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Food Menu Recommendations Based on Recommended Dietary Allowances using Genetic Algorithm

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ABSTRACT

Nowadays, there are still often unbalanced nutritional problems such as overnutrition or malnutrition. Many factors can affect it, one of which is an unbalanced diet. One solution that can be done is a system for optimizing nutritional needs. In this study, the method used for optimization is genetic algorithms. Genetic algorithms are one of the metaheuristic methods that are often used for optimization problems. A particular chromosome representation is designed to provide suitable solutions. The system can provide food recommendations with nutrients close to a person's nutritional needs by using the genetic algorithm. Based on the test results obtained, the difference in nutrition from food recommendations with nutritional needs is below 5 percent.

I. Introduction

Food is one of the basic human needs that must be fulfilled. Apart from being a source of energy, nutrients in food are also needed by human organs to function properly. Foods with balanced nutrients have 5 main components: carbohydrates, protein, fat, vitamin, and mineral (Taşğın, 2017). Balanced nutritional intake has a vital role in a person's growth, intelligence, and physical development (Lifshitz, 2009; Cusick et al., 2016). However, nowadays, there are still often unbalanced nutritional problems such as overnutrition or malnutrition (Le Nguyen et al., 2013). Many factors can affect it, one of which is an unbalanced diet.

Several efforts can be made to maintain balanced nutrition, one of which is to use an optimization system for nutritional needs as a regulator of the daily food menu (Fauziyah & Mahmudy, 2017; Dewi et al., 2021; Mustafa et al., 2017). There are still many who do not know the nutritional needs needed and often overeat for some people. With a nutritional optimization system, daily food patterns can be adjusted according to nutritional needs. Everyone has a different level of nutritional adequacy. The level of nutritional adequacy is the average nutritional intake per day to meet nutritional needs based on a person's physical condition and daily activities (Gerrior et al., 2006).

Genetic algorithms are part of the evolutionary and metaheuristic algorithms that are often used and popular to solve optimization problems (Oktaviani et al., 2018). Genetic algorithms imitate the concept of natural evolution where the best individuals will survive and the less good individuals will undergo natural selection. In addition, the operators used also imitate biological concepts such as mutation, crossover, and selection (Albadr et al., 2020). Genetic algorithm is a population-based method so it is very useful for solving large scale optimization problems (Shahab et al., 2021) and can find solutions that are outside the local optimum solution. So that the solution obtained is almost close to the most optimal solution (Xu, 2021).

In this study apply genetic algorithms as a method to optimize nutrition. The results of the nutritional optimization are given in the form of food menu recommendations (breakfast, lunch, dinner, and snacks). The system searches for combinations of foods with total nutrition close to nutritional needs by using genetic algorithms. The combination of foods with the smallest difference with nutritional needs will be used as the system's best solution or food recommendations.

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II. Method

A. Nutritional adequacy

Everyone has a different level of nutritional adequacy. The level of nutritional adequacy is the average nutritional intake per day to meet nutritional needs based on a person's physical condition and daily activities. Nutritional needs such as carbohydrates, fats, and proteins can be determined based on a person's total energy needs by using equation (1) or equation (2) as follows to get the Basal Metabolism Rate (BMR) (Picolo et al., 2016).

$$Female = 665 + (9{,}6 * Weight) + (1{,}8 * Height) - (4{,}7 * Age) \quad (1)$$
$$Male = 66 + (13{,}7 * Weight) + (5 * Height) - (6{,}8 * Age) \quad (2)$$

The calculation of the need for carbohydrates, protein, and fat as a source of energy needs is based on the categories specified in Table 1.

Table 1. Recommended Needs for Carbohydrates, Protein and Fat

Category	Carbohydrate (%)	Protein (%)	Fat (%)
Toddler	70	10	20
Child & Teen	55	15	30
Adult	65	15	20

B. Chromosome Representation and Fitness Function

It is necessary to determine the chromosome representation used in the early stages to compose a genetic algorithm structure. The chromosome representation is adjusted according to the expected solution (Rody et al., 2019). The system that will be built is a food menu recommendation with the distribution of the daily menu, namely breakfast, lunch, dinner, and two snacks. Based on the designed food menu, the chromosome representation that will be used is as follows:

Pi = [m1 m2 m3 s1 s2] = [2 4 1 6 7] (3)

Explanation:

- m1, m2, m3 is number of main foods at main food's dataset.
- s1, s2 is number of snacks at snack's dataset.

To get the fitness value, it is necessary to accumulate the nutritional content contained in the chromosomes and calculate the difference from the required nutritional needs. For more details, it can be explained in Table 2.

Table 2. Chromosome Representation and Nutritional Difference

Gen	Food Number	Carbohydrate	Protein	Fat
M1	2	37.30	4.00	1.20
M2	4	22.60	7.40	2.10
M3	1	40.20	7.00	34.40
S1	6	24.30	1.00	0.80
S2	7	25.50	25.50	44.40
Total		149.90	44.90	82.90
Target		304.51	60.90	81.20
Difference		154.61	16.00	1.70

The fitness value is calculated by using equation (4):

$$fitness = \frac{1000}{\Delta C*4 + \Delta P*4 + \Delta F*9} \quad (4)$$

Explanation:
ΔC = difference between total and target carbohydrates
ΔP = difference between total and target protein
ΔF = difference between total and target fat

C. Crossover and Mutation

Crossover is a genetic operator that crosses between two individuals to produce a new individual (Mahmudy et al., 2020). In this study, the type of crossover that will be used is uniform crossover. This type of crossover is exchanging genes from both parents at certain indices based on the mask. The value in the mask is a binary number [0,1], and its length is the same as the length of the parent chromosome. If the value for mask is equal to 0 then no gene exchange will be carried out, whereas if the value for the mask is equal to 1 then gene exchange will be carried out.

Mask = [1 0 0 1 0]
P1 = [2 4 1 6 7] → C1 = [3 4 1 2 7]
P2 = [3 5 9 2 8] → C2 = [2 5 9 6 8]

The mutation is a genetic operator that changes one or more genes on a chromosome or individual. The population will be randomly selected to generate new individuals from the mutation process (Rikatsih et al., 2019). In this study, the type of mutation used is a single-point mutation. One of the genes on the chromosome will be randomly selected to modify its value. The selected point will be changed its value with a range of values according to the dataset.

Selected point = 3
P = [2 4 1 6 7] ➔ M = [2 4 9 6 7]

D. Selection Method

Selection of individuals in the population genetic algorithm is carried out to select individuals in the population and offspring that will be maintained in the next generation. The quality of the chromosomes depends on the fitness value. Chromosomes or individual with a high fitness value has a high chance of being used as a solution (Seisarrina et al., 2018). The selection method to be used is Tournament Selection. A total of k individuals will be randomly selected in the population and the offspring for a tournament, as illustrated in Figure 1. The individual who has the best fitness values will pass and enter the next generation population. The tournament continues until the entire new population is filled.

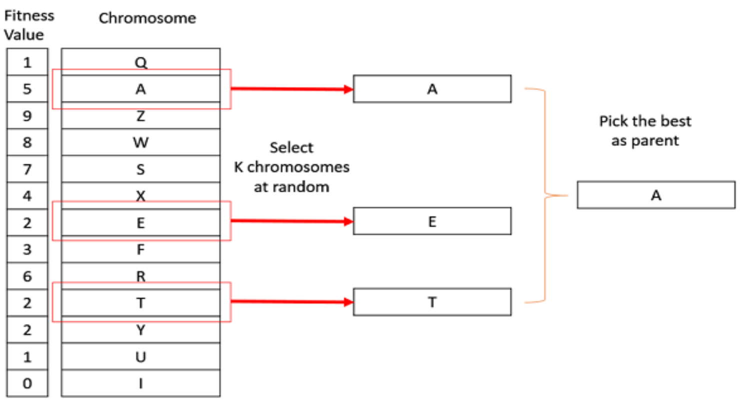

Fig. 1. The Illustration of Tournament Selection

III. Results and Discussion

A. Genetic Algorithm Parameter Testing

The test aimed to obtain the best parameters of the genetic algorithm in solving the problem of optimizing daily nutritional needs. The tests carried out were testing the population size, the combination of cr and mr, and the number of generations. The test was carried out 10 times for each condition.

1) Population Size Testing

The best population size parameter is obtained based on the average of the best fitness values obtained from the population size test. To test the population size parameter, another genetic algorithm parameters used are cr = 0.5. mr = 0.5, and number of generations = 50. The results of the population size test can be shown in Table 3 and Figure 2.

Based on the population size test results in Table 3 and Figure 2, it is found that the average best fitness value is at a population size of 80, which is 83,483. So, it can be said that the best population size parameter is 80.

2) Cr and Mr Combination Testing

The best cr and mr parameter is obtained based on the average of the best fitness values obtained from the cr and mr combination test. To test the combination cr and mr parameter, another genetic algorithm parameters used are population size = 50 and number of generations = 50. The results of the cr and mr combination test can be shown in Table 4 and Figure 3.

Table 3. The Results of Population Size Test

Pop Size	Number of Test							Average Fitness
	1	2	3	...	8	9	10	
10	25.79	47.04	25.54	...	33.7	14.59	118.76	39.51
20	41.36	21.94	36.94	...	20.85	37.75	58.55	38.788
30	46.02	85.18	45.27	...	32.39	32.21	109.65	57.486
40	41.07	18.48	30.46	...	76.1	25.32	37.91	43.024
50	45.07	44.13	88.81	...	73.37	68.63	39.7	72.922
60	59.59	43.42	50.51	...	57.34	114.94	94.07	59.415
70	42.19	44.82	65.75	...	105.93	37.41	74.29	59.516
80	62.62	84.1	81.83	...	91.83	63.17	104.38	83.483
90	135.32	39.75	56.53	...	50.94	55.16	103.84	68.000
100	59.95	46.23	49.9	...	123.15	79.94	52.55	67.962
110	48.38	112.23	131.23	...	87.64	88.57	48.47	80.05

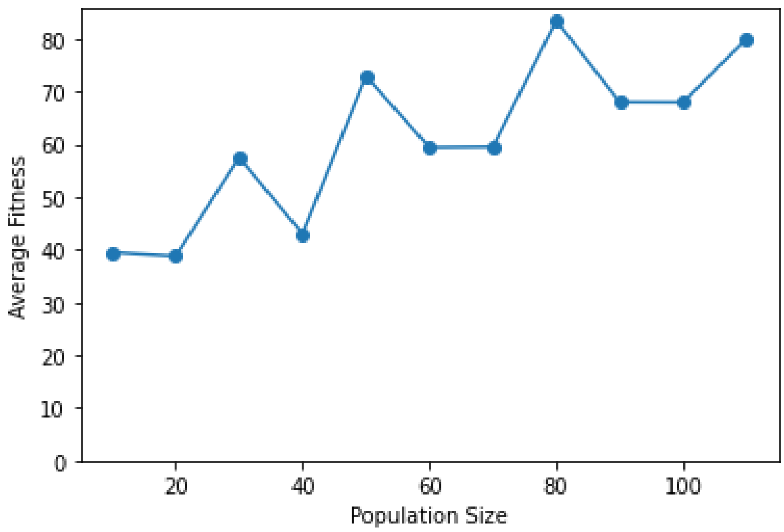

Fig. 2. Population size test graph

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Table 4. The Results of Cr and Mr Combination Test

Cr	*Mr*	Number of Test							*Average Fitness*
		1	2	3	...	8	9	10	
0	1	52.63	68.35	37.68	...	35.84	59.24	48.08	57.213
0.1	0.9	56.66	43.52	88.5	...	57.44	46.38	72.99	53.46
0.2	0.8	144.51	42.9	42.72	...	185.53	34.48	67.2	73.824
0.3	0.7	62.11	84.32	44.78	...	60.24	41.07	39.67	53.778
0.4	0.6	35.15	43.54	101.94	...	87.18	57.54	51.95	59.043
0.5	0.5	44.39	62.19	48.83	...	146.41	49.31	51.49	60.18
0.6	0.4	40.47	53.5	27.62	...	32.86	46.38	72.73	64.066
0.7	0.3	24.02	51.81	49.88	...	99.01	90.91	31.08	55.234
0.8	0.2	82.99	40.24	42	...	40.93	37.74	102.88	50.112
0.9	0.1	29.82	21.62	38.67	...	33.22	43.14	21.16	33.213
1	0	20.36	57.05	17.46	...	16.26	26.35	23.65	27.463

Based on the results of testing the combination of the values of cr and mr in Table 4 and Figure 3, it was found that the highest average fitness value was at cr = 0.2 and mr = 0.8, which was 73.824. So, it can be said that the best combination of cr and mr values is 0.2 and 0.8.

3) Number of Generations Testing

The best number of generations parameter is obtained based on the average of the best fitness values obtained from the number of generations test. To test the number of generations parameter, another genetic algorithm parameters used are population size = 50, cr = 0.5., and mr = 0.5. The results of the number of generations test can be shown in Table 5 and Figure 4.

Based on the results of testing the number of generations in Table 5 and Figure 6, it was found that the highest average fitness value is in the number of generations of 110, which is 90.956. However, the number of generations 70 and 80 have an average fitness value close to the highest average fitness value with a value of 85.74 and 86.901, respectively. In order to shorten the computation time, the optimal number of generations chosen is 70.

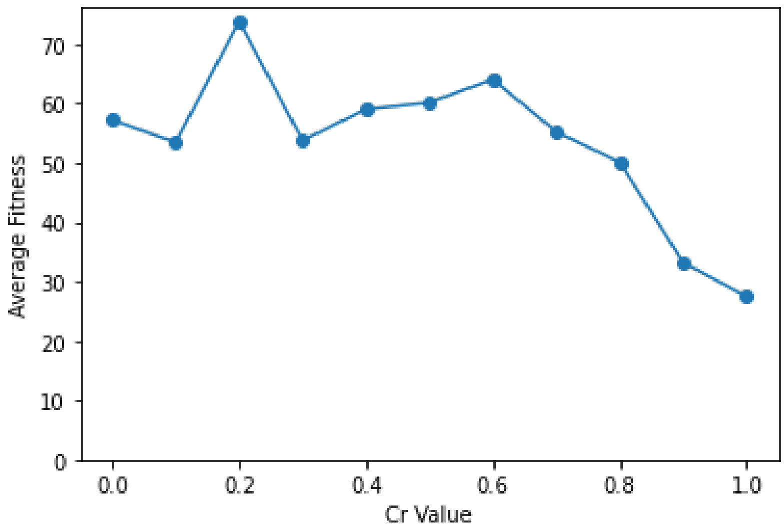

Fig. 3. Cr and Mr Combination Test Graph

Table 5. The Results of Number of Generations Testing

Num Gen	Number of Test							*Average Fitness*
	1	2	3	...	8	9	10	
10	28.29	11.27	23.56	...	15.39	19.83	28.5	22.54
20	28.74	22.97	35.19	...	41.29	25.54	27.93	34.895
30	29.97	17.96	78.31	...	33.34	38.24	51.47	44.116
40	41.08	37.76	47.87	...	112.23	105.15	29.31	56.419
50	81.17	67.16	41.65	...	85.76	44.09	29.33	60.976
60	42.96	63.05	34.49	...	23.89	121.36	89.05	63.155
70	129.7	123.92	143.47	...	59.24	32.5	98.62	85.74
80	214.13	61.05	149.48	...	50.92	95.33	47.42	86.901
90	50.99	26.02	50.76	...	78.74	60.5	45.66	49.026
100	70.32	58.07	119.62	...	78.06	63.45	121.07	76.789
110	70.57	70.87	259.74	...	37.02	188.32	77.7	90.956

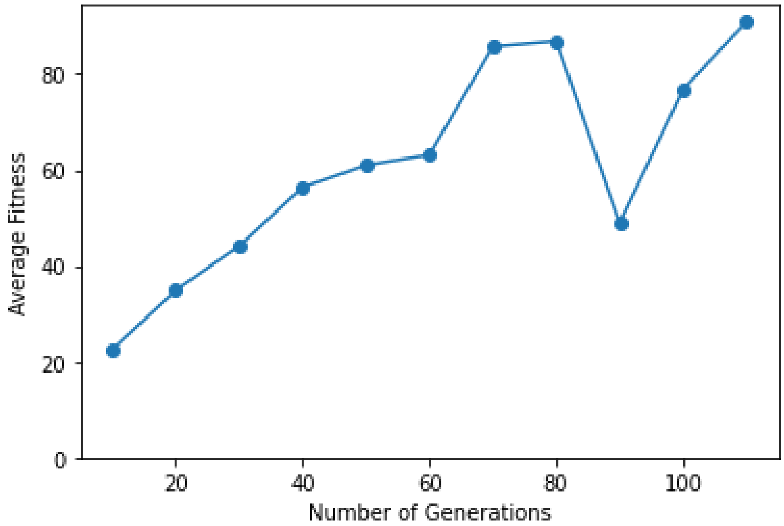

Fig. 4. Number of Generations Test Graph

Table 6. Input Parameter of System Testing

Age	Gender	Body Weight (Kg)	Body Height (cm)	Daily Activity
12	Female	38	145	Lightly active
15	Male	45	156	Moderately active
17	Male	45	160	Very active
20	Male	54	173	Lightly active
21	Female	50	170	Moderately active
22	Female	48	165	Sedentary
25	Male	65	180	Super active
28	Female	56	169	Moderately active
30	Female	54	171	Lightly active
35	Male	75	180	Very active

Table 7. The Results of Food Recommendation System Test

No	Energy Need	Total Food Energy	Nutritional Difference			Fitness Value
			Carbohydrate	Protein	Fat	
1	1683 kcal	1679 kcal	0.29 %	2.53 %	0.14 %	102.04
2	2108 kcal	2110 kcal	0.72 %	3.1 %	0.09 %	53.36
3	2357 kcal	2361 kcal	0.57 %	1.81 %	0.62 %	54.92
4	2110 kcal	2113 kcal	0.25 %	2.03 %	1.02 %	63.29
5	2080 kcal	2082 kcal	0.03 %	0.47 %	0.8 %	193.42
6	1571 kcal	1559 kcal	0.13 %	3.75 %	1.4 %	68.63
7	3204 kcal	3213 kcal	0.7 %	2.62 %	1.1 %	29.22
8	2116 kcal	2102 kcal	0.18 %	1.7 %	1.34 %	73.58
9	1842 kcal	1825 kcal	0.2 %	2.14 %	2.54 %	56.69
10	3028 kcal	3002 kcal	0.24 %	4.21 %	0.27 %	39.28
Average			0.33 %	2.44 %	0.93 %	73.443

B. Figure

From the results of population size test, combination of cr & mr test, and number of generations test, the most optimal genetic algorithm parameters are population size = 80, cr = 0.2, mr = 0.8, and number of generations = 70. These parameters will be used in system testing. The system testing is aimed at assessing the genetic algorithm in optimizing daily nutrition. The system created will be tested with several input parameters in Table 6.

Each input parameter will be tested on the system to see the difference in the nutritional content obtained. The difference in nutritional content will be represented in the form of a percent which is obtained by means of the difference in nutrition / nutritional needs * 100%. The results of the system tests carried out are shown in Table 7.

From the test results obtained, the system is able to provide food recommendations with a nutritional difference below 5%. Likewise, the total food energy recommended by the system is able to approach the daily nutritional needs of the user. It can be concluded that the genetic algorithm is able to optimize nutritional needs quite well.

IV. Conclusion

This research implements a genetic algorithm to optimize nutrition and food recommendations. The results of food recommendations in breakfast, lunch, dinner, and snack menus using a genetic algorithm. The results of food recommendations have a nutritional difference below 5% of daily nutritional needs, so it is very effectively used for optimization problems. The subsequent study will apply a better chromosome representation and combine it with another method to get better food recommendations.

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