Hindawi
Mobile Information Systems
Volume 2023, Article ID 3979020, 14 pages
https://doi.org/10.1155/2023/3979020

Research Article

m-Health of Nutrition: Improving Nutrition Services with Smartphone and Machine Learning

Yu Liu ,[1] Huaiyan Jiang ,[1] Yumei Qi,[2] and Jinsheng Yang[1]

[1]*School of Microelectronics, Tianjin University, Tianjin 300072, China*
[2]*Department of Nutriology, Tianjin Third Central Hospital, Tianjin 300072, China*

Correspondence should be addressed to Huaiyan Jiang; jianghyan@tju.edu.cn

Received 21 October 2022; Revised 22 March 2023; Accepted 8 April 2023; Published 8 May 2023

Academic Editor: Gabriele Civitarese

Balanced and adequate nutrient intakes are increasingly desired for people, especially those affected by chronic diseases. How to help people to realize appropriate nutrient consumption is an issue that should be addressed in smart healthcare. This study proposes a novel smartphone-based platform that includes dietary records, nutrition data analysis, and online nutritional guidance to improve remote nutrition services. Positive results from a trial conducted in cooperation with a hospital confirm the platform's promising capabilities in nutrition guidance and disease management. Additionally, to explore how nutrient intake impacts human health, this study took the relationship between hypertension and nutrient intake, and personal information as a case study. The findings indicate that our platform can provide detailed nutrient analysis services, and machine-learning-based prediction methods can accurately predict the user's blood pressure with little error.

1. Introduction

According to nutrition science, the nutrients contained in food may affect people's health in different ways. The World Health Organization (WHO) issues numerous scientific tutorials to emphasize the importance of nutrient intake so that public health can be improved by nutrition theory and techniques [1]. Some organizations propose standard nutrient intake criteria for different groups to provide daily food intake references [2, 3]. Many databases for the nutrients of food are also constantly updated and enriched all over the world [4–6]. However, the reference criteria only provide a general suggestion, and nutrient intake should be considered in combination with the individual's dietary needs, especially for persons who are suffering from chronic diseases such as obesity, hypertension, and diabetes [7].

The personalized dietary suggestions provided by professional dietitians are generally based on different dietary questionnaires, these traditional methods lead to some difficulties in collecting dietary data and converting them into nutrition data. As long-term and detailed food records are required by dietitians, consumers may quit treatments due to being unwilling to complete burdensome paper diaries. Additionally, the complex interaction of factors such as nutrients, diseases, and personal physical conditions makes accurate nutrition analysis difficult.

Recent advancements in mobile communication and smartphones facilitate increasingly convenient dietary monitoring and evaluation solutions. Dietary intake can be recorded by inputting text, sending chewing movements monitored by sensors, and recognizing food photos taken by smartphones. However, these methods need to be improved, such as being cumbersome to use and requiring additional equipment to be worn. Moreover, most of them do not consider the further comprehensive analysis of users' nutrients and health data.

In view of the shortcomings of existing nutrition data collection and analysis, this paper proposes a smartphone-based nutrient-service platform to improve public health by analysing users' dietary data and personal information, and takes hypertension as a case study to explore the relationship between nutrients and human health. The contributions of this study are as follows:

(1) Compared with other nutrition data collection methods, the proposed platform integrates three forms of text, speech recognition, and "custom dishes" to simplify the recording process.

(2) A large food-nutrient database is constructed in the platform for converting food into nutrients, including 1280 ingredients, more than 5000 dishes, and more than 20,000 packaged foods.

(3) The platform can generate personalized reference nutrient intakes based on user-health profiles and the guidance of professional dietitians, and compare them with the actual nutrient intake of the user through radar charts. A trial with diabetic patients demonstrated the effectiveness of the platform for nutritional guidance and disease management.

(4) A case study of the prediction of blood pressure through nutrient intake and personal information is presented. This can be combined using the platform to promote nutrition services, as well as interdisciplinary research in nutrition science and artificial intelligence.

2. Related Work

Nutrients can be divided into macronutrients and micronutrients, which are chemical components in food essential for people to stay healthy [1]. Unfortunately, many people around the world are suffering from serious health problems caused by unbalanced nutrient intakes. On the one hand, unconsciously consuming excessive sugars, salt, or saturated fats has become a major risk factor for many diseases such as hypertension and other chronic diseases. On the other hand, over 2 billion people worldwide suffer from micronutrient deficiencies, also known as "hidden hunger." People's increasing demand for healthy diets is promoting the rapid development of food-related research [8].

A significant number of studies have confirmed the vital effects of different nutrients on health. For example, alleviating the progression of Alzheimer's disease and Parkinson's disease [9–11], decreasing the incidence of type 2 diabetes mellitus [12], and reducing the risk of acute respiratory infection and strengthening the immune system for COVID-19 [13, 14]. However, the findings of most of these studies were obtained through traditional methods such as questionnaires and statistics to collect and analyse large amounts of data, which is very time-consuming and laborious. Therefore, there is an urgent need for a more efficient and less resource-intensive method to conduct dietary nutrition analysis.

Mobile health (m-Health) is an emerging field of healthcare that is well suited for dietary nutrition tracking and monitoring due to its ease of use, remote tracking, and long-term management advantages. One way m-Health enables diet health management and analytics is through a mobile application embedded in smartphones [15, 16]. For example, recognizing and detecting chewing activity through a smartphone application to precisely monitor food intake [17]. Wearable devices are combined with application for monitoring food consumption and automatic analysis of stress status [18]. Assessment of dietary consumption and nutrient intake through food intake or food pictures is obtained by the application [19–21]. Many mobile applications for chronic diseases also present users with personalized nutritional advice, such as appropriate menus and dishes suggestions for hypertensive patients to promote healthy eating behaviors [22]. Targeted dietary guidance is provided to diabetic users based on the collection and analysis of their dietary data [23]. In particular, the global popularity of COVID-19 makes implementing of m-Health even more crucial. It allows people to access services for diet and nutrition monitoring remotely and to consult distantly with healthcare professionals [24, 25].

The ultimate objective of m-Health is to create customized nutritional recommendations for users through comprehensive data analysis. The successful application of machine learning in areas such as stock prediction, personalized customer experience, and disease diagnosis and management has highlighted its robust data analysis and mining capabilities [26–29]. Therefore, machine-learning can analyse big dietary data to explore correlations between dietary habits and health outcomes deeply. For instance, researchers in [30] explored the effect of dietary factors on atherosclerotic cardiovascular disease (ASCVD) using Bayesian kernel machine regression (BKMR). Reference [31] analysed dietary records to identify prediabetes patients by various machine learning algorithms such as random forest (RF). In [32], multiple healthy dietary guidelines for improving antimicrobial resistance are given through the output of machine learning models. Literature [33–35] and highlighted the strong effect of vitamins on obesity, vascular dementia, and Alzheimer's disease through various machine learning algorithms. Essential conclusions that selective nutritional intake effectively reduces COVID-19 infection and mortality have also been drawn using multiple regression models and classification algorithms [36, 37].

The combination of m-Health and machine learning is gaining popularity in diet management due to the availability of personalized and accurate insights. Although the above methods can help maintain and improve dietary health, they still have some drawbacks, such as the need to wear additional devices to monitor eating behaviors, record diet content only in textual form, and provide only a few nutrient intake analyses. Moreover, most nutritional health findings generated by the analysis are based on data filtered through a large amount of work, requiring more convenient access to actual user data. This paper presents a novel approach to implementing the diet and nutrition monitoring. We develop a nutrient-service platform that incorporates three recording methods and an extensive database to support the recording of a complete and detailed diet, and conduct a trial with a specialized hospital to evaluate the performance and usability of the platform. In addition, we applied machine learning to explore the relationship between nutrient intake and human health. Our platform has a great application value compared to current work, especially in terms of convenience in enabling remote, long-term dietary and nutritional health monitoring and disease management.

3. Methods

3.1. Overview of the Proposed Nutrient-Service Platform. Figure 1 shows an overview of the proposed nutrient-service platform implemented as a smartphone application. This platform is aimed at helping people in different states (e.g., chronic disease patients and pregnant women) eat better to improve their quality of life. The data recorded by users is stored in the cloud, including dietary data and personal user information. The personal user information is used to generate the corresponding user-health profile, and the dietary data are converted into nutrients according to the food-nutrient database built by ourselves. Furthermore, a convenient and efficient connection between users and dietitians is established in this platform to enable reliable data exchange and professional nutrition advice to be provided.

3.1.1. User-Health Profile. The proposed platform forms the user-health profile based on the answers to an online questionnaire to collect users' personal information. Personal information describes the user's primary status, such as age, height, weight, gender, and disease status, which can be modified or updated. Then, as described in "Data Processing and Analysis," the platform judges and analyses the data of the user-health profile to generate the corresponding daily reference nutrient intakes. Table 1 shows a simple example; the two left columns are the questionnaire questions and user answers included in the user-health file, and the right two are the user's corresponding reference nutrient intakes generated by the platform.

3.1.2. Dietary Data Recording. This platform has three ways to facilitate data recording: (1) Searching the partial or complete names of ingredients or dishes to record the food and quantity. (2) People's daily food is often composed of many different ingredients, so this platform provides the "custom dishes" function; that is, users can select and add ingredients from the database to make their dishes. (3) Recording through the voice format of "name + quantity," such as apple, 50 g and rice, 200 g.

In the third method of speech recognition recording, we use automatic speech recognition (ASR) and fuzzy query to match the speech with the food-nutrient database, as shown in Figure 2. The user enters the speech in the agreed voice format and uses ASR to convert the voice into a string for transmission to the server. After that, the server uses regular expressions to filter out special characters, such as punctuation in the string. The string is then split to obtain a list of strings containing the names of the food. Later, execute the fuzzy query for the food-nutrient database based on the string list to return the user a list of five foods containing food names. Finally, the user selects the correct food from the list for recording.

For the nutrient data, we built a food-nutrient database including 1280 ingredients, more than 5000 dishes, more than 20,000 packaged foods, and their corresponding contents of over 40 nutrients to meet the recording requirements, as shown in Figure 3. This platform also invites professional doctors to record instructional videos explaining how to estimate food consumption accurately.

3.1.3. Data Processing and Analysis. All the data submitted by users on the platform are stored, encrypted, and further analysed on the data-processing platform. For example, the daily reference nutrient intakes are inferred from the user-health profile, as shown in Table 1. The recorded dietary data are converted into nutrient intakes according to the map matching the user's records and food-nutrient database. Moreover, those data can be consulted by dietitians in a convenient and accessible format, such as nutrient intakes or relevant medical examination data for users over a period.

3.1.4. Nutrient Intake Evaluation. The converted nutrient intake is compared with the daily reference values through radar charts so that users have a clear view of their dietary statuses, as shown in Figure 4. The reference nutrient intakes of people in different states and with different diseases following consultation with professional dietitians, as well as various items of professional nutrition advice, are stored on the platform. Based on the large-scale intelligent analysis and accumulation of data, the platform can make judgments and adjust the vertex values of radar charts; that is, the daily reference nutrient intake values are set accordingly upon analysing the user-health profile. For instance, patients with hypertension consume 800–1000 mg of calcium daily, and the low-sodium diet recommended for chronic glomerulonephritis suggests that the daily sodium intake should not exceed 500 mg.

3.1.5. Online Consultation with Dietitians. Considering the need for professional nutrition advice, the platform establishes a connection between users and hundreds of doctors and dietitians who have complete and authentic files to ensure the accuracy and credibility of the advice. As shown in Figure 5, the platform provides two ways for users to get professional nutrition advice: online consultation and posthealth questions.

The online consultation method allows users to find a proper doctor or dietitian for consultations by searching names, hospitals, and departments. As shown on the left in Figure 5, the user asks the doctor what to focus on in the diabetic diet, and the doctor will make careful judgments and recommendations based on the user's needs. Meanwhile, the analysis results in "data processing and analysis" will be available and shown to this doctor as the reference for her or his diagnosis and for providing appropriate nutrition guidance, or tuning the vertex values of the radar charts. Posting a health question means the user posts the question on the platform along with keywords (e.g., disease, recovery, and weight loss) to get guidance. As shown on the right in

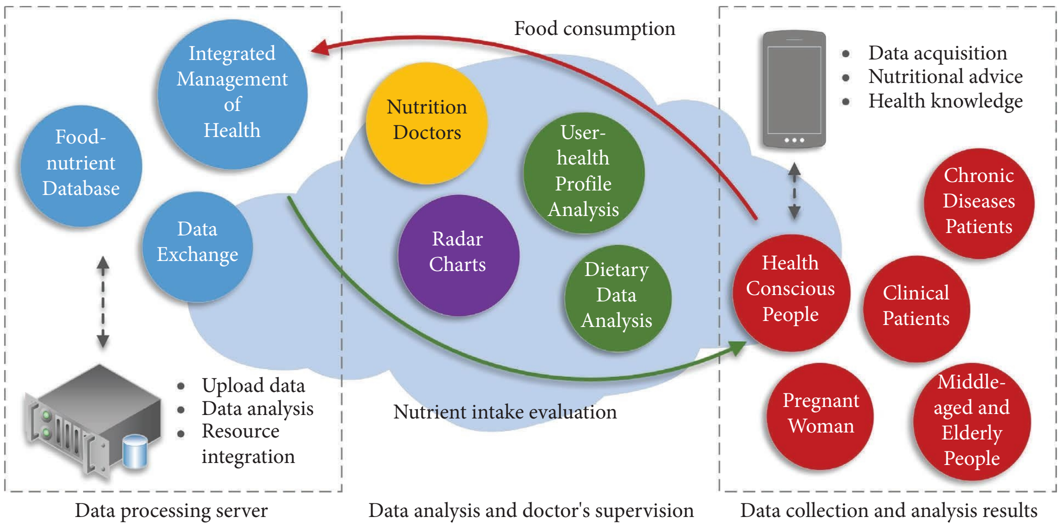

Figure 1: An overview of the proposed nutrient-service platform.

Table 1: A sample of a user-health profile and the corresponding daily reference nutrient intakes.

Question	Answer	Nutrients	Reference nutrients intake
Age	35	Energy (kcal)	2138
Height (cm)	180	Protein (g)	80
Weight (kg)	70	Fat (g)	60
Gender	Male	Carbohydrate (g)	285
Working hours (hr)	4–8	Water (ml)	2500
Working intensity	Office work	Dietary fiber (g)	25
Exercise frequency	2 times/week	Ca (mg)	800
Sleeping time (hr)	6–8	P (mg)	720
Dietary status	Regular	K (mg)	2000
Food preference	Meat food	Na (mg)	1500
Water (ml)	2000–3000	Mg (mg)	330
Drinking	Rarely	Fe (mg)	20
Smoking	No	Zn (mg)	7.50
Chronic disease	Hypertension	Se (μg)	60
Usage requirement	Balanced diet	Cu (mg)	0.80
—	—	Mn (mg)	4.50
—	—	Cholesterol (mg)	250
—	—	Purine (mg)	200
—	—	Vitamin A (mg)	0.70
—	—	Vitamin E (mg)	14
—	—	Vitamin B1 (mg)	1.20
—	—	Vitamin B2 (mg)	1.20
—	—	Vitamin B3 (mg)	12
—	—	Vitamin C (mg)	100

cm = centimeter; kg = kilograms; hr = hours; ml = milliliters; kcal = kilocalories; g = grams; mg = milligrams.

Figure 5, a user posts a question about what diseases can be caused by excessive fat intake. The question will then be displayed on the platform, and doctors in the relevant field will respond.

3.1.6. Additional Functions. The platform has additional functions such as dietary records being able to be queried, generating professional medical reports, recommending diets, and health knowledge according to the data recorded by the user, recording mood, and supporting users to post to increase communication and sharing. In addition, the platform can monitor and record heart rate, sleep, and weight changes through the smart bracelet and body fat proportions via Bluetooth.

3.1.7. Data Security and Privacy. Users, including doctor users and normal users, log in to the platform only through a personal account and manage all their data. Doctors can access the data of normal users only during the consultation. The data uploaded and stored in the server on the interaction between doctors and patients in the platform is encrypted using the MD5 message-digest algorithm (MD5) to resist external

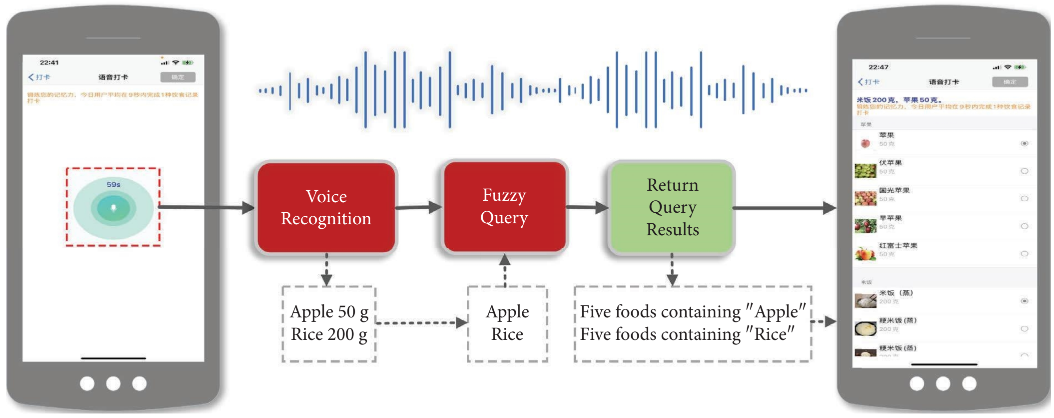

Figure 2: The flow of the voice-based recording method: apple, 50 g and rice, 200 g.

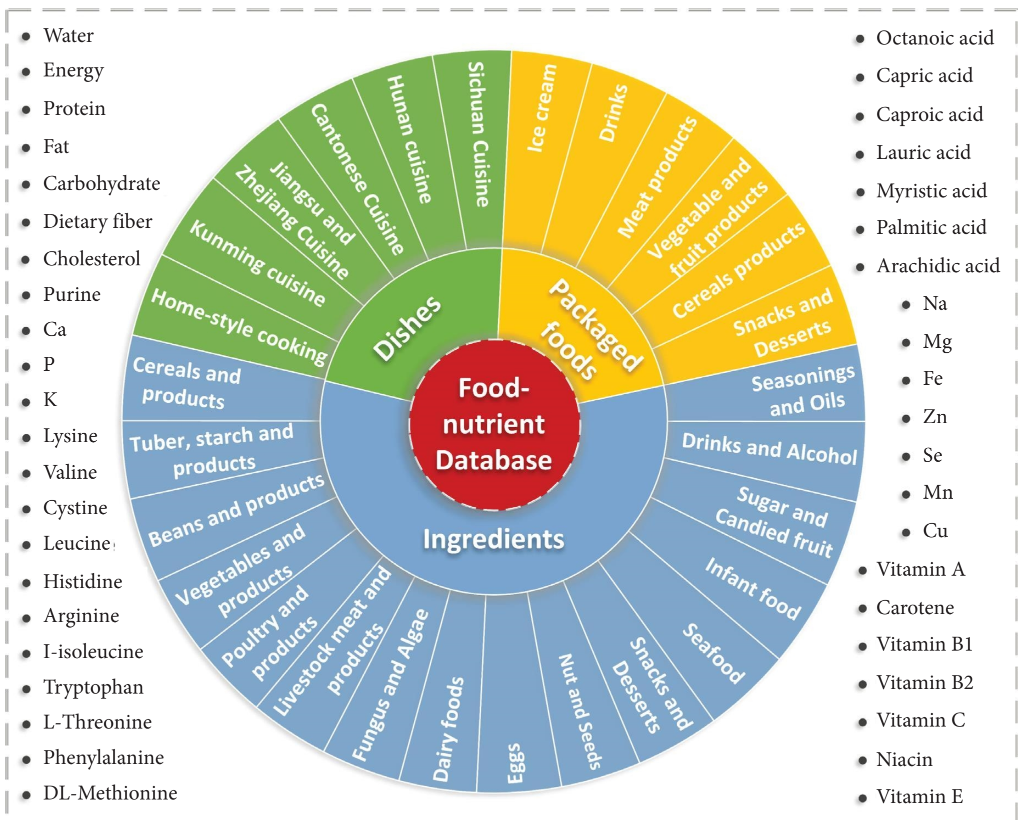

Figure 3: The food-nutrient database.

attacks [38]. Any processing performed on personal data by the platform, such as collection, recording, storage, and statistical analysis, is used to improve and optimize the service. The platform does not share user data with any third party for commercial purposes to ensure users' data security and privacy.

Figure 4 presents the details of each process of the proposed nutrient-service platform, which can run on iOS and Android smartphones. The main innovations and contributions of this platform are multiple nutrient intake analyses, easily understood radar charts for nutrient intake evaluation, a self-designed large food-nutrient database, and the connection between users and dietitians. This platform facilitates professional nutrient intake evaluation and guidance, and effectively integrates unevenly distributed and limited medical resources. With the accumulation of data and the development of data-driven technology, the platform's performance will gradually be enhanced.

3.2. Performance Evaluation of the Proposed Platform

3.2.1. Effectiveness Evaluation of Nutritional Guidance and Disease Management. To evaluate the performance of the proposed platform for dietary monitoring, nutritional

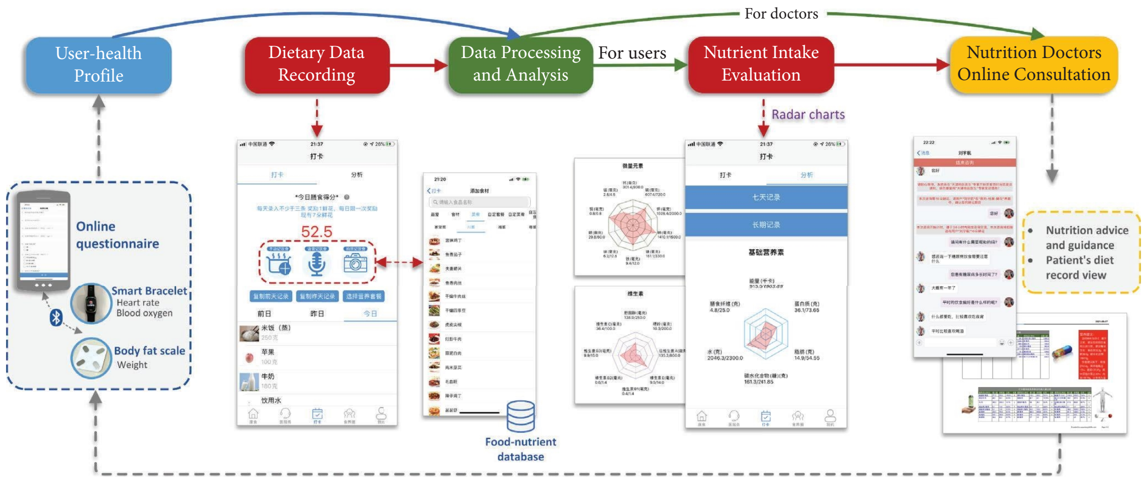

FIGURE 4: The workflow of the proposed nutrient-service platform.

FIGURE 5: The presentation of online consultation and posthealth question.

guidance, and disease management, we conducted a small trial in collaboration with Tianjin Third Central Hospital. The trial was performed on patients with type 2 diabetes. The study objective was to assess whether the platform implementation could provide practical nutritional guidance to patients and improve their disease status. Specifically, the trial was divided into the following main steps.

(1) Develop the trial protocol: diabetes is a lifelong disease, and diet plays a critical role in the prevention, occurrence, and management of diabetes [39]. An important indicator of diabetes monitoring status is glycated hemoglobin (HbA1c), with a standard range of 4–6% [40]. The trial lasted 14 days and required all participants to take a medical test at the beginning and one at the end to obtain HbA1c and record their complete diet content through the proposed platform during the trial. Meanwhile, a dietitian will review the participants' diet and nutrient intake records and give nutritional advice daily during the trial to assist participants in adjusting the diet content. Finally, evaluate the effectiveness of the proposed platform to provide personalized remote dietary guidance and disease management for diabetic patients based on a comparison of the two HbA1c.

(2) Recruit trial participants: the dietitians at the Tianjin Third Central Hospital primarily completed the recruitment of trial participants, and 10 participants were enrolled. All participants must be type 2 diabetic patients with the devices and environment to run the proposed platform and the ability to use its features. Prior to the trial, the dietitian clarified the

trial protocol, the possible benefits and risks, and the need for cooperation. The trial was conducted with confirmation that participants were fully informed and agreed to the trial protocol.

(3) Collect and analyse data: the data collected in the trial were mainly dietary data and HbA1c data. Dietary data was collected through the proposed platform, which required participants to record their complete diet daily and send it through the platform to the dietitians for review. The HbA1c data were obtained through medical tests. Both medical tests were undertaken at the same hospital to ensure the reliability of the data. Participants were not asked to change their medication and lifestyle habits during the trial to exclude the effect on the trial results.

3.2.2. Usability Assessment of the Platform. At the end of the trial, we also collected user experiences through telephone interviews to assess the usability of the proposed platform. The target users for this telephone interview were 10 trial participants and 2 dietitians for 12 people, and the final number of participants in the telephone interview was 12, with a rate of 100%. The main obtained usage perceptions were functional usage, platform performance, and platform compatibility. The users rated 1–5, representing very dissatisfied, average, satisfied, and very satisfied, respectively.

(1) Function usage: this aspect included user satisfaction with the three dietary recording methods, evaluation of whether the food-nutrient database can satisfy the recording needs, and the effectiveness assessment of the remote guidance by the dietitians.

(2) Platform performance: this aspect included an evaluation of the difficulty of using the platform and whether the platform was stuck, unexpectedly quit, or could not be loaded during use.

(3) Platform compatibility: this aspect included whether the installation failed due to incompatibility with the operating system when using the platform.

3.3. A Case Study: Exploring the Relationship between Nutrient Intake and Blood Pressure. The proposed platform is a multidimensional data collection tool. The most important goal is to analyse the multidimensional data collected from users to perform nutrition-related health management, such as diet control, chronic disease progress monitoring, and disease indicators prediction. Due to the short running time of the platform and the insufficient amount of data collected, and the data contained in the China Health and Nutrition Survey (CHNS) [41] is very similar to the type and structure of data we collected, we used CHNS data to conduct the blood-pressure prediction experiments to demonstrate one of the health management functions of the platform that the platform implements after collecting enough data.

Raised blood pressure is the leading risk factor for cardiovascular diseases, chronic kidney disease, and diabetes globally [42]. A strong correlation exists between blood pressure and diet, such as higher intakes of total fat, saturated fatty acids, and carbohydrates are associated with higher blood pressure [43]. To explore the potential relationship between blood pressure and various nutrients, we conducted a case study using machine learning to predict blood pressure using nutrient intakes and personal information. Specifically, our proposed case study had the following characteristics:

(1) A sample set was established based on the CHNS, which includes the intakes of 26 types of nutrients, 5 items of personal information, and blood pressure data. (2) The correlation between personal information and blood pressure was calculated to obtain effective features for the more reasonable model. (3) The GBDT was applied to construct the prediction model for blood pressure estimation. (4) A blood pressure prediction scheme was formed by taking nutrient intake and personal information as input. The experimental results demonstrate that the predicted results can be used as a reference for dietitians' diagnoses.

3.3.1. Database Preparation. CHNS is an ongoing open cohort and international collaborative project conducted in China since 1989. It collects detailed information on participants' dietary intakes for three consecutive days and blood pressure during every survey. We chose dietary intake and blood pressure data out of three surveys from 2006 to 2011. All the dietary data were converted into data for 26 types of nutrients according to the China food composition [4], and the average of several diastolic and systolic pressure values were used to represent every participant's blood pressure status.

People's blood-pressure responses are different under different physical statuses, so personal information needs to be considered in addition to nutrient intake. We selected hypertensive or not, height, weight, hipline, waistline, gender, and age from the CHNS and calculated the correlation between them and blood pressure. Figure 6 shows the F-value estimated from the correlation. Therefore, we retained five items of personal information highly related to blood pressure as the relevant features for the blood-pressure prediction model.

After eliminating all samples with missing values, more than 29,400 sets of data were obtained, forming a sample set containing the intakes of 26 nutrients and 5 items of personal information as features, and blood-pressure values as labels. In Table 2, the data of three people are selected as an example to illustrate this sample set.

3.3.2. Gradient Boosting Decision Tree for Relationship Analysis. As the blood pressure values are continuous, regression analysis referred to as the estimation of continuous variables has been widely used for solving prediction tasks. Therefore, considering a linear dependence between the input feature matrix and the output blood pressure value, one straightforward solution is to model the correlation analysis between nutrient intakes, personal information and blood pressure as a regression problem.

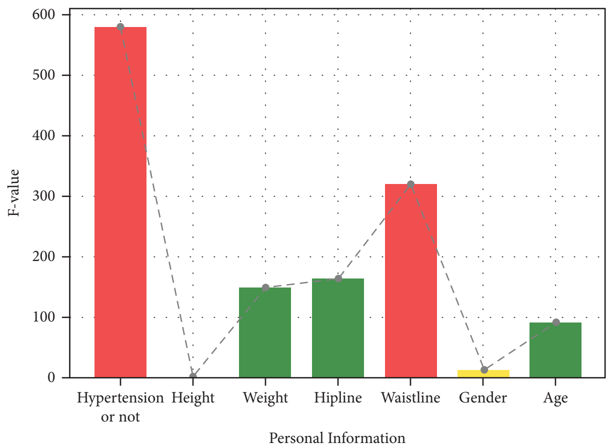

Figure 6: The F-values of the personal information.

Table 2: The daily nutrient intake and blood pressure values for three samples in the sample set.

Nutrients & personal information	Sample 1	Sample 2	Sample 3
Water (ml)	478.78	743.15	522.2
Energy (kcal)	753.1	1187.63	570.13
Protein (g)	21.65	58.22	27.44
Fat (g)	12.75	41.14	16.91
Carbohydrate (g)	143.19	160.03	81.61
Dietary fiber (g)	5.83	14.1	4.73
Cholesterol (mg)	305.83	489.62	290.67
Ash (g)	3.63	9.29	5.17
Vitamin A (mg)	0.22	0.54	0.21
Carotene (mg)	0.63	1.86	0.42
Retinol (mg)	0.12	0.23	0.14
Vitamin B1 (mg)	0.27	1.28	0.25
Vitamin B2 (mg)	0.4	0.97	0.58
Niacin (mg)	5.4	11.78	5.32
Vitamin C (mg)	38.67	89.78	47
Vitamin E (mg)	4.07	14.23	4.49
Ca (mg)	106.2	528.57	359.37
K (mg)	972.33	1827.07	940.97
P (mg)	351.87	1013.58	442.5
Na (mg)	234.37	721.41	480.07
Mg (mg)	155.8	263.2	112
Fe (mg)	6.16	14.23	6
Zn (mg)	3.24	12.42	3.8
Se (μg)	18.64	47.97	26.77
Cu (mg)	0.71	1.2	0.45
Mn (mg)	2.76	7.74	1.59
Weight (kg)	72	72.8	60
Hipline (cm)	106	101.5	102
Waistline (cm)	96	91.5	83
Age	76	47	32
Hypertension	Yes	Yes	No
Systolic pressure	139.33	150	108.67
Diastolic pressure	88	80	70

ml = milliliter; kcal = kilocalorie; g = gram; mg = milligram; μg = microgram; cm = centimeter; kg = kilogram.

GBDT, also known as multiple additive regression tree (MART), is a machine learning algorithm widely used to solve regression and classification problems. It is a gradient boosting algorithm that uses decision tree as the base learner, composed of multiple decision trees. Each tree is constructed based on the negative gradient of the loss function (residual error) of the previous tree. Finally, the conclusions of all trees are accumulated as the final result according to the construction order. There are four loss functions for the GBDT regression model, and we select mean square deviation "ls" to establish the blood pressure prediction model. Given a dataset $\mathcal{X} = \{(x_1, y_1), \cdots, (x_N, y_N)\}$, the formula of "ls" loss function is as follows:

$$L(y_i, f(x_i)) = \frac{1}{2}(y_i, f(x_i))^2 \leftrightarrow y_i - f(x_i). \quad (1)$$

For regression model candidates, we try to use some common regression models, i.e., decision tree (DT), k-nearest neighbors (KNN), adaptive boosting (AdaBoost), and extremely randomized trees (extra-trees), to verify the effectiveness of the proposed GBDT-based blood pressure prediction scheme. We apply data normalization into data preprocessing to improve efficiency and prevent potential performance diminished.

One inevitable phenomenon in an actual application is that the collected data is corrupted by noise, leading to the performance diminished. Similarly, the CHNS data used in the case study may also have some deviations. To better exploit the nonlinearity of the learned features, inspired by the recent progress of denoising autoencoder (DAE) [44], and back-propagation neural network (BNN) for a wide range of machine learning tasks, we propose to design a deep architecture by stacking multiple layers of feature encoders to ensure the more robust feature representation can be learned to reduce the influence of noise, and build the mapping between 31 features and the blood pressure value based on BNN.

3.3.3. Model Establishment and Validation. Figure 7 shows the experimental flowchart of blood pressure prediction using different models.

(1) Model Design. GBDT has several essential parameters that need to be optimized, including the number of regression trees (n_estimators), learning rate, maximum depth of each tree (max_depth), and the minimum number of samples required to split the nodes(min_samples_split). We use the grid search method to adjust these parameters to achieve the best performance, and experiment results show that the best parameter values of the blood pressure prediction model are 200, 0.1, 4, and 3, respectively. We also adjust the best parameters of other prediction models.

(2) Model Evaluation. We use the hold-out method to evaluate the robustness and reliability of the model. The hold-out method divides the data set into two mutually exclusive sets in a certain ratio, which is used as the train set and the test set. We use the train_test_split method to split the dataset into a train test and a test set in the ratio of 7 : 3

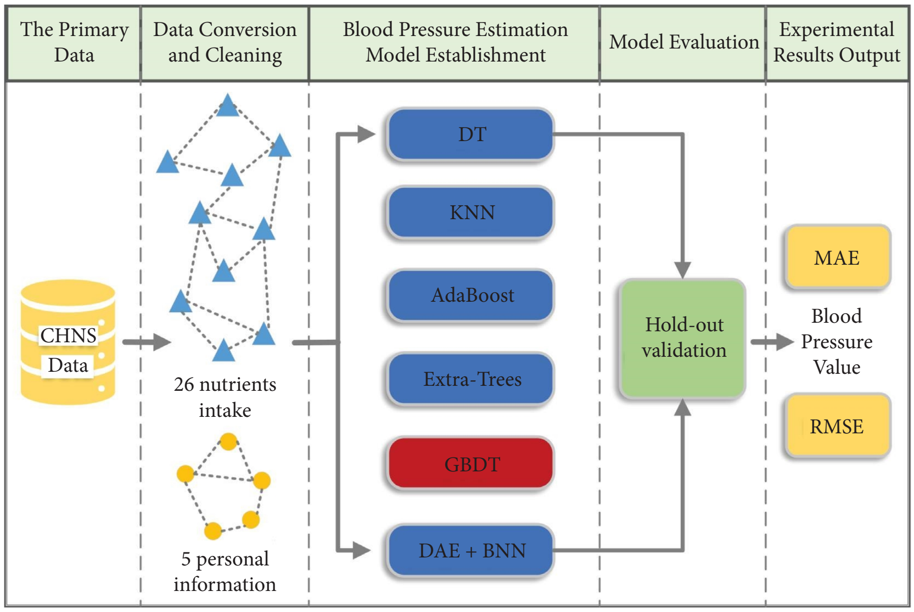

Figure 7: The flowchart for the blood pressure prediction model.

Table 3: Results of the small trial for type 2 diabetes.

Trial participant	Gender	Age	Days of diet recording	HbA1c-the first medical test	HbA1c-the second medical test	Comparison of two HbA1c
1	Male	50	13	6.8	6.7	Decrease
2	Male	58	12	10.6	10.5	Decrease
3	Female	57	14	8.3	7.8	Decrease
4	Male	59	14	6.1	6.1	Unchanged
5	Male	65	12	7.1	7.0	Decrease
6	Female	63	14	8.7	7.9	Decrease
7	Female	51	14	5.8	5.8	Unchanged
8	Male	40	11	7.3	7.5	Increase
9	Female	48	14	9.7	9.2	Decrease
10	Male	53	14	8.0	8.0	Unchanged

and 8 : 2, and set 20 different random_state to achieve random partitioning of the data in the train and test sets, respectively. Finally, we report the model performance using the average outcomes (95% confidence intervals and 95% CI) of multiple runs on different and random dataset partitions.

The mean absolute error (MAE) and root mean square error (RMSE) metrics are used to measure the deviation between predicted ranks and their ground truth values, as in

$$\mathrm{MAE} = \frac{1}{N}\sum_{i=1}^{N}\left|y_i - \hat{y}_i\right|,$$
$$\mathrm{RMSE} = \sqrt{\frac{1}{N}\sum_{i=1}^{N}\left(y_i - \hat{y}_i\right)^2}, \quad (2)$$

where $\{y_1, \ldots, y_N\}$ is the truth travesty and $\{\hat{y}_1, \ldots, \hat{y}_N\}$ is the predicted ranks.

4. Results

4.1. Analysis of the Platform Performance. Table 3 presents the results of the trial with type 2 diabetes as the study population, including the gender and age of each participant, the total number of days the diet was recorded during the trial, the actual HbA1c values obtained from the two medical tests, and the comparative results of the two HbA1c. The comparison of HbA1c shows that at the end of the trial, 6 participants have a decrease in HbA1c levels ranging from 0.1 to 0.8, 3 remain unchanged, and 1 has an increase of 0.2. HbA1c reflects the glycemic status in the past two months [40]. Although this trial was conducted for a short period of only 14 days, it is evident that the majority of the participants had a decrease in HbA1c, indicating the effectiveness of the combination of the platform and the dietitian for nutritional guidance. Meanwhile, the diet data recorded by all participants in the platform are stored on the server. Therefore, dietitians can analyse these data

Table 4: Performance comparison of six blood pressure prediction models: 26 nutrients intake and 5 personal information.

Prediction model	Train-test split	Systolic pressure (95% CI)		Diastolic pressure (95% CI)	
		MAE	RMSE	MAE	RMSE
DT	7 : 3	15.53 (15.46, 15.60)	20.60 (20.51, 20.70)	10.42 (10.39, 10.46)	13.57 (13.51, 13.63)
	8 : 2	15.41 (15.32, 15.50)	20.42 (20.30, 20.54)	10.40 (10.35, 10.45)	13.54 (13.46, 13.62)
KNN	7 : 3	12.16 (12.12, 12.20)	16.14 (16.05, 16.23)	8.25 (8.23, 8.28)	11.01 (10.98, 11.06)
	8 : 2	12.21 (12.17, 12.25)	16.18 (16.11, 16.25)	8.20 (8.16, 8.24)	10.93 (10.86, 10.99)
AdaBoost	7 : 3	13.04 (12.84, 13.24)	16.43 (16.23, 16.62)	7.95 (7.88, 8.01)	10.22 (10.14, 10.29)
	8 : 2	12.84 (12.62, 13.07)	16.25 (16.03, 16.46)	7.93 (7.86, 8.00)	10.19 (10.12, 10.27)
Extra-trees	7 : 3	15.91 (15.39, 16.42)	20.46 (19.95, 21.00)	10.56 (10.52, 10.60)	13.77 (13.70, 13.83)
	8 : 2	15.60 (15.51, 15.68)	20.68 (20.57, 20.79)	10.49 (10.43, 10.54)	13.63 (13.54, 13.72)
DAE + BNN	7 : 3	12.78 (12.68, 12.88)	17.39 (17.21, 17.57)	7.95 (7.87, 8.04)	10.56 (10.44, 10.67)
	8 : 2	12.75 (12.63, 12.86)	17.28 (17.11, 17.44)	7.84 (7.78, 7.90)	10.40 (10.31, 10.48)
GBDT	7 : 3	10.65 (10.62, 10.68)	14.22 (14.18, 14.27)	7.18 (7.16, 7.19)	9.40 (9.38, 9.43)
	8 : 2	10.53 (10.46, 10.60)	14.07 (13.97, 14.17)	7.15 (7.12, 7.18)	9.35 (9.30, 9.40)

professionally to find the causes of patients with unsatisfactory HbA1c control and make timely individual guidance and adjustments.

Regarding the experience of using the platform, in terms of function usage, users gave positive feedback with a mean score of 4.75 (3 users rated 4 and 9 users rated 5), stating that the platform functions are easy to understand and use, the food-nutrient database can meet the recording needs, and is suitable for long-term nutrition monitoring and disease management without the need for hospital visits. The ratings of 5 for both platform performance and platform compatibility indicate that the platform can operate stably during use. In addition, the two dietitians believe that the platform has considerably reduced their work of recording and analysing data. The diet and nutrient intake data collected through the platform has provided them with adequate references for making guidance. Moreover, one patient suggests that the "custom dishes" function would simplify the recording process more if the record could be modified on the existing dishes instead of adding ingredients one by one.

4.2. Analysis of the Case Study Results. Table 4 lists the average experimental results of six blood pressure prediction models used in this case study on different dataset partitions. From Table 4, the best outcomes for each model were obtained at the train-test split of 8 : 2, and the MAE and RMSE metrics of GBDT are lower than those of other models under different partitions. The GBDT prediction model outperforms all the other methods for systolic pressure prediction. As for diastolic pressure prediction, AdaBoost and DAE + BNN achieve similar results to GBDT, but the running time is much longer than GBDT in practice.

Figure 8 intuitively shows more details about the experimental results of six blood pressure prediction models. The x-axis and y-axis represent the different random_state and MAE metric, respectively. We can see GBDT prediction model has lower MAE values in both systolic and diastolic pressure prediction than other methods and has robust prediction performance under different dataset partitions.

Figure 9 shows the top 12 features that play an important role in blood pressure prediction, calculated and ranked by calling the feature_importances_ method in the model. Specifically, the Gini impurity is a measure of data impurity, and the tree nodes are split based on selecting the feature that minimizes the Gini impurity after splitting as the optimal feature. The feature importance is eventually calculated based on the Gini impurity of all nodes split on that feature. Figure 9 indicates that although the order is different, hypertension, age, weight, and waistline are the most 4 important features on both systolic and diastolic blood pressure, which are the same risk factors associated with hypertension suggested by some studies [45]. The features ranked 5–7 are Na, Fat, and Vitamin C. According to common medical knowledge, sodium and fat intake will significantly affect the blood pressure status, and proper supplementation of vitamin C can help lower blood pressure [46]. Ranks 8–12 have different features affecting systolic and diastolic blood pressure, but both include water and vitamin E. Downing a lot of water in a short-time can cause a certain increase in blood pressure, and minerals contained in water can also affect blood pressure, such as water sodium [47]. Appropriate vitamin E intake can improve blood pressure status, such as by reducing systolic blood pressure [48].

In order to intuitively observe the relationship between nutrients intake and blood pressure from the blood pressure value, we exclude 5 personal information from the input and only use 26 nutrients intake data for experiments. The results in Table 5 show that nutrient intake can also predict blood pressure within a certain degree of error. Compared with Table 4, it is also consistent with the common medical sense that blood pressure is also affected by age and weight in addition to nutrients intake [49].

5. Discussion

This study aims to provide a more convenient and effective way to popularize personalized nutrition management through the integrated use of m-Health and machine learning. Based on this focus, we designed and implemented a mobile application for dietary nutrition data collection and analysis, demonstrated the platform's usability through

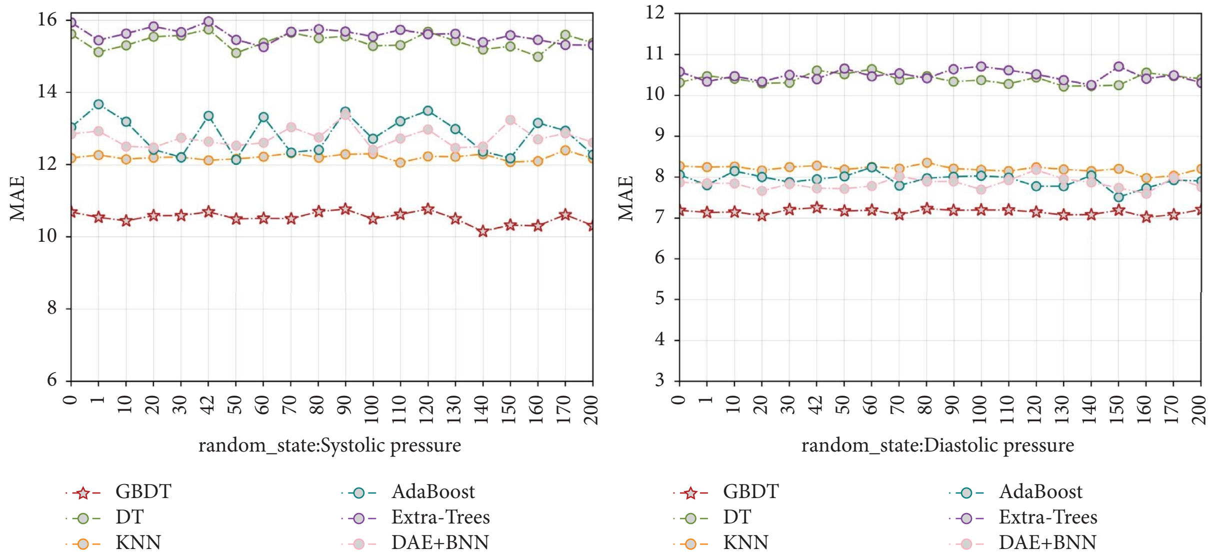

Figure 8: Experimental results with hold-out validation: systolic pressure and diastolic pressure (train-test split of 8 : 2).

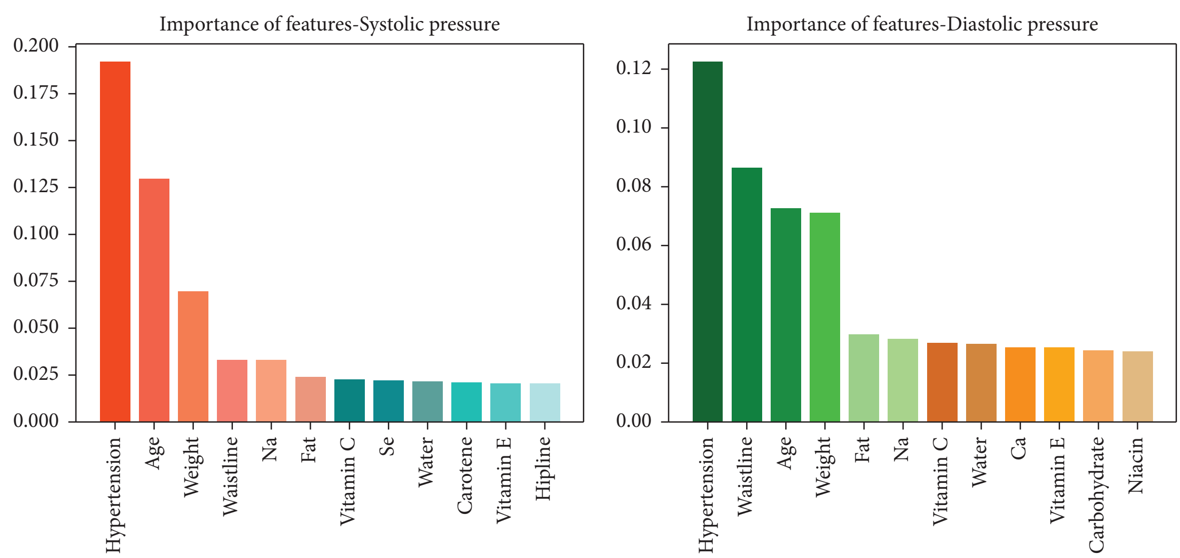

Figure 9: The top 12 features in blood pressure prediction.

Table 5: Performance comparison of six blood pressure prediction models: 26 nutrients intake.

Prediction model	Train-test split	Systolic pressure (95% CI)		Diastolic pressure (95% CI)	
		MAE	RMSE	MAE	RMSE
DT	7 : 3	19.95 (19.86, 20.05)	26.20 (26.08, 26.31)	12.06 (12.00, 12.13)	15.75 (15.66, 15.83)
	8 : 2	19.89 (19.81, 19.97)	26.14 (26.01, 26.27)	12.06 (11.96, 12.15)	15.70 (15.56, 15.83)
KNN	7 : 3	15.20 (15.15, 15.25)	19.85 (19.77, 19.23)	9.20 (9.17, 9.22)	11.92 (11.87, 11.96)
	8 : 2	15.17 (15.11, 15.24)	19.83 (19.75, 19.91)	9.18 (9.15, 9.21)	11.89 (11.84, 11.94)
AdaBoost	7 : 3	17.15 (16.88, 17.43)	20.79 (20.55, 21.03)	10.47 (10.16, 10.78)	13.01 (12.71, 13.31)
	8 : 2	17.36 (17.11, 17.60)	20.98 (20.76, 21.20)	11.09 (10.73,11.44)	13.58 (13.23, 13.94)
Extra-trees	7 : 3	20.47 (19.54, 21.41)	25.82 (25.00, 26.64)	12.11 (12.07, 12.15)	15.75 (15.68, 15.82)
	8 : 2	19.99 (19.89, 20.08)	26.17 (26.08, 26.26)	12.07 (12.01, 12.12)	15.72 (15.63, 15.81)
DAE + BNN	7 : 3	13.84 (13.73, 13.94)	18.81 (18.66, 18.97)	8.36 (8.32, 8.41)	11.21 (11.12, 11.29)
	8 : 2	13.60 (13.51, 13.69)	18.46 (18.36, 18.56)	8.33 (8.28, 8.39)	11.10 (11.03 11.18)
GBDT	7 : 3	13.73 (13.68, 13.77)	18.21 (18.14, 18.28)	8.22 (8.19, 8.24)	10.94 (10.90, 10.99)
	8 : 2	13.70 (13.64, 13.76)	18.18 (18.10, 18.27)	8.19 (8.16, 8.22)	10.91 (10.85, 10.97)

a small trial, and conducted a case study exploring the relationship between nutrients and blood pressure. The positive results, in which HbA1c levels decreased in 6 of the 10 participants who enrolled in the trial, indicate the ability of the proposed platform to provide personalized nutritional guidance and its potential for disease management and improvement. The outcome of the case study showed that the GBDT-based scheme could predict blood pressure within a smaller error range, demonstrating the feasibility of predicting blood pressure values through nutrient intake and personal information.

Several strengths of this study need to be highlighted.

First, the proposed platform provides three ways to record diet, which significantly simplifies the recording process compared to other mobile health platforms that only have one.

Second, our vast database satisfies the recording needs and provides a more detailed and comprehensive reference for self-health management and dietitians' judgment and guidance.

Third, the platform can effectively realize remote, long-term diet monitoring and disease management, alleviating the problem of an unbalanced distribution of medical resources.

Fourth, the results of case studies provide more abundant evidence on nutrition for health management. The data gradually accumulated by the platform will support more in-depth analysis based on machine learning and serve as information support for clinical research.

The limitations of this study should be stated. The platform needs to collect more data due to its short operation period. As the use of the platform gradually increases, we will accumulate sufficient and long-term actual data to explore the relationship between dietary nutrition and health. In addition, more feedback from real users is needed to enrich the platform's features further.

6. Conclusion and Future Issue

This paper put forward a mobile nutrient-service platform to provide convenient and real time remote service for users, including diet records, intelligent analysis of multiple nutrition data, and online nutritional guidance for self-health management. Users can download and use the platform through the website [50]. The promising potential of the platform for personalized nutrition guidance and disease management is demonstrated through a trial with type 2 diabetes as a study subject. Moreover, the scheme takes the relationships between nutrient intake, personal information, and blood pressure as a case study. This noninvasive blood pressure measurement can be the basis for diagnosis and provide appropriate health advice for people.

At present, this platform has realized all the functions mentioned in the paper and will be further improved in the following future work: multivariate heterogeneous data acquirement: adding the collection of personal background (religion, culture, and tradition), habits (sedentary and stay up late), body measurement (waist and hip circumference), and other nutrients data. Nutrients including amino acids may exceed 100 dimensions with the expansion of data. The abundant data could help data-driven technology, such as machine learning, to depict users' more comprehensive health status to provide more appropriate and personalized nutrition recommendations.

Wearable devices: Extend dynamically changing personal information acquired by smart bracelet and body fat scale for analysis, such as exercise and body fat percentage.

Food image recognition: food image recognition can improve the completeness of records by recognizing foods that are indistinguishable for the user, enabling more appropriate management of nutritional intake.

Association analysis between the chronic diseases and nutrient intake: evidence suggests that nutrient intake plays an essential role in the occurrence and progression of many chronic diseases. We will explore the meaningful connections between these diseases and nutrient data to help people form a healthier lifestyle.

Along with the rapid advance and broad application of information technology, the transition towards intellectualization and digitalization is the development trend of health care, and the wide application of the smartphone can make medical resources integrated and utilized effectively. In this paper, we propose a nutrition data collection and analysis approach based on smartphone and machine learning as a starting point to improve the nutrition service. Our future work will continue to focus on the discussion and research of nutrition and health data. Overall, providing help and advice for people's healthy lives is warranted as the key ultimate objective of our proposed approach.

Data Availability

The data used to support the findings of this study are available from the China Health and Nutrition Survey (CHNS) upon request.

Conflicts of Interest

The authors declare that they have no conflicts of interest.

Acknowledgments

This research was funded by the National Natural Science Foundation of China under grant no. 61771338, Tianjin Key Research Project (18ZXRHSY00190), and Yunnan Key Research Project (2018IB007).

References

[1] World Health Organization, "E-library of evidence for nutrition actions (eLENA), nutrients," 2023, http://www.who.int/elena/nutrient/en/.

[2] Chinese Nutrition Society, *Chinese Dietary Reference Intakes*, Science Press, Beijing, China, 2013 edition, 2014.

[3] European Food Safety Authority, "Nutrition topic, dietary reference values," 2023, https://www.efsa.europa.eu/en/topics/topic/dietary-reference-values.

[4] Y. Yang, G. Wang, and X. Pan, *China Food Composition: Book 1*, Peking University Medical Press, Beijing, China, 2nd edition, 2009.

[5] Government of Canada, "Nutrition and healthy eating, nutrient data," 2, https://www.canada.ca/en/health-canada/services/food-nutrition/healthy-eating/nutrient-data.html.

[6] United States Department of Agriculture and Agricultural Research Service, "Food and nutrient database for dietary studies," 2023, https://www.ars.usda.gov/northeast-area/beltsville-md-bhnrc/beltsville-human-nutrition-research-center/food-surveys-research-group/docs/fndds/.

[7] P. J. Stover, C. Garza, J. Durga, and M. S. Field, "Emerging concepts in nutrient needs," *The Journal of Nutrition*, vol. 150, no. 1, pp. 2593S–2601S, 2020.

[8] W. Min, S. Jiang, L. Liu, Y. Rui, and R. Jain, "A survey on food computing," *ACM Computing Surveys*, vol. 52, no. 5, pp. 1–36, 2019.

[9] E. Celik and N. Sanlier, "Effects of nutrient and bioactive food components on Alzheimer's disease and epigenetic," *Critical Reviews in Food Science and Nutrition*, vol. 59, no. 1, pp. 102–113, 2019.

[10] A. L. Cremonini, I. Caffa, M. Cea, A. Nencioni, P. Odetti, and F. Monacelli, "Nutrients in the prevention of alzheimer's disease," *Oxidative Medicine and Cellular Longevity*, vol. 2019, Article ID 9874159, 2019.

[11] M. Ciulla, L. Marinelli, I. Cacciatore, and A. D. Stefano, "Role of dietary supplements in the management of Parkinson's disease," *Biomolecules*, vol. 9, no. 7, p. 271, 2019.

[12] S. De la Cruz-Ares, F. M. Gutiérrez-Mariscal, J. F. Alcalá-Díaz et al., "Quality and quantity of protein intake influence incidence of type 2 diabetes mellitus in coronary heart disease patients: from the CORDIOPREV study," *Nutrients*, vol. 13, no. 4, p. 1217, 2021.

[13] M. Iddir, A. Brito, G. Dingeo et al., "Strengthening the immune system and reducing inflammation and oxidative stress through diet and nutrition: considerations during the COVID-19 crisis," *Nutrients*, vol. 12, no. 6, p. 1562, 2020.

[14] N. Ali, "Role of vitamin D in preventing of COVID-19 infection, progression and severity," *Journal of Infection and Public Health*, vol. 13, no. 10, pp. 1373–1380, 2020.

[15] G. Ferrara, J. Kim, S. Lin, J. Hua, and E. Seto, "A focused review of smartphone diet-tracking apps: usability, functionality, coherence with behavior change theory, and comparative validity of nutrient intake and energy estimates," *JMIR mHealth and uHealth*, vol. 7, no. 5, p. e9232, 2019.

[16] G. K. Garge, C. Balakrishna, and S. K. Datta, "Consumer health care: current trends in consumer health monitoring," *IEEE Consumer Electronics Magazine*, vol. 7, no. 1, pp. 38–46, 2018.

[17] N. A. Selamat and S. H. M. Ali, "Automatic food intake monitoring based on chewing activity: a Survey," *IEEE Access*, vol. 8, pp. 48846–48869, 2020.

[18] L. Rachakonda, S. P. Mohanty, and E. Kougianos, "ILog: an intelligent device for automatic food intake monitoring and stress detection in the IoMT," *IEEE Transactions on Consumer Electronics*, vol. 66, no. 2, pp. 115–124, 2020.

[19] J. S. Ahn, D. W. Kim, J. Kim, H. Park, and J. E. Lee, "Development of a smartphone application for dietary self-monitoring," *Frontiers in Nutrition*, vol. 6, p. 149, 2019.

[20] T. Ege, Y. Ando, R. Tanno, W. Shimoda, and K. Yanai, "Image-based estimation of real food size for accurate food calorie estimation," in *Proceedings of the 2019 IEEE Conference on Multimedia Information Processing and Retrieval (MIPR)*, pp. 274–279, San Jose, CA, USA, March 2019.

[21] Y. Lu, T. Stathopoulou, M. F. Vasiloglou, S. Christodoulidis, Z. Stanga, and S. Mougiakakou, "An artificial intelligence-based system to assess nutrient intake for hospitalised patients," *IEEE Transactions on Multimedia*, vol. 23, pp. 1136–1147, 2021.

[22] R. Sookrah, J. D. Dhowtal, and S. D. Nagowah, "A DASH diet recommendation system for hypertensive patients using machine learning," in *Proceedings of the 2019 7th International Conference on Information and Communication Technology (ICoICT)*, pp. 1–6, Kuala Lumpur, Malaysia, July 2019.

[23] A. Pinto, J. Viana, D. Martinho et al., "Improving the lifestyle behavior of type 2 diabetes mellitus patients using a mobile application," in *Proceedings of the 2022 IEEE Symposium on Computers and Communications (ISCC)*, pp. 1–5, Rhodes, Greece, June 2022.

[24] M. Sharma, "M-health services for COVID-19 afflicted and infected victims," *EAI Endorsed Transactions on Pervasive Health and Technology*, vol. 7, no. 27, 2021.

[25] N. Hasan, Y. Bao, and R. Chiong, "A multi-method analytical approach to predicting young adults' intention to invest in mHealth during the COVID-19 pandemic," *Telematics and Informatics*, vol. 68, Article ID 101765, 2022.

[26] M. Sharma, S. Sharma, and G. Singh, "Performance analysis of statistical and supervised learning techniques in stock data mining," *Data*, vol. 3, no. 4, p. 54, 2018.

[27] R. Sarath Kumar Boddu, A. A. Santoki, S. Khurana, P. Vitthal Koli, R. Rai, and A. Agrawal, "An analysis to understand the role of machine learning, robotics and artificial intelligence in digital marketing," *Materials Today: Proceedings*, vol. 56, pp. 2288–2292, 2022.

[28] M. Sharma, "Research and google trend for human neuropsychiatric disorders and machine learning: a brief report," *Psychiatria Danubina*, vol. 33, no. 3, pp. 354–357, 2021.

[29] K. C. H. Tsang, H. Pinnock, A. M. Wilson, and S. A. Shah, "Application of machine learning algorithms for asthma management with mHealth: a clinical review," *Journal of Asthma and Allergy*, vol. 15, pp. 855–873, 2022.

[30] Y. Zhao, E. N. Naumova, J. F. Bobb, B. Claus Henn, and G. M. Singh, "Joint associations of multiple dietary components with cardiovascular disease risk: a machine-learning approach," *American Journal of Epidemiology*, vol. 190, no. 7, pp. 1353–1365, 2021.

[31] N. Birk, M. Matsuzaki, T. T. Fung et al., "Exploration of machine learning and statistical techniques in development of a low-cost screening method featuring the global diet quality score for detecting prediabetes in rural India," *The Journal of Nutrition*, vol. 151, no. 2, pp. 110S–118S, 2021.

[32] A. Oliver, Z. Xue, Y. T. Villanueva et al., "Association of diet and antimicrobial resistance in healthy US adults," *mBio*, vol. 13, no. 3, pp. e0010122–22, 2022.

[33] W. Tang, W. Zhan, M. Wei, and Q. Chen, "Associations between different dietary vitamins and the risk of obesity in children and adolescents: a machine learning approach," *Frontiers in Endocrinology*, vol. 12, p. 816975, 2022.

[34] G. Murdaca, S. Banchero, M. Casciaro et al., "Potential predictors for cognitive decline in vascular dementia: a machine learning analysis," *Processes*, vol. 10, no. 10, p. 2088, 2022.

[35] G. Murdaca, S. Banchero, A. Tonacci, A. Nencioni, F. Monacelli, and S. Gangemi, "Vitamin D and folate as predictors of MMSE in Alzheimer's disease: a machine learning analysis," *Diagnostics*, vol. 11, no. 6, p. 940, 2021.

[36] M. Y. Shams, O. M. Elzeki, L. M. Abouelmagd, A. E. Hassanien, M. A. Elfattah, and H. Salem, "HANA: a healthy artificial nutrition analysis model during COVID-19 pandemic," *Computers in Biology and Medicine*, vol. 135, Article ID 104606, 2021.

[37] N. Jafari, M. R. Besharati, M. Izadi, and A. Talebpour, “COVID and nutrition: a machine learning perspective,” *Informatics in Medicine Unlocked*, vol. 28, Article ID 100857, 2022.

[38] K. K. Kumar, E. Ramaraj, B. Srikanth, A. S. Rao, and P. B. V. N. Prasad, “Role of MD5 message-digest algorithm for providing security to low-power devices,” in *Proceedings of the 2022 6th International Conference on Intelligent Computing and Control Systems (ICICCS)*, pp. 352–358, Madurai, India, May 2022.

[39] S. H. Ley, O. Hamdy, V. Mohan, and F. B. Hu, “Prevention and management of type 2 diabetes: dietary components and nutritional strategies,” *The Lancet*, vol. 383, no. 9933, pp. 1999–2007, 2014.

[40] S. I. Sherwani, H. A. Khan, A. Ekhzaimy, A. Masood, and M. K. Sakharkar, “Significance of HbA1c test in diagnosis and prognosis of diabetic patients,” *Biomarker Insights*, vol. 11, pp. S38440–104, 2016.

[41] National Institute for Nutrition and Health (NINH), “China health and nutrition survey. Survey data,” 2015, https://www.cpc.unc.edu/projects/china.

[42] B. Zhou, P. Perel, G. A. Mensah, and M. Ezzati, “Global epidemiology, health burden and effective interventions for elevated blood pressure and hypertension,” *Nature Reviews Cardiology*, vol. 18, no. 11, pp. 785–802, 2021.

[43] A. Mente, M. Dehghan, S. Rangarajan et al., “Association of dietary nutrients with blood lipids and blood pressure in 18 countries: a cross-sectional analysis from the PURE study,” *Lancet Diabetes & Endocrinology*, vol. 5, no. 10, pp. 774–787, 2017.

[44] M. Chen, K. Weinberger, F. Sha, and Y. Bengio, “Marginalized denoising auto-encoders for nonlinear representations,” in *Proceedings of the 31st International Conference on Machine Learning (PMLR)*, vol. 32, no. 2, pp. 1476–1484, Beijing, China, June 2014.

[45] L. Wang, M. Heizhati, D. Zhang et al., “Excess weight loss is a vital strategy for controlling hypertension among multi-ethnic population in northwest China: a cross-sectional analysis,” *Medicine*, vol. 98, no. 36, Article ID e16894, 2019.

[46] U. N. Das, “Vitamin C for type 2 diabetes mellitus and hypertension,” *Archives of Medical Research*, vol. 50, no. 2, pp. 11–14, 2019.

[47] M. R. R. Talukder, S. Rutherford, C. Huang, D. Phung, M. Z. Islam, and C. Chu, “Drinking water salinity and risk of hypertension: a systematic review and meta-analysis,” *Archives of Environmental & Occupational Health*, vol. 72, no. 3, pp. 126–138, 2017.

[48] M. R. Emami, M. Safabakhsh, S. Alizadeh, O. Asbaghi, and M. Z. Khosroshahi, “Effect of vitamin E supplementation on blood pressure: a systematic review and meta-analysis,” *Journal of Human Hypertension*, vol. 33, no. 7, pp. 499–507, 2019.

[49] B. Zhou, J. Bentham, M. Di Cesare et al., “Worldwide trends in blood pressure from 1975 to 2015: a pooled analysis of 1479 population-based measurement studies with 19·1 million participants,” *The Lancet*, vol. 389, no. 10064, pp. 37–55, 2017.

[50] Y. Liu and H. Jiang, “The nutrient-service platform proposed in this manuscript was designed and completed by ourselves,” 2022, https://kangshilife.com/.