Knowledge and Information Systems (2023) 65:3753–3775
https://doi.org/10.1007/s10115-023-01897-4

REGULAR PAPER

FoodRecNet: a comprehensively personalized food recommender system using deep neural networks

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Received: 12 July 2022 / Revised: 1 April 2023 / Accepted: 25 April 2023 /
Published online: 7 May 2023

Abstract

Today, the huge variety of foods and the existence of different food preferences among people have made it difficult to choose the right food according to people's food preferences for different meals. Also, achieving a pleasant balance between users' food preferences and health requirements, considering the physical condition, diseases/allergies of users, and having a suitable dietary diversity, has become a requirement in the field of nutrition. Therefore, the need for an intelligent system to recommend and choose the proper food based on these criteria is felt more and more. In this paper, a deep learning-based food recommender system, termed "FoodRecNet", is presented using a comprehensive set of characteristics and features of users and foods, including users' long-term and short-term preferences, users' health conditions, demographic information, culture, religion, food ingredients, type of cooking, food category, food tags, diet, allergies, text description, and even the images of the foods. The appropriate combination of features used in the proposed system has been identified based on detailed investigations conducted in this research. In order to achieve a desired architecture of the deep artificial neural network for our purpose, five different architectures are designed and evaluated, considering the specific characteristics of the intended application In addition, to evaluate the FoodRecNet, this work constructs a large-scale annotated dataset, consisting of 3,335,492 records of food information, users and their scores, and 54,554 food images. The experiments conducted on this dataset and the "FOOD.COM" benchmark dataset confirm the effectiveness of the combination of features used in FoodRecNet. The RMSE rates obtained by FoodRecNet on these two datasets are 0.7167 and 0.4930, respectively, which are much better than that of competitors. All the implementation source codes and datasets of this research are made publicly available at https://github.com/saeedhamdollahi/FoodRecNet.

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Keywords Recommender systems · Artificial neural networks · Deep learning · Food recommender · Food · Health rules

1 Introduction

Today, the usage of machine learning-based intelligent systems has become a requirement to meet most of the people's daily needs. Among these, intelligent recommender systems are also used in various applications [1–8]. Regarding the diet, due to the broad range of foods and differences in food preferences, as well as the current lifestyle and limited time to choose and prepare the right food [9], it feels more than ever that we need a system to suggest food according to food preferences and the health criteria of a diverse range of people. Such a system can have very constructive and helpful applications in web-based systems or mobile applications and play a key role in e-commerce, the food industry, restaurant, and hotel management.

Given the different tastes and food preferences as well as health criteria, this recommending system should be able to create a model of users' preferences, based on their previous choices and scores, as well as considering their demographic and health information to identify and recommend foods that are appropriate for the user's physical condition and health.

Each food has several characteristics, such as ingredients, type of cooking, type of meal, and category. In addition, other valuable features can be obtained from the recipe of food along with the image of the food. Features such as calories, fat, and other nutrients are also important both medically and in health. On the other hand, different people have various characteristics such as long-term and short-term food preferences, demographic information, culture, religion, physical activity level, allergies, and various diseases that affect the food choices for different meals [10, 11]. Each of these characteristics can be involved in choosing the right food and be an effective aid to any food recommendation system.

Recommender systems are generally divided into main categories of collaborative filtering, content-based, knowledge-based, and hybrid methods depending on the algorithm type used to implement them [12, 13]. In the field of food recommender systems, various methods have been proposed so far, with the basis of them being the same methods as mentioned above. Some food recommendation methods focus only on the user's preference [14–20], some focus on health criteria [21, 22], and some offer a combination of the two approaches [23, 24]. Methods such as similarity criteria, matrix factorization, and machine learning methods are used in approaches based on user preference [16, 18, 20, 25, 26]. Approaches based on health criteria usually use rules based on the variables of health and physical condition of the user [21, 22, 24, 27].

Methods based on similarity criteria check all available foods and create a list of foods with the highest similarity scores to foods preferred by the user. Such methods are called memory-based methods. However, according to the experiments conducted in this research, they usually require extensive computation when the number of foods increases and simple similarity criteria cannot accurately discern all aspects of the user's preference or use all types of complex data about foods and users.

On the other hand, model-based methods recommend foods by creating a model of the user's preference. These types of methods usually use matrix factorization and machine learning methods. However, according to experiments, in the matrix factorization method [28], as the number of users and foods increases, the dimensions of the matrices become larger, and in addition to the need for lots of calculations, memory problems also occur.

Deep learning technology [29], as one of the newest and most powerful methods of machine learning, has not received much attention in the field of food recommender systems. In cases, such as [18, 20, 25, 30–33] where the deep learning method has been applied, limited features have been used to create a model of user preferences, while, in contrast to the matrix factorization method that essentially has memory problems, in the deep learning-based methods, we can use data generators to read data in small batches and use them in the training phase of the system.

In this paper, a deep learning-based food recommender system, termed "FoodRecNet", is presented using a comprehensive set of characteristics and features of foods and users. Features such as food ingredients, type of cooking, food category, food tags, and items such as diet, allergies, diseases, culture, and religion are used to create a food feature vector to extract an accurate model of the user's food preferences. Also, based on the assumption that the text description and the images of foods contain useful information to recommend better foods, we extract some features from them and add them to the feature vector. The food image is important because users may be interested in different colors and textures of the food based on its ingredients and the cooking styles [33]. The deep neural network is designed and evaluated in five different architectures to build the best learning model by considering the various categories of features used in the proposed method. Moreover, the users' short-term preferences and the users' health and demographic information are used to solve the recommender system's cold-start problem [34, 35]. The users' health information enables the system to use health criteria and the user's preference to recommend the right food for the user's health status.

Furthermore, to evaluate the proposed method, this work constructs an extensive dataset of real-world information and characteristics of foods, and food ratings given by real-world users, from recipes published on AllRecipes,[1] which is the largest social network focused on food [32, 36–39] with 1.5 billion visits per year [32]. The collected dataset contains 3,335,492 records and 54,554 food images. The experiments conducted on this dataset and the FOOD.COM benchmark dataset [16] demonstrate the appropriate performance of the proposed approach compared with other available methods.

In the next section, previous related works are briefly reviewed. Then, in Sect. 3, the details of the FoodRecNet are presented. In Sect. 4, the experimental results are reported and discussed. Finally, in Sect. 5, the conclusion and ideas for future work are offered.

2 Related works

As stated in Sect. 1, recommender systems are generally divided into the following four main categories [12]:

(1) *Collaborative filtering methods* in these methods, items previously liked by users similar to the target user are suggested. The similarity between two different users is calculated using the choices they have made in the past. Collaborative filtering methods are the commonly used method in recommender systems and can be implemented in a user-based or an item-based way [40–44]. For example, in an online store, users who are similar to the target user are selected using similarity criteria, and then, items that these users have preferred in the past are suggested to the target user.

(2) *Content-based methods* in content-based recommender systems, items are offered to the user, similar to the items the user has previously preferred [12]. The similarity of the

[1] https://www.allrecipes.com/.

two items is calculated using the features of the items. For example, for a user who has previously rated seafood positively, the recommender system recognizes the interest in this type of food, thus recommending seafood in the future.

(3) *Knowledge-based methods* in these methods, items are offered to the user based on previous knowledge about the features of the items and how useful it is for the user [12]. For example, fried or high-calorie foods are not recommended for the elderly or those with a high body mass index (BMI).

(4) *Hybrid methods* any method implemented by combining two or more of the methods mentioned above falls into the hybrid method category. The purpose of creating hybrid methods is to cover the weaknesses of one method, using other method's strengths, and solving the cold-start problem [12, 45].

In implementing all the above-categorized recommender systems, different methods and algorithms based on data mining techniques (such as association rules, clustering, and classification), matrix factorization, optimization algorithms, and deep learning algorithms are utilized [46]. Food recommender systems are also designed based on the same methods and algorithms. Some food recommender systems focus on individual preferences [16, 19, 25, 47], some on medical and health criteria [24, 31, 48], and others on a combination of both [23]. Also, several previous studies have used similarity criteria [14, 17] to recommend the food, and others have developed a model of the user's food preference and used it to recommend appropriate foods. In the following, we review the existing research conducted in each of these methods.

Methods based on similarity criteria El-Dosuky et al. [23] developed an algorithm for recommending food using a combination of health and similarity criteria, according to the user's preference. In this research, the TF-IDF algorithm and cosine similarity criterion was used. Freyne et al. [14] first transferred users' food ratings to the ingredients of those foods and then used the ingredient ratings to calculate the similarity of users and the ratings of other foods. Almeida [17] used the Rocchio and TF-IDF algorithms to create feature vectors based on the user's preferred ingredients, then used them to calculate the similarity of users and foods feature vectors the ratings of foods. Bianchini et al. [19] proposed the PREFer algorithm. In this algorithm, using similarity criteria, foods were filtered according to the user's preference and by content-based filtering, and then candidate menus for the meal (including appetizers, main course, dessert, and others) were created and at the end, menus are refined and ranked. Finally, Teng et al. [15] proposed an algorithm for recommending alternative ingredients by calculating the similarity of ingredients and capturing the relationships between ingredients based on pointwise mutual information (PMI).

Methods based on the user preference model Lin et al. [16] proposed the CTRMF algorithm. In this study, a content-driven matrix factorization approach was used to model the latent dimension of recipes, users, and features and estimate the food scores. Also, matrices of food features, cooking procedure and bias coefficients were added to the computational process. Ge et al. [18] developed an algorithm for recommending food based on user's preferences using user ratings, food tags and matrix factorization. Mokdara et al. [20] developed a method based on deep neural networks and the user's interested ingredients and favorite dishes. The model predicts the next dishes using a temporal prediction model on the profile and eating history. Finally, Twomey et al. [25] proposed a multilingual recommendation algorithm based on different food features. However, only a limited part of the features in a simple network structure was applied in these methods. In addition, health criteria have not been considered in these researches.

Methods based on visual features Meng et al. [33] proposed the PiNET algorithm based on visual features for food recommendation. Elsweiler et al. [48] used the visual features of food to recommend healthy and low-fat foods. Gao et al. [32] proposed the HAFR algorithm using visual features of food and artificial neural networks. Yang et al. [30, 31] also proposed PlateClick and Yum-Me algorithms based on the visual features of food. In these methods, in addition to using limited features, a simple network structure was used.

Methods based on health criteria Suksom et al. [21] proposed a food recommending algorithm using rules based on health criteria. Elsweiler et al. [24] tried to balance the user's preference and health criteria. Agapito et al. [22] developed the DIETOS algorithm, which, by receiving the values of the user's health criteria, diagnoses the possible disease of the users and recommends the appropriate diet for them. Vairale et al. [27] developed a method for recommending food to thyroid patients using the TF-IDF and KNN algorithms plus medical criteria.

In summary, in previous studies, simple similarity criteria could not accurately and comprehensively determine a user's food preference. On the other hand, in these methods, it is necessary to examine all foods or all users to calculate the similarities that will be high in cost and processing in real applications and high-volume data. In matrix factorization methods, besides the difficulty of including various features in the calculations, with the increase in the number of foods and users, the dimensions of the matrices increase, and the problem of high processing costs for calculations and memory problems arise.

In contrast, our hypotheses are based on the principle that deep learning methods, one of the newest and most powerful machine-learning methods, can create an accurate model that includes the various features and aspects of foods and users. However, previous deep learning-based food recommender systems have used only a part of the available features, and the created models do not include all the quantitative, qualitative, visual aspects and features of food. In addition, extracting medical and health rules and using them in combination with the user's preference model for food recommendations can also have very positive effects on the quality of the recommendations.

3 Proposed method: FoodRecNet

In the proposed method, unlike the existing food recommender approaches, a comprehensive set of numerical, textual, and visual features is used to model the user's preference. Furthermore, in addition to the user's long-term preference, short-term preference and health criteria are also used. On the other hand, food recommender systems presented in previous studies have mainly used methods based on simple similarity criteria or matrix factorization. In contrast, in the proposed method, employing a tailored deep learning-based method can result in a better model based on the user's preference.

3.1 Overview of FoodRecNet

The general structure of FoodRecNet is shown in Fig. 1. As shown in this figure, when a user works with the application to select food, the proposed recommender system starts providing the service. FoodRecNet consists of six parts: (1) food and user ontology, (2) databases (including foods database, users database, and rates database), (3) long-term user preference learning model, (4) short-term user preference extraction, (5) health rules extraction, and (6) recommender interface. In the following, each part is described in separate subsections.

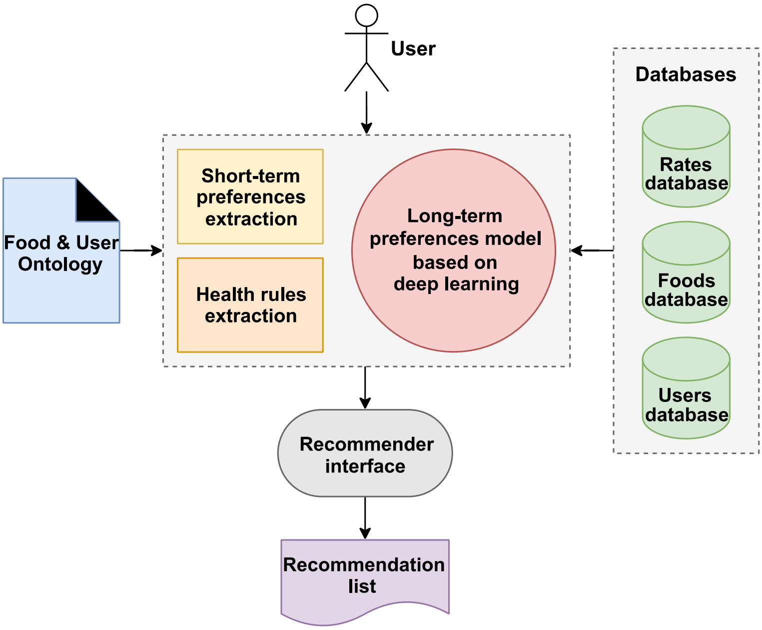

Fig. 1 The general structure of FoodRecNet

3.2 Food and user ontology

As previously stated, each food has different features such as food ingredients, food categories, and tags assigned to the food. In addition, the user also has features such as demographic information, health information, and information about the preference and level of interest in different food categories. These features are used to create food and user feature vectors to create the users' preferences model. Figures 2 and 3 show the ontology created for the user and the food, using the various features considered in FoodRecNet.

3.3 Databases

As shown in Fig. 1, the data used in FoodRecNet include the following three databases:

(1) *Foods database* food information and all related features used by the proposed system are stored in the food database. This database contains information such as food ingredients, food categories, tags assigned to each food, and information such as the description text about how the food is cooked and the food's image.
(2) *Users database* the demographic and health information of the users is stored in the user database. This database contains information such as age, gender, height, weight, and the daily activity level of users.
(3) *Ratings database* all comments and ratings that users have recorded for different foods are stored in the ratings database. This database contains information, such as rating, comment text, comment date, user ID, and food ID.

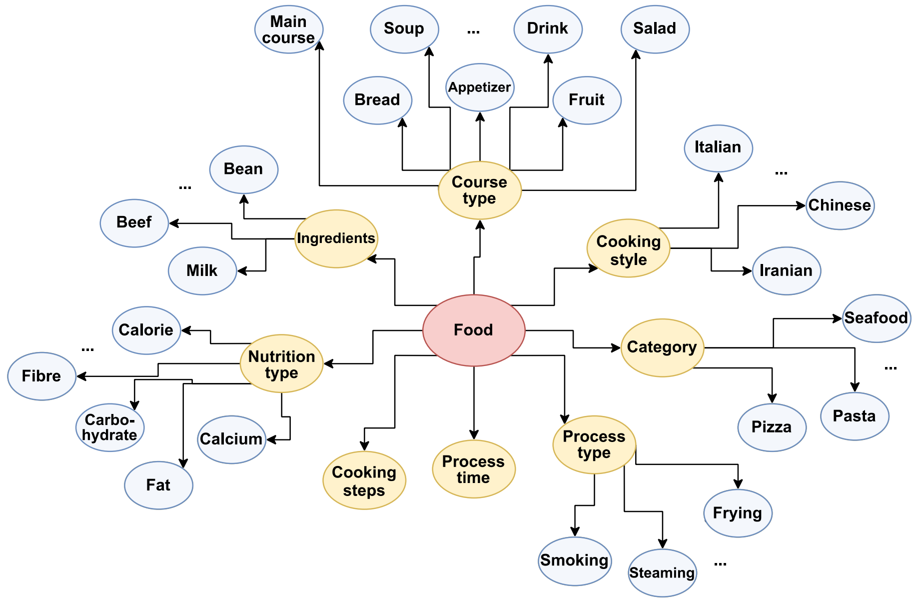

Fig. 2 Food ontology

3.4 Long-term user preferences model

In this section, we create a model of long-term food preference of users by using the food and user features introduced in the relevant ontologies and using the information in the introduced databases. We use deep learning algorithms to create the desired model. Assuming that F is the set of all available food features and N_f is the total number of features. Using the defined features, we extract the long-term preference model of the user. In the following, details for creating each step of the model are explained.

3.4.1 Food feature vector

Assuming N_r is the total number of available foods, the food feature matrix R is defined as $N_r \times N_f$, where each column pertains to a feature of the food, and each row is a feature vector of the food. If the food r has the feature f, then cell R_{rf} equals 1 and otherwise is zero.

$$R_{rf} = \begin{cases} 1 & \text{if } r \text{ contains } f \\ 0 & \text{otherwise} \end{cases} \tag{1}$$

3.4.2 User feature vector

Assuming N_u is the total number of available users, the user feature matrix U is defined as $N_u \times N_f$, each row of it is a feature vector belonging to a user. Initially, all columns are set to zero by default. Then, all the points that user u has given to different foods are collected to create the user feature vector using the features of each of these foods.

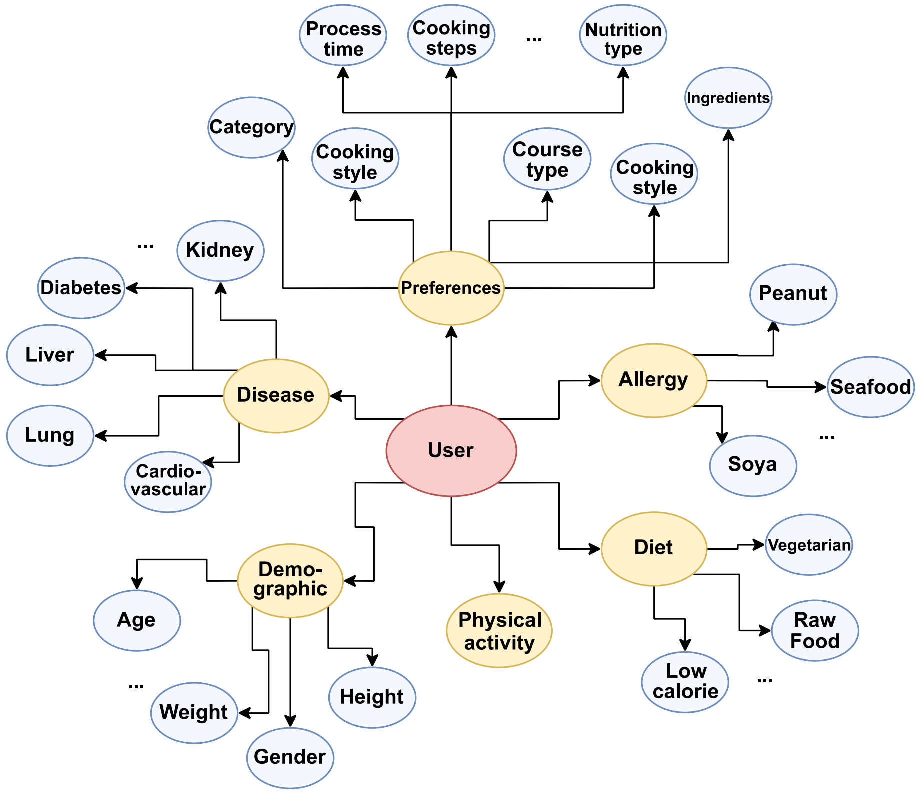

Fig. 3 User ontology

Considering that in the dataset used for experiments in this research, users' scores are in the range of 1 to 5; it is necessary to first convert these values to the bipolar form and the range of − 1 to + 1. The conversion of scores to bipolar is done because, if the scores are in the range of 1 to 5, the feature that did not receive a score remains zero, which means the lowest value and holding a negative opinion about that feature, while in the bipolar form, the zero means a neutral opinion. Consequently, in the proposed method, the scores 1, 2, 3, 4, and 5 become − 1, − 0.5, 0, 0.5, and 1, respectively. These bipolar scores are then entered in Eq. (2), and the row U_u feature values are updated.

$$U_{uf} = U_{uf} + \left(S_{ur} \times R_{rf}\right) \tag{2}$$

where U_{uf} is the feature f of the user u feature vector. S_{ur} is the score given by the user u for food r, and R_{rf} is the feature f of the feature vector of food r.

Finally, all features of row U_u are normalized to be in the range of − 1 to + 1. For this purpose, the absolute value of the largest number of the feature in row U_u is calculated, and all the values of the row are divided to create a normalized vector. Also, in all calculations, the decimal part of the last values obtained for the features is considered only up to 3 decimal places to make the obtained feature vector more general, as follows:

$$U_{uf} = \frac{U_{uf}}{|\max(U_u)|} \tag{3}$$

3.4.3 Food words vector

The recipe text also contains many valuable features that can be used to train the recommender model. To create a food word vector, we first remove all the stop words from the recipe sentences. Then, from all the words in the recipe, we select 5,000 repetitive words to create the food word vector and ignore the rest of the words. Finally, these 5,000 words are orderly indexed.

Assuming that N_r is the total number of available foods and N_w is the total number of words selected to create the vector, the food word matrix W is defined as $N_r \times N_w$, where each column belongs to a word in the text of the food, and each row is a vector of words related to the food. Thus, if the text of food r contains the word w, cell W_{rw} equals 1 and otherwise zero.

$$W_{rw} = \begin{cases} 1 & \text{if } r \text{ contains } w \\ 0 & \text{otherwise} \end{cases} \tag{4}$$

3.4.4 Other features vector

In addition to the previous vectors, another vector containing seven features is created for each food. This vector contains preparation time, servings, number of preparation steps, number of food ingredients, calories, average scores of the user, and average food scores. To normalize the values of these features and convert them from zero to one, each of these values is divided by the largest value of that particular feature in the dataset.

3.4.5 Deep learning algorithm

The parallel and multiple structure architecture of deep learning algorithms is used to create the desired learning model. Each parallel segment receives a portion of the inputs in this method, which can be a feature vector, text, or image. Since each parallel segment imports a set of specific features with different types, such as vector or image, inside the network, different deep neural network architectures such as fully connected networks and convolutional networks are needed to be applied in parallel to the generated network. The aim is to create a learning model that can estimate the score of foods that have not been rated by the user, based on the feature vectors of the user and the users previously rated foods. The learning model is designed in five different architectures with different inputs to compare their performance and select the best one. In the following, each of these architectures is described separately.

Architecture 1: Consists of a user feature vector and food feature vector Figure 4 shows the structure of the artificial neural network designed in this architecture. In this architecture, the user and food feature vectors are entered into the network in parallel from two input layers and concatenated after passing through several dense intermediate layers that have a ReLU (rectified linear unit) activation function [29]. Then, after passing through several other intermediate dense layers with a ReLU activation function, they reach the output layer. There is also a neuron in the output layer with a linear activation function. Finally, the score given by user u to food r is considered as the network output. After training this artificial neural network, the score given by a user to a food can be estimated. Given that the purpose of the artificial neural network is a regression operation, we use the Adam optimization method [29] and the RMSE (root mean squared error) criterion as a cost function.

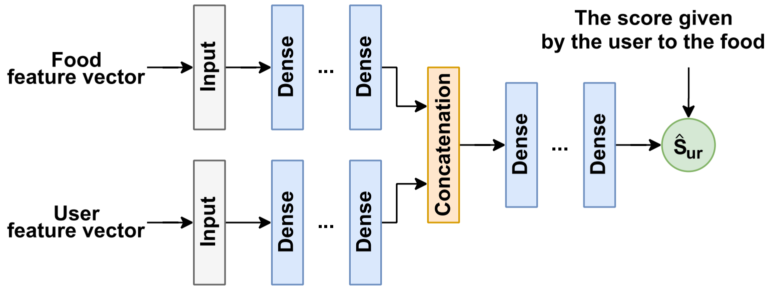

Fig. 4 Architecture 1: Consists of a user feature vector and food feature vector

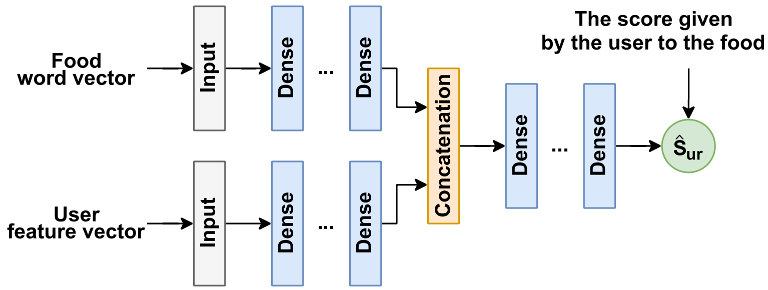

Fig. 5 Architecture 2: Consists of a user feature vector and food words vector

The experiments conducted by applying different combinations of functions in this study show that combining the ReLU activation function in the middle layers and the linear activation function in the output layer and the Adam optimization method and RMSE criterion produces good results for regression problems.

This learning system is trained using a training dataset to achieve the desired recommender model. The created model will have the ability to produce the expected output for the test inputs as the desired recommendation.

Architecture 2: consists of a user feature vector and food words vector This architecture is designed in a parallel structure, similar to Architecture 1. The difference is that instead of the food feature vector, the food words vector is used. Figure 5 shows the structure of the artificial neural network designed for this architecture. In this architecture, the user feature vector and the food words vector are entered into the network in parallel, and after passing through the middle layers similar to Architecture 1, they reach the output layer. In this architecture, activation functions and optimization methods are identical to Architecture 1.

Architecture 3: consists of a user feature vector and food image Figure 6 shows the structure of the artificial neural network designed in this architecture. This architecture, like previous architectures, is designed in parallel. This time, the user feature vector and the food image are entered into the network from the input layers. In this architecture, the image features of food are extracted by middle layers of the neural network and sent to the subsequent layers. The user feature vector, similar to Architecture 1, passes through dense intermediate layers. However, the food image passes through multiple convolution and max pooling 2D [29] layers, and after a Flatten operation, it passes through other dense layers as well. Finally, the resulting two final layers are concatenated and pass through another dense intermediate

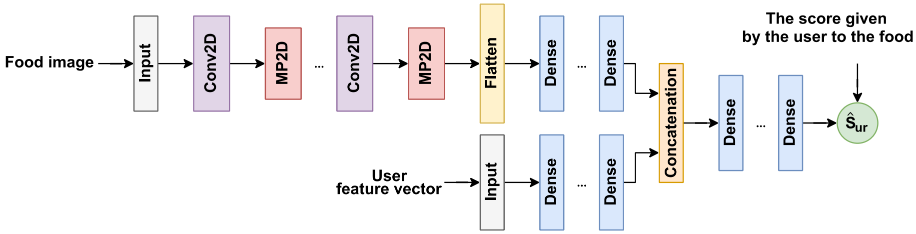

Fig. 6 Architecture 3: Consists of a user feature vector and, food image

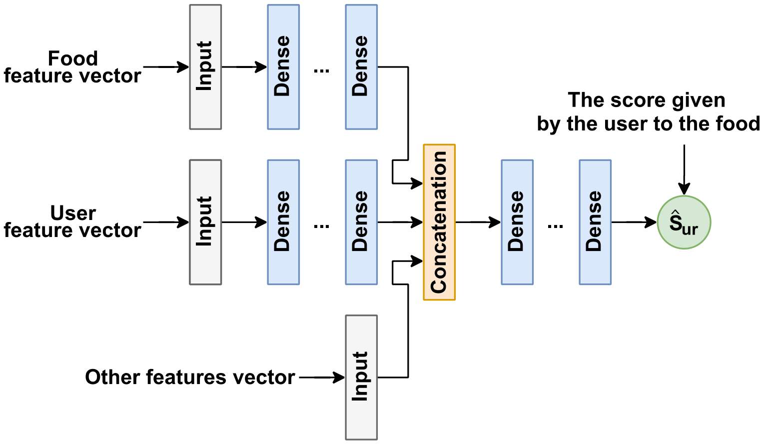

Fig. 7 Architecture 4: Consists of a user feature vector, food feature vector, and other features vector

layer to the output layer. In this architecture, activation functions and optimization methods are identical to Architecture 1.

Architecture 4: consists of a user feature vector, food feature vector, and other features vector Figure 7 shows the structure of the artificial neural network designed for this architecture. In this architecture, together with the user feature vector and the food feature vector, the other features vector is also entered into the network. The goal is to add more features of both the food and the user to understand the user's food preference better. To this end, other features vector enters the network at the stage where user feature vector and food feature vector are concatenated after passing through several intermediate layers. Finally, after passing through several other intermediate layers, they reach the output layer. In this architecture, activation functions and optimization methods are identical to Architecture 1.

Architecture 5: consists of a user feature vector, food feature vector, food words vector, food image, and other features vector Figure 8 shows the structure of the artificial neural network designed for this architecture. In this architecture, five inputs, including the user feature vector, the food feature vector, the food words vector, the food image, and the other features vector, enter the network in parallel. The food feature vector and the food words vector pass through the dense intermediate layers after entering the network. The image of the food, similar to Architecture 3, once entering the network, passes through multiple

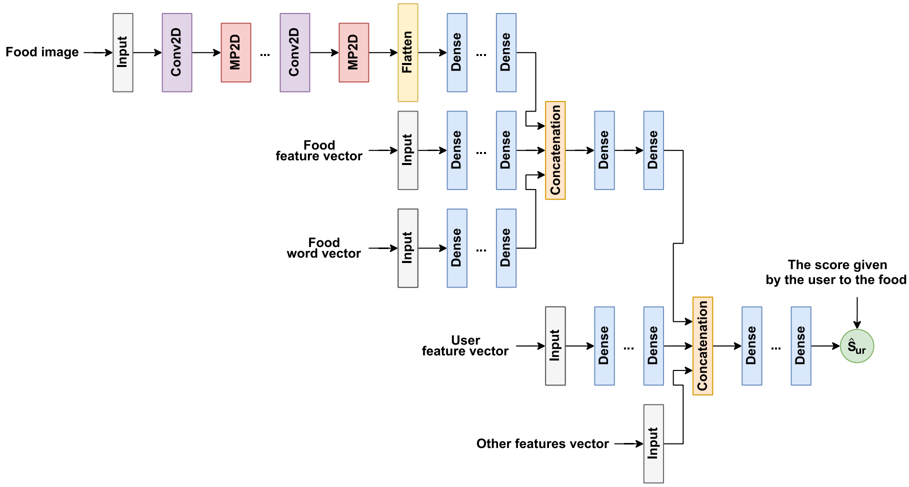

Fig. 8 Architecture 5: Consists of a user feature vector, food feature vector, food words vector, food image, and other features vector

convolution and max pooling 2D layers, then Flatten operation, and then passes through several dense layers. In the next step, three obtained layers are concatenated to form a single feature layer for the food.

On the other hand, the user feature vector, after entering the network, passes through several dense middle layers. Finally, the food features layer, the user features layer, and other features vector are concatenated, and after passing through several dense intermediate layers, they reach the output layer. In this architecture, activation functions and optimization are also identical to Architecture 1.

3.5 Short-term user preference extraction

In addition to the previous parts that focus on the long-term preference of the user, our other hypothesis is that we can filter the list of foods properly by using features such as types of meal, ingredients, events, ceremonies, cooking styles, among others. In other words, when users are choosing a food, this kind of information can give us some clues about their short-term preference in order to filter out some of the items from the whole food list. In this case, in addition to maximizing the use of short-term system information, the processing load of subsequent parts of the system will also be reduced.

Furthermore, by using the users' short-term preference information, we will be able to solve the cold-start problem and create a list of recommendations based on this information for new users who have not yet registered any comments and transactions in the comments database, and we are not able to create feature vectors and their long-term preference models.

3.6 Health criteria extraction

In addition to the user's food preference, which is analyzed using different food features, health criteria are also an essential parameter that can influence the food recommendation process. Therefore, during the first step, a questionnaire is provided to the user to collect

Table 1 The interpretation of BMI values

BMI value	Category
Under 16.5	Severely underweight
16.5–18.5	Underweight
18.5–25	Normal
25–30	Overweight
30–35	Obese Class I
35–40	Obese Class II
More than 40	Obese Class III

demographic information and health indicators. This information includes height (in centimeters), weight (in kilograms), age, gender, level of physical activity (low/medium/high), cardiovascular disease (Yes/No), liver disease (Yes/No), kidney disease (Yes/No), lung disease (Yes/No), diabetes (Yes/No) as well as diet type (choice from categories and tags in the dataset) and allergies (choice from ingredients in the dataset).

For each disease, expert dietitians select the categories of harmful foods related to the disease and those that are beneficial for the disease and register them in the system. Foods in the harmful category receive a score of − 1, and foods in the beneficial category receive a score of + 1, and the rest of the categories receive a score of zero or neutral. For example, a food that has two harmful categories or labels gets two points -1.

Diet and allergies are used to filter the initial list of foods. Thereby, only foods in the list of diets chosen by the user are selected. Foods that contain selected allergenic ingredients are also removed from the list.

Then, using the user's height and weight information, body mass index (BMI) is calculated. BMI is a metric to calculate a person's body fat based on weight and height and is an appropriate indicator for calculating an excess of weight. Equation (5) is used to calculate the BMI:[2]

$$BMI = \frac{\text{Weight(kg)}}{\text{Height}^2\left(\text{m}^2\right)} \tag{5}$$

which is the division of weight (kilogram) per square value of height (meters). The interpretation of BMI values is presented in Table 1.

For each of the categories in Table 1, the dietitian selects and records the categories of harmful foods for the individual in that particular BMI class and those that are beneficial. Like the previous section, foods in harmful food categories receive a score of − 1, and beneficial food categories receive a score of + 1, and the rest of the categories receive a score of zero or neutral. So, for example, a food with two harmful categories or labels will receive 2 points of − 1.

Next, using the information in the daily calorie requirement table [49] available on the Health.gov reference website (which determines the number amount of calorie needed by each person on a day according to age, gender, and amount of physical activity) and based on the demographic information of the users, we obtain the of calorie they need daily. Given that each person typically consumes three main meals and two snacks during the day, we divide the specified daily amount by four to get the maximum allowable calories for each main meal. Also, by dividing this amount by eight, the maximum allowable calories for each

[2] https://en.wikipedia.org/wiki/Body_mass_index.

snack can be calculated. Considering the user intends to prepare the main meal or snack, if the food calories are calculated as more than the allowable limit, the user will receive a score of − 1 and otherwise a score of + 1.

For other items in the diet, such as fat (saturated and trans), cholesterol, carbohydrates, fiber, protein, and sugar, the dietitians determine and record the maximum permissible amounts for daily and for each meal in the system, according to the information of the person's age and gender. This information is also available in the nutrition guide table [50] at the Health.gov reference website. The maximum amount allowed for each main meal and each snack can be calculated using the same equation as in the previous section. If the amount in the food is over the allowable limit, it receives a score of − 1, otherwise + 1.

In the following, the total points obtained for food health factors and the maximum points that can be received for health factors, according to the categories, labels, and minerals examined, are calculated. The food health score is calculated using the following equation:

$$S_{ur}^{h} = \frac{H_{ur}}{H_{ur}^{t}} \times 5 \tag{6}$$

where S_{ur}^{h} is food r th health score according to the health information of user u. H_{ur} is the sum of all scores obtained for food r health factors according to user u health information, and H_{ur}^{t} is the maximum score that can be obtained for health factors, according to the categories, labels, and minerals examined, for food r according to user u health information.

3.7 Recommender interface and recommendation list

In the last stage of the proposed recommender system, based on the long-term preference model (created based on previous transactions and user opinions) as well as recognizing the user's short-term preference according to his current choices and considering the user's demographic, physical information, and health criteria specified by the dietitian in the system, the final list of food recommendations is provided. To this end, first, to obtain a smaller list, the list of all foods in the database is filtered based on the short-term user preference. Then, for each of the foods on this list, the long-term preference score and the health criterion score are calculated, and the final food score using the following equation and the weight coefficient of each is obtained.

$$S_{ur}^{f} = \alpha S_{ur}^{p} + (1 - \alpha) S_{ur}^{h}, 0 < \alpha < 1 \tag{7}$$

where S_{ur}^{f} is the final score of food r for user u concerning all components of taste and health, S_{ur}^{p} is the score of food r for user u, obtained using the long-term preference module. S_{ur}^{h} is the score of food r for user u, obtained using the health module, and α is the weight coefficient of each of the components of taste and health, which is a number between zero and one.

Finally, we arrange the scores list in descending order and offer n food(s) with the highest score to the user. Also, as shown in Eq. (7), using health information and criteria, we can somehow solve the cold-start problem and create a list of recommendations based on this information for new users who have not yet registered comments and transactions in the comments database. For such cases, this is done by decreasing the weight factor for the score from the long-term preference and increasing the weight factor for the score of the health criteria in Eq. (7).

4 Experiments

In this section, the performance of FoodRecNet is evaluated. In the following, first, the datasets used in the experiments and the evaluation criteria are introduced. Then, the results of the conducted experiments and the comparisons with other methods are presented.

4.1 Datasets

In order to evaluate the FoodRecNet, the following two datasets are used:

(1) *AllRecipesRec3M dataset* One of the most important and vital steps in this research was extracting and collecting a comprehensive dataset done by the authors. For collecting this dataset, a dedicated web crawler was created and run on the Allrecipes.com website, which is the largest social network focused on food [32, 36–39] with 1.5 billion visits per year [32], and the target data was extracted. Data of 1,340,260 users, 69,835 foods, 4,240,144 comments and scores, 2,400 categories and food tags, 7,779 food ingredients, and some other information related to the amount of calorie, minerals, and health as well as food images were collected. Data related to users who submitted less than three comments were filtered and removed from the dataset to increase the accuracy of the data. Due to the lack of comments, the feature vector created for these users cannot be accurate. Also, foods that lacked ingredients information, mineral or health information, or lacked an image was filtered and removed. All the above information is required to run the proposed algorithm successfully. Then, to reduce the number of features and the length of the food and user feature vectors, identical ingredients were combined.

Finally, after refining the data, records of 300,807 users, 54,554 foods, and 2,975,564 comments and scores remained. Also, 2,376 categories and tags and 2,191 food ingredients were selected, which in total, 4,567 features constitute the user and food feature vectors. Also, a total of 54,554 food images (one image per food) with a size of 320 × 240 pixels was collected for this dataset. This dataset is named “AllRecipesRec3M” that is publicly available for research community. A summary of characteristics and statistics of the AllRecipesRec3M dataset is presented in Table 2. Figure 9 shows some examples of food images in the dataset.

(2) *FOOD.COM dataset* this dataset, referenced in [16], has been collected from the www.Food.com website, which is a reference for food recipes, and includes user data, foods, and user ratings for various foods. Foods have features such as food ingredients, categories, and food tags. Altogether, there are 5,073 food ingredients and 465 categories and tags for each food, which in total, 5,538 features constitute the user and food feature vectors. A summary of the characteristics and statistics of this dataset is presented in Table 3.

Table 2 Characteristics and statistics of AllRecipesRec3M dataset

Number of users	300,807
Number of foods	54,554
Number of ratings	2,975,564
Average number of ratings per user	9.89
Average number of ratings per food	54.54

Fig. 9 Examples of food images in AllRecipesRec3M dataset

Table 3 Characteristics and statistics of FOOD.COM dataset

Number of users	24,741
Number of foods	226,025
Number of ratings	956,826
Average number of ratings per user	4.23
Average number of ratings per food	38.67

4.2 Evaluation criteria

In the experiments conducted to evaluate the performance of the FoodRecNet recommender system and compare it with other methods, considering that the common RMSE criterion has been used in previous methods such as Refs. [16, 51], the same criterion is used to have a fair comparison. This metric is calculated as Eq. (8):

$$\mathrm{RMSE} = \sqrt{\frac{1}{N_s} \sum_{(u,r)\in S} \left(\hat{s}_{ur} - s_{ur}\right)^2} \tag{8}$$

where N_s is the total number of data points, s_{ur} is the score given by user u to the food r, and $\hat{s}_{ur}$ is the estimation of the system from the score given by user u to the food r. The RMSE criterion actually calculates the error value of the scores estimated by the model. Thus, a lower value of this metric means better performance.

4.3 Implementation and settings

All the implementation source codes and the provided datasets are made publicly available at https://github.com/saeedhamdollahi/FoodRecNet. Python programming language,[3] and Keras,[4] and TensorFlow libraries[5] are used to implement the FoodRecNet. In all five architectures, user feature vector, food feature vector, and food words vector, after entering the network in parallel structure, pass through four dense layers with a ReLU activation function,

[3] https://www.python.org/.

[4] https://keras.io/.

[5] https://www.tensorflow.org/.

which have 1024, 512, 256, and 128 neurons, respectively. Also, the food image, once entering the network in a parallel structure, passes through 10 layers of convolution 2D and max pooling 2D with ReLU activation function. All convolution 2D layers have a 3 × 3 kernel size, and all Max Pooling 2D layers have a 2 × 2 pool size. The convolution 2D layers have 32, 64, 128, 256, and 256 filters, respectively. The output of these layers becomes flattened and passes through four dense layers with a ReLU activation function and has 1024, 512, 256, and 128 neurons, respectively. Finally, the outputs of all parallel structures are joined in one layer, and after passing through three dense layers with a ReLU activation function and with 256, 128, and 64 neurons, reach the dense output layer with a linear activation function and one neuron.

Only in Architecture 5, first, the outputs of all features, including food feature vector, food word vector, and food image, are concatenated in one layer, and after passing two dense layers having 256 and 128 neurons with a ReLU activation function, are concatenated with the output of other parallel structures including the user feature vector and other features vector, and then enter the final three dense layers and finally reach the output.

In order to input data into the neural network, data generators are used to read the data in small batches from the disk and enter the network. Thereby, the memory limitation problem is completely solved. Finally, the created deep neural networks are run in three epochs with a batch size of 32.

For both datasets, introduced in Sect. 4.1, 80% of the total data is used to train the models, and the remaining 20% for testing purpose. The training and test data are selected randomly so that the results are comparable with other methods fairly.

4.4 Experiment 1: results on AllRecipesRec3M dataset

The FoodRecNet is separately trained for each architecture introduced in SubSect. 3.4.5 using the training set of the AllRecipesRec3M dataset and then tested by the test set. The RMSE rates obtained on the test set by five architectures are presented in Table 4.

As shown in Table 4, the RMSE rates for Architecture 1 (consisting of user feature vector and food feature vector) and Architecture 2 (consisting of user feature vector and food words vector) are 0.7590 and 0.7579, respectively, very close to each other. Therefore, it can be concluded that the text of the recipe and the description of the food contain valuable features that enable us to create the recommender model with reasonable accuracy, as well as utilizing the food feature vector.

Also, the RMSE value for Architecture 3 (consists of user feature vector and food image) is 0.7846, which is not much different from the results of previous architectures. Nevertheless, this is an interesting result showing that images of foods alone also contain valuable information to help the recommender system.

Table 4 Results on the AllRecipesRec3M dataset

Architecture	RMSE
1	0.7590
2	0.7579
3	0.7846
4	0.7171
5	**0.7167**

Best result is shown in bold

Table 5 The count of neural network parameters and duration of training phase for each architecture

Architecture	Parameters count	Duration of training (h)
1	10,840,321	6
2	11,283,713	6
3	17,627,969	22
4	10,842,113	6
5	28,937,921	25

In Architecture 4, other features vector, including preparation time, servings, number of preparation steps, number of food ingredients, calories, average scores of the user, and average food scores, are used along with the user and food feature vectors. The RMSE value for this architecture is 0.7171, which indicates a significant improvement compared to previous architectures and the positive impact of the features used.

In Architecture 5, the aggregation of all feature vectors and food images is used. The RMSE value for this architecture is 0.7167, the best performance among all five architectures tested, showing the positive effect of using text and visual features together with other features to create the optimal recommender model.

Regarding the processing time of the proposed method, due to the fact that in the application phase of the neural networks, the calculation of output is done instantaneously, the only important time is the duration of the neural network training. In order to analyze this point, the number of parameters in each of five architectures and the time required to train each network are summarized in Table 5.

As shown in Table 5, with the increase in the number of network parameters, the duration of network training also increases. Also, networks with image data also need more time for training. However, the process of training the model is an offline process and does not have a special effect on the system efficiency in the application stage. Although in the proposed system, the longest training time, which is related to the most complex architecture, is about one day, which is not a long time considering the large number and variety of features used in it.

Our all experiments have been performed on a system with an Intel Core i7-6700H CPU, NVIDIA GeForce GTX 960 M graphics card, 12 GB RAM, Ubuntu 19.10 64-bit operating system environment and using GPU processing.

4.5 Experiment 2: results on FOOD.COM dataset

The FOOD.COM dataset is used to compare the performance of FoodRecNet with other existing methods. Because this dataset lacks the text of the recipes and food images and features such as preparation time, servings, number of preparation steps, and calories of foods, Architecture 4 is used to test and compare the results. Also, the other features vector includes only the average scores of the user and the average scores of the food.

To compare the results, the methods presented in Refs. [16, 51] are considered as the results of these studies are available on the FOOD.COM dataset. The performance of different methods on this dataset is compared in Table 6. The results for Refs. [16, 51] have been reported directly from the related publications.

From Table 6, it is evident that the RMSE rate obtained by the proposed method is much lower than the error value obtained by [16, 51]. The error reduction rate, which is approximately 0.1, is a significant improvement in the expected accuracy of the system and

Table 6 Results on the FOOD.COM dataset

Method	RMSE
FoodRecNet	**0.4930**
[51]	0.5777
[16]	0.5813

Best result is shown in bold

will play an effective role in improving the quality of the system's recommendations. This significant improvement is due to the use of a comprehensive set of features, covering all aspects of foods and users and applying a well-designed and tailored deep neural network, which can create an accurate model of the user's food preference using a rich set of features.

4.6 Experiment 3: effectiveness of short-term preference and health criteria

As stated in Sect. 3, to deal with the cold-start problem, in the proposed method, in addition to the long-term preference of the user, by using the filters and features that the users select when searching and reflecting their short-term preference, we filter the list of foods and use the remaining list as input to the recommender system and subsequent processes. Also, using the demographic information and users' health condition, in addition to having a positive effect on the cold-start problem, enables the recommender system to provide recommendations tailored to the physical condition and health of the user. In our experiments, the α coefficient (in Eq. (7)) is set to 0.5 to give a same weight to food preference and health criteria.

In experiments that were performed on limited data from the dataset, as well as 20 users who were selected with different age, gender, and physical conditions, half of the users registered an average of 20 comments and scores for food from different groups, and the other half of the users were allowed to record a maximum of two comments and scores while interacting and searching the system. In addition, both groups also completed all the information and health questionnaires in the system. Finally, two lists of recommendations were created for each individual, one based solely on the long-term preference model and the other based on both long-term and short-term preference components and health criteria.

According to the recommendations provided by FoodRecNet to these users, 18 users stated that the recommended list, based on both long-term and short-term preference and health criteria, was closer to their opinion and taste and confirmed the improvement of the performance of the recommending system. Two other users also stated that the two lists of recommendations were not much different, which indicates the system's success in dealing with the cold-start problem and the proper use of short-term preference information.

The nutritionist also reviewed the recommended lists and confirmed that in every 20 cases, the recommendation lists had been created based on all the components of preference and health, according to each user's physical condition and health.

5 Conclusion and future works

In this research, a food recommender system, termed FoodRecNet, based on deep learning methods, was developed using a comprehensive set of characteristics of users and foods. In the developed system, a food feature vector was created using features of food ingredients, food categories, and tags. Also, using these features and previous user scores, the user feature vector (including demographic information, health information, and information about the preference and level of interest in different food categories) was created. Then, using the text of the recipe, the food words vector was created. The other features vector was also created using features such as preparation time, servings, number of preparation steps, number of food ingredients, calories, average scores of the user, and average food scores. Moreover, food images were also used to extract the visual features of food. Finally, using a deep neural network, a user preference model was built to estimate the score of foods for which the user had not registered a score, according to the user's previous preference. The developed system was evaluated in five different architectures, considering the specific characteristics of the target application.

In addition, to train and evaluate the FoodRecNet, a large-scale dataset of real-world information and characteristics of users and foods, named AllRecipesRec3M, containing 3,335,492 records and 54,554 food images, was constructed in this work. FoodRecNet was tested on the AllRecipesRec3M dataset and the FOOD.COM benchmark dataset. The results showed that it had significant performance compared to the competitors. Furthermore, extensive experiments were conducted to compare and analyze the performance of various architectures introduced for different combinations of features.

Furthermore, in this study, short-term user preference, demographic information, and user health condition were used to mitigate the cold-start problem in recommender systems. The user's health information enabled the FoodRecNet to use health criteria and the user's preference to recommend the right food considering the user's health status.

Among the limitations of this study, we can point out the lack of suitable datasets with the necessary volume and features for this work, which made us decide to create a new dataset that includes the necessary features. In the same way, there were no suitable previous studies that used this volume and type of features so that it could be used in comparisons, and we had to settle for a few limited ones.

As a future direction, research in improving the neural network structure, using structures that have performed well in other similar applications, is of interest. We are also interested in using much more features of the users and foods, which can still improve the quality of the recommendations. We also believe that the text analysis of user comments can also contain valuable features and information to improve the recommender algorithm.

Author contributions SHO contributed to the conceptualization; data curation; formal analysis; investigation; methodology; validation; visualization; writing—original draft; writing—review and editing. MH was involved in the conceptualization; data curation; formal analysis; investigation; methodology; project administration; resources; supervision; validation; visualization; writing—review & editing.

Funding The authors declare that no funds, grants, or other support was received during the preparation of this manuscript.

Data availability The datasets generated and/or analyzed during the current study are available from the corresponding author on reasonable request.

Declarations

Conflict of interest The authors have no relevant financial or non-financial interests to disclose.

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