Research Article

An Improved Solution for Sustaining Health Using ADIET Recommender System

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Abstract

A deep understanding of a balanced diet required by our body for the perfect amount of vitamins and nutrients in order to stay fit and healthy and be in a good shape has been taken up by many researchers who primarily work on building an efficient balanced diet recommender system. Moreover, unlike previous works, the focus of our study is not only on just recommending food items at random but also to offer a list of items keeping in mind one's taste, choice, and/or preference. Such systems provide a tailor-made diet chart with a perfect balance of health requirements and one's dietary needs without having to keep visiting health and nutrition experts. In this paper, a diet recommender system is proposed using k-modes clustering and RDF (resource description framework)ontology. Here, based on one's preference and the calories and other nutrition requirements, the food items are recommended. The developed system takes into account the amount of carbohydrates, fats, proteins, etc. required by any individual as per one's age and vital statistics. For every cluster, the respective centres are created, and the food items are recommended based on the choices made by the user. At the end, the experimental results are shown where it is inferred that the system performs quite well. Thus, the work contributes to the society by implementing proper health management based on optimally balanced diet recommendations. It is high time to define and implement sustainable approaches towards health management with proper nutritional intake to create an efficient food industry that

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can aid people in adopting healthy eating habits by transforming the recommendations into simplified dietary advice expressed in terms of foods and food patterns.

Keywords: Nutrition,balanced diet, k-modes clustering, machine learning, diet recommender system

Introduction

Insufficient nutrition contributes to disease development and it is extremely crucial to understand the food consumption patterns and analyse the appropriateness of diet and eating habits. Research on balanced diet recommender systems focuses primarily on giving food suggestions and recommending nutritious food in order to help people maintain healthy life standards. Food is one of the integral parts of a person's life. Some people try new dishes all the time, while there are also people who do not want to take health risks and prefer eating normal or plain meals. Moreover, intake of many calories may lead to other health issues. Typically, the major focus in recommender systems is on finding the most accurate recommendation algorithms. What needs to be considered include diversity, recommender persistence, user demographics, serendipity, robustness, etc. It can be said that users tend to be more satisfied with recommendations when there is a higher intralist diversity, there is almost no privacy issues, and the recommendation list is not labelled at all.

A balanced diet is a diet that fulfils the nutrition requirement of the body for proper functioning and which does not harm the body in any way as the amount of fats, proteins, carbohydrates and minerals are balanced in perfect proportions. According to the World Health Organization, there are parameters which need to be maintained for a healthy diet. The first one focuses on the intake of calories in almost the same amount that one burns every day. Secondly, there should be a limit on the amount of fat intake. Not more than 30% of the calories should come from fats. The third point says that everyday intake of at least 400 grams of less starchy fruits and vegetables are required for a healthy diet. Fourth is the amount of sugar intake, which should be less than 10% of what accounts for the total calorie intake and not more than 5 grams per day.

In this paper, we focus on generating a recommender system of balanced diet that is both healthy and nutritious and also meets one's preferences. It uses the techniques of collaborative filtering coupled with algorithms of k-modes clustering. The system asks the user to input his/her profile (see Proposed system design below) and then the result displays a list of food items from among the vast pool of food items that the user would like to choose from. Looking at the drastic health deterioration in a large percentage of the population, there is a need for such a recommender system. It not only helps people adopt a healthy food style but also takes care of their tastes and eating habits. The futuristic agenda is to create an ecosystem that adheres to health promotion and better lifestyle, both at the personal as well as the professional front.

This paper is divided into the following sections: Section 2 discusses some of the well-known previous works related to the food recommendation domain; Section 3 brings to the fore an overview of recommender systems; Section 4 describes the proposed diet recommender system, the working principle, and explains the k-modes clustering algorithm we have used in developing the system; Section 5 presents the results and analysis followed by future scope of development and conclusion in the end.

Previous work

The model proposed in this paper is similar to other works on diet recommender system anda few popular ones are discussed here.

Medina-Moreiraet al. (2017) have proposed a system that deals with a variety of subjects related to the control of glucose quantity in the blood, such as diet, physical activity, mood, medication, and treatment. They have used a collaborative base filtering algorithm to generate health recommendations for the users.

Mino and Kobayashi (2009)have proposed a method to recommend cooking recipes for a diet considering the user's schedule. Different users have different lifestyles and different patterns of consuming calories each day and burning them through physical activities. So, each person follows one's own schedule. Calories from carbohydrates, lipids, proteins, and salts is calculated and increase in the amount of vegetable intake is suggested for a healthy diet. Chavan et al. (2016),Faiz et al. (2014), and Lee et al. (2010) recommended food from a database created by collecting data related to diet for different prakriti- and season-wise diet from different sources (websites, books, dieticians) using fuzzy logic and ontology after creating a user profile.

Priyambadha and Arwan (2013) present ontology-based recommendations for type-2 diabetics while Chen et al. (2015) propose a diet recommendation system for patients suffering from chronic diseases using RDF and OWL ontologies, decision trees and Java API. Diet recommender systems such as DIETOS (Agapito et al., 2016), PREFer (Bianchini et al., 2017) and Yum-Me (Yang et al., 2017) aim to offer the users a personalized menu using a system based on RDF and OWL ontologies and a web interface.

Oh et al. (2010) have presented a time-division layered context integration algorithm to for a context-aware recommender system for a Korean diet and which receives the user's profile, physiological signals, and environmental information to recommend appropriate food. An online recommender for personalized nutrition was developed by Franco (2017). It takes into account the dietary intake using the food frequency questionnaire (FFQ) and provides a personalized nutrition advice for adults.

Rehman and Khalid (2017) have proposed a cloud-based diet recommender system that can be used for diet recommendation to patients suffering from various diseases. The recommendation is done according to the user's pathological reports. Massimo (2017)has developed a food recommender that lets the users record their preferences in the form of both ratings and user tags. The effectiveness of the tags is then explored in improving the quality of the food recommender system.

Much research has been done for building a balanced diet recommender system based on several clustering techniques and classification approaches. For instance, in Ahmad and Dey (2007), the authors have suggested a way to cluster objects that works well for numeric and categorical features while Hartigan et al. (1979) have provided a descriptive study on k-means clustering algorithm applicable to recommenders. Asanov (2011) discusses the traditional approaches of classification and the modern approaches developed lately using a movie recommender. Several other works have discussed collaborative filtering approaches and various parameters for the clustering algorithms (Herlocker et al 2004).

Overview of the recommender systems

Recommender systems can be worked with in two ways. First is collaborative filtering and the second is content-based filtering. In collaborative filtering, the system collects the user's past choices, ratings, actions, and behaviours to perform the task. On the other hand, in content-based filtering, the system examines the properties of one item and based on that recommends items with similar properties. In the process of recommendation, the list of probable choices is grouped under one unit and after matching the items against the required constraints, they are given top-to-bottom ratings and are recommended as per the preference of the user. The constraints can be either the ratings by the user or inferred through their actions. There are two types of datasets using which information on any food item can be represented: categorical datasets and numeric datasets.

Categorical datasets

When the data is represented in a numeric form in which they do not represent their actual mathematical meanings but only the relative values. Such datasets are called categorical datasets. Categorical dataset defines any food item with certain values to represent the corresponding taste. For any food item, say chicken, the values given to them will be as follows: sweet–0, sour–0, bitter-0, salty–1 savoury–1. This means that the food item will be grouped on the basis of its taste.

In other words, this dataset is used on data items that can be grouped.

Numeric datasets

A numeric dataset conveys a quantitative representation of the numbers in which each of those numerals is a measurable quantity. These numbers have mathematical significance and can be added, subtracted, averaged, and so on. So, numeric datasets have meaning as a measurement. Numeric datasets can be further subdivided into two categories: continuous and discrete. As the name suggests, discrete datasets are the values that can be counted. Continuous data,on the other hand, represents measurements and therefore their values cannot be counted but they can still be measured.

Proposed system design

This section describes the architecture of the proposed work. The balanced diet recommender system uses a database that provides the algorithm the necessary elements to work upon, i.e., the names of the food items or the essential nutrients that the food contains. Both categorical and numeric datasets have been used in the model. Several independent modules have been implemented and by using the interactions between them, it is possible to extend its activities and formulate new capabilities. All these modules are designed using RDF (resource description framework)ontology. RDF ontology is a triple or a 3-state model in which each and every fact or knowledge or every sentence is broken down into 3 different parts: subject, predicate, and object (SPO). When combined, they are called RDF triplets. For instance, Figure 1 depicts an example RDF ontology structure that states that the film ABCD(S) is a dance drama (O) shot in India (P).

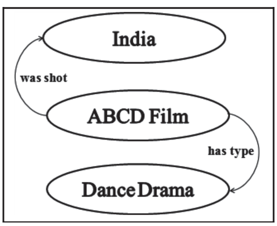

Figure 1. An example RDF ontology structure.

RDF is useful because it provides us with benefits of and primitives for lightweight ontology systems like food recommender systems. Resource in RDF includes photo, image, video, etc.;description includes attributes, features, and relationships among these resources; framework includes the language and its syntax for the descriptions provided. It dictates a relationship denoted by a predicate between the subject and its corresponding related object. Essentially, a triplet ❰SPO❱ says that O is the value of attribute P for the subject S. In fact, any subject usually has many values of its attributes which are described via the predicate. These triplets can be represented either in a table form or using a RDF graph. Table 1 shows names of some sample food items. Items that are chosen are popular in the Indian, Chinese, and European cuisines.

Table 1. Names of some sample food items.

Names
Chicken curry
Chicken tikka
Roasted lamb
Hakka noodles
Vegetable KungPao

Figure 2 is a screenshot showing the nutritional values of different (raw) food items to be used as ingredients in various recipes. The screenshot is taken from the database for the different items mentioned in Authority of Ministry of Health(2008), where the various ingredients of different recipes and their corresponding nutritional values are given along with the kilo calories present in each item.

Food Name	Measure	Weight	Energy	Energy	Protein	Carbohydrate	Total Sugar	Total Dietary Fibre	Total Fat	Saturated Fat	Cholesterol	Calcium	Iron	Sodium	Potassium	Magnesium	Phosphorus	Thiamin	Riboflavin	Niacin	Folate
		g	kcal	kJ	g	g	g	g	g	g	mg	mg	mg	mg	mg	mg	mg	mg	mg	NE	DFE
Breads, Cereals and Other Grain Products																					
French toast, homemade	1 slice	65	149	623	5	16	N/A	0.7	7	1.8	75	65	1.1	311	87	11	76	0.1	0.21	2.1	37
Pancake, buckwheat, prepared from mix (13cm diam)	1	40	73	305	3	10	2	1.1	3	0.6	20	89	0.7	191	80	27	143	0.1	0.09	1.2	9
Pancake, homemade with butter and syrup (13cm diam)	1	50	112	468	3	20	2	0.8	3	1.0	11	85	0.5	211	78	9	118	0.1	0.11	1.1	23
Pancake, plain, from complete mix (13cm diam)	1	40	64	266	1	11	N/A	0.4	2	0.2	3	36	0.4	180	50	6	96	0.1	0.06	0.8	15
Pancake, plain, frozen, ready-to-heat (13cm diam), heated	1	41	94	393	2	18	4	0.7	1	0.3	4	25	1.4	209	30	6	153	0.2	0.19	2.1	27
Pancake, plain, homemade (13cm diam)	1	38	86	361	2	11	N/A	0.5	4	0.8	22	83	0.7	167	50	6	60	0.1	0.11	1.1	21
Potato pancake, homemade (8cm diam)	1	37	112	467	2	13	1	1.0	6	0.6	23	12	0.7	191	277	16	46	0.1	0.06	1.4	15
Waffle, homemade	1	37	103	432	3	14	2	0.5	4	0.7	33	44	0.9	146	58	7	53	0.1	0.15	1.7	37
Waffle, plain, frozen, ready-to-heat, heated	1	33	87	364	2	13	2	0.8	3	0.5	8	77	1.5	260	42	7	139	0.1	0.16	1.9	22
Rice, Pasta and Other Grains																					
Barley, pearled, cooked	125mL	83	102	426	2	23	tr	2.0	tr	0.1	0	9	1.1	2	77	18	45	0.1	0.05	2.2	13
Bulgur, cooked	125mL	96	80	334	3	18	tr	2.7	tr	tr	0	10	0.9	5	65	31	38	0.1	0.03	1.7	17
Couscous, cooked	125mL	83	93	388	3	19	tr	0.7	tr	tr	0	7	0.3	4	48	7	18	0.1	0.02	1.5	12
Quinoa, cooked	125mL	73	70	293	2	13	N/A	1.3	1	0.1	0	11	1.7	4	138	39	77	tr	0.07	1.0	9
Macaroni, cooked	250mL	148	209	873	7	42	1	1.8	1	0.1	0	10	2.1	1	46	27	80	0.3	0.14	4.0	184
Noodles, Chinese, chow mein	60mL	11	60	252	1	7	tr	0.4	4	0.5	0	2	0.5	50	14	6	18	0.1	0.05	0.9	16
Noodles, egg, cooked	250mL	169	225	940	8	42	1	1.9	2	0.5	56	20	2.7	12	47	32	117	0.3	0.14	4.3	176
Pasta, fresh-refrigerated, cooked	250mL	169	220	920	9	40	N/A	3.7	3	0.7	69	17	2.0	140	36	24	88	0.3	0.29	4.0	101
Pasta, fresh-refrigerated, spinach, cooked	250mL	169	223	933	9	41	1	2.2	3	0.6	56	32	1.8	20	63	41	96	0.4	0.21	4.4	159

Figure 2. Nutritional values of different food items.

Table 2 partially contains several attributes of the food – tastes (sweet, salty, sour, bitter and savoury), origin of food (Indian, Chinese, and European), and category (veg or nonveg). Table 2 is maintained using a categorical dataset (where "0" is used to represent the absence and "1" is used to represent the presence of the attribute value). A part of the Table 2 (corresponding to the foods mentioned in Table 1) is shown below.

Table 2. Attributes of the foods.

Food	Taste					Origin			Category	
	Sweet	*Salty*	*Sour*	*Bitter*	*Savoury*	*Indian*	*Chinese*	*European*	*Veg*	*Nonveg*
Chicken curry	0	1	0	0	1	1	0	0	0	1
Chicken tikka	0	1	1	0	1	1	0	0	0	1
Roasted lamb	0	1	0	0	1	0	0	1	0	1
Hakka noodles	0	1	0	0	0	0	1	0	1	0
Vegetable Kung Pao	1	0	1	0	0	0	1	0	1	0

A user profile that contains the details of the user is maintained. These details include the vital statistics of the user and his/her daily requirements of nutrition. All nutritional requirements are for a single meal. Following are the features asked by the system to be recorded in the user profile:

1. Name of the user
2. Height
3. Weight
4. Age
5. Gender
6. Amount of calorie required per meal
7. Amount of protein required
8. Amount of carbohydrate required
9. Amount of fats required (all on basis of per meal)
10. The last food consumed

The calorie, sugar content, fat content, and protein content of the last food consumed would be summed with the amount of every new food consumed throughout the day. The total amount of calorie, fat, sugar, and protein consumed is stored in the user profile that is used later for recommendations. Height, weight, and age are enquired through a questionnaire while other parameters such as nutritional requirements are calculated using calorie, sugar content, fat content, and protein content. Food items are to be rated by the user on a scale of 1 to 5, which will instantiate the user preferences to ease the recommender in making decisions for the user. The provided ratings are also maintained in the user profile.

Figure 3 shows the RDF ontology of the dietary recommender system, in which the circles denote the classes, the rectangles are the features of each class, and the directed edges mark the relationship by a predicate between the subject and the corresponding object.

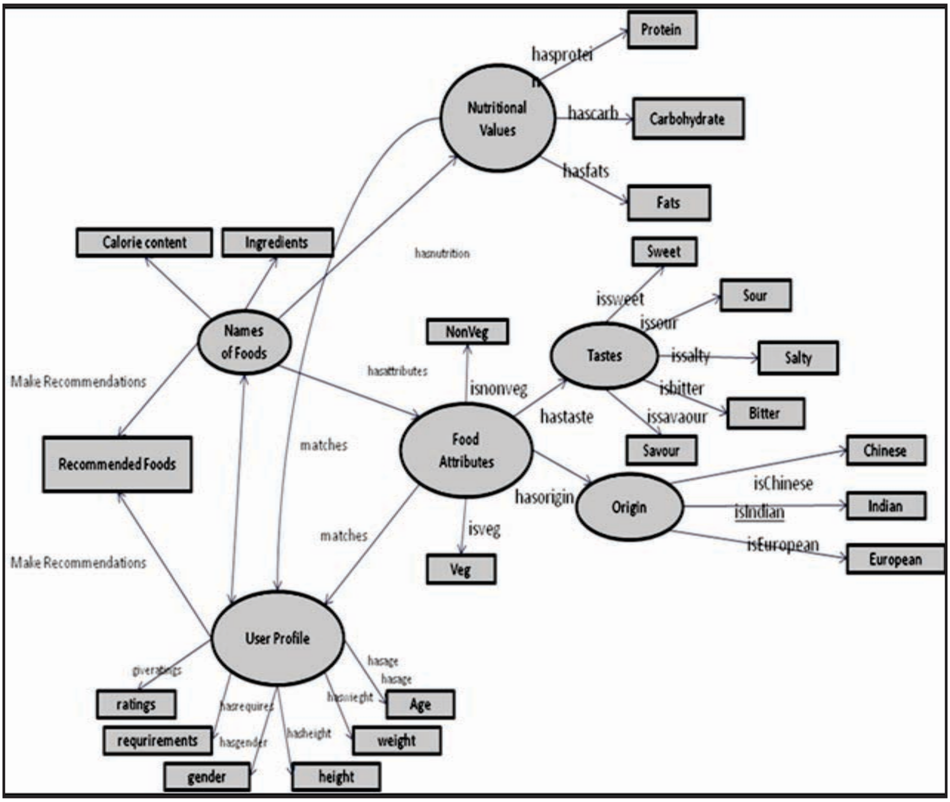

Figure 3. RDF ontology structure of the proposed dietary recommender system.

Figure 3 represents the subjects with their related features. For instance, the subject User Profile has features like Age, Height, Weight, Gender and Requirements (nutrition required) and the food Ratings. Similarly, every food (Food Attributes) has their own specifications like Origin and Tastes, and categories like Veg or Nonveg. Each food is identified by its name and the ingredients used in making that recipe. The calorie content of the foods is also maintained along with the nutrition content of every raw ingredient.

Working principle

Initially, the foods are clustered into 6 overlapping clusters using k-modes clustering algorithm. K-modes clustering algorithm is preferred here because it has already been proven that k-modes clustering algorithm is more efficient with categorical datasets than k-means or k-median clustering algorithms. A brief account of k-modes clustering is given below.
The similarity measure between object A and the centre of cluster C is written as follows,

$$\text{Ø}(aj,cj) = 1 - n_j^r / n_j \quad \text{when } aj = cj$$
$$= 1 \quad \text{when } aj \neq cj \qquad (1)$$

where c_j is the categorical value of attribute j in C_j; n_j is the number of objects in cluster j; and n_j^r is the number of objects whose attribute value is r. As per the equation (1), if the object a_j is not equal to the centre on the same attribute c_j, then the distance is 1 simply because they are dissimilar and the distance between them is the largest. However, when a_j is equal to the cluster point c_j, then the formula (1) has to be used. This formula identifies objects appearing the same in one cluster. Then, this value Ø (a_j, c_j) would be very small, and the distance would be the smallest. The more frequent the value of j in n^r, the more frequently n^r / n would be closer to 1 and the distance would be smaller. The distance function thus uses a frequency-based method to update the nodes. The algorithm given by Huang et al.(1999) is as follows.

To cluster a categorical dataset A into k clusters, the k-modes clustering process consists of the following steps:

Step 1: Select k unique objects as the initial cluster centres (modes).
Step 2: Calculate the relative distances between each object and the cluster centre; allot the object to their respective cluster whose mode has the shortest distance to the object.
Step 3: Select a new mode each time for each cluster and compare it with the previously obtained mode. If they are different, go back to Step 2; otherwise, halt.
Step 4: Repeat the previous step until all objects are properly assigned to clusters.

After the user has logged into the system, she or he is asked to rate the food items. The items to be rated are those which are closest to the 6 centroids of the 6 clusters formed. The user ratings would be taken in an interactive fashion through a questionnaire in which users would be asked to rate six food items (in the range 1 to 5) and this ratings would be added to the user profile (Figure 3). Along with the ratings, the user is asked to enter his or her weight, height, and age.

The daily amount of protein required by a person is calculated as follows:
$$\text{protein required} = 0.8 \times \text{body weight (in kg)} \tag{2}$$
For a person whose weight is over 85 kilograms, the protein required is calculated as:
$$\text{protein required} = 1.4 \times \text{body weight (in kg)} \tag{3}$$

For the measurement of the calorie intake or basal metabolic rate (BMR) value, the Mifflin – St. Jeor formula is used as it provides better accuracy (Franken field et al., 2005):

BMR for men(metric)
$$10 \times \text{weight (in kg)} + 6.25 \times \text{height (in cm)} - 5 \times \text{age (in years)} + 5 \tag{4}$$
BMR for woman(metric)
$$10 \times \text{weight (in kg)} + 6.25 \times \text{height (in cm)} - 5 \times \text{age (in years)} - 161 \tag{5}$$
The amount of fats required by the body is calculated as:
$$\text{Minimum fat–calorie} = 0.2 \times \text{BMR value} \tag{6}$$
$$\text{Maximum fat–calorie} = 3.5 \times \text{BMR value} \tag{7}$$

Total body fats (in grams) required is calculated as follows:
$$\text{Minimum} = \text{Minimum fat-calorie} / 9 \tag{8}$$
$$\text{Maximum} = \text{Maximum fat–calorie} / 9 \tag{9}$$
$$\text{Cholesterol limit} = 0.1 \times \text{BMR value} \tag{10}$$

Sugar limit = 37.5 grams (for men) (11)
Sugar limit = 25 grams (for women) (12)

All these formulas have been taken from Johnson et al. (2009)and the guidelines of American Heart Association (2015). Using the above information (formulas 2–12), the user profile is created and next task is to recommend food items. The food items which are in close proximity to the food that is rated the most are chosen as recommendation using a similarity measure algorithm. From the set of food items, those that do not satisfy the constraints provided for maintaining a balanced dietare discarded.

The following algorithm checks the user details and preferences and produces the set of foods by matching the nutritional requirement criteria so that most appropriate food items can be decided by the system.

Let F be the food that is rated the highest by the user.

Identify the cluster to which F belongs and produce a set of foods that are in close proximity to F, i.e.,are most similar to F.

A[1. . .n] = Set of Foods produced.
Get the total amount of calorie, protein, fat, sugar consumed throughout the day by the user stored in the user profile.
Fore a chitemin A, [1 <= I <= n]
    if calorie (A [i]) + Total calorie consumed > calorie (required by user))
then A = A – A [i]
    if protein(A[i]) + Total protein consumed > protein (required by user))
        thenA = A – A [i]
    if fats (A [i]) + Total fats consumed > fats (required by user))
        then A = A – A [i]
    if sugar (A [i]) + Total sugar consumed > sugar (required by user))
        then A = A – A [i]
recommend (food[i])

From the set of the food items recommended, the user can choose the food of his/her choice and the calorific value along with protein, fat, and sugar contents of that specific food is stored into the database for further analysis for the next iteration. This is how the prototype operates and suggests food items by viewing the user choices as well as guiding the user regarding the calorie intake. The entire system is implemented on the Python platform.

Results and analysis

In this section, a screenshot of an interactive session with the recommender system is shown andthe user ratings taken(Figure 4).The food items are then displayed according to his/her choiceand nutritional requirements (Figure 5).

```
welcome to the food recommender system
we will be taking some quiz to create your user profile
male or female?
m
your age plz:
21
may i know how tall you are(in cms):
165
what is your weight:
65
how much would you rate ['Garlic chicken']
3
how much would you rate ['Omlette']
2
how much would you rate ['Chicken rezala']
3
how much would you rate ['Fish Munchurian']
5
how much would you rate ['Aloo posto']
2
how much would you rate ['Roasted Sweet potatoes']
1
```

Figure 4. Screenshot showing the ratings given by a user.

```
['Fried fish']
[]
['Prawn curry']
[]
['Baked prawn ']
[]
['Baked fish']
['Egg curry']
[]
[]
['Fish Munchurian']
[]
['Chilli Fish']
[]
[]
['Chicken curry']
['Chicken kebabs']
[]
['Tandoori chicken ']
```

Figure5. Screenshot showing the list of food Items recommended by the recommender system.

It can be seen that the user who gives highest rating for Fish Manchurian(see Figure 4) gets Fish Manchurian as are commended food item(see Figure 5). Along with it other food items are also recommended that are similar to Fish Manchurian. The other recommended items consist mainly of Chinese origin and most have fish as a main ingredient. Hence it can be said that food items, both as per the user's preference and its nutritional value, are recommended by the system based on the data available in the user profile.

Evaluation of the system

To evaluate the efficacy and effectiveness of the system, the values of precision, recall and F-measure metrics are calculated. These metrics have traditionally been used for evaluating the performance of information retrieval systems.

Recall = correctly recommended items / total relevant items (13)
Precision = correctly recommended items / total recommended items (14)
F-score = 2 / ((1 / recall)+(1 / precision)) (15)

The evaluation was conducted in a real-life scenario. The developed system was tested for a few users. A segment of one user's interaction with the system is shown in previous figures (Figures 4 and 5). First the user's ratings were taken interactively, then the list of recommended food items was displayed. Table 3 summarizes the precision, recall, and F-score measures calculated for 5 different users.

From the values of recall and precision mentioned in Table 3, it can be concluded that the proposed recommender system works quite fairly. It can also be seenthat

Table 3. Performance measures of the proposed recommender systems.

User	Food items	Relevant food items	Number of correct recommendations	Precision	Recall	F-score
User 1	10	6	5	0.50	0.83	0.624
User 2	11	7	6	0.54	0.86	0.662
User 3	10	7	6	0.60	0.86	0.706
User 4	12	9	7	0.58	0.77	0.663
User 5	11	8	6	0.54	0.86	0.663

more relevant food items are recommended for Users2, 3, and 5. Further, almost all recommended food items are correct for User 2.

Future work

The system allows a user to eat a balanced diet and that too as per his/her preferences and choices without having to botherabout the calorie intake. Thus, it helps in maintaining proper fitness and health. This can be used by dieticians, gym trainers and (in certain cases) doctors to prescribe required food to the patients seeking dietary advices. It can also be used in various corporate offices and academic institutes where due to irregular eating patterns and/or habits developed through excessive workload or stress, the health of an office personnel or faculty or research staff is at risk. The system can be further developed to an extent so as to aid diabetic patients in maintaining their diet plan with proper portions of sugar and fat contents. With proper suggestions and medical supervision, this can come one step closer to recommending food items for critical patients fighting with cancers and cardiac diseases.

Conclusion

This paper on dietary recommender system has the potential in cultivating healthy eating habits by recommending food according to people's requirements exclusively based on their profiles. The main aim is to improve the quality of life by improving theirhealth via nutritious food and helping in reducingmetabolic weight by consumption of a balanced diet. Thus, this system, which is coded in python,takes into account the protein, fat, and carbohydrate requirements of a user and works efficiently in recommending proper food items, ensuring a healthy life. Altering dietary habits is a very complex process, and dietary recommendations without considering an individual's choices, preferences,and behaviour will not succeed in the long run. Food preference is generally built on culture, traditions, and exposure to a variety of food during an individual's lifetime, and so an efficient dietary recommendation system will act as a boon for creating a healthy ecosystem.

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