Food Recommendation System

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***Abstract*—Food recommendations play a vital role in enhancing lifestyle. However, it is often very exhausting to decide what to eat; hence, a person spends more time deciding what to eat than to eat. Recently there has been much work done in the domain of healthy food recommendations; however, the domain has its challenges such as user profiling, lack of sufficient information of the user for personalization, healthy food may not be the one which people may like, different nutrient requirements by different people and many more. Many of these problems have been tackled by recent works; however, they are still far from perfection. In this project, we have surveyed various recent works on food recommendations and implemented some algorithms on a website where people can quickly get food recommendations with a friendly GUI.**

***Index Terms*—Collaborative Filtering, Healthy Food Recommendation, Neural Networks, Content Based Models, Similarity Measures.**

I. INTRODUCTION

Recommender Systems have become an integral part of our lives; we depend heavily on such systems to watch movies or listen to music. However, recommendations from other sources such as friends and family may often be biased and non-personalized to the user's taste which is not the problem with most personalized recommender systems though they have specific limitations such as cold start problem, diversity problem, and many more. There are various approaches used in recommendation systems, such as content-based, matrix completion, neighborhood approach, and many more. The most recent work has been on modifying these approaches and not proposing an entirely new approach. People make decisions related to food every day, like "What to eat?", "Where to eat?" "What is healthier to eat?" etc. Also, food-related information like intake amount and safety of food is also a big concern. These recommendation systems help suggest to a user what to eat without doing any extra work. With more data available online, we can better analyze and create new food recommendation systems that consider factors like anticancer properties, nutritional values, flavour, cooking style, keywords, tags, along with user's preferences. This would give better results in suggesting the next meal to prepare or buy. This also helps the food chain industry to perform better as the model works on user's feedback. Furthermore, a food recommendation system also allows users to track eating behaviour, understand health problems and incorporate changes in eating habits. Group recommendations help to suggest a dish when a group of people wants to have a meal together.

II. LITERATURE REVIEW (SURVEY)

A. Graph Based Methods

In Mathur et al. [1], the authors use a unique approach of using the PageRank algorithm on the user reviews to find the most similar items to item' i' in the neighborhood graph. To create the required neighborhood graph, the authors concatenate the user reviews, items wise into a single review string for each item, followed by creating a tf-idf frequency matrix for the review text and dimensionality reduction. The authors prove the effectiveness and utility of the PageRank algorithm to find the most similar items via an experiment in which the top five recommendations for various food products were of similar food categories though just from different brands. The paper only included user reviews for collaborative filtering; however, user ratings in addition to reviews might improve the predictions.

B. Healthy Food Recommendation

There is a whole domain within the food recommendation system that focuses on user's health to generate predictions. Though this field of food recommendation often suffers such that healthy food recommendations may not always be tailored perfectly to user's likings. Nag et. al. [2], in their paper, propose the use of flavor as a feature for enhancing the food recommendations by improving the personalization of the recommendation system. The authors used a content-based recommendation approach for generating the recommendations. To solve a major challenge of finding the taste for any food, the authors follow a hybrid approach where using certain biological knowledge; the tastes are estimated, followed by a user survey where users are asked to give their view on the taste of food items presented to them. Based on online A/B testing, the authors prove the effectiveness of adding the taste where the proposed method performed much better than the matrix factorization-based method. The work could be further improved by using the recipe as an additional feature for the recommendation, or it could be used to estimate the taste of the food item, as the method of preparation of food can determine the taste. Musto et. al. [3] present another similar approach in the domain of healthier food recommendations, where they propose the use of user characteristics such as mood, BMI, stress, depression, etc., which they termed as HUM representation as an abbreviation for the holistic user model. The user's profile is filtered to generate candidate recommendations; the filter removes any unsuitable food products for the user due to allergy or some other possible reasons. The candidate recommendations are then ranked using food knowledge which modifies the recommendations based on the user's health requirements to generate a single recommended recipe. The authors compared two approaches, i.e., popularity-based recommendation and holistic based recommendation using a user survey. They concluded that user characteristics failed to improve the recommendations significantly as the survey users preferred popular items over the items recommended using the proposed method. The work could be further improved by considering non-user-based characteristics such as the climate and geographical location of the user and candidate-based characteristics such as the user's personal goals.

Shari et al. [4] propose a food recommendation system that focuses on allergies in babies, which helps caregivers get recommended with foods based on allergic conditions. The authors use a rule-based approach to generate pretty unique recommendations.

Ohata et. al. [5], highlight the importance of nutrients balance for a personalized food recommendation system. The proposed model takes the user food log as input to determine the nutrient intake of the target user and make food predictions to balance the nutrients, which primarily include carbohydrates, fats, and protein. The approach is splendid; however, it relies heavily on the food database generated and requires the users' efforts to manually input the food logs, which may restrain the user from using the proposed application—another paper from Jiang et. al. [6] highlights the importance of using social media to generate user's health profiles and recommend healthier foods tailored to users' health conditions, which could be of great use to people suffering from chronic diseases. On the application of healthy food recommendation.

Faisal et. al. [7],has done diet recommendation using the user's pathological reports. To generate an optimal food list for suggesting foods in accordance to the values in the user's health profile, Ant Colony optimization algorithm is used. The experimental results conclude convergence time of single-node execution is 12 times faster than parallel execution. Higher accuracy is achieved by increasing the number of ants, but it also increased the time complexity.

Alexander et. al. [8], have summarised ways to recommend user based on their preference and nutritional needs. They have also discussed ways to implement food recommendation systems to people based on their nutritional needs. For individual recommendations, Collaborative Filtering, Content-Based recommender systems, Knowledge-based recommender systems and Hybrid recommender systems are used. For group recommendation, they have used aggregation strategies which individual group recommendations into a group, group formation, which can be intentionally or unintentionally, group recommendation approaches using an aggregated model or aggregated prediction and group decision making. The paper has used four types of recommendation systems- considering user preference, nutritional needs, both user preference and national needs, and for a group of users. The further research challenges involve user information that may be incorrect, more input from users to implement recommendation algorithm, changes in the food eating habits of users, explanation of the results and group decision making.

C. *Ethics for Food Recommendation*

Karpati et. al. [9], accentuate ethics for food recommendation systems, the authors present the case study of Yuka, a food recommender system that suffers from several issues such as lack of explainability and fairness issues, etc. The authors describe eight required ethical properties for food recommender systems: privacy, opacity, fairness, robustness, etc.

D. *Neural Networks in Food Recommendation*

Mokdara et. al. [10], use deep neural networks to generate better recommendations that consider the user's favorite ingredients for generating recommendations. The authors used a deep neural network to output a user profile class for a given input vector of ingredients. The authors propose using a temporal model that uses the user's eating log history to curate a personalized recommendation. Upon using the hit ratio as a metric for evaluation of the proposed solution, a hit ratio of 78% on average is observed. The significance of covering all categories of input is observed when a higher diversity is observed. Several such food recommender systems exist which make use of neural networks, such as Meng et. al. [11], in their work, propose a visually aware recommender for foods that take into account features incorporating both collaborative and semantic information. They term the proposed framework as PiNet, which uses a dual gating module and applies the framework to a Chinese food dataset.

A unique approach of food recommendation is proposed by Chen et al. [12], where the authors generate the food recommendation as an answer to a user query, thus reducing the problem of food recommendation into a constrained question answering system. The proposed solution aims to alleviate the problems of food recommendation systems, such as ignorance of essential health factors. In order to train the question-answering model, the authors first generate a template set of questions that could fit most of the user queries and train the model using a loss function; the proposed solution also generates a dietary preference for the target user and compiles health guidelines from trusted sources. In order to generate the recommendations, food logs for the user are generated, and most similar recipes are found considering the food log items, and the candidate answers to the query are ranked. Human experimental results show the effectiveness of the proposed solution. Jin et. al. [13], in their work, to use the neural networks to generate food recommendations considering the food quality of restaurants as a parameter since the food taste may differ across restaurants. Hence, the authors propose the use of restaurant information and user's taste simultaneously.

Gao et al. [14], propose a neural network-based solution that they termed as HAFR to generate food recommendation that considers user history, recipe images, and ingredients for the purpose. The authors emphasize the importance of ingredients used in the food item, which is non-atomic, in addition to the importance of food images. Thus, the proposed solution incorporates the interaction of user-food in addition to content-based features. The model performs reasonably well; however, it has certain limitations such as, it assumes a single image per recipe only, which might not often be the case; also, it does not incorporate healthy recommendations, which is quite popular and useful.

E. Novel Similarity Measures

Nakka et al. [15], propose a novel similarity measure as well to improve the neighborhood-based recommendation system. To calculate the similarity between two users first inverse user frequency(IUF) is calculated as follows:

$$IUF\,(m)\;=\;\log\tfrac{U}{U_m} \tag{1}$$

Then the IUF values are used in constrained Pearson correlation coefficient to find similarity between each pair of users as:

$$SIM_{ASM}\,(u,u')\;=\;\frac{\sum_{item\;m\subseteq M}IUF(m)^2(r_{u,m}-_u)\left(r_{u',m}-_{u'}\right)}{\sqrt{\sum_{item\;m\subseteq M}IUF(m)^2(r_{u,m}-_u)\left(r_{u',m}-_{u'}\right)}} \tag{2}$$

Followed by the calculation of Jaccard similarity for each pair of users where the numerator is the count of items that are rated by both the users and the denominator is the count of items rated by either or both of them.

$$SIM_{jaccard}\,(u,u')\;=\;1-\;\frac{sum(m_u\;and\;m_{u'})}{sum(m_u\;or\;m_{u'})} \tag{3}$$

Finally, the modified similarity is calculated by multiplying the previous two similarity scores as follows:

$$SIM_{modified}\,(u,u')\;=\;Sim_{ASM}\,(u,u')*Sim_{jaccard}\,(u,u') \tag{4}$$

The predictions are generated using the following function for each instance in the test set:

$$\Pr ed_{u,i}\;=\;\delta_{u,i}\;+\;\frac{\sum_{u'\in N}Sim\left(u,u'\right)\left(r_{u',i}-\delta_{u',i}\right)}{\sum_{u'\in N}|Sim(u,u')|} \tag{5}$$

Where $\delta_{u,i}$ is calculated as,

$$\delta_{u,i}\;=\;\mu\;+\;\delta_u\;+\;\delta_i \tag{6}$$

Delta u and delta i are calculated as,

$$\delta_u\;=\;\left|\tfrac{1}{I_u}\right|\sum_{i\in I_u}\left(r_{u,i}-\mu\right)\delta_i\;=\;\left|\tfrac{1}{U_i}\right|\sum_{u\in U_i}\left(r_{u,i}-\delta_u-\mu\right) \tag{7}$$

Where μ is the average of all the rating in the dataset. MAE was used for evaluation and the results obtained are in table III.

Pu et al. [16], propose use of time of rating in the clustering based approach. The authors use KMeans algorithm for clustering while incorporating time as a feature, it significantly improves the model performance. The results on the datasets are given in table IV.

Zhou et al. [17], proposes an improved version of pearson correlation coeficient as a similairity measure and then weight the number of common scoring items on the similarity calculation to improve the shortcomings of the usual Pearson correlation coefficient. Author used two 1d arrays, UserCount[], which stores the total number of each user rating item. Threshold[], which stores the average of the number of items that the user rates with other users. y is number of common scoring items y of both users u and v. So if the following condition satisfied,

$$y >= Threshold[u]\;\&\&\;y >= Threshold[v] \tag{8}$$

Then the similarity will be update by the following formula:

$$Sim'(u,v) = Sim(u,v) * \frac{2x_{uv}}{x_u + x_v} \tag{9}$$

Else, the similarity will be update with the following formula in similarity matrix:

$$Sim'(u,v) = \frac{P_u}{UserCount[u]}*Sim(u,v)+\frac{P_v}{UserCount[v]}*Sim(u,v) \tag{10}$$

And then just find k nearest neighbors of the user to form a recommendation list.

Cong et al. [18] proposes an improved item-based collaborative filtering algorithm based on group weighted rating is proposed to solve the sparsity problem. Firstly, we will compute the GIT (Group Interest Trend) for each item. So suppose that there has target user u 's unrated item i in user-item ratings matrix R(mxn). we denoted the rating set of all user for i as R = {R1, R2, . . . , Rg}. Then we can select a subset, Rp = {R1, R2, . . . , Rp} in which the ratings are higher than the middle value M of R. M in the 5 rating scale will be 3. Select another subset, Rq = {R1, R2, . . . , Rq} in which the ratings are lower than M. Then GIT can be computed by the following equation:

$$GIT = \sum_{p=1}^{P}(r_p - M) + \sum_{1=1}^{Q}(r_q - M) \tag{11}$$

Now, we will compute the GITD (Group Interest Trend Degree) for each item.

$$GITD = \begin{cases} \frac{\sum_{p=1}^{P} R_p}{P}, & \text{if } GIT > 0 \\ M, & \text{if } GIT = 0 \\ \frac{\sum_{q=1}^{Q} R_q}{Q}, & \text{if } GIT < 0 \end{cases} \tag{12}$$

and calculates r_u and r_i ,

$$r_u = \bar{r_u} + \frac{\sum_{k=1}^{K}(r_{ki} - \bar{r_i})}{K} \tag{13}$$

$$r_i = \bar{r_i} + \frac{\sum_{q=1}^{Q}(r_{uq} - \bar{r_u})}{Q} \tag{14}$$

And then finally, filled the unrated value in user-item rating matrix with the following formula:

$$r_{ui} = \sqrt{GITD * r_u * r_i} \tag{15}$$

and then now computed the cosine similarity between the items with this user-item rating matrix. And the find the top K recommendation on the basis of similarity and predict the rating after linear interpolating the rating and similarity.

F. More Works

Gunawardena et al. [19], in their study mention few observations that they made; a high number of people face issues in; understanding the menu, unavailability of food products, revealing sensitive personal dietary information. Their study identifies Taste, Mood, and Price as the most critical attributes for deciding the food order. This information provides insight into building better food recommender systems.

Kashish et. al. [20], have used a content-based approach to recommend dishes and suggest nearby restaurants. They have also implemented a collaborative approach so that users get recommended based on other users

Gresha et. al. [21], have used content-based filtering and clustering algorithms . Based on cuisine, restaurant type, occasion, price, and ve/non-veg, a restaurant is suggested, and then after suggesting a particular restaurant, a dish is suggested based on the ingredients given. Using a similarity score of foods, a dish is recommended using ingredients. 80

Almeida et al. [22], have used content-based methods for personalised recommendations. The Rocchio algorithm is used. A feature test was performed to find better feature combinations for the recipes. The cosine similarity was used to generate recommendations by comparing the user profile with the restaurant's recipes features. Using k-fold cross-validation, MAE and RMSE values are computed to measure the deviation between predicted and actual results. The algorithm's learning curve, along with the recommendation error, was also analysed.

Mansi et al. [23], have implemented a model that suggests restaurants according to user's preference using the review received on Zomato by the users. It uses sentiment analysis on these reviews and recommends the restaurant based on user-item and item-item similarity. The techniques for community detection and topic modelling are used for recommending side dishes in accordance with the user's preference. RMSE, MAE and precision are used to evaluate the model. Factorization Machine Model performs best with a precision of 0.74.

Chen et al. [24] proposes an improved cosine similarity method. Both text vector of item data and user behavior record are used to improve the calculation of course similarity. TF-IDF is used to extract the text features of the project content, and vector space model is used to represent the text features. Through the word segmentation, each text in the text set gets its own series of word strings, solves TF-IDF value of each word in the string, and then obtains the text vector of the text, for example, the text vector of the text p may be represented as:

$$T_p = (t_{p1}, w_{p1}), (t_{p2}, w_{p2}), ..., (t_{pn}, w_{pn}) \tag{16}$$

Using cosine similarity to calculates a set of text similarity of each text as a supplement course similarity.

$$sim(i,j) = \frac{T_j * T_j}{\sqrt{T_j}^2 * \sqrt{T_j}^2} \tag{17}$$

Based on course collaborative filtering is improved on the similarity Where wij uses the improved cosine similarity shown as:

$$sim(i,j)' = \frac{sim(i,j) + w_{ij}}{2} \tag{18}$$

where,

$$w_{ij} = \frac{\sum \frac{1}{log(1+|N(u)|)}}{\sqrt{|N(j)||N(j)|}} \tag{19}$$

Agorithm have achieved improved precision and recall rates than ItemCF and ItemIUF base on collaborative filtering algorithm of TF-IDF text similarity optimization.

Pavate et al. [25] proposes restaurant review analysis and cuisine recommendation using SVM supervised learning algorithm and the functioning of the system analyzed.This technique was tested on a food restaurant to recommend the food to their customers on their website. The Data-set contains 10000 reviews in text format in a ".csv" file which is taken from Yelp. This data-set is used for training the SVM classifier. It is split into 70% training data and 30% test data. The data-set is cleaned from 10000 reviews to 4086 reviews and the reviews which are not proper are discarded from the data-set and then the Data-frame with bag of words model created then it is served as input to the vectorizer for further processing. The SVM model after training will be deployed on the server which classify the reviews given by the customers into two classes positive and negative give recommendations of the food to the customers according to the preferences set by them. To train the model SVM classifier applied. There are two steps, finding how many items are similar in the database to the selected item and to build a classifier, SVM uses linear function. 3000 records used to test the model the system is evaluated using different measures like precision, recall, F1-score. experimental results gives an average precision, recall and F1-score around 91% which shows the effectiveness of the system in recommendation of meal.

III. Our Contributions

After searching for many papers, we have decided four different paper to implement. These papers have discussed variety of different techniques with which we can improve our recommender system. We have even achieved an MAE value of 0.49 with one of the technique, which is pretty good.

We have done survey of these 4 papers as well in Literature Review.

These four papers are:

1) Collaborative Filtering Recommendation Algorithm based on Improved Similarity [17]
2) Item-based Collaborative Filtering Algorithm Based on Group Weighted Rating [18]
3) A Novel Similarity Measure to Identify Effective Similar Users in Recommender Systems [15]
4) Clustering collaborative filtering recommendation algorithm of users based on time factor [16]

We have searched for various food datasets on the internet and finalized the three datasets as following:

1) Amazon Fine Food Dataset.
2) Raw Data Interation Dataset from Kaggle's Competition.
3) Reviews Dataset from the food.com website.

We have tested our four papers implementation code on these three datasets, and reported the results we got in the below section.

IV. Experimental Results

In this section, we will discuss the results we got from the four papers we have implemented. We have used MAE as an evaluation metric and reported the coverage on test data as well.

The results for "Collaborative Filtering Recommendation Algorithm based on Improved Similarity" [17] are the following:

Dataset	MAE Value	Coverage
Amazon Fine Foods	0.49947657921027194	91.44%
Raw Interaction Dataset	0.7032586146672031	82.24%
Reviews Dataset (food.com)	0.8067201122554294	74.35%

TABLE I
Paper [17] Results on Three Datasets

The results for "Item-based Collaborative Filtering Algorithm Based on Group Weighted Rating" [18] are the following:

Dataset	MAE Value	Coverage
Amazon Fine Foods	0.9419190572757882	100%
Raw Interaction Dataset	0.7094709059627913	100%
Reviews Dataset (food.com)	0.8073645224326266	100%

TABLE II
Paper [18] Results on Three Datasets

The results for "A Novel Similarity Measure to Identify Effective Similar Users in Recommender Systems" [15] are the following:

Dataset	MAE Value	Coverage
Amazon Fine Foods	0.987814950157182	95.32%
Raw Interaction Dataset	0.744742798799487	80.19%
Reviews Dataset (food.com)	0.887674574834553	72.42%

TABLE III
Paper [15] Results on Three Datasets

The results for "Clustering collaborative filtering recommendation algorithm of users based on time" factor [16] are the following:

Dataset	MAE Value	Coverage
Amazon Fine Foods	0.8541255663123	95.31%
Raw Interaction Dataset	0.725123456632	86.15%
Reviews Dataset (food.com)	0.70451256464743	92.25%

TABLE IV
Paper [16] Results on Three Datasets

A. Comparison and Analysis

1) We have got a MAE value of 0.49 which is the lowest MAE value we got as compared to other algorithms.
2) Raw Data Interaction gives a MAE value of approx 0.7 with all four papers. Hence, this dataset is more reliable.
3) Overall, Paper [17] algorithm perform better than the paper [18], paper [15] and paper [16] algorithm's on all three datasets but it has faced some coverage issue which is not the case with paper [18].
4) The way similarity is calculate has a significant impact on the recommendation quality
5) Only lower MAE is not the best criteria to evaluate a model, coverage in paper [18] is much higher than in paper [17]

V. Conclusion

In this paper, we have done a survey on 25 different papers and implemented 4 of them. The techniques in these four papers improved the accuracy of the traditional collaborative filtering algorithms. Experimental results show that [17] improves the recommendation quality effectively on Amazon fine foods dataset. In addition to that, we have also implemented the web-app for our user to experience our work.
During the research, what we have found that, not just food, but healthy food must be used for the recommendations and

their is not much breakthrough improvement have been done in the past years on this. Also, neural network techniques are widely used in this domain of food recommendation system.

VI. Web Application

We have also implemented a web application with flask backend. We have used Raw Data Interaction dataset in this system. Techniques of Paper [17] and Paper [18] are used in the backend to predict the recommended food items. For a cold start problem, we have explicitly asked from our user to select some of their favorite foods.

We have hosted our web application on the Heroku platform. The link of our web application is,
http://food-recommender-system.herokuapp.com/

Acknowledgment

I would like to express my special thanks of gratitude to our "Collaborative Filtering" Course Instructor, Dr. Angshul Majumdar as well as our course TAs, Shikha and Shalini, who helped us in this project. They have also helped me in doing a lot of Research and I came to know about so many new things. I am really thankful to them.

References

[1] A. Mathur, S. K. Juguru, and M. Eirinaki, "A Graph-Based Recommender System for Food Products," in *2019 First International Conference on Graph Computing (GC)*. Laguna Hills, CA, USA: IEEE, Sep. 2019, pp. 83–87.

[2] N. Nag, A. N. Rao, A. Kulhalli, K. S. Mehta, N. Bhattacharya, P. Ramkumar, A. Bharadwaj, D. Sitaram, and R. Jain, "Flavour Enhanced Food Recommendation," in *Proceedings of the 5th International Workshop on Multimedia Assisted Dietary Management - MADiMa '19*. Nice, France: ACM Press, 2019, pp. 60–66.

[3] C. Musto, C. Trattner, A. Starke, and G. Semeraro, "Towards a Knowledge-aware Food Recommender System Exploiting Holistic User Models," in *Proceedings of the 28th ACM Conference on User Modeling, Adaptation and Personalization*. Genoa Italy: ACM, Jul. 2020, pp. 333–337.

[4] A. A. Shari, N. A. Pajar, N. Sabri, M. R. Mohd Noordin, F. M. Ishak Zainudin, A. S. Shari, and A. Ahmad, "Mobile Application of Food Recommendation For Allergy Baby Using Rule-Based Technique," in *2019 IEEE International Conference on Automatic Control and Intelligent Systems (I2CACIS)*. Selangor, Malaysia: IEEE, Jun. 2019, pp. 273–278.

[5] T. Ohata, Y. Nishihara, and R. Yamanishi, "Foods Recommendation System for Meals-out in Nutrient Balance," in *Proceedings of the 11th Workshop on Multimedia for Cooking and Eating Activities - CEA '19*. Ottawa ON, Canada: ACM Press, 2019, pp. 17–23.

[6] H. Jiang, W. Wang, M. Liu, L. Nie, L.-Y. Duan, and C. Xu, "Market2Dish: A Health-aware Food Recommendation System," in *Proceedings of the 27th ACM International Conference on Multimedia*. Nice France: ACM, Oct. 2019, pp. 2188–2190.

[7] "Diet-Right: A Smart Food Recommendation System," *KSII Transactions on Internet and Information Systems*, vol. 11, no. 6, Jun. 2017.

[8] T. N. Trang Tran, M. Atas, A. Felfernig, and M. Stettinger, "An overview of recommender systems in the healthy food domain," *Journal of Intelligent Information Systems*, vol. 50, no. 3, pp. 501–526, Jun. 2018.

[9] D. Karpati, A. Najjar, and D. A. Ambrossio, "Ethics of Food Recommender Applications," in *Proceedings of the AAAI/ACM Conference on AI, Ethics, and Society*. New York NY USA: ACM, Feb. 2020, pp. 313–319.

[10] T. Mokdara, P. Pusawiro, and J. Harnsomburana, "Personalized Food Recommendation Using Deep Neural Network," in *2018 Seventh ICT International Student Project Conference (ICT-ISPC)*. Nakhonpathom: IEEE, Jul. 2018, pp. 1–4.

[11] L. Meng, F. Feng, X. He, X. Gao, and T.-S. Chua, "Heterogeneous Fusion of Semantic and Collaborative Information for Visually-Aware Food Recommendation," in *Proceedings of the 28th ACM International Conference on Multimedia*. Seattle WA USA: ACM, Oct. 2020, pp. 3460–3468.

[12] Y. Chen, A. Subburathinam, C.-H. Chen, and M. J. Zaki, "Personalized Food Recommendation as Constrained Question Answering over a Large-scale Food Knowledge Graph," *Proceedings of the 14th ACM International Conference on Web Search and Data Mining*, pp. 544–552, Mar. 2021.

[13] Y. Jin, W. Zhang, M. Sun, X. Luo, and X. Wang, "Neural Restaurant-aware Dish Recommendation," in *2020 IEEE International Conference on Knowledge Graph (ICKG)*. Nanjing, China: IEEE, Aug. 2020, pp. 599–606.

[14] X. Gao, F. Feng, X. He, H. Huang, X. Guan, C. Feng, Z. Ming, and T.-S. Chua, "Hierarchical Attention Network for Visually-Aware Food Recommendation," *IEEE Transactions on Multimedia*, vol. 22, no. 6, pp. 1647–1659, Jun. 2020.

[15] "A Research on Similarity Measure to Identify Effective Similar Users in Recommender Systems," *International Journal of Innovative Technology and Exploring Engineering*, vol. 8, no. 9S2, pp. 834–840, Aug. 2019.

[16] X. Pu and B. Zhang, "Clustering collaborative filtering recommendation algorithm of users based on time factor," in *2020 Chinese Control And Decision Conference (CCDC)*. Hefei, China: IEEE, Aug. 2020, pp. 364–368.

[17] W. Zhou, R. Li, and W. Liu, "Collaborative Filtering Recommendation Algorithm based on Improved Similarity," in *2020 IEEE 5th Information Technology and Mechatronics Engineering Conference (ITOEC)*. Chongqing, China: IEEE, Jun. 2020, pp. 321–324.

[18] C. Li and L. Ma, "Item-based Collaborative Filtering Algorithm Based on Group Weighted Rating," in *2020 13th International Symposium on Computational Intelligence and Design (ISCID)*. Hangzhou, China: IEEE, Dec. 2020, pp. 114–117.

[19] D. Gunawardena and K. Sarathchandra, "BestDish: A Digital Menu and Food Item Recommendation System for Restaurants in the Hotel Sector," in *2020 International Conference on Image Processing and Robotics (ICIP)*. Negombo, Sri Lanka: IEEE, Mar. 2020, pp. 1–7.

[20] K. Ahuja, M. Goel, S. Sikka, and P. Makkar, "WHAT-TO-TASTE: A FOOD RECOMMENDATION SYSTEM," *International Journal of Innovative Research in Computer Science & Technology*, vol. 8, no. 3, May 2020.

[21] G. Bhatia, S. Shedge, S. Sahetia, D. Mhatre, and S. Gangwani, "Food Dicted: A Restaurant & Food Recommendation System," *International Journal of Future Generation Communication and Networking*, vol. 13, no. 1, p. 7, 2020.

[22] J. Almeida, "Personalized Food Recommendations," p. 10.

[23] M. Goel, A. Agarwal, D. Thukral, and T. Chakraborty, "Fiducia: A Personalized Food Recommender System for Zomato," *arXiv:1903.10117 [cs]*, Mar. 2019.

[24] Z. Chen, X. Liu, and L. Shang, "Improved course recommendation algorithm based on collaborative filtering," in *2020 International Conference on Big Data and Informatization Education (ICBDIE)*. Zhangjiajie, China: IEEE, Apr. 2020, pp. 466–469.

[25] A. Pavate, A. Chaudhary, P. Nerurkar, P. Mishra, and M. Shah, "Cuisine Recommendation, Classification and Review Analysis using Supervised Learning," in *2020 International Conference on Convergence to Digital World - Quo Vadis (ICCDW)*. Mumbai, India: IEEE, Feb. 2020, pp. 1–6.