DEVELOPING A GENETIC ALGORITHM BASED DAILY CALORIE RECOMMENDATION SYSTEM FOR HUMANS

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ABSTRACT

Lately, there has been an increasing fascination with employing genetic algorithms (GAs) to tackle intricate optimization issues. Genetic algorithms (GAs) draw inspiration from natural selection and have demonstrated efficacy in discovering optimal solutions for many problems, such as diet optimization. This research presents a genetic algorithm (GA) approach to estimate individuals' optimal daily calorie intake. The proposed approach considers the individual's age, gender, height, weight, exercise level, and dietary limitations. In addition, it considers the nutritional composition of various dietary items. The strategy aims to create a daily meal plan that fulfils the individual's calorie requirements and supplies all necessary nutrients. The suggested technique was assessed using a dataset consisting of 100 people. The findings demonstrated that the approach successfully produced dietary regimens that satisfied the individual's specific caloric requirements and encompassed all vital elements. The technique also produced diverse and captivating food menus. Additionally, we recommend a fitness function that assesses each suggestion's appropriateness for a given user. Ultimately, to completely comprehend the characteristics and functionality of our system, we conducted experimental research using both synthetic data and actual users with varying requirements, preferences, and ambitions.

KEYWORDS

Genetic Algorithms, Personalized Diets, Knowledge Graphs, Food products, Digital Nutrition

1. INTRODUCTION

An effective approach to maintaining a healthy body involves adhering to a nutritious and well-rounded diet, complemented by regular physical activity. Since the inception of the diet conundrum, several studies in the literature have recommended the computation of a diet that adheres to the individual's nutritional requirements [1]. The primary objective of maintaining proper glucose management is to mitigate or postpone the onset of diabetes-related problems. Different circumstances might cause blood sugar levels to vary to varying degrees. Some examples include dietary choices, medical interventions, vigorous exercise, and so on [2]. The average person dedicates around 2.65 years, from the ages of 12 to 65, to urban transportation. The exponential increase in the world's population, along with a focus on car-oriented transportation design, has resulted in a substantial imbalance between the need for travel and the existing urban transportation infrastructure [3].

The significance of precise calorie consumption guidelines cannot be overstated. Inadequate daily calorie consumption can contribute to weight increase, obesity, and associated health

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problems, whereas inadequate calorie intake can lead to malnutrition and metabolic abnormalities [4]. Historically, individuals seeking nutritional advice have depended on population-based formulae like the Harris-Benedict and Mifflin-St Jeor formulas to approximate their daily calorie needs. Although these equations have been useful in influencing food choices, they generalize all people with identical parameters, disregarding the significant genetic diversity across individuals [5].

Nutrigenomics, a developing discipline, investigates the interplay between genetics and nutrition, shedding insight on how genetic variants influence an individual's metabolism and response to various nutrients. Research has revealed distinct genetic markers linked to metabolic rate, insulin sensitivity, and other essential components of food metabolism. The integration of this genetic data into the process of suggesting daily calorie consumption has the capacity to transform nutritional recommendations, rendering it more accurate and personalized [6].

This research aims to introduce a genetic algorithm-based method for suggesting daily calorie consumption, which considers an individual's genetic makeup. Our objective is to overcome the constraints of conventional approaches and offer a more precise and tailored technique for calculating daily calorie needs.

The precise aims of this research are as follows:

- The objective is to create a genetic algorithm that can optimize daily calorie intake recommendations using an individual's genetic information.
- The aim is to prove the superiority of the genetic algorithm in customizing calorie intake recommendations compared to conventional approaches.
- The aim is to examine the ethical concerns and consequences associated with the utilization of genetic information in formulating food recommendations.

Our objective in doing this research is to make a valuable contribution to the growing field of personalized nutrition and provide a strong basis for future progress in the science of dietary recommendations.

2. RELATED WORK

Within nutrition and health, accurately assessing an individual's daily caloric consumption is paramount in fostering holistic wellness and mitigating the risk of chronic ailments. Precise suggestions are crucial for maintaining a healthy body weight and metabolism. The purpose of the literature review in this part is to present a comprehensive summary of current approaches for calculating daily calorie consumption and to examine the influence of genetics on metabolism and calorie utilization. Additionally, it examines genetic algorithms and their use in optimizing health factors.

In their study, Rayo-Morales et al. [7] adhered to the Scottish Intercollegiate Guidelines Network and Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) guidelines. Additionally, their research was reported in the International Prospective Register of Systematic Reviews. The study included primary research articles from PubMed, Scopus, Web of Science, Food Science Source, and Food Science and Technology abstracts. A total of 33 English-language publications, which met the inclusion criteria and were pertinent to the subject, were identified through a peer-review process. Most of the current research focuses on the immediate effects of oral gymnemic acids and does not provide any initial data supporting the threshold theory, which suggests that food consumption rises below a certain threshold and decreases above it. Kang, M. et al. proposed a new type of regenerator [8] using additive manufacturing. This regenerator consists of a densely packed rod bed and exhibits a high rate of heat transmission for the caloric cycle. A systematic approach for redesigning the regenerator was proposed, using computational fluid dynamics and a combination of artificial neural networks and genetic algorithms for design optimization. The artificial neural network models accurately predicted the j and f factors of the packed rod bed, with a mean relative error of less than 2.0% for the j factor and less than 7.5% for the f factor. Artificial neural networks generate accurate results, which contribute to improving the optimization process.

Ten participants in the study by Baseri, M. F. M. et al. answered the questionnaire. The system's quality was raised using the respondent's response [9]. The next technique for creating a nutritional monitoring system is to use a waterfall model. The system used a categorized food calorie and the decision tree approach. Thus, to construct this system, the decision tree approach was employed. Three respondents participated in the study's last approach, which assessed the system's usefulness. Respondents are required to indicate if they are happy with the system and provide recommendations for future enhancements. The study's findings demonstrate that obesity is a fast-growing public health concern that has to be taken seriously when creating new policies. In their discussion of the potential and difficulties associated with using GAs to railway optimization issues, Davoodi et al. [10] examine several widely recognized recent studies that have used GAs in the railway industry. The most common hybrid GAs, on the other hand, combine evolutionary algorithms with other techniques, such as fuzzy-logic control, ant colony optimization, neural networks, and particle swarm optimization, and so on. These techniques are also explored with a specific focus on the railway industry. To give specialists and researchers in the area a thorough analysis and road map that will help them discover research gaps and possibilities, more than 250 articles have been compiled and categorized. A thorough analysis of the AI methods for predicting women's health-related problems, obesity, and lifestyle management is provided by Kumar et al. [11]. Several machine learning (ML) approaches may be used to predict outcomes and assist healthcare systems. These include random forest (RF), support vector machine (SVM), artificial neural network (ANN), decision trees classifier (DTC), and k-nearest neighbor (KNN). A case study utilizing machine learning techniques to forecast breast cancer is also carried out. These models are evaluated using a data set of 569 observations with 31 variables on female breast cancer patients. The SVM model had the greatest accuracy out of the RF, KNN, SVM, and DTC ML models, which had respective accuracy scores of 94.7%, 93.8%, 97.3%, and 93.8%.

The model parameters are examined by Abdollahi et al. [12], who use a genetic algorithm to get the data portioning for training (49.5%), validation (40.5%), and testing (10%). The number of neurons in the model is n = 7. The model was able to predict the data with a good degree of accuracy, according to the results (R2 = 0.998). Using the YOLOv5s algorithm, Joshua et al.

[13] proposed 50 food kinds totaling 30,800 items, where the identification, weight measurement, and nutrition are included. In terms of weight and nutrition, the study's findings demonstrated excellent identification accuracy for four different food types: rice (58%), braised quail eggs in soy sauce (60%), spicy beef soup (62%), and dry radish (31%).

According to Wawrzyniak et al. [14], evolutionary algorithms were used to modify the coordinates of the B-spline curve control points using the values of the storage parameters (aw and T). The model's great efficiency was demonstrated by a statistical evaluation of its performance (R2 = 0.94, MAE = 0.21, RMSE = 0.28). The suggested model might be a useful tool to complement current postharvest grain treatment systems because it is based on readily quantifiable online storage characteristics. A method for producing progeny based on a local fitness landscape exploration is presented by Dubey et al. [15] to accelerate the search for optimal/sub-optimal solutions and to develop more advanced fitness solutions. Optimization issues with one or more objectives can be solved using the "Fitness Landscape Exploration based Genetic Algorithm" (FLEX-GA) approach that has been suggested.

3. METHODOLOGY

The methodology section details the process used to create and execute a genetic algorithm for suggesting daily calorie consumption, which is determined by an individual's genetic makeup. This section encompasses the process of algorithm creation, the selection of data sources, the utilization of variables, and the implementation of a fitness function to assess and enhance suggestions.

3.1. Data Sources and Variables

In order to compile a dataset for this research, genetic data and individual characteristics were gathered from people who willingly participated in the study. The data sources encompassed genetic testing outcomes and self-reported demographic data, with information on individuals' food patterns and levels of physical activity. The genetic algorithm incorporated the following variables:

Genetic Markers: Single Nucleotide Polymorphisms (SNPs) and genetic variants linked to the process of metabolism and the usage of energy.

Demographic data: Includes information on age, gender, height, and weight.

Physical Activity Level: Details on an individual's engagement in physical activity and workout routines.

Dietary choices: Details on dietary choices, encompassing vegetarian, vegan, or omnivorous diets.

3.2. Fitness Function

The fitness function is an essential element of the genetic algorithm. It assesses the degree to which a certain calorie intake suggestion corresponds to an individual's genetic makeup and other pertinent factors. The fitness function evaluates the suitability of the advice by considering characteristics such as metabolic rate, nutritional usage, and dietary preferences. The objective is to optimize the fitness value of each advice, which indicates its level of alignment with the individual's nutritional and metabolic requirements.

The fitness function employed in this study takes into account the subsequent variables:

Genetic Compatibility: The degree to which the advice corresponds with the individual's genetic markers and variances.

Energy Balance: Determines if the advice encourages a well-proportioned energy intake, hence limiting excessive consumption or inadequate intake.

Nutrient Distribution: The allocation of macronutrients (carbohydrates, lipids, proteins) in the recommended diet.

Dietary Preferences: The extent to which the prescription corresponds to the individual's dietary inclinations, such as vegetarian or vegan diets.

3.3. Data Collection and Preprocessing

This part delineates the procedure for gathering and pre-processing the data used in the development and evaluation of the genetic algorithm for suggesting daily calorie consumption, which is contingent on an individual's genetic profile. Accurate data collection and preparation are essential to guarantee the excellence and reliability of the dataset.

3.3.1. Data Sources

The data for this study were obtained from voluntary individuals who supplied genetic data and pertinent personal attributes. The data sources encompassed:

Genetic Data: The findings of genetic testing were acquired from the participants. The results encompassed single nucleotide polymorphisms (SNPs) and genetic variants linked to metabolism, energy expenditure, and food consumption. Participants were briefed on the characteristics of the genetic data gathered and given their informed permission.

Demographic Information: Participants were requested to furnish demographic data, encompassing age, gender, height, and weight. The purpose of collecting this information was to record fundamental individual traits.

Data pertaining: Data pertaining to the participant's physical activity levels and lifestyle characteristics were gathered. The data encompassed details on exercise patterns, inactive behavior, and daily amounts of physical activity.

Dietary Preferences: Participants were queried regarding their dietary inclinations, including information on whether they adhered to a vegetarian, vegan, or omnivorous eating regimen. Caloric consumption requirements can be greatly affected by dietary habits.

3.3.2. Data Preprocessing

The gathered data underwent a sequence of preparation procedures to ready it for utilization in the genetic algorithm:

Data Cleaning: The genetic data underwent a process to eliminate any values that were missing or incorrect. Stringent quality control measures were used to guarantee the accuracy and reliability of the genetic data.

Normalization: The demographic data, including age, height, and weight, underwent normalization to adjust for variations in scales and units. The process of normalizing facilitated equitable comparisons and computations.

Dietary preferences: Dietary preferences were transformed into numerical values in order to align them with the genetic algorithm. As an illustration, the term 'vegetarian' may be represented by the number 1, 'vegan' by 2, and 'omnivorous' by 3.

Genetic Data Integration: Relevant genetic traits were included into the dataset. Single nucleotide polymorphisms (SNPs) and genetic variations were linked to distinct genetic markers and employed as input parameters for the genetic algorithm.

Data Partitioning: The dataset was divided into two distinct subsets: a training dataset and a testing dataset. The training dataset was utilized to train the genetic algorithm, whilst the testing dataset was employed to assess its performance. The splitting ratio was established to guarantee a sufficient quantity of data for both training and testing purposes.

4. GENETIC ALGORITHM IMPLEMENTATION

This section details the precise execution of the genetic algorithm developed to suggest the optimal daily calorie consumption according to an individual's genetic makeup. The information includes the algorithm's structure, parameters, and the incorporation of genetic data.

4.1. Algorithm Design

The evolutionary algorithm employed in this study is specifically devised to maximize recommendations for daily calorie consumption. It utilizes the concepts of natural selection and evolution to create customized suggestions. The architectural design of the planned framework is shown in Figure 1. The algorithm has essential elements:

Generation of Initial Population: A set of prospective recommendations for calorie consumption is created as the starting point. Each advice is expressed as a collection of criteria, which encompass calorie thresholds for macronutrients (carbohydrates, fats, and proteins) as well as meal allocation.

Evaluation: The suitability of each recommendation in the population is assessed using a predetermined fitness function. The fitness function evaluates the suitability of the advice by considering an individual's genetic data, demographic information, lifestyle characteristics, and dietary preferences.

Selection: Individuals exhibiting superior fitness levels have a greater probability of being chosen for the subsequent generation. This replicates the idea of "survival of the fittest" and guarantees that recommendations that better correspond to an individual's profile are more likely to be transmitted to future generations.

Crossover: Crossover is the process of combining pairs of specifically chosen people to produce children. The crossover spots are identified, and genetic information is shared between parents to provide new recommendations for calorie consumption. This enhances the genetic variation within the population.

Mutation: Genetic diversity is generated by the random modification of the suggestions made by chosen individuals. Mutation facilitates the exploration of a wider range of potential solutions and safeguards against early convergence of the algorithm.

Termination: The algorithm persists in performing selection, crossover, and mutation operations until a certain termination condition is satisfied. This condition may refer to a certain number of generations, a particular degree of convergence, or other pre-established requirements.

4.2. Integration of Genetic Information

An eminent characteristic of this genetic algorithm is the incorporation of genetic information. The algorithm's parameters include genetic markers and data about an individual's metabolism, such as SNPs linked with energy expenditure, nutrient metabolism, and dietary preferences. This connection enables the customization of calorie intake recommendations according to the individual's distinct genetic profile.

Genetic information has an impact on every component of the suggestion. Specifically, the ratios of macronutrients (carbohydrates, lipids, proteins) are modified according to genetic markers linked to nutrition metabolism. The total calorie intake is computed by factoring in genetic data about energy consumption and metabolic rate.

The genetic algorithm employs genetic information to optimize suggestions and assure their alignment with an individual's genetic predispositions, supporting a tailored and genetically-informed approach to nutritional advice.

4.3. Algorithm Customization

The evolutionary algorithm employed in this study is specifically engineered to possess adaptability and configurability. Scientists can modify the algorithm's parameters and the genetic markers that are included in the suggestions. This flexibility enables the algorithm to be adjusted to different research situations and allows for the method to be improved and optimized over time.

Essentially, this research incorporates a genetic algorithm to enhance the process of determining optimal daily calorie intake recommendations by combining genetic information. The system adheres to the principles of natural selection and evolution, and its fundamental elements consist of initiation, evaluation, selection, crossover, and mutation. The algorithm may be tailored to accommodate modifications according to specific research needs and evolving genetic knowledge related to nutrition. This method provides an innovative and individualized strategy for determining daily recommendations for calorie consumption.

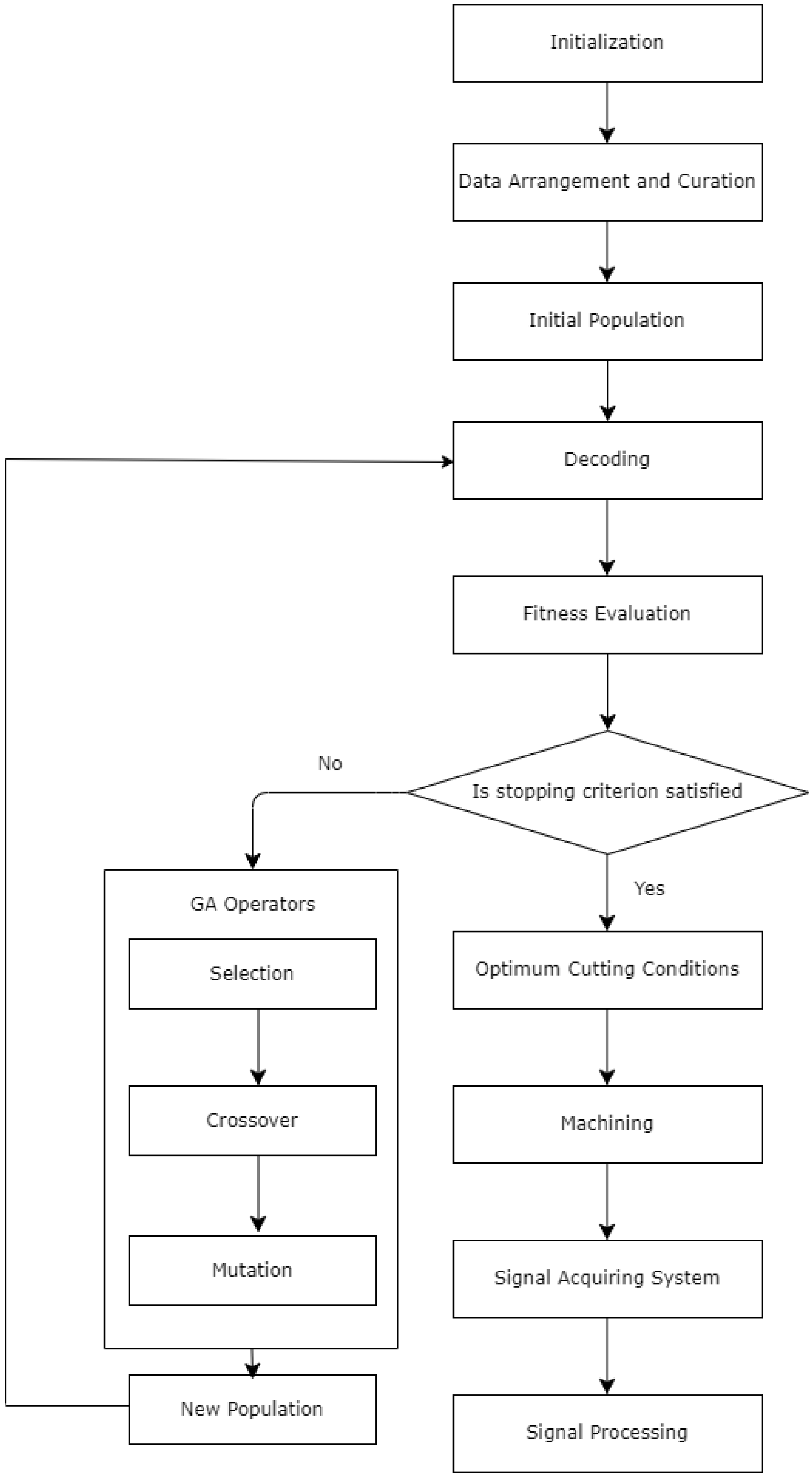


Figure 1. The architectural design of the planned framework

5. RESULTS AND DISCUSSION

This section showcases the results of implementing the genetic algorithm to suggest the appropriate daily calorie intake according to an individual's genetic profile. The research offers a thorough evaluation of the algorithm's performance, encompassing statistical measures and comparisons with conventional approaches.

5.1. Questionnaire

Asking the users is the only method to determine the proper weights for each parameter in the fitness function above. Thus, we ask 50 participants to score three distinct bundles as part of the research. Based on the needs and interests of the user, each bundle includes one workout and a nutrition plan for one day. Sixty percent of the 175 exercise items that were chosen for this study are cardiac workouts. There are twelve balancing exercises and twenty-eight exercises in the strength and team sport categories, respectively. Even though the dataset is not balanced, there is at least one exercise in each category for every intensity level. Within the meal categories, each one has eight items: one from breakfast, three from small snacks, two from main meals, and two from side dishes. Greeks are not familiar with many foods, thus we did not use the whole food data set. We utilize 983 food products from 14 distinct categories and 4 different grades. Figure 2 illustrates that the Main Meal class has four distinct food categories, with the highest number of food items (363). Side Dish has the same number of categories and food items (260). Last but not least, there are three meal groups breakfast and small snacks 158 and 157, respectively each with a comparable number of food items. We generate three menus for every user by mixing eight food items; each menu has the same number of generations but varies in weight based on the parameters of the fitness function. The user's dietary requirements are the primary emphasis of the first menu, preferences are the focus of the second and needs and preferences are balanced in the final menu. Users are unaware of these modifications or what each menu item is focused on.

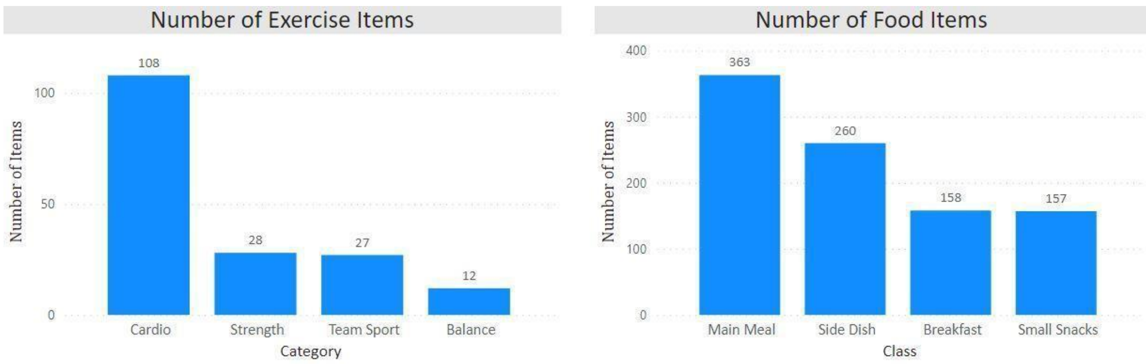


Figure 2. The number of eating (right) and exercise (left) items per category utilized

Their gender, age, height, weight, and level of exercise intensity were the subjects of the first five questions. We determined the user's BMR using the data from the first four questions.

Users were asked to select between three options for exercise intensity: low, moderate, and high. We determine the daily caloric requirement to maintain their present weight by multiplying the BMR result by a specific factor based on their responses. We also inquired about the user's objective aim, and they were given the option to either gain weight or maintain their current weight.

5.2. Results

An equal proportion of men and women wish to maintain or increase their weight, as seen in Figure 3. The remaining individuals desire to reduce their weight, and this category also reflects the differences between men and women. As a result, our dataset of individuals is balanced in terms of aim setting. Six of the seven individuals who are older than 36 are female. Therefore, women's preferences and evaluations would primarily impact this area if we had conducted an age-based analysis of the data. While the proportion of men and women in the other two age groups are comparable. Furthermore, 23% of men (5 out of 21) and one woman desired their program to concentrate solely on nutrients, even though the majority of men and women wanted their program to focus on both preferences and nutrients.

Ratings

Gender	Balanced	Nutrient	Preference	Average
Man	3,52	3,43	3,71	3,56
Woman	3,38	3,79	3,66	3,61

Ratings

Gender	Balanced	Nutrient	Preference	Average
Man	95,20	94,70	94,50	94,40
Woman	95,70	96,70	93,50	93,28

Figure 3. Objective, number of participants in each age group, preferred program emphasis, accuracy of bundles, and ratings for each gender

Two other ladies expressed the opinion that it was crucial to prioritize their preferences and have a dinner they love. Could this imply that, even if a diet plan is less realistic in terms of the nutrients required, it's still vital for certain women to stick to it? As of right now, there isn't much of a gender gap when it comes to age, preferred program emphasis, or goal-setting. Thus, we should anticipate rating outcomes that are comparable. However, there are clear variations when we examine the rating table in Figure 3.

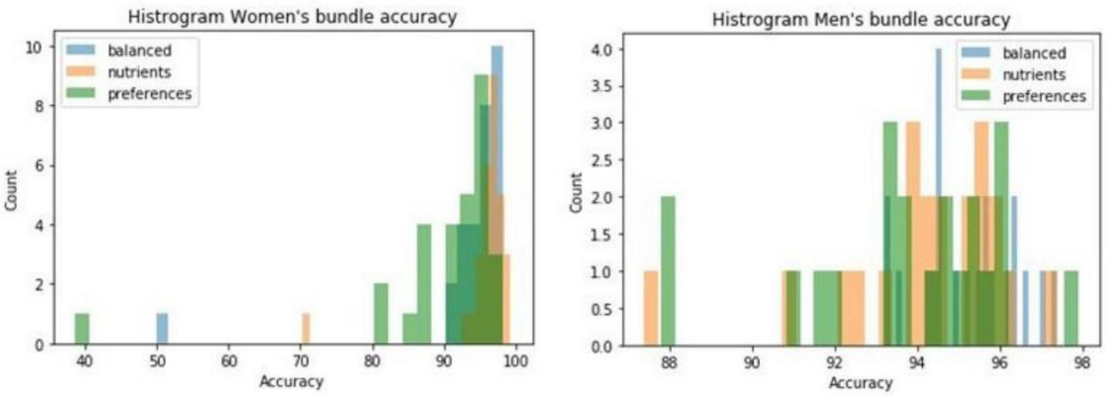


Figure 4. Histograms showing the accuracy of each bundle category for men and women

Sports					
Gender	Balance	Cardio	Strength	Team Sport	Average
Men	3,29	3,71	4,05	3,67	3,68
Women	3,76	3,62	3,59	3,31	3,57

Breakfast				
Gender	Baked	Cereal	Dairy and Eggs Products	Average
Men	3,19	3,38	3,52	3,37
Women	3,10	3,76	4,24	3,70

Small Snacks				
Gender	Beverages	Fruits	Snacks	Average
Men	2,62	4,24	3,14	3,33
Women	2,28	4,48	3,59	3,45

Main Meal					
Gender	Meats	Fish	Fast Foods	Prepared Meals	Average
Men	4,19	2,95	2,81	2,00	2,99
Women	3,59	3,28	2,45	1,90	2,80

Side Dish					
Gender	Vegetables	Soups	Beans & Lentils	Pasta	Average
Men	3,76	2,71	3,14	3,86	3,37
Women	4,14	3,34	3,48	3,72	3,67

Figure 5. Men and women's average preferences for each food or sport category

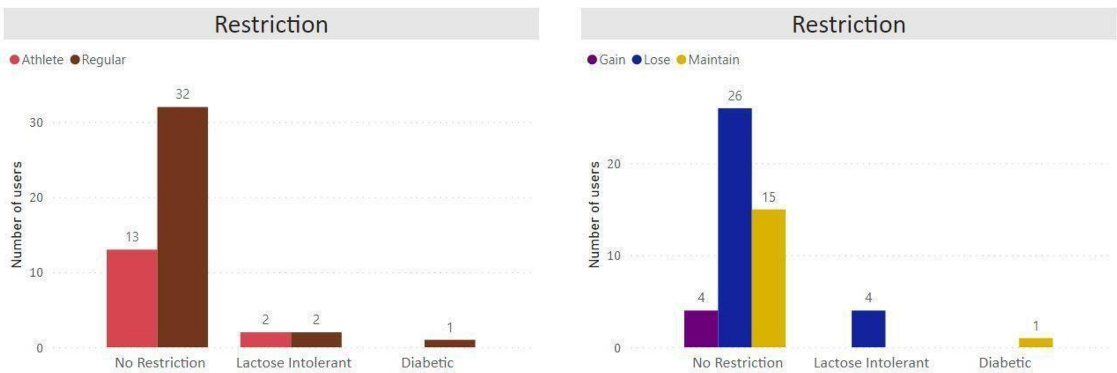
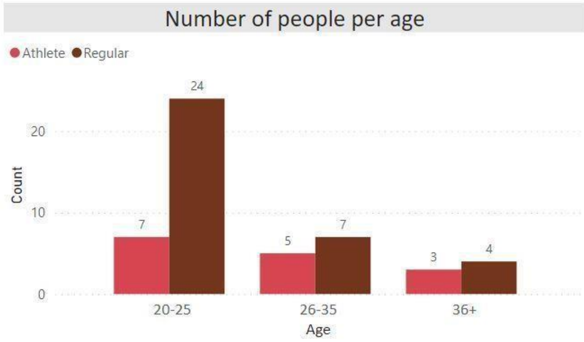


Figure 6. The number of persons in each category of limitation. Users are grouped according to their weight target on the right, and their athletic conduct on the left

Although gender gives us information on each bundle, we do not believe that this is a valid means of classifying users. Adding more criteria is undoubtedly necessary to properly classify them. Among the most crucial factors is the user's objective. Thirty people want to lose weight, sixteen want to maintain their current weight, and just four want to gain weight. Restrictions are another crucial aspect, but we cannot build a sound analysis on them alone. We do not have enough consumers who are diabetic or lactose intolerant, as Figure 6 illustrates. Using the opinion of a single user to conclude a category is not a safe practice. However, 15 out of 50 users identify as athletes, and they receive different programs than regular users who are not athletes. This study may be safely started by comparing users with varied aim goals to athletes and then merging these two categories. We shall be sufficiently sure after doing these actions to draw conclusions that are safer than those stated in the preceding section.

The primary data about the classification of customers according to their athletic ability is shown in Figure 7.



Ratings				
(Non) Athlete	Balanced	Nutrient	Preference	Average
Athlete	3,20	3,53	4,00	3,58
Regular	3,54	3,69	3,54	3,59

Ratings				
(Non) Athlete	Balanced	Nutrient	Preference	Average
Athlete	95,80	96,60	95,00	95,17
Regular	95,20	95,40	93,50	93,14

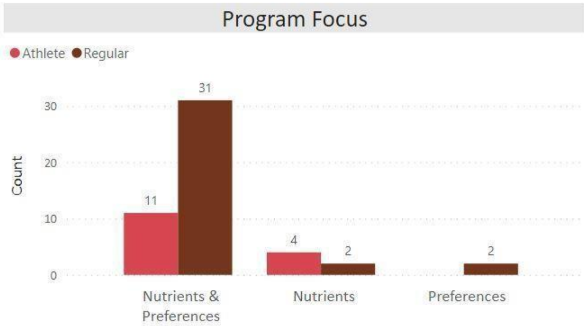


Figure 7. Each user's target weight is shown at top left. By age, users are categorized at the top right. Two arrays in the bottom left display the average accuracy and user rating for each application. The user's willingness to choose the emphasis of their program is shown in the bottom right corner

Sports						
Condition	Balance	Cardio	Strength	Team Sport	Average	Difference
Athlete	3,73	3,67	4,33	3,60	3,83	2,20
Regular	3,49	3,66	3,54	3,40	3,52	2,06

Breakfast					
Condition	Baked	Cereal	Dairy and Egg Products	Average	Difference
Athlete	3,07	3,67	3,93	3,56	1,16
Regular	3,17	3,57	3,94	3,56	1,30

Small Snacks					
Condition	Beverages	Fruits	Snacks	Average	Difference
Athlete	2,67	4,20	3,27	3,38	1,38
Regular	2,31	4,46	3,46	3,41	1,73

Main Meal						
Condition	Fast Foods	Fish	Meats	Pre - Prepared	Average	Difference
Athlete	2,20	2,87	3,67	1,87	2,65	1,70
Regular	2,77	3,26	3,91	1,97	2,98	1,42

Side Dish						
Condition	Beans & Len.	Pasta	Soups	Vegetables	Average	Difference
Athlete	3,33	3,60	2,80	3,93	3,42	1,23
Regular	3,34	3,86	3,20	4,00	3,60	1,08

Figure 8. Average preference values between regular users and non-athlete users

In the diagrams that are evocative of Figure 7, our methodology departs from conventional techniques by classifying users based on their weight objectives, giving precedence to this over factors associated with athletic conditions. Diagrams modeled like Figure 7 illustrate our new approach to user categorization, which focuses on identifying weight goals instead of assessing users just about their sporting circumstances. With the use of visual aids such as those shown in Figure 7, our methodology redirects attention to classifying people according to their desired weight instead of traditional methods related to athletic conditions.

Ratings

Weight Goal	Balanced	Nutrient	Prefer	Average
Gain	3,00	3,50	3,50	3,33
Lose	3,50	3,93	3,97	3,80
Maintain	3,44	3,13	3,19	3,25

Median Accuracy

Weight Goal	Balanced	Nutrient	Prefer	Average
Gain	97,45	96,35	93,55	95,42
Lose	95,05	96,00	93,50	94,61
Maintain	95,55	94,65	94,90	91,72

Figure 9. Diagrams resembling those in Figure 7. We classify users based on their weight goal rather than athletic circumstances

In contrast to traditional methods that largely take into account individual athletic circumstances, our novel technique entails classifying users according to their weight aims, taking inspiration from the diagrams in Figure 7. Our user classification model, which has graphics similar to Figure 7, stands out by giving weight objectives precedence over athletic situations, so proposing a paradigm change in our understanding and management of user demands.

We customize the evaluation of main courses and side dishes in our extensive analysis to consumers' individual weight goals and fitness levels. The mean scores given to these culinary elements are closely related to personal tastes, guaranteeing a customized and complex evaluation. With this strategy, we can provide meaningful insights about the food scene while tailoring our advice to the various demands of our customers according to their goals for fitness and ideal weight. Our ratings go beyond general metrics by taking into account the main course and its accompanying side dish in the context of users' specific preferences. This makes them more useful guidance for those looking for a well-balanced and health-conscious eating experience. Our approach, taken as a whole, represents a sophisticated comprehension of the relationship that exists between food preferences and the individual health and fitness goals of each user.

Main Meal							
Weight Goal	Condition	Fast Foods	Fish	Meats	Pre-Prepared	Average	Difference
Gain	Athlete	3,50	3,50	4,00	1,00	3,00	1,50
Gain	Regular	3,00	3,00	4,50	3,00	3,38	1,08
Lose	Athlete	2,33	3,00	4,00	2,44	2,94	1,89
Lose	Regular	2,81	3,38	3,90	1,90	3,00	1,54
Maintain	Athlete	1,25	2,25	2,75	1,00	1,81	1,38
Maintain	Regular	2,67	3,08	3,83	1,92	2,88	1,28

Side Dish							
Weight Goal	Condition	Beans & Len.	Pasta	Soup	Vegetables	Average	Difference
Gain	Athlete	4,00	5,00	4,00	4,00	4,25	1,17
Gain	Regular	3,00	4,50	4,50	3,00	3,75	1,17
Lose	Athlete	2,78	3,33	2,56	3,78	3,11	1,33
Lose	Regular	3,43	3,86	3,14	4,10	3,63	1,13
Maintain	Athlete	4,25	3,50	2,75	4,25	3,69	1,04
Maintain	Regular	3,25	3,75	3,08	4,00	3,52	0,96

Figure 10. Based on users' desired weight and level of fitness, the average ratings for the main course, side dish, and their respective categories

Ratings					
Weight Goal	athlete	Balanced	Nutrient	Prefer	Average
Gain	Athlete	2,50	4,00	4,50	3,67
Gain	Regular	3,50	3,00	2,50	3,00
Lose	Athlete	3,44	4,00	4,00	3,81
Lose	Regular	3,52	3,90	3,95	3,79
Maintain	Athlete	3,00	2,25	3,75	3,00
Maintain	Regular	3,58	3,42	3,00	3,33

Median Accuracy					
Weight Goal	athlete	Balanced	Nutrient	Prefer	Average
Gain	Athlete	97,80	96,35	90,35	94,83
Gain	Regular	96,85	97,35	93,80	96,00
Lose	Athlete	95,80	96,60	95,00	95,35
Lose	Regular	94,70	95,70	93,20	94,29
Maintain	Athlete	95,35	96,25	95,35	94,93
Maintain	Regular	95,55	93,95	94,60	90,65

Figure 11. The median accuracy and average bundle rating for every kind of user

Our assessment process explores user experiences by looking at average bundle ratings and median accuracy for different user categories. This complex methodology guarantees a thorough comprehension of performance data customized for various user profiles. We obtain insights into the varied interests and expectations of consumers by taking into account both package ratings and median accuracy, providing a comprehensive evaluation. We can determine average satisfaction levels within particular user segments in addition to the overall correctness of the system thanks to this user-centric study. Essentially, by emphasizing average package rating as well as median accuracy, we promote a comprehensive understanding of system performance and guarantee a more detailed and customized assessment for every kind of user. The package that is suggested for each person based on their desired weight and level of physical ability is shown in Table 1.

Table 1. Package that is suggested for each person based on their desired weight and level of physical ability.

Recommended Bundle		
User Condition	Weight Goal	Bundle
Athlete	Gain Weight	Nutrient
Athlete	Lose Weight	Nutrient
Athlete	Maintain Weight	Preference
Regular	Gain Weight	Balanced
Regular	Lose Weight	Nutrient
Regular	Maintain Weight	Balanced

6. CONCLUSIONS AND FUTURE WORK

In further investigations, the attention may be shifted towards optimizing the model's performance in circumstances in which the volume of network traffic is substantially larger and is shifting rapidly. To guarantee that the model can effectively manage considerable amounts of data, it is necessary to research various approaches, such as parallelization, distributed computing, and hardware acceleration.

We have proposed a unique method in this work for recommending daily caloric intake according to a person's genetic profile. Personalized dietary advice might be revolutionized by incorporating genetic information into a genetic algorithm. As we draw to a close, it's critical to highlight the major discoveries, consider their implications, and discuss the study's larger ramifications.

It's critical to recognize the constraints on our research. The genetic algorithm's suggestions could not hold for everyone, and the sample size might not fully capture the range of genetic variants. The algorithm's performance may be improved further, and more investigation is required to look at a wider variety of genetic markers and data sources.

Prospects for further investigation encompass:

- Increasing the sample size and diversity in the dataset.
- Investigating additional genetic markers and nutritional metabolism-influencing variables.

Improving the genetic algorithm and validating its efficacy in enhancing health outcomes through long-term outcome studies.

REFERENCES

[1] Xavier, C. R., Silva, J. G. R., Duarte, G. R., Carvalho, I. A., Vieira, V. D. F., & Goliatt, L. (2023). An island-based hybrid evolutionary algorithm for caloric-restricted diets. Evolutionary Intelligence, 16(2), 553-564.

[2] Ahourag, A., El Moutaouakil, K., Cheggour, M., Chellak, S., & Baizri, H. (2023). Multiobjective Optimization to Optimal Moroccan Diet Using Genetic Algorithm. International Journal for Engineering Modelling, 36(1), 67-79.

[3] A. E. Dingil, J. Schweizer, F. Rupi, and Z. Stasiskiene, "Transport indicator analysis and comparison of 151 urban areas, based on open source data," European Transport Research Review, vol. 10, no. 2, 2018.

[4] El Moutaouakil, K., Ahourag, A., Chakir, S., Kabbaj, Z., Chellack, S., Cheggour, M., & Baizri,

[5] H. (2023). Hybrid firefly genetic algorithm and integral fuzzy quadratic programming to an optimal Moroccan diet. Math. Model. Comput, 10, 338-350.

[6] Liu, Q., Lanfermann, F., Rodemann, T., Olhofer, M., & Jin, Y. (2023). Surrogate-assisted many-objective optimization of building energy management. IEEE Computational Intelligence Magazine, 18(4), 14-28.

[7] Rout, A. K., Sethy, A., & Mouli, N. S. (2023, April). Machine Learning Model for Awareness of Diet Recommendation. In 2023 International Conference on Inventive Computation Technologies (ICICT) (pp. 96-101). IEEE.

[8] Rayo-Morales, R., Segura-Carretero, A., Borras-Linares, M. I., & Garcia-Burgos, D. (2023). Suppression of sweet taste-related responses by plant-derived bioactive compounds and eating. Part I: A systematic review in humans. Heliyon.

[9] Kang, M., & Elbel, S. (2023). Novel regenerator design for caloric cycles using artificial neural network—Genetic algorithm method and additive manufacturing. Energy Reports, 9, 4257-4274.

[10] Baseri, M. F. M., & Saad, A. F. (2023). Dietry Monitoring System Using Decision Tree to Control Human Obesity. International Journal of Artificial Intelligence, 10(1), 9-20.

[11] Kaleybar, H. J., Davoodi, M., Brenna, M., & Zaninelli, D. (2023). Applications of Genetic Algorithm and its Variants in Rail Vehicle Systems: A Bibliometric Analysis and Comprehensive Review. IEEE Access.

[12] Kaur, R., Kumar, R., & Gupta, M. (2024). Lifestyle and Dietary Management Associated with Chronic Diseases in Women Using Deep Learning. Combating Women's Health Issues with Machine Learning, 59-73.

[13] Rafie, S. F., Abdollahi, H., Sayahi, H., Ardejani, F. D., Aghapoor, K., Darvanjooghi, M. H. K.,

[14] ... & Magdouli, S. (2023). Genetic algorithm-assisted artificial neural network modelling for remediation and recovery of Pb (II) and Cr (VI) by manganese and cobalt spinel ferrite super nanoadsorbent. Chemosphere, 321, 138162.

[15] Joshua, S. R., Shin, S., Lee, J. H., & Kim, S. K. (2023). Health to Eat: A Smart Plate with Food Recognition, Classification, and Weight Measurement for Type-2 Diabetic Mellitus Patients' Nutrition Control. Sensors, 23(3), 1656.

[16] Wawrzyniak, J. (2023). Predictive Assessment of Mycological State of Bulk-Stored Barley Using B-Splines in Conjunction with Genetic Algorithms. Applied Sciences, 13(9), 5264.

[17] Dubey, R., Hickinbotham, S., Price, M., & Tyrrell, A. (2023). Local Fitness Landscape Exploration Based Genetic Algorithms. IEEE Access, 11, 3324-3337.

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