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Food Nutrition Optimization and Prediction System Based on Intelligent Algorithm

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***Abstract*—This paper therefore presents the use of an intelligent algorithm in developing a food nutrition optimization and prediction system where the system can collect nutrition data on food, constructs a nutrition prediction model, applies an optimization algorithm according to requirements in order to reach its nutritional needs. The use of a machine learning model of the system therefore makes it possible to accurately predict nutrients in the food formula. The experimental results show that the artificial neural network model performs well in capturing complex nutrient relationships and has a high prediction accuracy. Next, the genetic algorithm and particle swarm algorithm are used to optimize the food formula, successfully balancing the intake ratio of different nutrients and achieving specific optimization goals. The system has shown its effectiveness in multi-objective optimization tasks through experimental verification. It can adjust the food formula according to the input health needs and ensure that the nutrients meet the expected standards. This study shows that intelligent algorithms have significant application potential in the prediction and optimization of food nutrients, providing strong support for future personalized nutrition plans. Through the training and verification of the model and the performance evaluation of the optimization algorithm, the system has shown broad application prospects in the fields of nutrition and health management and the food industry.**

Keywords-intelligent algorithm; food nutrients; prediction model; optimization algorithm; nutritional requirements

I. Introduction

A. Research Background and Importance

With the increase in attention paid by modern society to diets that entail good nutrition, the formulation of personalized nutrition has become an extremely important research field. It is only by reasonable optimization of nutrients within food that nutritional requirements for different groups of people will be satisfied, but it will have an important effect on the prevention of chronic diseases and improvement in life quality. Most of the conventional methods for nutrient analysis and optimization rely on experts' experiences, which is unsatisfactory and cannot handle large quantities of data in a complex manner [1]. With the development of artificial intelligence technology, nutrition optimization solutions based on intelligent algorithms have gradually become possible. Artificial intelligence can learn and predict through a large amount of dietary data, helping to develop more accurate and personalized nutrition plans, thereby improving overall health [2].

In recent years, the application of machine learning and intelligent algorithms in the field of food science has made significant progress. These technologies can use complex models to capture the nonlinear relationship between nutrients in food and provide a basis for the optimization of food formulas through big data analysis [3]. For example, intelligent optimization methods such as genetic algorithms and particle swarm algorithms have been widely used in the optimization of food nutrients. These algorithms have shown strong performance in solving multi-objective optimization problems [4]. The cross-integration of food industry and nutrition science provides a new technical path for the formulation of personalized nutrition programs and brings broad application prospects to related industries.

B. Research Objectives

The research work presented in this paper develops an intelligent algorithm-based nutrient optimization and prediction system for food nutrition. It optimizes the nutrient content of food formulae using optimization techniques like Genetic Algorithm and Particle Swarm Algorithm, combined with precise prediction of nutrient content in food formulae. By this system, food formulism can self-regulate in the light of health needs for different groups of people to make certain that the nutrient content can meet personalized needs. The core objective of this study is to balance the intake ratio of different nutrients under the framework of multi-objective optimization, improve nutrition value, and ensure the quality meets personalized health requirements. The system verifies its effectiveness through experiments and further evaluates its application prospects in nutrition and health management and the food industry.

II. Analysis of Food Nutrient Content and Identification of Key Factors

A. Food Nutrient Content and its Classification

Food nutrition is a very important research object in food science, and there are many classifications of it. In general, nutrient content is classified based on the types of nutrients, including macronutrients and micronutrients. The main macronutrients include proteins, fats, and carbohydrates,

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which provide energy to the body, forming the material basis necessary for maintaining life activities [5]. Dietary fiber is also often included when discussing macronutrients because it cannot only provide a mass effect to the human body but also has its own bioactivities. Micronutrients include vitamins and minerals. Despite not being direct contributors of energy, they play a significant role in maintaining metabolism, immunity, and the repair of body tissues [6]. Classification may also be according to either processing that food undergoes. For example, NOVA classifies foods into unprocessed or minimally processed foods, processed food, and ultra-processed foods, etc., which represent the influence of their processing degree on nutritional components [7].

The food contents and nutrient distribution vary widely between food categories. For example, meat and fish provide high proteins and fat, while fruits and vegetables are sources of dietary fiber, vitamins, and minerals. However, with increased processed foods over the recent years, the added sugars and sodium in ultra-processed foods have greatly increased, while the nutritional content has remained very low, hence posing a potential threat to health. Understanding the category of nutrients of food could help in conducting a better nutrition management and health intervention [8].

B. Key Factors Affecting Food Nutrients

There are many factors affecting food nutrients, which can be mainly divided into the type of food, production method, processing process, and conditions of storage. First, the source and type of food determine the basis of its natural nutritional composition. For example, animal foods are usually high in saturated fat and cholesterol, while plant foods are rich in unsaturated fatty acids and dietary fiber [9]. Organically grown crops tend to be higher in antioxidants and lower in pesticide residues, thus attesting to the overall nutritional quality of the food. Secondly, the nutritional value in food is greatly influenced by the mode of production. This has been deduced from studies [10].

What's more, processing, such as heat treatment, drying, and fermentation, is another influencing factor affecting the nutritional content of food. In processing, high temperatures may destroy some kinds of vitamins. Vitamin C and B vitamins are much more easily destroyed under high-temperature conditions compared with minerals, which are relatively stable [11]. Finally, storage conditions also play an important role in affecting food's nutritional content. Long-term storage, especially at unsuitable temperature and humidity, will yield a loss of nutrients through oxidation of fatty acid oxidation and vitamin loss. Therefore, the knowledge of these critical factors enables maximization of nutritional values during food production and consumption.

C. Data Analysis Methods and Feature Selection

In the analysis of food nutritional components, data analysis methods and feature selection are key steps in building efficient prediction models. Traditional statistical methods such as principal component analysis (PCA) and factor analysis (FA) are often used to identify the main nutrients in food and simplify data dimensions [12]. Through these methods, researchers can transform complex nutritional data in food into several main components, thereby effectively performing nutritional analysis and classification. For example, researchers used PCA to analyze 28 nutrients in food and successfully simplified them into 8 main nutritional patterns, thereby identifying the clustering characteristics of nutrients in food [13].

In the context of machine learning, more intelligent algorithms are applied to the data analysis of food nutrients. Algorithms such as support vector machines (SVM) and random forests can perform high-precision classification and prediction based on nutritional data [14]. Besides, other feature selection techniques such as genetic algorithms and particle swarm optimization algorithms are also widely adopted in the process of optimization when selecting the most representative nutritional features with a view to improving the predictive ability of the model effectively. By employing these advanced analytics tools, researchers can gain more profound insights into the nutrient structure of food and science basis for personalized nutrition plans [15].

III. NUTRITIONAL COMPONENT PREDICTION MODEL BASED ON INTELLIGENT ALGORITHMS

A. Overview and Application of Intelligent Algorithms

The application of intelligent algorithms in food nutritional component prediction has gradually become a research hotspot. By introducing machine learning and deep learning models, large-scale food nutritional data can be effectively utilized to accurately predict the changes in nutritional components in food formulas. Common intelligent algorithms include linear regression, decision trees, support vector machines (SVM), artificial neural networks (ANN), etc. These algorithms have their own characteristics and are suitable for different data and problem scenarios.

Linear regression is suitable for processing linear relationship data, and the formula is as follows:

$$y = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \ldots + \beta_n x_n + \grave{o} \tag{1}$$

Among them, y is the predicted value, β_0 is the intercept, $\beta_1, \beta_2, \ldots, \beta_n$ are regression coefficients, $x_1, x_2, \ldots, x_n$ are input features, and $\grave{o}$ is the error term. This formula represents the linear relationship between the input features and the target output.

For more complex nonlinear problems, artificial neural networks (ANNs) in deep learning can learn nonlinear relationships between features through multi-layer structures. Its basic feedforward neural network formula is:

$$y = f(Wx + b) \tag{2}$$

Among them, W is the weight matrix, xxx is the input feature vector, b is the bias, and f is the activation function. This formula is used in each layer of the neural network calculation process, and the prediction results are optimized by continuously iterating and updating the parameters.

B. Selection and Design of Prediction Model

In the application of nutrient component prediction, different models are suitable for different types of data and goals. We need to choose a suitable model based on the scale, dimension, distribution and task requirements of the specific data.

Suppose we use a linear regression model to predict a nutrient in food. Linear regression can be defined as:

$$\hat{y} = X\beta + \grave{o} \tag{3}$$

Among them, $\hat{y}$ is the predicted nutrient value, X is the input feature matrix, β is the coefficient vector to be optimized, and ò is the error. By minimizing the sum of squared errors, the optimal coefficient β can be obtained.

At the same time, for more complex nutrient relationships, deep learning models such as convolutional neural networks (CNN) or recurrent neural networks (RNN) can capture the spatiotemporal correlation of features. Taking RNN as an example, its prediction formula is:

$$h_t = f(W_h h_{t-1} + W_x x_t + b) \tag{4}$$

Among them, h_t is the hidden state of time step t, W_h is the weight matrix from hidden layer to hidden layer, W_x is the weight matrix input to hidden layer, x_t is the input of time step t, b is the bias, and f is the activation function. This model is suitable for processing time series data or predicting changes in nutritional components during food processing.

C. Model Training and Verification

When training a model, we usually use supervised learning methods to optimize model parameters through existing labeled data. During the training process, the goal is to minimize the loss function, such as the mean square error (MSE), which is:

$$\text{MSE} = \frac{1}{n}\sum_{i=1}^{n}(y_i - \widehat{y_i})^2 \tag{5}$$

Among them, n is the number of samples, y_i is the actual value, and $\widehat{y_i}$ is the predicted value. Minimizing MSE can ensure the prediction accuracy of the model for the training data.

IV. FOOD NUTRITION OPTIMIZATION SYSTEM

A. Setting Optimization Goals and Constraints

In food nutrition optimization, the goal is usually to optimize the food formula according to specific health needs (such as low sugar, low fat, high protein, etc.) so that it can meet the expected nutritional goals while meeting the taste and processing requirements. The optimization goal is usually defined as minimizing or maximizing a specific nutritional index or a comprehensive nutritional value score.

For example, suppose we want to minimize the fat content in the food while ensuring that the protein and carbohydrate content meet health needs. The optimization goal can be expressed as:

$$\text{minimize } F(x) = w_1 \cdot \text{Fat}(x) + w_2 \cdot \text{Carbs}(x) + w_3 \cdot \text{Protein}(x) \tag{6}$$

$$a_i \le x_i \le b_i, \forall i \tag{7}$$

Among them, $F(x)$ is the objective function, x represents the decision variable of the recipe, w_1, w_2, w_3 are the weight coefficients of each nutrient, representing the weight ratio of fat, carbohydrate and protein respectively. By setting different weights, the optimization direction can be adjusted according to different nutritional needs. a_i and b_i are the lower and upper limits of the decision variable x_i, respectively, to ensure that the content of each nutrient is kept within a reasonable range during the optimization process.

B. Application of Optimization Algorithms

To optimize the nutritional content, commonly used intelligent optimization algorithms include genetic algorithms (GA) and particle swarm optimization (PSO). These algorithms are based on the principles of biological evolution and group behavior and can quickly find approximate optimal solutions in complex multidimensional spaces. They are suitable for multi-objective problems such as food formula optimization.

Genetic algorithm: Genetic algorithm gradually evolves the optimal solution by simulating the process of natural selection and gene recombination. Its basic process includes individual encoding, selection, crossover, mutation and iteration. The objective function is updated in the following way:

$$P^{(t+1)} = \text{Selection}(P^{(t)}) + \text{Crossover}(P^{(t)}) + \text{Mutation}(P^{(t)}) \tag{8}$$

Among them, $P^{(t)}$ is the individual population of the t th generation, selection, crossover and mutation represent individual selection, gene recombination and mutation operations respectively, and the new individual population $P^{(t+1)}$ is generated by these operations.

Particle Swarm Algorithm: Particle Swarm Algorithm searches for the optimal solution by simulating the movement of particles in the group in multidimensional space. The speed and position of each particle are updated according to its own experience and the experience of the group. The particle position update formula is:

$$v_i^{(t+1)} = w \cdot v_i^{(t)} + c_1 r_1 (p_i - x_i^{(t)}) + c_2 r_2 (g - x_i^{(t)}) \tag{9}$$

$$x_i^{(t+1)} = x_i^{(t)} + v_i^{(t+1)} \tag{10}$$

Among them, $v_i^{(t)}$ are the velocity and position of particle i at the t th generation, p_i is the optimal position of the particle itself, g is the global optimal position, www is the inertia weight, c_1 and c_2 are learning factors, and r_1 and r_2 are random numbers.

C. System Design and Implementation

To apply the above optimization process to practice, it is necessary to design an integrated food nutrition optimization system. The system mainly includes the following modules:

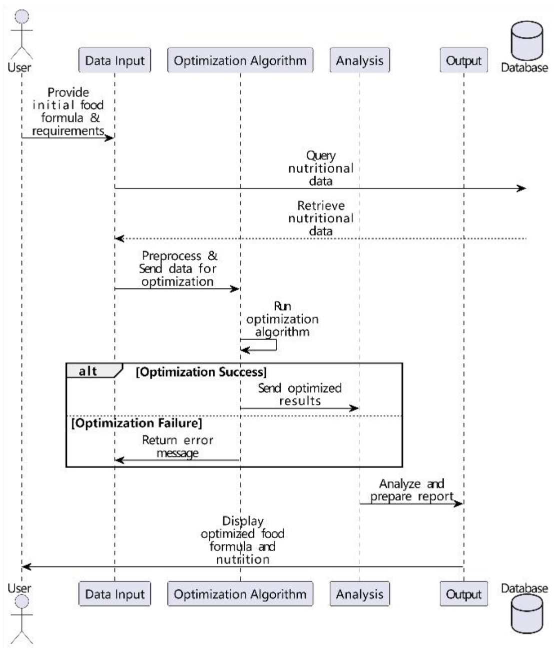

Figure 1. System module operation process

As shown in Figure 1, the user first provides the initial food formula and nutritional requirements. The system obtains relevant nutritional data and pre-processes it through the "data input and processing module". Next, the "optimization algorithm module" runs the optimization algorithm and sends the results to the "analysis module" for analysis. Finally, the optimized formula and nutritional composition results are displayed to the user through the "output module". If the optimization fails, the system returns an error message to the user.

V. EXPERIMENT AND RESULT ANALYSIS

A. Experimental Design and Data Set Introduction

This experiment aims to verify the effectiveness of intelligent algorithms in predicting and optimizing food nutrients. To this end, multiple food data sets were selected, including the nutritional components of different food categories, including the content of common nutrients such as carbohydrates, proteins, fats, and vitamins. The data sets are derived from public databases and have been standardized to ensure data quality and consistency.

The characteristics of the data sets are as follows (Table I):

TABLE I. THE CHARACTERISTICS OF THE DATA SETS

Dataset Characteristics	Description
Number of Samples	300 food items
Feature Dimensions	10 key nutritional components
Target Variable	Comprehensive nutrition score
Data Distribution	Non-linear, multi-modal distribution
Train/Test Split	80% training, 20% testing

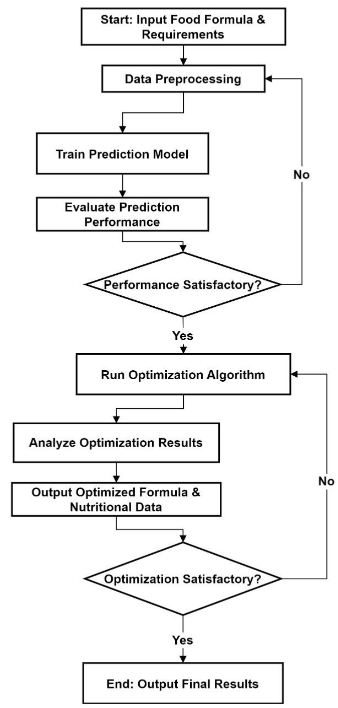

Figure 2. The experimental process

The experimental process starts with the user inputting food formula and nutritional requirements (Figure 2). The system first pre-processes the data. Then, the system trains the prediction model and evaluates the performance of the model. If the performance is satisfactory, the system enters the optimization stage, runs the optimization algorithm and analyzes the results. If the optimization result is not satisfactory, the system will feedback and optimize again until it is satisfactory. If the model evaluation does not meet the standards, it will also be fed back to the data processing link for adjustment.

B. Performance Evaluation of Prediction and Optimization System

To evaluate the performance of the system, we use mean squared error (MSE) and accuracy to measure the effect of the prediction model. At the same time, for the optimization algorithm, we use the convergence speed of the objective function, and the quality of the final optimization result as evaluation indicators. Table II shows the MSE and accuracy of three different prediction models on the test set:

TABLE II. MSE AND ACCURACY OF THREE DIFFERENT PREDICTION MODELS ON THE TEST SET

Model	MSE	Accuracy (%)
Linear Regression	0.032	85.4
Decision Tree	0.025	88.7
Neural Network (ANN)	0.018	91.3

As can be seen from the table, artificial neural network (ANN) outperforms other models in both MSE and accuracy, indicating that it is more suitable for dealing with complex nonlinear relationships between nutrients.

For optimization algorithms, the performance comparison of genetic algorithm (GA) and particle swarm algorithm (PSO) is shown in Table III:

TABLE III. PERFORMANCE COMPARISON OF GENETIC ALGORITHM (GA) AND PARTICLE SWARM ALGORITHM (PSO)

Algorithm	Convergence Time (s)	Final Objective Value
Genetic Algorithm (GA)	15.3	0.879
Particle Swarm (PSO)	12.8	0.856

As can be seen from the table, the particle swarm optimization (PSO) has a faster convergence time, while the genetic algorithm (GA) has a slight advantage in the final objective function value. Both algorithms show good optimization effects and can effectively meet the set nutritional goals.

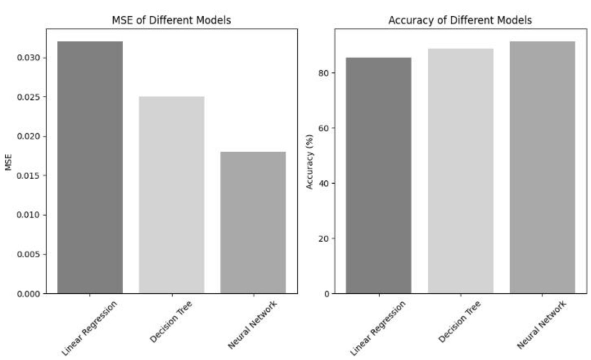

Figure 3. Comparison of MSE and accuracy of three different models on the test set

Figure 3 shows the comparison of MSE and accuracy of three different models on the test set. It can be clearly seen that the neural network model has the lowest MSE and the highest accuracy, indicating that it has an advantage in capturing complex nutritional composition relationships.

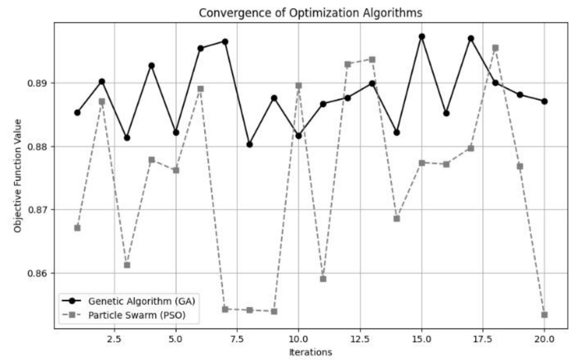

Figure 4. Convergence curves of genetic algorithm and particle swarm algorithm

Figure 4 shows the convergence curves of genetic algorithm and particle swarm algorithm. The genetic algorithm can be stable after fewer iterations, and the particle swarm algorithm converges faster, but the final convergence value is slightly lower than that of the genetic algorithm.

C. Result Analysis and Discussion

The experimental results show that intelligent algorithms have significant advantages in the prediction and optimization of food nutrients. The following conclusions can be drawn through performance evaluation:

① Effectiveness of prediction model: The neural network model performs well in capturing the complex nonlinear relationship between food nutrients, especially in MSE and accuracy, which is significantly better than other models.

② Comparison of optimization algorithms: The particle swarm algorithm (PSO) performs better in convergence speed and is suitable for fast optimization scenarios, while the genetic algorithm (GA) is more outstanding in target value accuracy and is suitable for tasks that require fine optimization.

③ Comprehensive performance: When dealing with multi-objective optimization tasks, the system can effectively balance different nutritional needs and ultimately provide food formulas that meet health requirements, verifying the practicality and flexibility of the system.

VI. CONCLUSION

This study focuses on the optimization and prediction system of food nutrients based on intelligent algorithms, aiming to achieve accurate prediction and optimization of nutrients in food formulas through machine learning and optimization algorithms. First, through the analysis of food nutrients, the key factors affecting nutrients were determined, and a prediction model was constructed based on these factors. The experimental results show that artificial neural networks (ANNs) perform well in capturing the complex nonlinear relationship between nutrients and achieve a high prediction accuracy. Secondly, intelligent optimization methods such as genetic algorithms (GAs) and particle swarm algorithms (PSOs) were used to optimize food formulas, balancing the intake ratio of different nutrients while meeting specific nutritional needs, achieving the optimization goal.

The practicality and effectiveness of intelligent algorithms in the prediction and optimization of food nutrients were verified through experimental performance evaluation. The system can not only accurately predict nutritional changes in food formulas, but also automatically adjust the formulas through optimization algorithms to meet the personalized health needs of users. The research results show that intelligent algorithms have important application potential in dealing with multi-objective optimization problems, improving food nutritional quality, and supporting personalized nutrition plans.

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