make personal food choices, while also taking into account variables such as age, sex, and level of physical activity.

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2. Materials and methods

2.1 Data Acquisition

The type of food under analysis consists of single-serving menu items. Primary data collection was conducted at a commercial restaurant, specifically Rempah Bistro. There are five selected menu items in this study, each described as follows:

1. Rendang: Rice, rendang, and cassava leaf teri curry
2. Sate Ayam: Rice, Pamekasan chicken satay
3. Soto Betawi: Rice, Betawi soto
4. Gado-Gado: mixed vegetables with lontong and peanut sauce
5. Nasi Goreng: Baroma village-style fried rice

2.2 Food Data Pre-processing

The data analysis and pre-processing phase involves examining the composition of each menu and labeling the composition based on the laboratory analysis and the Indonesian food composition list/table (D/TKPI). Nutrisurvey is primarily used to determine the nutritional content of each food. If nutritional contents are unavailable, data from (D/TKPI) is used. The Nutrisurvey application has been used to process those data and calculate the nutritional content of each food. By utilizing the data, the nutritional content of each menu is obtained by adding up the nutritional contents of all compositions in the menu. This information is crucial for developing an intelligent and precise system that selects and recommends typical food for specific consumers. Considering the volume of the served food in one menu and analyzing the food compositions in the selected menu, the nutritional values of the five selected menu items are shown in Table 1.

Table 1. The nutritional values of the five selected menu items based on Nutrisurvey

Code	Nutritional Contents	Rendang	Sate ayam	Soto Betawi	Gado-gado	Nasi Goreng
3	Calory (kcal)	524.55	605.75	362.65	505.6	617.2
4	Protein (gram)	31.1	37.45	17.4	14.45	22.3
5	Fat (gram)	20.6	30.95	11.8	28.1	40.25
6	Carbohydrate (gram)	56.4	43.6	45.25	55.15	41.05
7	Sodium (milligram)	344.05	269.85	101	174.1	159.55
8	Cholesterol (milligram)	33.9	91.65	43.55	45.05	158.4
9	Saturated fatty acid (SFA, gram)	9.5	7.15	5.8	7.7	9.85
10	Mono-unsaturated fatty acid (MUFA, gram)	5.6	12.85	4.4	11.45	11.5
11	Poly-unsaturated fatty acid (PUFA, gram)	3.55	7.8	0.8	7.3	15.85

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Table 2. Formula and constraints for daily nutritional requirements

Nutritional requirements	Medical condition				
	Healthy	**Healthy [*]**	**Cardiovascular disease**	**Hypertension**	**Diabetes**
Protein (gram)	$0.15xCalory$ (Mahan and Raymond 2012)				$25xWxAf^{**}$ (PERKENI 2021)
Fat (gram)	$0.25xCalory$ (Mahan and Raymond 2012)		$< 0.25xCalory$ (Mahan and Raymond 2012)	$0.25xCalory$ (Mahan and Raymond 2012)	
Carbohydrate (gram)	$0.60xCalory$ (Mahan and Raymond 2012; Kemenkes 2014; PERKENI 2021)				
Sodium (mg)	< 2000 (Kemenkes, 2014)	< 2000 (Kemenkes, 2014)	< 2000 (Kemenkes, 2014)	< 1000 (Kemenkes, 2014)	< 2000 (Kemenkes, 2014)
Cholesterol (mg)	Unlimited	< 300 (Kemenkes, 2014)	< 200 (Kemenkes, 2014)	< 300 (Kemenkes, 2014)	< 200 (Kemenkes, 2014)
SFA (gram)		$< 0.07xCalory$ (Mahan and Raymond 2012; Kemenkes 2014; PERKENI 2021)			
MUFA (gram)		$< 0.15xCalory$ (Mahan and Raymond 2012; Kemenkes 2014; PERKENI 2021)			
PUFA (gram)		$< 0.1xCalory$ (Mahan and Raymond 2012; Kemenkes 2014; PERKENI 2021)			

** Healthy individuals with healthy lifestyle*
***Af: physical activity factor: male = 1.65; and female = 1.55*

A total 10 individual types and their corresponding nutritional adequacy values have been identified and are presented in Table 3. Note that in the table, the nutritional needs and adequacy values for the 10 types of individuals were calculated by presuming the weight, height, age, and physical activity, as also shown in the table. In the real implementation, the difference in the four parameters (weight, height, age, and physical activity) will result in more consumer variability.

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Table 3. Nutritional requirements for different types of consumers (30% of daily nutritional requirements).

		Medical condition	**Healthy**		**Healthy [1]**		**Diabetes [2]**		**Hypertension**		**Cardiovascular disease [3]**	
		Sex [4]	**F**	**M**	**F**	**M**	**F**	**M**	**F**	**M**	**F**	**M**
		Weight	55	65	55	65	55	65	55	65	55	65
		Height	160	165	160	165	160	165	160	165	160	165
		Age	30	30	30	30	30	30	30	30	30	30
		Physical activity	1.55	1.65	1.55	1.65	1.55	1.65	1.55	1.65	1.55	1.65
Nutritional requirements (30% of daily)	(3)	Calory (kcal)	653	760	653	760	639	804	653	760	653	760
	(4)	Protein (gram)	24	29	24	29	24	30	24	29	33	38
	(5)	Fat (gram)	18	21	18	21	18	22	18	21	<15	<17
	(6)	Carbohydrate (gram)	98	114	98	114	96	121	98	114	98	114
	(7)	Sodium (mg)	<600	<600	<600	<600	<600	<600	<300	<300	<600	<600
	(8)	Cholesterol (mg)	Unlimited		<100	<100	<60	<60	<100	<100	<60	<60
	(9)	SFA (gram)			<5.1	<5.9	<5.0	<6.3	<5.1	<5.9	<5.1	<5.9
	(10)	MUFA (gram)			<14.5	<16.9	<10.7	<13.4	<14.5	<16.9	<14.5	<16.9
	(11)	PUFA (gram)			<7.3	<8.4	<7.1	<8.9	<7.3	<8.4	<7.3	<8.4

Note:
1) healthy individuals with healthy lifestyle
2) for individuals with diabetes, macro-nutrients (calory, protein, fat, and carbohydrate) are considered sufficient if the nutritional values of foods are in the range of 80-100% of the nutritional requirements.
3) for individuals with cardiovascular disease, the total fat in foods should be taken as the upper limit, while the other macro-nutrients (calory, protein, fat, and carbohydrate) are considered sufficient if the nutritional values of foods are in the range of 80-100% of the nutritional requirements.
4) female = F, male = M

2.3 Genetic Algorithm for Consumer-Food Pattern Matching

The framework for this food recommender system employs pattern matching to consider food variability and consumer variability based on nutritional needs (age, sex, physical activity, disease, and nutritional status). In this study, the genetic algorithm (GA) is applied to find the best pattern matching between food and consumer variability. The GA chromosomes' formula, containing each nutritional components of the five menu was first established. Then, a formula for calculating nutritional needs for healthy person, person with hypertensions, person with cardiovascular diseases, and person with diabetes were compiled and confirmed. The GA algorithm was developed for pattern

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matching for selecting food using elitism based on the value of fitness function has been tested and validated on five ready-to-eat plate foods as mentioned earlier, including Nasi goreng, Sate ayam, Gado-gado, Rendang, and Soto Betawi. The proposed food selection based on GA is depicted in Figure 1.

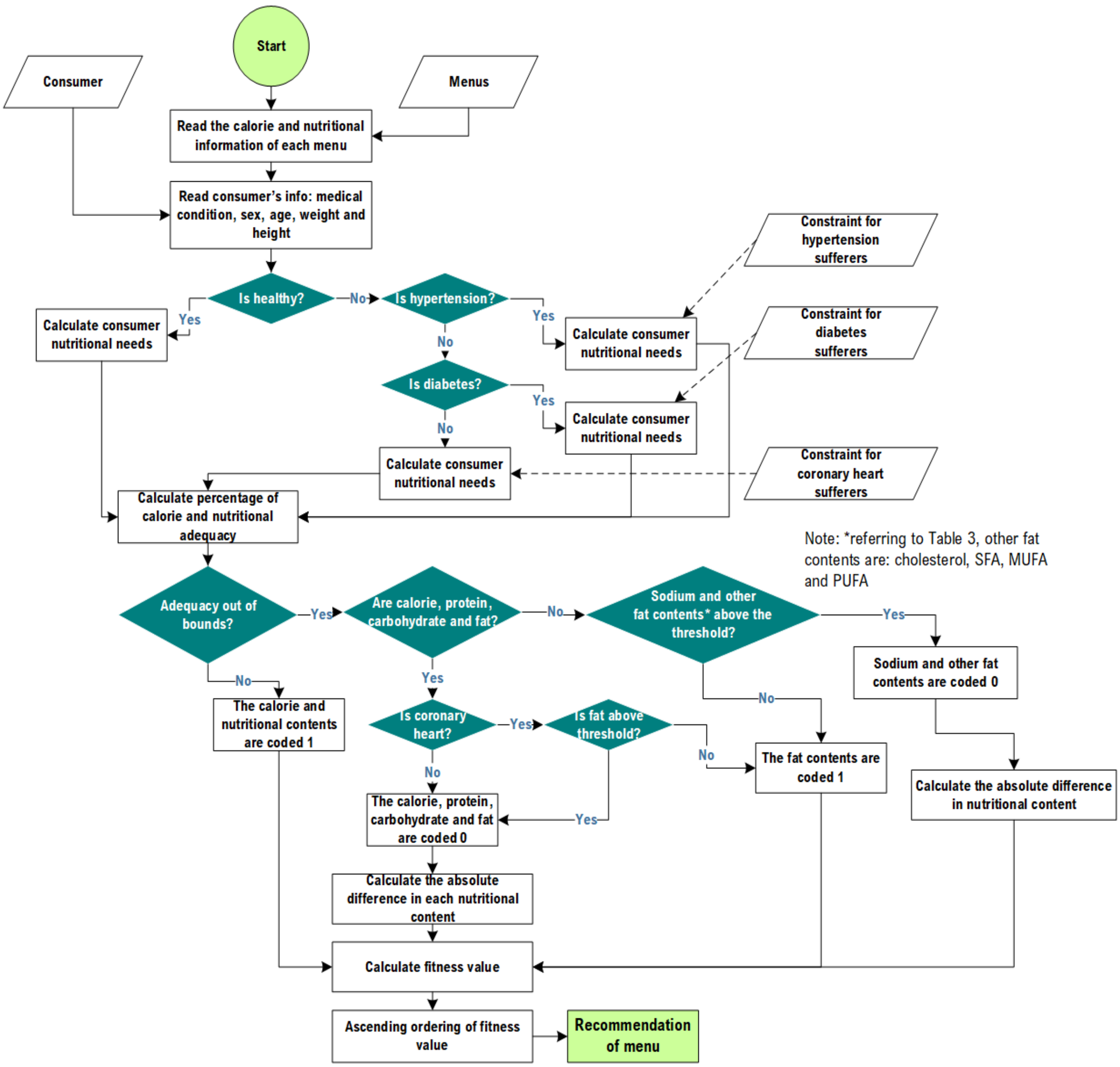

Figure 1. The framework of food recommender system

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3. Results and discussion

A system has been designed to assist consumers in choosing foods with nutritional contents appropriate to sex, age, weight, height and non-communicable diseases (NCDs) medical conditions, especially for consumers with cardiovascular disease, diabetes, and hypertension history. A total of five selected menus have been determined (Table 1), and the calorie and nutritional content of these foods are specific to the location of its provider (restaurant). Referring to Table 3, the calorie and nutritional needs of specific consumers were calculated and advice was given on choosing foods that meet their nutritional needs and are good for their health. A GA-based approach has been used to determine a list of food choices that suit consumers' calorie and nutritional needs.

3.1 Food Selection Elicitation

In accordance with the objectives of this research, the multi-objective GA technique has been applied in a food recommendation system developed to obtain the best food choices that accommodate the trade-off between nutritional adequacy and individual preferences of consumers with an NCDs history. The best fit between food content and consumer calorie and nutritional needs was used as the first technique of food selection elicitation. Table 1 and Table 3 have been used to calculate the percentage of calorie and nutritional adequacy of five selected menus for specific consumers with an NCDs history. A dish meets consumers' need with hypertension and cardiovascular disease history, if calory, protein, fat and carbohydrate contents and later called as macronutrients are in the adequate range of 80 - 120%. Meanwhile, the adequate range for consumers with a diabetes history is 80 - 100%. For consumers with an NCDs history, the need of sodium, cholesterol, SFA, MUFA and PUFA (later will be called as micronutrients) in Table 3 were set as the upper limit, so that adequacy will be 100% if the content in the food was less than or equal to the upper limit values, otherwise it was given value 0 (zero). The nutritional adequacy (%) of consumer with an NCDs history for each food can be expressed by the following equation:

$$NA(i) = \begin{cases} \dfrac{NC_k}{NN_k} x100, & k = 3,4,5,6 \\ 100, & NC_k \leq NN_k \; and \; k = 7,8,\dots,11 \\ 0, & NC_k \geq NN_k \; and \; k = 7,8,\dots,11 \end{cases}$$

where, NA: nutriotional adequacy (%); i: food's type; NC: food nutritional content; NN: consumer nutritional needs; k: nutritional code.

A female consumer with a diabetes history, the percentage of calorie and nutritional contents adequacy of five selected menus can be expressed as a set of chromosomes presented in Table 4.

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Table 4. Percentage of calories and nutritional contents adequacy of five selected menus for consumers with diabetes history.

(0)	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
Menu [1]			Calory	Protein	Fat	Carbohydrate	Sodium	Cholesterol	SFA	MUFA	PUFA
0	0	1	96.5	93.0	226.6	42.8	100	0	0	100	0
0	1	0	94.7	156.2	174.3	45.5	100	0	0	100	0
0	1	1	79.1	60.3	158.2	57.5	100	100	0	100	0
1	0	0	82.0	129.7	116.0	58.8	100	100	0	100	100
1	0	1	56.7	72.6	66.4	47.2	100	100	0	100	100

Note: Code of menu, 001 (Nasi goreng kampung); 010 (Sate ayam); 011 (Gado-gado); 100 (Rendang); 101 (Soto betawi)

Furthermore, binary values 1 and 0 were used to represent calorie and nutritional contents that met the adequacy range and constraints. The binary code for calorie and nutritional content was summed up by row (based on food type), as presented in Table 5.

Table 5. Binary code of calories and nutritional contents adequacy of five selected menus for consumers with diabetes history.

(0)	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	Sum
Menu			Calory	Protein	Fat	Carbohydrate	Sodium	Cholesterol	SFA	MUFA	PUFA	
0	0	1	1	1	0	0	1	0	0	1	0	**4**
0	1	0	1	0	0	0	1	0	0	1	0	**3**
0	1	1	0	0	0	0	1	1	0	1	0	**3**
1	0	0	1	0	0	0	1	1	0	1	1	**5**
1	0	1	0	0	0	0	1	1	0	1	1	**4**

Note: Code of menu, 001 (Nasi goreng kampung); 010 (Sate ayam); 011 (Gado-gado); 100 (Rendang); 101 (Soto betawi)

The second food selection elicitation technique that has been applied was calculating the absolute difference between consumer nutritional needs and the nutritional content of food which has a binary value of 0 in Table 5, and can be expressed by the following equation:

$$dN_i = Abs(NC_k - NN_k), \qquad k = 3, 4, \ldots, 11$$

where, dN: nutriotional absolute difference; i: food's type; NC: food nutritional content; NN: consumer nutritional needs; k: nutritional code.

Then the absolute differences were summed up by row (by food type). In the same case, a female consumer with diabetes history, the calculation results can be presented as a set of chromosomes in Table 6.

Table 6. Absolute differences in nutrient contents that do not meet nutritional adequacy percentages and constraints for female consumers with diabetes history.

(0)	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	Sum
Menu			Calory	Protein	Fat	Carbohydrate	Sodium	Cholesterol	SFA	MUFA	PUFA	
0	0	1	0	0	22.49	54.86	0.0	98.4	4.9	0.0	8.8	**189.4**
0	1	0	0	13.47	13.19	52.31	0.0	31.7	2.2	0.0	0.7	**121.6**
0	1	1	133.77	9.53	10.34	40.76	0.0	0.0	2.7	0.0	0.2	**205.9**
1	0	0	0	7.12	2.84	39.51	0.0	0.0	4.5	0.0	0.0	**62.8**
1	0	1	276.73	6.58	5.96	50.66	0.0	0.0	0.8	0.0	0.0	**349.5**

Note: Code of menu, 001 (Nasi goreng kampung); 010 (Sate ayam); 011 (Gado-gado); 100 (Rendang); 101 (Soto betawi)

3.2 Final Food Selection and Recommendation

Based on the principle of multi-objective optimization technique, a fitness function formula has been proposed in this study. Recommendations for final food selection from five selected menus are determined based on the fitness function value. The fitness function value is calculated by dividing the total binary code (Table 5) by the total absolute difference in the nutritional content of each menu (Table 6), and is expressed using the following formula:

$$Fit_i = {\sum_3^k BC_i}\Big/{\sum_3^k dN_i} \qquad k = 3, 4, \dots, 11$$

where, Fit: fitness value; i: food's type; k: nutritional code; BC: binary code of calory and nutritional contents (Table 5); and dN: absolute difference of nutritional contents (Table 6). By using the formula, the fitness values of the five selected menus for female consumers with diabetes history can be calculated and presented in Table 7.

Table 7. Fitness value of five selected menu for female consumers with diabetes history.

Menu			Sum of Binary	Sum of Absolute Difference	Fitness Value	**Rank**
0	0	1	4	189.38	0.021	**3**
0	1	0	3	113.50	0.026	**2**
0	1	1	3	197.33	0.015	**4**
1	0	0	5	54.00	0.093	**1**
1	0	1	4	340.76	0.012	**5**

Note: Code of food, 001 (Nasi goreng kampung); 010 (Sate ayam); 011 (Gado-gado); 100 (Rendang); 101 (Soto betawi)

3.3 Food Recommendation Based on Health Status

Food choice recommendations for specific consumers with NCDs history in Table 3 have been successfully carried out using the developed system. The system has been developed using a tree-tier architecture approach. The GA-based model was implemented on the back-end side, and the interface

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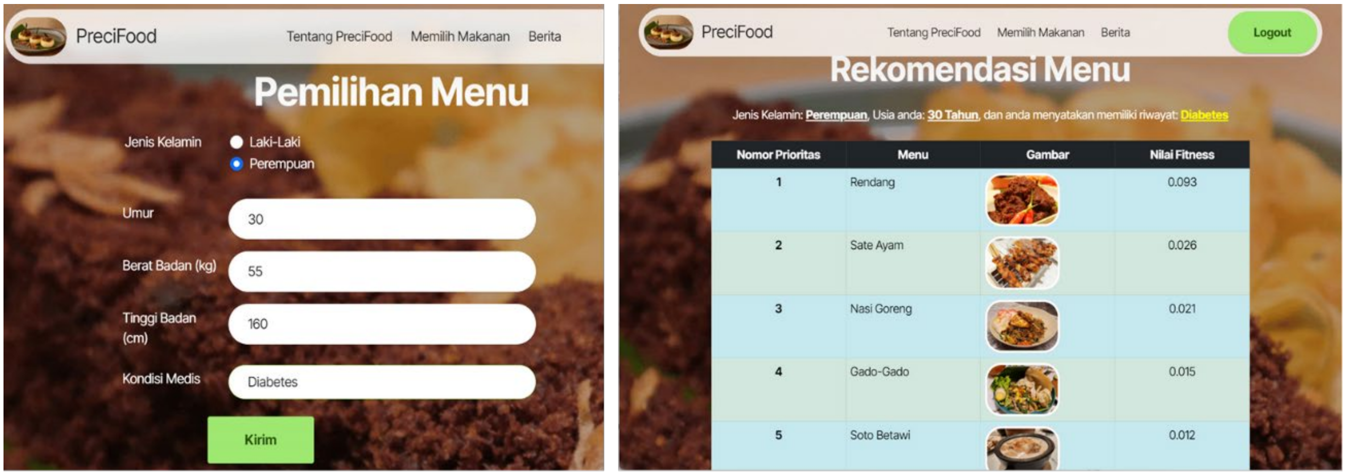
was implemented on a web-based services, as presented in Figure 2. The system was successful in providing recommendations for healthy food choices that suit consumers' specific needs, as presented in Table 8.



(a) (b)

Figure 2. The food recommendation system interface: (a) specific consumer data inputting; and (b) recommendation and ranking of food choice.

Table 8. Final selection and recommendation of five selected menus for specific consumers with NCDs history

Medical Condition	Sex	Ranking of food choice				
		Rendang	Sate Ayam	Soto Betawi	Gado-Gado	Nasi Goreng
Diabetes	F	1	2	5	4	3
	M	1	3	4	2	5
Hypertension	F	2	3	5	1	4
	M	3	2	5	4	1
Cardiovascular disease	F	2	5	3	1	4
	M	5	4	2	3	1

Based on Table 8, the recommended food for female and male consumers with a history of diabetes based on priority value was Rendang. The macronutrient content of Rendang best suits the needs of consumers with a history of diabetes. Likewise, the cholesterol, mono-unsaturated fatty acid (MUFA) and poly-unsaturated fatty acid (PUFA) contents were below the upper limit values presented in Table 3. Female consumers with a history of hypertension were recommended to choose Gado-Gado, because the adequate fulfillment of macronutrients and micronutrients particularly sodium,

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cholesterol and MUFA contents were also below the upper limit value. Male consumers with a history of hypertension were advised to choose Nasi Goreng because the macro and micronutrient contents were closest to their needs. Meanwhile, female and male consumers with a history of cardiovascular disease were advised to consume Gado-Gado and Nasi Goreng respectively. This is because the saturated fatty acid (SFA) content in these two foods were low, and those were also below the upper limit value for consumers with a history of cardiovascular disease.

However, consumers were still given the freedom to choose one of the recommended foods with a lower priority value.

4. Conclusion

This study introduces an innovative AI-based food recommender system that leverages a GA to address the imperative need for personalized nutrition. In the face of escalating diet-related health issues, the research emphasizes the significance of individual food selection in achieving a healthier and more sustainable food system. By incorporating diverse technological methodologies, including machine learning techniques, the proposed system demonstrates the potential to guide consumers towards healthier food choices.

The application of the GA framework, considering individual factors like sex, age, weight and medical conditions, allows for intelligent food pattern matching. The results, based on the analysis of five menu items, showcase the system's effectiveness in offering personalized food recommendations for consumers with specific NCDs history. The multi-objective optimization technique employed in the system strikes a balance between nutritional adequacy and individual preferences, further enhancing its practicality and usability.

The presented approach contributes to the growing field of AI-driven solutions for personalized nutrition, offering a promising method to address the challenges associated with diet-related NCDs. As technology continues to advance, integrating intelligent systems into daily food choices holds potential for positively impacting public health by promoting individual well-being and encouraging a shift towards healthier dietary habits. The findings of this study underscore the importance of merging technology and nutrition science to create tailored solutions that cater to the diverse nutritional needs of individuals. Future development of food recommender system includes testing/validation of its applicability and suitability to provide recommendations that consider the balance of nutritional adequacy and individual preferences, especially for consumers with a history of NCDs. Apart from that, measuring the level of consumer acceptance of this system needs to be carried out to ensure its usability.

In the research conducted, the sole selection technique employed for the Genetic Algorithm was elitism. This approach, however, has its drawbacks. One of them is the slower rate of convergence,

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which is due to the minimal differentiation between the superior chromosomes and the others. Additionally, it necessitates sorting, which adds to the computational cost, making it a resource-intensive method. It is urged for future research to use different selection methods such as roulette wheel selection, tournament selection, steady-state selection, etc to further maximize the advantages provided by the GA algorithm.

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