Literature Review: Meal Selection Using Genetic Algorithms

Introduction

Diet is closely related to health good eating habits have a positive effect on human health, while improper diet will lead to obesity, type **2 diabetes** and other chronic diseases related to diet so a Dietary planning is necessary and also a complex optimization problem that requires balancing multiple nutritional constraints, cost limitations, and personal preferences. Traditional methods, while effective, often struggle with scalability and adaptability when the number of dietary variables increases. In recent years, computational intelligence techniques—especially **Genetic Algorithms (GA)**—have emerged as powerful tools for solving such multidimensional and nonlinear optimization problems. This literature review explores three scholarly papers that successfully apply genetic algorithms to the problem of meal or diet planning, analyzing the modeling approach, objective functions, constraints, genetic encoding strategies, and experimental outcomes. These optimization tasks often vary by geography, cultural food patterns, and health-related restrictions. As populations grow and diversify, ensuring nutritional sufficiency across communities becomes increasingly complex. Technology and artificial intelligence provide scalable solutions to assist policymakers, nutritionists, and individuals in making better food choices.

Paper 1: Optimization using Genetic Algorithm in Food Composition

Authors: Adriyendi, Yeni Melia

Published in: International Journal of Computing and Digital Systems, 2021

Link:https://www.researchgate.net/publication/357234565_Optimization_using_Genetic_Algorithm_in_Food_Composition

This paper applies Genetic Algorithm (GA) to optimize daily food composition based on Indonesian nutritional guidelines. The approach is based on converting consumption of vegetable protein, animal protein, carbohydrates, vegetables, fruits, and water into a mathematical model with a **24**-hour framework. The authors used **crossover and mutation** techniques across multiple generations to generate optimal diet combinations.

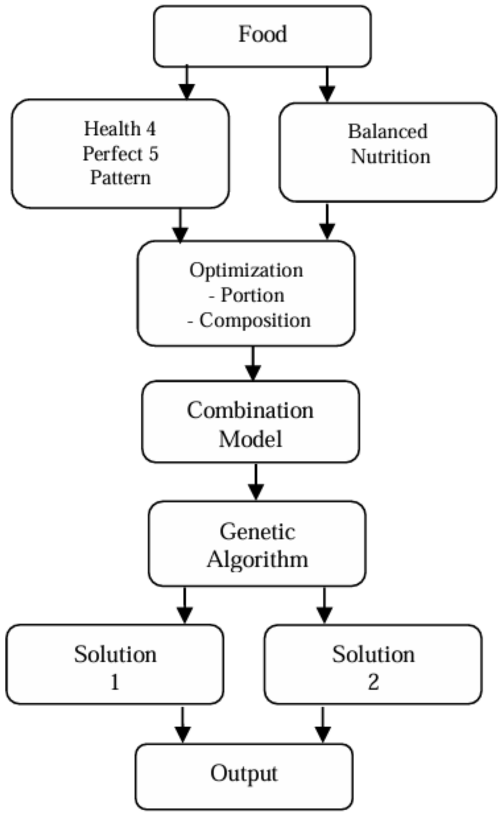

Figure 1. Structure of paper

Process Structure (Based on Figure 1): The optimization process consists of seven key elements:

1. **Food Element**: A data source providing information on available foods and their nutritional content.
2. **Nutritional Guidelines**:
    - **Healthy 4 Perfect 5 Pattern (Guide 1)**: A framework for structuring healthy eating habits.
    - **Balanced Nutrition (Guide 2)**: A guideline emphasizing nutrient-appropriate food consumption based on seven principles:
        - Eat a variety of foods regularly.
        - Maintain a clean lifestyle.
        - Exercise and monitor body weight.
        - Consume milk (categorized as a complementary/non-food item).

- Substitute milk with nutritionally equivalent foods/drinks if needed.
- Measure portion sizes for each food type.
- Drink 2 liters (8 glasses) of mineral water daily.

3. **Optimization Process**: A computational step to determine optimal food portions and compositions tailored to individual needs.
4. **Combination Model**: A mathematical formulation representing the relationships between food, nutrients, and dietary constraints.
5. **Genetic Algorithm**: A computational intelligence method used to solve the mathematical model, generating potential solutions by mimicking natural selection processes.
6. **Solution Output**: Alternative solutions (Solution 1 and Solution 2) representing different feasible food menus.
7. **Optimal Output**: The final optimized outcome, including:
    - Food menu recommendations.
    - Nutritional content details.
    - Meal timing schedules.
    - Food composition based on three models: Food Model, Consumption Model, and Composition Model.

Balanced Nutrition Framework (Figure 2): The Balanced Nutrition guideline promotes healthy eating by ensuring food compositions meet bodily nutrient needs. It is visually represented in Figure 2. The emphasis on portion control, variety, and hydration aligns with public health recommendations for sustainable nutrition.

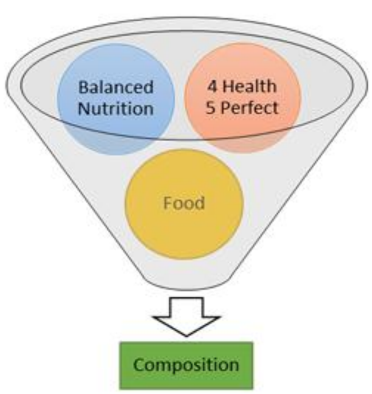

Figure 2. Composition framework

Two main solutions were derived through this process, each representing a distinct set of optimal food servings to meet the nutritional needs of healthy individuals.

The GA configuration involved a mutation rate of 50%, crossover rate of 5%, population size of 6, and max generation of 36. The fitness function measured deviation from the ideal total of 24 food servings per day. The evaluation phase compared initial and optimized solutions (6.13 vs. 3.22 average objective function value), showing notable improvement. A data model was created with variables representing different nutrient sources (e.g., 3a for vegetable protein, 8c for carbohydrates).

Final solutions (e.g., Chr [4] and Chr [6]) had zero deviation from the target nutritional requirement and included well-balanced values for all six food categories. The outcomes are presented as food, consumption, and composition models. These models not only serve as guidelines for individuals but also provide a foundation for public health nutrition policies in Indonesia. This work successfully demonstrates GA's potential in dietary modeling by translating qualitative guidelines into quantitative plans.

In addition to numerical improvements, the paper presents detailed chromosome tables that trace the evolution of solutions across generations. Table 6 illustrates the initialization phase, while Tables 7–10 show the step-by-step transformation through selection, crossover, and mutation. For example, chromosomes with high deviation values in the early generation (e.g., 9.20, 8.80) were replaced by those with minimal or zero deviation (e.g., 0.15 and 0).

Moreover, Figure 6 to Figure 8 visualize various GA stages, including initial population percentages, selection probabilities, and comparative analysis of Solutions 1 and 2. These visual aids enhance the understanding of GA's internal process and justify the convergence patterns observed in the optimization.

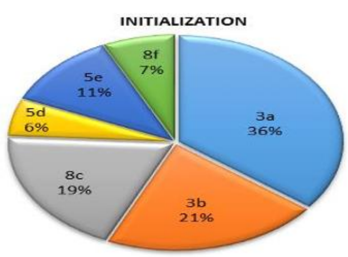

Figure 6. Graphic of initialization

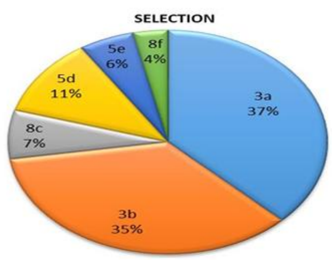

Figure 7. Graphic of selection

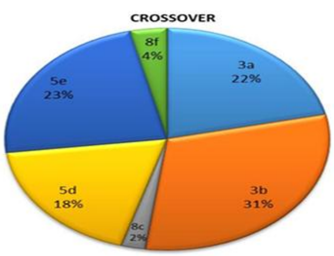

Figure 8. Graphic of crossover

Paper 2: Towards Automatically Generating Meal Plan Based on Genetic Algorithm

Authors: Nan Jia, Jie Chen, Rongzheng Wang, Mingliang Li

Published in: Soft Computing, Springer, 2024

Link:
https://www.researchgate.net/publication/377332321_Towards_automatically_generating_meal_plan_based_on_genetic_algorithm

Overview:
This paper proposes a novel method to automatically generate personalized, healthy meal plans that balance users' taste preferences with nutritional health standards using a genetic algorithm (GA). The approach addresses the challenge of creating meal plans that are both appealing to users and compliant with health guidelines, given the prevalence of unhealthy dietary habits and the complexity of optimizing recipe combinations.

Problem Context:

- Diet significantly impacts health, with improper eating habits linked to chronic diseases like obesity and type 2 diabetes.
- Analysis of 49,752 online Chinese recipes revealed that 62% are unhealthy, and user engagement (e.g., comments, favorites) often favors unhealthy recipes, highlighting the need for guided healthy meal planning.
- Challenges include balancing taste and health, and managing the large search space of recipe combinations for multiple meals over days.

Proposed Method:

Step 1: Recipe Recommendation

A multi-perspective convolutional neural network with an attention mechanism generates personalized recipe recommendations based on user preferences.

A recommendation score is calculated for each recipe based on its ranking in the recommendation list, reflecting user taste preferences.

Nutritional content (calories, protein, fat, carbohydrates, sodium) is computed from recipe ingredients using a Chinese food nutrition database.

Step 2: Meal Plan Generation

The meal plan generation is framed as an integer linear programming problem, aiming to maximize the recommendation score while ensuring nutritional content meets health standards (low fat, carbohydrates, and sodium).

A genetic algorithm approximates the solution by iteratively selecting recipe combinations for breakfast, lunch, and dinner, constrained by health criteria.

Recipes are categorized into breakfast, lunch, and dinner subsets to align with Chinese eating habits.

Health Scoring:

Recipes are scored based on fat, carbohydrate, and sodium content, with scores ranging from 3 (healthiest) to 9 (least healthy). Meal plans with scores of 3–5 are considered healthy.

The GA uses a fitness function that prioritizes high recommendation scores for healthy plans and penalizes unhealthy ones.

Experimental Results:

Dataset: 49,752 recipes, with health scores indicating 38.4% are healthy (scores 3–5).

Performance:

- The recipe recommendation model outperformed baselines (e.g., NeuCF, ItemKNN) with a Hit Ratio of 0.219 and NDCG of 0.118.
- Over 80% of generated meal plans were healthy (scores 3–5), with an average recommendation score of 22.7, indicating user satisfaction.
- A survey of 81 volunteers rated meal plans highly (83% scored ≥6/10, with 26% giving 7/10).
- Compared to random and hybrid methods, the proposed method generated healthier plans (80% vs. 20–40% healthy) with higher user satisfaction and reasonable recipe diversity.

Contributions:

- Captures user preferences via recommendation scores and nutritional content as constraints.
- Uses GA to efficiently solve the NP-hard problem of meal plan generation, reducing time complexity to $O(nmk)$.
- Demonstrates practical applicability through high user satisfaction and health compliance.

Future Work:

Improve recipe recommendation accuracy with better user-recipe datasets.

Develop a prototype system for real-world application, potentially collaborating with health agencies to refine and implement the system.

Paper 3: Personalized Nutrition Plans Using Genetic Algorithms: Optimizing Diets Based on Individual Genomic Data

Authors: Rakesh Gupta, Jahid Ali, Vishali, Dinesh Mahajan

Published in: International Journal of Food and Nutritional Sciences (IJFANS), 2022

Link:

https://ijfans.org/uploads/paper/5925423059dd457c60277c42d13c0b72.pdf

This paper introduces a genetic algorithm (GA)-based approach to create personalized nutrition plans by leveraging individual genomic data. Unlike generic dietary guidelines, this method uses nutrigenomics to tailor diets to genetic variations, optimizing health outcomes. GAs, inspired by natural selection, efficiently navigate complex dietary optimization, integrating genetic markers with nutritional needs to produce precise, individualized plans.

Key Points:

1. **Problem Context**:
    - Traditional dietary guidelines overlook genetic variations affecting nutrient metabolism, limiting their efficacy.
    - Genomic advances enable personalized nutrition by identifying markers (e.g., SNPs) linked to nutrient absorption, metabolism, and health risks.
    - Optimizing diets across numerous variables (nutrients, preferences, genetics) requires robust computational tools like GAs.
2. **Proposed Method**:
    - **Data Integration**:
        - Genomic data from sequencing (e.g., SNPs for vitamin D metabolism) is paired with dietary guidelines (e.g., nutrient intakes).
        - A database links genetic profiles to nutritional needs, factoring in absorption rates, metabolic differences, and preferences (e.g., vegetarian diets).
        - Preprocessing standardizes data for consistency, addressing missing values and formatting issues.
    - **Genetic Algorithm Framework**:
        - **Chromosomes**: Encode dietary plans, detailing food types, nutrient ratios, and amounts.

        - **Fitness Function**: Scores plans based on nutritional adequacy, genetic alignment, and practicality (e.g., respecting food intolerances).
        - **Selection**: Uses tournament or roulette wheel methods to favor high-fitness plans.
        - **Crossover/Mutation**: Combines parent plans and introduces random changes to ensure diversity and avoid suboptimal solutions.
        - **Termination**: Halts after 50 generations, satisfactory fitness (95% best score), or convergence (120 minutes).
    - **Implementation**:
        - Coded to process integrated datasets, running simulations across diverse genetic profiles.
        - Manages data flow and optimizes plans efficiently, ensuring practical applicability.
3. **Results**:
    - **Performance Metrics** (Table 4):
        - 50 generations, 100 population size, 120-minute convergence.
        - Average fitness score: 85%; best: 95%; high solution diversity.
    - **Comparison with Traditional Guidelines** (Table 3):
        - **Nutritional Adequacy**: 92% (GA) vs. 75% (+22.7%).
        - **Genetic Alignment**: 85% vs. 60% (+41.7%).
        - **Preferences**: 88% vs. 70% (+25.7%).
        - **Feasibility**: 90% vs. 65% (+38.5%).
    - Simulations and case studies confirmed plans were practical, user-friendly, and genetically optimized (e.g., tailored vitamin D intake).
4. **Contributions**:
    - Establishes GAs as scalable for personalized nutrition, exploring vast dietary combinations.
    - Enhances precision via genetic markers, surpassing generic guidelines.

- Produces adoptable plans respecting individual needs and restrictions, fostering compliance.

5. **Challenges and Future Work**:

   - Comprehensive genetic data is costly and not universally accessible.
   - Integrating diverse preferences and variable dietary responses is complex.
   - Future efforts include improving data access, refining GA parameters, validating health outcomes via trials, and scaling for broader populations.

6. **Literature Review** (Table 1):

   - Cites studies like Bush et al. (2020) on holistic personalization, Ferguson et al. (2016) on precision nutrition, and Brouns et al. (2008) on folate metabolism SNPs.
   - Notes challenges in data integration and practical application, underscoring GA's role in overcoming these.

Conclusion:
The study demonstrates GAs' efficacy in personalized nutrition, integrating genomic and dietary data to produce tailored, effective plans. GA plans outperform traditional guidelines in nutritional adequacy, genetic alignment, preference adherence, and feasibility, offering a scalable nutrigenomics solution. As the field evolves, GAs will drive precise dietary interventions, enhancing health outcomes.

Comparison of Genetic Algorithm-Based Nutrition Papers:

This comparison evaluates three papers using genetic algorithms (GAs) for nutrition optimization:

1. Personalized Nutrition Plans Using Genetic Algorithms (UFANS, 2023)
2. Optimization Using Genetic Algorithm in Food Composition (IJCD, 2021)
3. Towards Automatically Generating Meal Plan Based on Genetic Algorithm (Soft Computing)

Objectives

- UFANS: Personalizes diets using genomic data (SNPs) for health optimization.
- IJCD: Optimizes general food composition based on Healthy 4 Perfect 5 (H4P5) and Guidelines of Balanced Nutrition (GBN) for public health in Indonesia.
- Soft Computing: Balances taste and health in meal plans using recipe recommendation scores.

Methodologies

- UFANS: Integrates genomic data with dietary guidelines; GA with 50 generations, 100 population size, evaluates nutritional adequacy and genetic alignment.
- IJCD: Uses a mathematical model (3a+3b+8c+5d+5e+8f=24); GA with 36 generations, 6 population size, 50% crossover, 5% mutation.
- Soft Computing: Combines recipe database and CNN scores; GA optimizes health and taste, details unspecified.

Data Inputs

- UFANS: Genomic data, dietary guidelines, user preferences.
- IJCD: GBN components (3 vegetable/animal protein, 8 carbohydrates, 5 vegetables/fruits, 8 water).
- Soft Computing: Recipe nutritional content and taste scores.

Outcomes

- UFANS: 95% best fitness, +41.7% genetic alignment, +22.7% nutritional adequacy vs. traditional guidelines.
- IJCD: Two solutions (e.g., 2.5 vegetable protein servings), three models (Consumption, Food, Composition).
- Soft Computing: 80% healthy plans, 83% user satisfaction (≥6/10).

Contributions

- UFANS: Advances nutrigenomics with precise, scalable plans.
- IJCD: Provides public health models to reduce malnutrition.
- Soft Computing: Enhances user adherence via taste-health balance.

Challenges & Future Work

- UFANS: Costly genomic data; future trials for health outcomes.
- IJCD: Generic approach; explore Particle Swarm Optimization.
- Soft Computing: Limited recipe diversity; improve nutritional constraints.

Summary Table

Aspect	UFANS (2023)	IJCD (2021)	Soft Computing
Objective	Genomic personalization	General nutrition	Taste-health balance
Data	Genomic, guidelines	GBN model	Recipe database, scores
GA	50 gen, 95% fitness	36 gen, 0.240806 fitness	80% healthy plans
Outcomes	+41.7% genetic alignment	Two solutions, three models	83% satisfaction
Challenges	Data cost	Generic approach	Cultural specificity

Conclusion

UFANS excels in genomic precision, IJCD in public health accessibility, and Soft Computing in user engagement, showcasing GAs' diverse applications in nutrition.