Meal Suggestions for Caregivers and Indecisive Individuals Without a Set Food Plan

Carlos A. S. Cunha(✉), Tiago R. Cardoso, and Rui P. Duarte

Polytechnic Institute of Viseu, Viseu, Portugal
{cacunha,tcardoso,pduarte}@estgv.ipv.pt

Abstract. Recommendation systems have played a crucial role in assisting users with decision-making across various domains. In nutrition, these systems can provide valuable assistance by offering alternatives to inflexible food plans that often result in abandonment due to personal food preferences or the temporary unavailability of certain ingredients. Moreover, they can aid caregivers in selecting the most suitable food options for dependent individuals based on their specific daily goals. In this article, we develop a data-driven model using a multilayer perceptron (MLP) network to assist individuals in making informed meal choices that align with their preferences and daily goals. Our study focuses on predicting complete meals rather than solely on predicting individual food items since food choices are often influenced by specific combinations of ingredients that work harmoniously together. Based on our evaluation of a comprehensive dataset, the results of our study demonstrate that the model achieves a prediction accuracy of over 60% for an individual complete meal.

Keywords: food recommendation · deep learning · autonomous nutrition

1 Introduction

Nutrition is a concern in modern societies that has to deal with old challenges and new problems to people's health. The leading challenges include the population's lack of domain knowledge and the particularities of individuals, such as their nutrition goals and food preferences [7]. Thus, people need assistance choosing their food to meet their nutritional goals.

Recommendation systems use historical data records to predict users' preferences. They have been widely adopted to recommend e-commerce products, movies, and music [4,15,16]. The importance of food preferences justifies the use of recommendation systems to support the food choices of one person during the

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day. Choices are made by the person directly or by an informal caregiver, as is the case of the elderly, particularly those suffering from some level of dementia.

This study addresses the problem of recommending food to people according to their preferences. Its relevance is described by the support of users or their caregivers deciding on meals adjusted to their energy objectives. Previous work on this topic addresses generic health and fitness support [5,11,14], and the recommendation of specific diets for specific target groups (e.g., diabetics) [12]. We explore deep-learning techniques for food recommendation based on the person's target daily calories and preferences to answer the following research questions:

– RQ1. How do we predict food combinations meeting the individual's preferences and the energetic and nutrient goals specified in the food plan designed by a nutritionist?
– RQ2. Which features are relevant for determining food preferences?
– RQ3. Which data preprocessing techniques are relevant to improve prediction accuracy?

The remainder of this article is structured as follows. Section 2 presents the related work. Section 3 describes the problem addressed in this article. Section 4 describes the data gathering and preprocessing methodology. Section 5 analyses behavioral patterns from the data. Finally, Sect. 6 presents the conclusion.

2 Related Work

The current body of research on food recommendation encompasses various objectives, ranging from providing general food recommendations to catering to specific groups, such as individuals with specific medical conditions or dietary needs.

2.1 Generic Recommendation

Food recommendation systems for general public addresses are designed for people that want to make food and lifestyle choices for better health and fitness. The context-aware food recommendation system presented in [11] is based on the user's profile, physiological signals, and environmental information to recommend food from Korean menus. Results have shown that integrating three contexts makes predicting approximately 95% of user intentions possible.

In [14], a food recommendation system based on user preferences and ingredients is presented. For food content-based recommendations, the authors explore graph clustering, food deep embedding, food similarity calculation, food clustering, and food-based rating prediction. They used deep-learning techniques and user similarity calculation, generation of the trusted network, graph representation of users, user clustering, and user-based rating prediction. The solution was evaluated using a dataset created by crawling the Allrecipes.com website. The results have outperformed other state-of-the-art approaches.

In [5] the authors created a food recommendation system using graph convolutional networks (FGCNs). They model several food-related relations: ingredient-ingredient, ingredient-recipe, and recipe-user. A real-world dataset collected from Allrecipes.com was used for model evaluation. The authors concluded that the presented solution outperforms four state-of-the-art works on recall and normalized discounted cumulative gain (NDCG) metrics.

A food recommendation approach based on many-objective optimization, given the user preferences, nutritional values, dietary diversity, and user diet patterns, is presented in [17]. A MyFitnessPal dataset was used for evaluation. The Positive Point-wise Mutual Information (PPMI) determines the correlation between food items and the evaluation of food preferences. The Simpson index is used as the diversity metric to promote food diversity, while Dynamic Time Wrapping (DTW) measures changes in diet patterns over time. Results show that PEA2+SDE Many-objective optimization algorithms exhibit the best results.

2.2 Specific Diets

In [12] it is proposed a food recommender system for diabetic patients. A Self-Organizing Map and K-mean algorithms support food clustering to provide food substitution within food groups. Clustering is established on the similarity of eight significant nutrients for diabetic patients. Food is categorized into 22 groups based on food characteristics (e.g., rice, juice) and three additional groups based on the impact on diabetics (i.e., normal, limited, and avoidable). Questionnaires addressed to users have shown an overall score of the solution of 3.64 on a scale of 0–5.

A diabetes self-care recommendation system for American Indians is presented in [1]. Food intake and physical workouts based on ontological profiles with general clinical diabetes guidelines are recommended utilizing users' smartphones. The profile is build-up from biological, cultural, socioeconomic, and environmental factors, encoded with professional guidelines as a rule set, which a forward chaining-based reasoner interprets to provide recommendations. Evaluation results by experts have shown accuracy levels between 90% and 100%.

In [2], a food recommendation approach for chronic kidney disease patients is presented. Selection of food for recommendation using the Naïve Bayes, Support Vector Machines, and Random Forest algorithms according to the blood potassium level of people was performed with accuracy levels close to 100%.

Contrasting with previous work, we consider the recommendation of complete meals based on their sequence during the day and the maximum calorie intake specified for that person. The combination of ingredients in a meal obeys cultural, diet type, and individual rules, which makes the meal the recommendation granularity.

3 Problem Statement

Food plans are built upon an energy amount the nutritionist determines for a specified individual based on their goals, physical condition, and clinical status. Energy is further broken down into macronutrients (i.e., carbohydrates, fat, or protein). Each macronutrient contributes a percentage of the total energy amount (Eq. 1). Several times, alcohol (ethanol) is forgotten in the decomposition of macronutrients, but it contributes to the amount of energy consumed by an individual.

$$energy = carbo + fat + protein + alcohol \tag{1}$$

Micronutrient values may be incorporated into the food plan. Still, their control is difficult when the person resorts to food equivalents frequently due to their appetite or availability of the recommended food.

Our work is bound to analyze macronutrients since they are frequently the main elements of the food plan for generic diets based on caloric intake. By contrast, some diseases need control of some micronutrients– e.g., potassium for chronic kidney disease [2]. However, we added the daily limit of sodium and sugar, as they are specified in most food plans due to their direct relation with obesity [8,10].

Food granularity represents another design decision for our solution. The recommended food granularity can be: (1) the meal; or (2) the food associated with the meal. We decided on (1) because several food combinations are commonly chosen (e.g., hamburgers, french fries, and coke are commonly eaten together).

Food preferences are not only individual but also culture-dependent. That means that meal prediction can be performed based on the preferences of a person or a community. The articulation between preference granularities can be complex since they involve variables such as the number of individual records available for personalized preference learning or the cohesion of food preferences in a specific community. Our work focuses on community preferences to predict the preferences of one individual based on the nutrients specified for their food plan.

Based on the aforementioned assumptions, the problem can be defined as follows: given the individual goals regarding nutrients G, the meal's day sequence s, the proper combination C of food for a specific meal, and the food nutrients N_G, the temporal context T, the model should predict the most appropriate food combination F for that person.

4 Model Building Methodology

We follow a traditional model-building methodology, starting with a data selection activity (Fig. 1). Data preprocessing, transformation, model training, and evaluation activities follow.

4.1 Dataset

To validate the effectiveness of our approach, we utilized a dataset sourced from MyFitnessPal [6]. This dataset comprises 587,187 days of food diary records

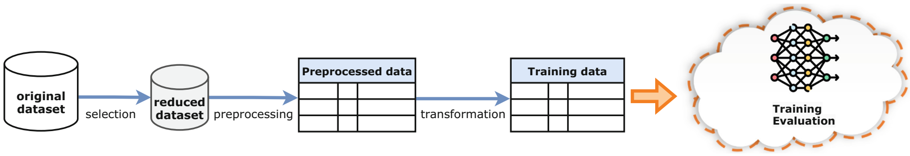


Fig. 1. Data preparation methodology

logged by approximately 9.9K MyFitnessPal users from September 2014 to April 2015.

The dataset includes the person's daily goals for calories and macronutrients (protein, carbs, and fat) and micronutrients (sodium and sugar). Each dataset record contains a list of food chosen by the person for one meal, their goals, and a sequence representing the meal order – i.e., the first meal of the day is represented as one, and the following meals increment this value.

4.2 Data Selection and Preprocessing

Data preparation is required to select, preprocess, and transform raw data stored in the original dataset. One important goal of data preparation is to filter outliers and provide the learning process with data in the appropriate form.

We reduced the dataset by considering users whose number of samples is above the $5th$ percentile to exclude outliers. A similar lower $5th$ percentile filter was applied to foods with few samples (Fig. 2).

	date	food_ids	goal_calories	goal_carbs	goal_fat	goal_protein	goal_sodium	goal_sugar	sequence	...
0	15/09/2014	{1,2,3,4,4}	1572	196	52	79	2300	59	1	...
1	16/09/2014	{5,1,2,3,6,7}	1832	229	61	92	2300	69	1	...
2	17/09/2014	{1,2,3,6,8,9,10}	1685	210	56	85	2300	63	1	...
3	18/09/2014	{1,6,2,3,11,12}	1597	199	53	80	2300	60	1	...
4	19/09/2014	{1,7,13,12,2,3,12,12}	1589	198	53	80	2300	60	1	...

Fig. 2. Table after preprocessing

Data preprocessing involved feature normalization and transformation of their representation. Normalization is performed according to the maximum and minimum values of each feature (Eq. 2). This technique gets all the scaled data in the range (0, 1).

$$x'_{i,n} = \frac{x_{i,n} - min(x_i)}{max(x_i) - min(x_i)} \tag{2}$$

4.3 Data Transformation

Data transformation unfolds features to unveil hidden data for training or prepare data for training and classification. Figure 3 shows the transformation of the *date* feature by extracting the *weekday*, *year*, *month*, and *year* features. These features are potentially good predictors since food intake is frequently associated with specific periods of the year (e.g., Christmas, summer, winter) or the week (e.g., weekdays or weekends).

Another data transformation is required to break down nonatomic features. *Food ids* are stored in the dataset, separated by commas in a single attribute. However, the breakdown of *food ids* results into a variable number of independent attributes. The one-hot encoding technique assigns the values in an attribute to multiple flag attributes and designates a binary value to them [13].

	food_ids
0	{1,2,3,4,4}
1	{5,1,2,3,6,7}
2	{1,2,3,6,8,9,10}
3	{1,6,2,3,11,12}
4	{1,7,13,12,2,3,12,12}

	1	2	...	10	...
0	1	1	...	0	...
1	1	1	...	0	...
2	1	1	...	1	...
3	1	1	...	0	...
4	1	1	...	0	...

	date
0	15/09/2014
1	16/09/2014
2	17/09/2014
3	18/09/2014
4	19/09/2014

weekday	year	mm	day
0	2014	9	15
1	2014	9	16
2	2014	9	17
3	2014	9	18
4	2014	9	19

Fig. 3. Feature transformation.

4.4 Model Creation

The training process involves several stages:

- dataset breakdown into train, test, and validation data;
- feature selection using the Random Forest algorithm [3];
- analysis and selection of appropriate hyperparameters;
- model training using a multilayer perceptron (MLP) network [9].

We randomly select 70% of the dataset for training, 10% for testing, and 20% for validation.

5 Results

This section presents the experimental results obtained by applying the methodology described in Sect. 4.

5.1 Data Normalization

Figure 4 shows the training and validation losses with and without normalization. We kept the normalized data for the following learning stages due to the visible classification performance improvement.

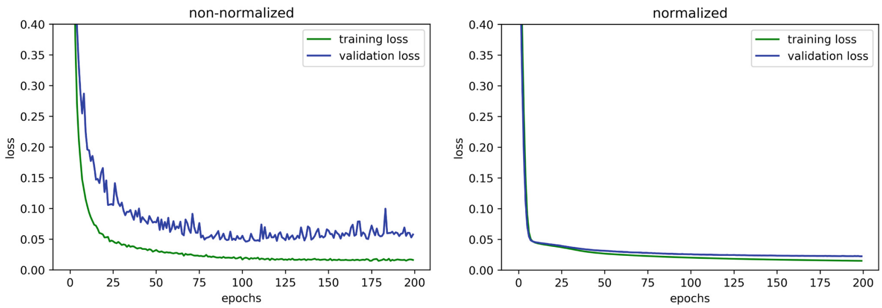


Fig. 4. Training and validation losses with and without normalization.

5.2 Feature Selection

Figure 5 presents the importance score of each feature selected by the Random Forest algorithm. The score provided by *user_id* shows that individual preferences greatly impact the selection of recommended food. As expected, the sequence – representing the day meal's number – is another important predictor since food intake patterns are associated with each meal during the day. A more surprising constatation is the score attributed to target goals, which unveils their higher discriminative power relative to meal nutrients. This result leads to the conclusion that the target nutrition goals of each person are fundamental food recommendation predictors.

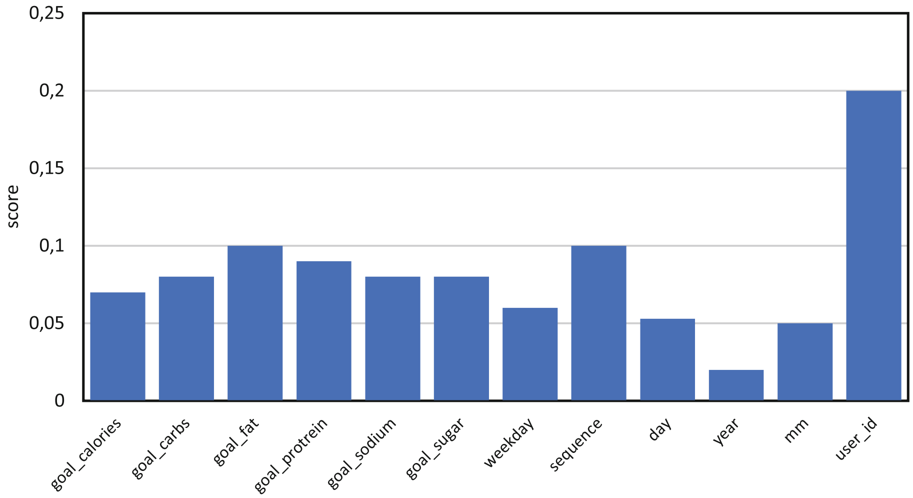


Fig. 5. Importance score of selected features obtained using Random Forest.

5.3 Hyperparameters Setting

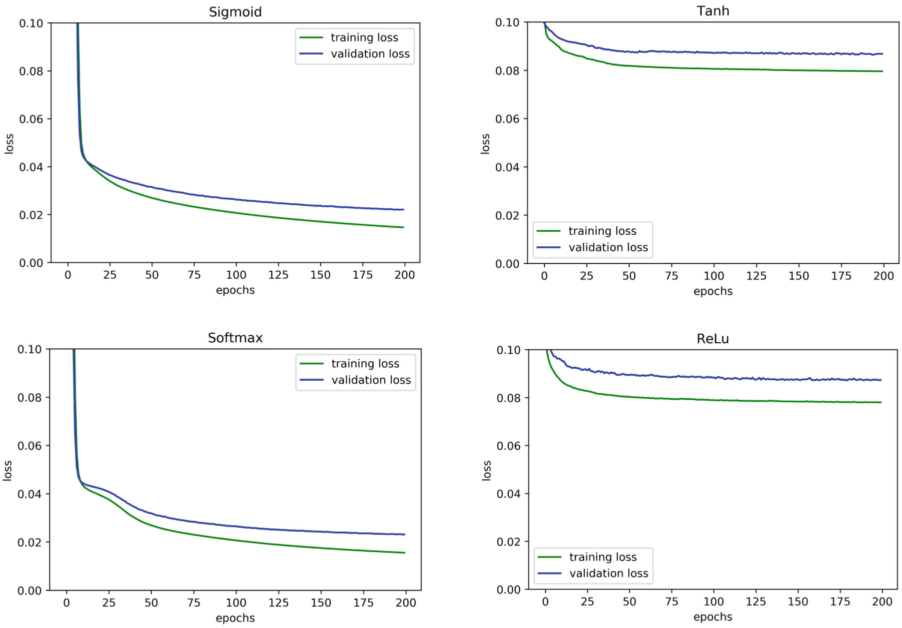
Table 1 lists hyperparameters evaluated through different settings.

Table 1. List of hyperparameters evaluated.

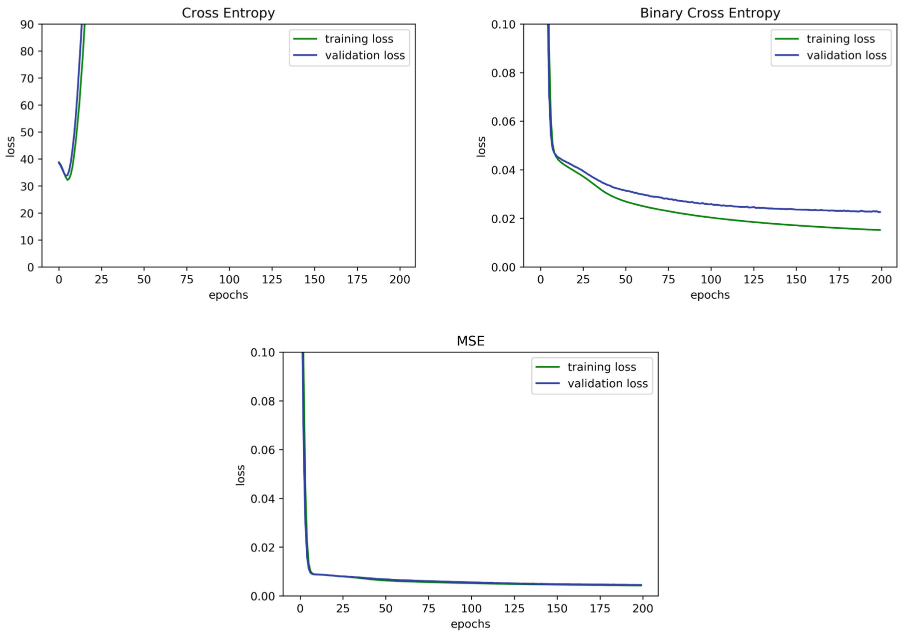
hyperparameter	tests
epochs	1–1000
batch	1–128
hidden layers	1–30
units	1–3000
activation function	*ReLU*, *Sigmoid*, *Tanh*, and *Softmax*
loss function	*Binary Cross-entropy*, *MSE*, and *Cross Entropy*
optimizers	*SGD*, *AdaGrad*, *RMSprop*, and *Adam*

As observable in Fig. 6a, the *Sigmoid* and *Softmax* activation functions have the best performance. The mean square error exhibits the best performance of all loss functions (Fig. 6b). In contrast, the optimizers RMSprop and Adam (Fig. 7) outperformed the other evaluated optimizers. From the analysis of Fig. 8a, it is noticeable that the optimal setting is achieved using one hidden layer.

According to the previous results, the experimental setting for the remaining tests involved the *Sigmoid* activation function, the *MSE* loss function, and the *RMSprop* optimizer. According to Fig. 8c, the batch size is 32 provides the best results.



a Performance of activation functions.



b Performance of loss functions.

Fig. 6. Performance of activation and loss functions.

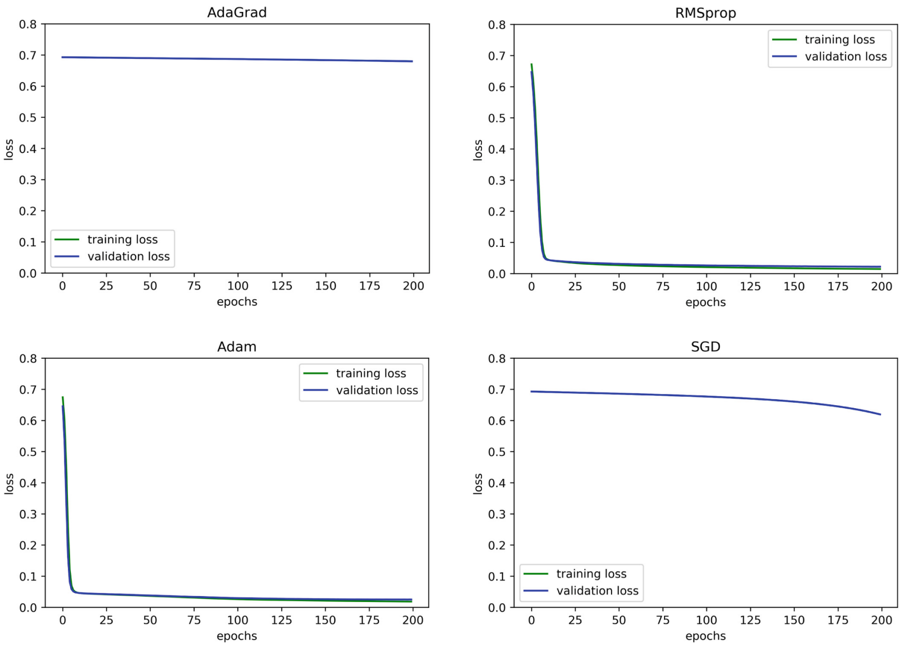
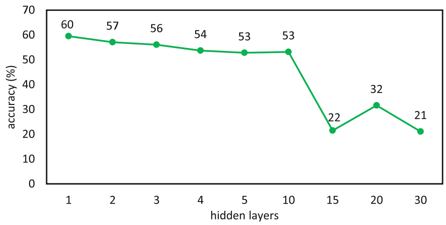
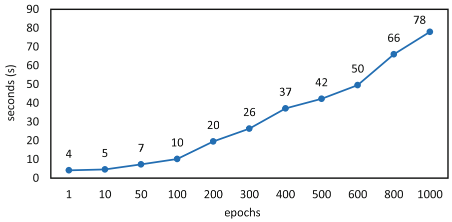


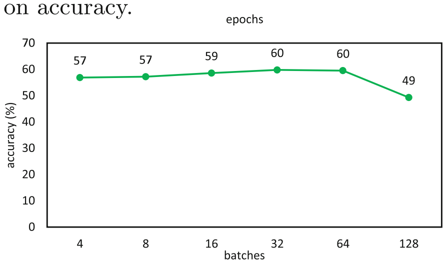
Fig. 7. Performance of optimizers.



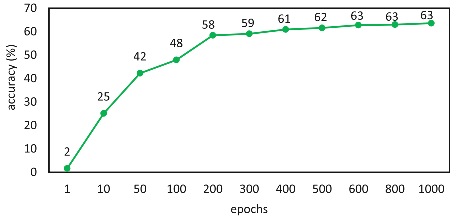
a Impact of the number of hidden layers on accuracy.



b Training time according to the number of epochs.



c Relationship between the batch size and accuracy.



d Accuracy according to the number of epochs.

Fig. 8. Experimental results.

5.4 Accuracy

The results shown that the maximum accuracy of 63% is obtained after 600 epochs (Fig. 8d) – i.e., the equivalent of 50 s in our machine (Fig. 8b).

6 Conclusion

Food recommendations can provide a significant contribution to the nutrition area. Food plans fail most of the time because people fail to accomplish the recommendations. It requires discipline to keep eating according to a plan. Plus, without proper education in the nutrition area, it is impracticable for regular people to change food when only equivalents are available or to evaluate the impact of extras on the target goals determined by the nutritionist.

This article contributes to state of the art on food recommendations by presenting an approach to help people choosing meals appropriate to their nutritional goals. Results have shown that energy and nutrient goals are essential predictors of meals. The user id's high discriminative power indicates that the accuracy levels of 63% can be improved by combining food recommendation models trained with historical data of a group of people with individual data. Thus, our future research will be aligned with the combination of models trained from people-group and individual datasets.

References

1. Alian, S., Li, J., Pandey, V.: A personalized recommendation system to support diabetes self-management for American Indians. IEEE Access **6**, 73041–73051 (2018). https://doi.org/10.1109/access.2018.2882138
2. Banerjee, A., Noor, A., Siddiqua, N., Uddin, M.N.: Food recommendation using machine learning for chronic kidney disease patients. In: 2019 International Conference on Computer Communication and Informatics (ICCCI), pp. 1–5 (2019). https://doi.org/10.1109/iccci.2019.8821871
3. Biau, G.: Analysis of a random forests model. J. Mach. Learn. Res. **13**(1), 1063–1095 (2012)
4. Chen, H.C., Chen, A.L.: A music recommendation system based on music data grouping and user interests. In: Proceedings of the Tenth International Conference on Information and Knowledge Management, pp. 231–238 (2001)
5. Gao, X., Feng, F., Huang, H., Mao, X.L., Lan, T., Chi, Z.: Food recommendation with graph convolutional network. Inf. Sci. **584**, 170–183 (2022). https://doi.org/10.1016/j.ins.2021.10.040
6. Ghongane, H.: MyfitnessPal Dataset. https://www.kaggle.com/datasets/zvikinozadze/myfitnesspal-dataset/discussion/194277
7. Herforth, A., Arimond, M., Álvarez-Sánchez, C., Coates, J., Christianson, K., Muehlhoff, E.: A global review of food-based dietary guidelines. Adv. Nutr. **10**(4), 590–605 (2019)
8. Mansoori, S., Liberatore, C., Ramirez, A., Chai, S.: Increased sodium consumption is associated with abdominal obesity in older adults. Curr. Dev. Nutr. **5**(Suppl_2), 1230 (2021). https://doi.org/10.1093/cdn/nzab055_040

9. Noriega, L.: Multilayer perceptron tutorial. School of Computing. Staffordshire University, vol. 4, p. 5 (2005)
10. Oh, S.W., Koo, H.S., Han, K.H., Han, S.Y., Chin, H.J.: Associations of sodium intake with obesity, metabolic disorder, and albuminuria according to age. PLoS ONE **12**(12), e0188770 (2017)
11. Oh, Y., Choi, A., Woo, W.: u-BabSang: a context-aware food recommendation system. J. Supercomput. **54**(1), 61–81 (2010). https://doi.org/10.1007/s11227-009-0314-5
12. Phanich, M., Pholkul, P., Phimoltares, S.: Food recommendation system using clustering analysis for diabetic patients. In: 2010 International Conference on Information Science and Applications, pp. 1–8 (2010). https://doi.org/10.1109/icisa.2010.5480416
13. Potdar, K., Pardawala, T.S., Pai, C.D.: A comparative study of categorical variable encoding techniques for neural network classifiers. Int. J. Comput. Appl. **175**(4), 7–9 (2017)
14. Rostami, M., Oussalah, M., Farrahi, V.: A novel time-aware food recommender-system based on deep learning and graph clustering. IEEE Access **10**, 52508–52524 (2022). https://doi.org/10.1109/access.2022.3175317
15. Schedl, M.: Deep learning in music recommendation systems. Front. Appl. Math. Stat. 44 (2019)
16. Song, Y., Dixon, S., Pearce, M.: A survey of music recommendation systems and future perspectives. In: 9th International Symposium on Computer Music Modeling and Retrieval, vol. 4, pp. 395–410. Citeseer (2012)
17. Zhang, J., Li, M., Liu, W., Lauria, S., Liu, X.: Many-objective optimization meets recommendation systems: A food recommendation scenario. Neurocomputing **503**, 109–117 (2022). https://doi.org/10.1016/j.neucom.2022.06.081