A New Dataset and Empirical Evaluation for Vietnamese Food Recommendation System

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Abstract

In the era of digitization, concern for health and quality of life has become a top priority. However, maintaining a balanced nutritional lifestyle remains a challenge for many, especially as daily life becomes increasingly hectic. Inadequate and imbalanced dietary habits can lead to various health issues, such as nutritional imbalances, a weakened immune system, and more. Many people have resorted to overusing dietary supplements as meal replacements, causing unwanted side effects on the body. Particularly, choosing suitable dietary regimes is crucial for individuals suffering from various illnesses. To address this issue and support consumers, especially in Vietnam, in selecting meals that match their tastes and nutritional needs while saving time, we have developed a Vietnamese food recommendation system. In this study, we constructed the Vietnamese food dataset - ViFoodRec and processed the data to create a high-quality dataset consisting of the foods dataset with over 5000 data points and the ratings dataset with approximately 180,000 data points. Furthermore, we applied Collaborative Filtering and Content-based Filtering techniques for recommending meals based on users preferences. In both methods, Pearson and Cosine are utilized. However, in the context of Content-Based Filtering, we incorporated four additional similarity measures, namely Jaccard, BM25, TfIdf Recommender, and a composite measure.

1 Introduction

Recommendation Systems, a field of Machine Learning, have seen significant development in recent years, driven by the rapid expansion of the internet. Unlike conventional classification or regression tasks, Recommendation Systems focus on predicting users' preferences and have been widely used in fields like e-commerce, movie, and music recommendation to help people overcome information overload (Thakker et al., 2021; Singh, 2020). The main entities in Recommendation Systems are users and items. Users represent individuals, while items can represent various entities such as movies, songs, books, videos, or even other users in social networks. Recommendation Systems aim to predict user interest in items by analyzing data, applying algorithms, and generating personalized suggestions. As a result, it saves a significant amount of time, costs, and energy expended in making specific actions.

Given the increasing interest in healthy eating habits and the widespread use of recommendation systems in various domains, food recommendation systems have gained significant traction globally. Studies have highlighted the potential health risks associated with unhealthy and imbalanced diets, including the development of chronic conditions such as cancer, diabetes, and obesity (Elsweiler and Harvey, 2015). Therefore, there is an urgent need to utilize recommendation methodologies to assist individuals in creating personalized yet scientifically grounded dietary regimens. However, the effectiveness of a food recommendation system relies heavily on accurately understanding users' food preferences and providing food options tailored to their tastes. Recent advances in online food applications have led to the development of many food recommendation systems tailored to individual user preferences (Morol et al., 2022; Shabanabegum et al., 2020). However, challenges persist in this domain, particularly regarding the diversity of food datasets from various countries (Wang et al., 2015; Li et al., 2022), but the lack of comprehensive and high-quality datasets on Vietnamese cuisine, thereby impeding the development of precise recommendation systems for users in Vietnam. To address this issue, we have undertaken the creation of a Vietnamese food dataset. Here are our key contributions:

- Introducing ViFoodRec, a new dataset for food recommendation research, which is of high quality and the first dataset on Vietnamese cuisine. Our dataset includes two subsets: "foods", which gathers information about popular dishes, traditional and modern cooking recipes, and "ratings", which gathers the culinary preferences of users in Vietnam. The dataset is publicly available for free access by the research community ([1]).

- We effectively employed Collaborative Filtering and Content-based Filtering on our dataset. Specifically, under Collaborative Filtering, we've implemented four memory-based models: User-user Cosine, User-user Pearson, Item-item Cosine, and Item-item Pearson, utilizing Cosine and Pearson similarity measures. In Content-based Filtering, we used Cosine, Pearson, Jaccard, BM25, and TfIdf measures. Additionally, we developed a composite measure integrating various individual measures for robust recommendations.

- The visualization of the Vietnamese food recommendation system enables users to request personalized food recommendations based on various dataset factors like dish type, calorie count, cooking duration, and more. This interactive functionality empowers users to explore tailored culinary options that suit their dietary preferences and lifestyle, enhancing their overall experience with the system.

The rest of this paper is organized as follows. Section 2 focuses on introducing related works. Next, in Section 3, we present the process of collecting and creating the dataset for use in the Vietnamese Food Recommendation System problem. In Section 4, the approaches to the problem are described in detail. Section 5 report the experimental process, analyze the results of the recommendation methods, and we visualize the system. Finally, in Section 6, we draw conclusions and future work.

2 Related Works

With the explosive growth of data on the Internet, Recommendation Systems have been proven to be effective in reducing information overload. Due to the importance of food for human life and health, extensive research efforts have been devoted to food-related studies (Wang et al., 2021b, 2019). According to the latest food survey (Min et al., 2019), food-related research falls into five main tasks, including perception (Ofli et al., 2017), recognition (An et al., 2017), retrieval (Chen et al., 2018), recommendation (Trattner and Elsweiler, 2017b), and monitoring (Farseev and Chua, 2017). Among these, many studies have successfully utilized multidimensional information for food recommendation to introduce delicious and healthy dishes to users, achieving high effectiveness (Song et al., 2023)Food recommendation studies can be divided into five categories (Trattner and Elsweiler, 2017a), specifically Content-based recommendation, Collaborative Filtering-based recommendation, Context-aware recommendation, Hybrid recommendation, and Health-aware recommendation. In this study, we apply two methods: Collaborative Filtering and Content-based Filtering.

Content-based Filtering, a widely used recommendation technique (Son and Kim, 2017), relies on item attributes to suggest similar items based on user interactions, commonly applied in music, movies, and e-commerce. It utilizes Semantic Analysis, TF-IDF, and Neural Networks to discern user preferences, offering personalized recommendations independently of other users' data. However, its limitation lies in recommending items with known attributes, risking overspecialization. Conversely, Collaborative Filtering (Schafer et al., 2007) focuses on user-item interactions, categorizing into Memory-based and Model-based approaches. Memory-based filtering utilizes techniques like Pearson Correlation, Cosine Correlation, or KNN, while Collaborative Filtering adapts with more user interaction data, despite facing issues like sparsity or cold start when data is insufficient. Our study encompasses experimentation with both methods to comprehensively understand each and determine the most suitable approach for recommendation tasks.

With advancements in recommendation techniques and the availability of large-scale food datasets, Food Recommendation Systems have emerged as powerful tools to address pressing societal issues (Mouritsen et al., 2017; Tian et al., 2021). By leveraging rich knowledge about food, these systems aid users in navigating vast online recipe databases, suggesting recipes tailored to their preferences and past behaviors (Khan et al., 2019). Current recipe recommendation methods mainly rely on similarities between recipes (Chen et al., 2020). Some methods have attempted to take

[1] https://github.com/QuocAn55/DS300

user information into account (Khan et al., 2019; Gao et al., 2019), but they only identify similar users based on duplicate-rated recipes among users, while ignoring relevant information between users and recipes, ingredients. Additionally, evolutionary methods have also been introduced (Alcaraz-Herrera and Palomares, 2019) personalized preferences. However, user preferences for food are very complex. Users may decide to try a new recipe because of ingredients, flavors, or recommendations from friends. Thus, recipe suggestions must consider these elements, necessitating a thorough understanding of the connections between users, recipes, and ingredients. Recent research studies like (Li et al., 2022) and (Wang et al., 2021a) have compiled datasets on user-recipe interactions, setting a benchmark for food recommendation research. However, to the best of our knowledge, we find that current food recommendation research on Vietnamese food datasets is still lacking to facilitate research on food recommendation, we constructed a Vietnamese food recommendation dataset and made it open source. In the next section, we elucidate its construction process and perform data analysis on it.

3 ViFoodRec

The ViFoodRec corpus is composed of two distinct sub-datasets: "foods," which encompasses detailed information about various dishes, and "ratings", including users' ratings.

3.1 Data collection

Using two powerful online data-scraping libraries, Selenium[2] and BeautifulSoup[3], we gathered information about Vietnamese dishes from two Vietnamese websites(monngonmoingay[4], cooky[5]). Initially, we used the Selenium library to interact with web pages. This tool helped us access web pages containing links to food information pages and collect all these links. The collected links were saved into a CSV file. Then, we utilized the features of BeautifulSoup to parse the HTML syntax of the web pages containing food information and extract necessary information about the food, such as the name, ingredients, cooking_method, etc. The data collected from these two websites was meticulously merged to create a comprehensive "foods" dataset. This process, illustrated in Figure 1, resulted in a dataset comprising 16 attributes and 5509 dishes, representing a diverse range of common Vietnamese culinary delights. For a detailed description of the columns in the "foods" dataset, please refer to the table in Appendix A.

To further illustrate the characteristics of this sub-dataset, several attributes are visualized in Figure 2 and 3. We observed that the "serving_size" attribute mainly ranged from 4 to 8, fitting the typical scale of Vietnamese families. The "cooking_time" attribute typically falls between 15 and 50 minutes, offering users flexibility in selecting dishes according to their available time. Nutritional information is provided to meet users' dietary needs. Additionally, the "description," "ingredients," and "cooking_method" attributes are detailed and easy to understand, facilitating users in cooking conveniently.

On the other hand, to construct the user ratings dataset for our study, we aggregated information on every dishes from the "foods" sub-dataset and collected evaluations from up to 100 users. Each participants was tasked with providing ratings for approximately 500 dishes from a total pool of 4,000, generating "ratings" dataset comprising 50,000 ratings. This sub-dataset is organized into three primary columns: user_id, food_id, and rating - where ratings span from 0.0, indicating strong dislike, to 5.0, representing extreme preference, with increments of 0.5. The frequency of ratings per dish varied between 2 and 26, while the number of dishes rated by each user ranged from 436 to 566, providing a comprehensive dataset to analyze user preferences and dish popularity.

3.2 Data preparation

Data preparation for Content-based Filtering: The initial "foods" dataset presented numerous issues, therefore, essential preprocessing methods were applied, including removing rows with null values and eliminating rows where all three attributes were identical, including "dish_name", "ingredients", and "cooking_method". To explain this, we observed that many dishes, despite having the same name, differed in ingredients and cooking methods, resulting in variations in taste. In other words, they were completely different dishes. After broadly removing noisy values, we proceeded to handle text values, which involved unicode normalization, removing emojis, trimming excess whitespaces, and replacing abbreviations.

[2]https://github.com/SeleniumHQ/selenium
[3]https://pypi.org/project/beautifulsoup4/
[4]monngonmoingay.com
[5]cooky.vn

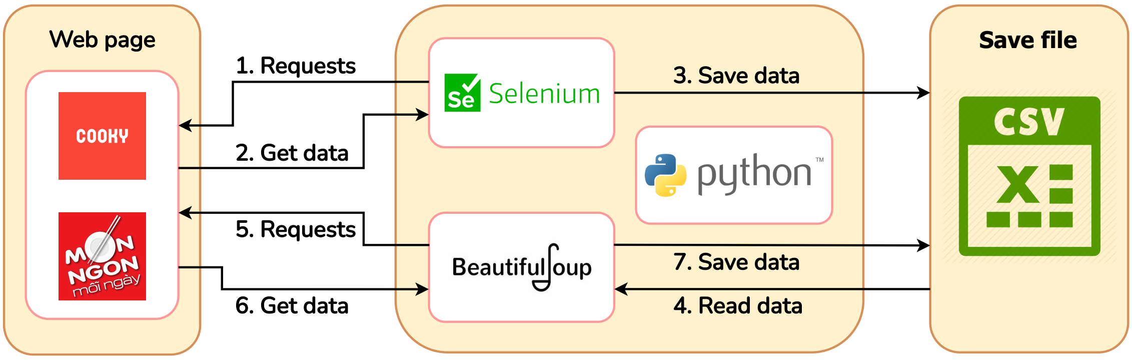

Figure 1: Data collection process for Content-based Filtering.

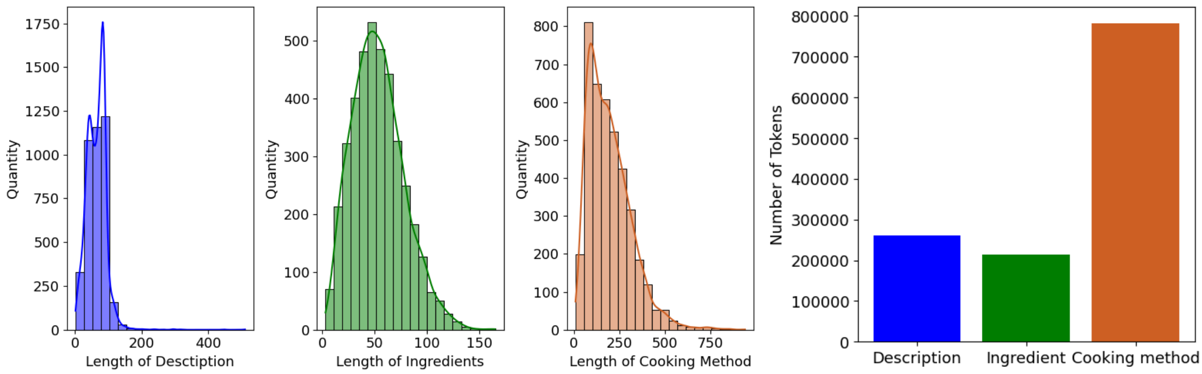

Figure 2: A visual analysis of some textual attributes.

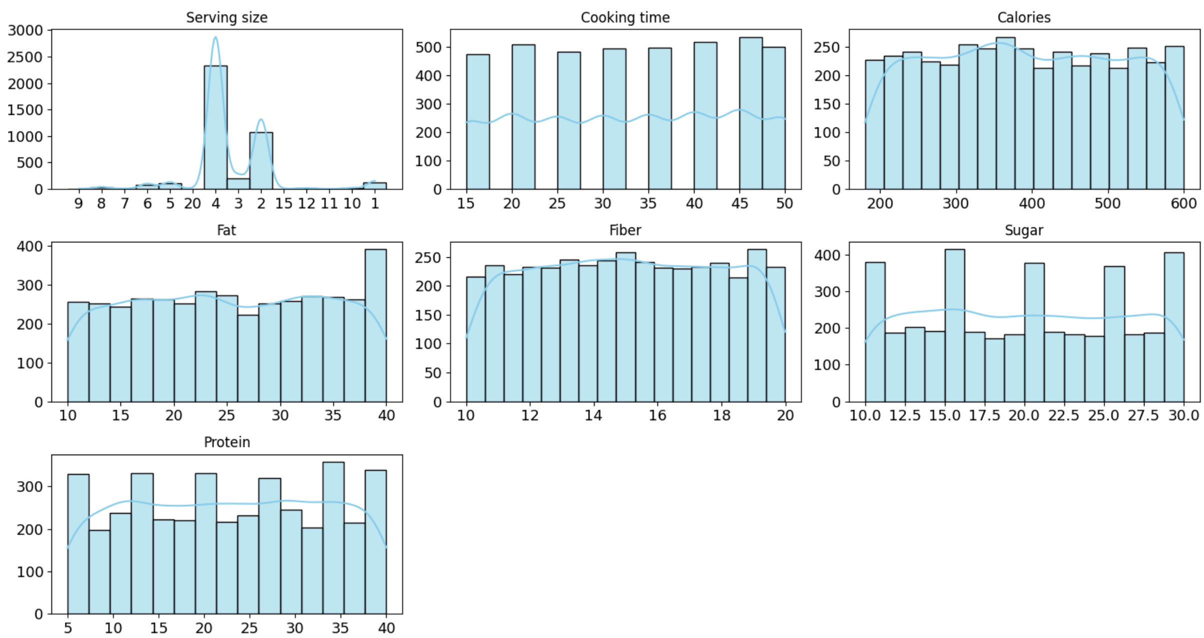

Figure 3: A visual analysis of some numerical attributes.

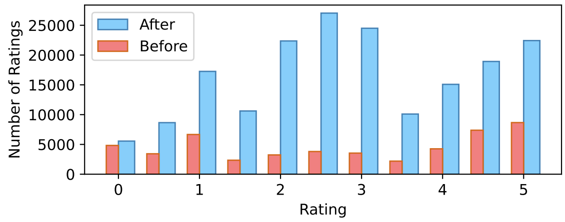

Figure 4: Statistics of the number of ratings before and after filling missing values.

Data preparation for Collaborative Filtering: In analyzing the "ratings" dataset, we found that some users had reviewed the same dish multiple times. To maintain data accuracy, we kept only the most recent review per user for each dish and removed older ratings. The dataset also had numerous missing data points that could affect system accuracy and performance. We addressed this by filling 40% of these gaps with the median value, a decision driven by computational limitations. This approach helped preserve the data's statistical integrity without significantly impacting the recommendation process. After these adjustments, the updated dataset contained around 180,000 ratings, with each dish receiving between 1641 and 1989 ratings and varying from 27 to 68 ratings per dish, maintaining a representative sample of user opinions. Figure 4 statistics of the number of ratings before and after filling missing values.

4 Methodology

4.1 Correlation measures

Correlation measures for Content-based Filtering: This study employs Cosine and Pearson correlation measures to enhance result accuracy in both Content-based and Collaborative Filtering. In addition, Content-based Filtering also incorporates TfidfRecommender, Jaccard, BM25, and a composite measure. Specifically, we employs TF-IDF vectorization paired with Cosine similarity for precise matching. Jaccard is calculated by the ratio of the intersection to the union of two sets, effectively comparing element similarity. BM25, on the other hand, uses IDF weights with term frequency TF to assess document-query relevance. Finally, the composite measure aggregates results from all individual metrics, applying a uniform weight of 0.2 to each correlation score. Foods achieving the highest composite scores are recommended to the user.

Correlation measures for Collaborative Filtering: Although Pearson and Cosine measures are used mutually, their definitions have been slightly modified to suit the Collaborative Filtering task. Instead of using attributes, both Pearson and Cosine use ratings from the users that are given to the items to calculate the similarity between users or items.

4.2 Our Approach

Our approach to Content-based Filtering: To begin with, we created a derivative of "foods" named "foods_modeling", containing a selection of just few essential attributes for Content-based Filtering, namely "dish_name", "ingredients", "description", "dish_tags", and "nutrient_content". These attributes were chosen for their ability to capture the unique characteristics of each dish and their potential to exhibit correlations with others in the dataset. The "foods_modeling" dataset underwent then vectorization using CountVectorizer or TF-IDF methods, excluding dish names, to facilitate the application of correlation metrics.

Operationally, our Content-based recommendation system suggests foods to users based on the attributes of dishes they have previously enjoyed. In more detail, when a user selects a favorite food item and specifies a correlation measure, the system calculates the similarity scores between the selected dish's attributes and those of other dishes in the dataset using the chosen correlation measure. The system then aggregates these scores to generate a list of recommended dishes. This aggregation process employs a weighted multiplication approach, with the weight list determined through extensive testing. Specifically, we varied weights from 0.1 to 0.9, increasing by increments of 0.05, and after conducting 80 trials for each configuration, we identified the most effective combinations, presented in Table 1.

Therefore, we observed that the "ingredients" attribute has the strongest capability to represent the characteristics of food items, while "nutrient_content" has the opposite effect. Figure 5 illustrates the entire food recommendation process using the Content-based Filtering method.

Our approach to Collaborative Filtering: Collaborative Filtering is widely used for recommendation systems, enhancing user experiences on online platforms like e-commerce websites and content recommendation systems. It doesn't require detailed product descriptions and is relatively reliable.

Table 1: Weight of attributes

Attribute	description	ingredients	nutrient_content	dish_tags
Weight	0.25	0.6	0.05	0.1

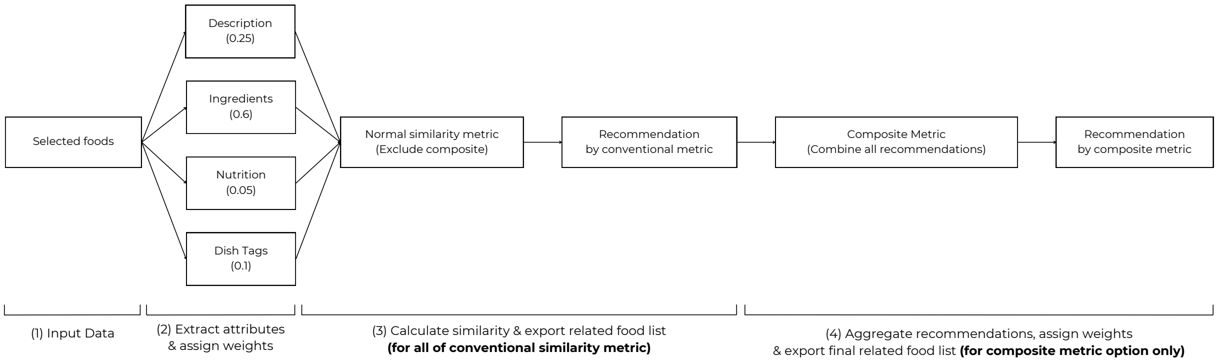

Figure 5: Recommendation process using Content-based Filtering method.

However, sparse data and the "cold start" problem pose challenges. In this study, we use Cosine and Pearson measures to compute similarity and focus on the memory-based approach for collaborative filtering.

User-user Collaborative Filtering focuses on the similarity between users, allowing us to provide product recommendations for a user based on the ratings of similar users. The basic idea is to identify users who are similar to the target user A and suggest products by calculating the similarity between user A and other users. For example, if user A and user B both rate a list of food items and user B has rated food item X while user A hasn't, we can use the ratings of user B on food item X to predict the rating of user A for this item. The similarity between users is calculated using either the cosine similarity formula or the Pearson similarity formula.

Item-item Collaborative Filtering, instead of relying on user information, uses product similarity to predict for users based on their ratings of related products. For example, to predict user A's rating for food item X, the process starts with identifying a set S of food items that are similar to item X. Next, it will be possible to forecast whether or not user A will enjoy food item X based on the ratings she gave the food items in set S. Similarly, user A's ratings of similar food items, such as Y and Z, can be used to predict user B's rating of item T. The similarity measure used here is comparable to the User-user collaborative Filtering method, which is Cosine similarity or Pearson similarity.

4.3 Evaluation measure

Content-based Filtering: In addressing the common challenge of lacking specific ground truth data in Content-based Filtering for food recommendations, our team labeled approximately 200 food items, about 5% of our dataset. We then identified the most relevant items, labeled them as "recommend". To measure the system's effectiveness, we employed evaluation metrics such as Precision@K and Mean Reciprocal Rank (MRR). Precision@K calculates the proportion of accurately recommended items within the top K suggestions, while MRR assesses the rank of the first correctly recommended item, ignoring the order of subsequent ones.

Collaborative Filtering: To evaluate the Collaborative Filtering method, we compared predicted and actual rating scores for 200 food items from a test set derived at a ratio of 1:900 from the original dataset. This ensured a low likelihood of users or items appearing only in the test set. We used Mean Squared Error (MSE), Root Mean Squared Error (RMSE), Mean Absolute Error (MAE), and Normalized Mean Absolute Error (NMAE) to measure performance, given the disparity between recommended and actual liked ratings. These metrics provided a comprehensive assessment of the recommendation system's accuracy.

5 Experimental Results

5.1 Content-based Filtering

To optimize computational efficiency and reduce processing time, we limited the number of neigh-

Table 2: Evaluating the methods with Precision@K

K	Composite	Cosine	Pearson	BM25	Jaccard	TfidfRecommender
K = 5	**0.49**	**0.47**	**0.47**	**0.26**	**0.26**	**0.24**
K = 10	0.33	0.29	0.29	0.15	0.19	0.15
K = 15	0.24	0.23	0.22	0.13	0.17	0.14
K = 20	0.20	0.18	0.18	0.12	0.13	0.13
K = 25	0.19	0.18	0.18	0.12	0.13	0.14
K = 30	0.16	0.15	0.15	0.11	0.12	0.13
K = 35	0.15	0.15	0.15	0.11	0.12	0.12
K = 40	0.14	0.12	0.11	0.09	0.08	0.11
K = 45	0.10	0.10	0.10	0.02	0.02	0.04
K = 50	0.11	0.11	0.11	0.04	0.04	0.06

Table 3: Evaluating the methods with Mean Reciprocal Rank

Neighbors	Composite	Cosine	Pearson	BM25	Jaccard	TfidfRecommender
n = 5	0.69	0.58	0.55	0.43	0.46	0.36
n = 10	0.66	0.57	0.53	0.43	0.44	0.35
n = 15	0.71	**0.62**	0.56	0.46	**0.48**	0.37
n = 20	0.70	0.60	0.55	0.45	0.45	0.37
n = 25	0.70	0.60	0.55	0.45	0.46	0.37
n = 30	0.72	0.61	0.57	0.46	0.47	0.38
n = 35	0.72	0.61	0.57	0.46	0.47	0.38
n = 40	**0.73**	**0.62**	**0.58**	**0.47**	**0.48**	**0.39**
n = 45	0.70	0.59	0.53	0.43	0.44	0.35
n = 50	0.71	0.60	0.54	0.44	0.45	0.37

bors from 5 to 50 in steps of 5 during our experiments, with evaluation results presented in Table 2 and Table 3. The content-based recommendation system showed modest success, achieving only average Precision@K values and MRR values ranging from 0.35 to 0.7. The composite metric, however, performed exceptionally well, leading in both MRR and Precision@K assessments. In contrast, the combination of Cosine similarity and TF-IDF scored the lowest, indicating its inefficacy. Other metrics yielded acceptable but unremarkable results within expected ranges. The optimal number of neighbors, identified as 15 based on our evaluations, was used for both system visualization and application deployment. Detailed outcomes of the best-performing correlation metrics are also documented in Table 4.

In discussing these results, we attribute the suboptimal performance of the methods to two main factors:

- We predict that there are still many noisy values in the dataset, which cannot adequately represent individual dishes, leading to ineffective extraction of attribute features.
- Evaluation results may somewhat depend on the ground truth labeling process. Once again, we believe that labeling based on human judgment, or, in other words, subjective factors, has influenced the evaluation results of the methods.

5.2 Collaborative Filtering

In the experimental process for Collaborative Filtering recommendation, we used the nearest neighbor count of 10 for all models, combined with two methods: User-user Collaborative Filtering, Item-item Collaborative Filtering and used two similarity measures: Cosine similarity and Pearson similarity. After conducting experiments and comparing them with 200 data points from the test set, we obtained the results in Table 5.

From Table 5, we find that the User-user Cosine method achieves the best results, with results on the MSE measure of 4.2581 and the RMSE measure of 2.0635. In contrast, the Item-item Cosine yielded the best results, with results on the MAE measure

Table 4: Best evaluation results of Correlation Metrics

Measure \ Result	**Composite**	**Cosine**	**Pearson**	**BM25**	**Jaccard**	**TfidfRecommender**
MRR	**73.03%**	62.12%	58.2%	47.1%	47.5%	39.1%
Precision@K	**49.12%**	47.2%	47.1%	26.4%	26.3%	24.4%

Table 5: Results of the models based on each similarity measure

Measure	**MSE**	**RMSE**	**MAE**	**NMAE**
User-user Cosine	**4.2581**	**2.0635**	1.7228	0.3445
User-user Pearson	5.4402	2.3324	1.9130	0.3826
Item-item Cosine	4.6168	2.1486	**1.6902**	**0.3380**
Item-item Pearson	6.5245	2.5543	2.1250	0.4250

of 1.6902 and the NMAE measure of 0.338. Meanwhile, the Item-item Pearson method performed the worst of all four indices, with results on the MSE measure of 6.5245, the RMSE measure of 2.5543, the MAE measure of 2.1250, and the NMAE measure of 0.4250.

6 Conclusion

In this study, we collected, constructed, and presented the Vietnamese Food Dataset, a novel dataset tailored for the food recommendation problem in Vietnam. The dataset encompasses a food set with over 5000 rows and 16 attributes, and a ratings set with over 180,000 ratings. Currently, with Collaborative Filtering methods, we have successfully implemented four memory-based models: User-user Cosine, User-user Pearson, Item-item Cosine, and Item-item Pearson. The best results we have achieved are 4.2581 MSE, 2.0635 RMSE for User-user cosine, 1.6902 MAE, and 0.3380 NMAE for Item-item cosine in the Collaborative Filtering method, and 49.12% Precision@k and 73.03% MRR for the Content-based Filtering method. Additionally, for the Content-based Filtering method, we have also successfully implemented the content-based model. Beside that, through this combination of a user-centric approach and a powerful development framework, we successfully transformed our complex system into a locally accessible and intuitive web application.

In the future, we will expand our Vietnamese food information dataset by collecting data from various websites and including new attributes such as user comments, ratings on different aspects, prices, search history, and more. Additionally, we will implement various recommendation methods and techniques, such as Collaborative Filtering using model-based approaches, Knowledge-Based Recommender Systems, Demographic Recommender Systems, Hybrid and Ensemble-Based Recommender Systems, to enhance prediction accuracy. We also plan to develop a feature in our food recommendation system that suggests dishes suitable for users' health. This feature will analyze individual health data to recommend appropriate food choices.

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References

Hugo Alcaraz-Herrera and Iván Palomares. 2019. Evolutionary approach for'healthy bundle'wellbeing recommendations. In *HealthRecSys@ RecSys*, pages 18–23.

Yongsheng An, Yu Cao, Jingjing Chen, Chong-Wah Ngo, Jia Jia, Huanbo Luan, and Tat-Seng Chua. 2017. Pic2dish: A customized cooking assistant system. In *Proceedings of the 25th ACM international conference on Multimedia*, pages 1269–1273.

Jing-Jing Chen, Chong-Wah Ngo, Fu-Li Feng, and Tat-Seng Chua. 2018. Deep understanding of cooking procedure for cross-modal recipe retrieval. In *Proceedings of the 26th ACM international conference on Multimedia*, pages 1020–1028.

Meng Chen, Xiaoyi Jia, Elizabeth Gorbonos, Chinh T Hoang, Xiaohui Yu, and Yang Liu. 2020. Eating healthier: Exploring nutrition information for healthier recipe recommendation. *Information Processing & Management*, 57(6):102051.

David Elsweiler and Morgan Harvey. 2015. Towards automatic meal plan recommendations for balanced nutrition. In *Proceedings of the 9th ACM Conference on Recommender Systems*, pages 313–316.

Aleksandr Farseev and Tat-Seng Chua. 2017. Tweet can be fit: Integrating data from wearable sensors and multiple social networks for wellness profile learning. *ACM Transactions on Information Systems (TOIS)*, 35(4):1–34.

Xiaoyan Gao, Fuli Feng, Xiangnan He, Heyan Huang, Xinyu Guan, Chong Feng, Zhaoyan Ming, and Tat-Seng Chua. 2019. Hierarchical attention network for visually-aware food recommendation. *IEEE Transactions on Multimedia*, 22(6):1647–1659.

Mansura A Khan, Ellen Rushe, Barry Smyth, and David Coyle. 2019. Personalized, health-aware recipe recommendation: an ensemble topic modeling based approach. *arXiv preprint arXiv:1908.00148*.

Ming Li, Lin Li, Qing Xie, Jingling Yuan, and Xiaohui Tao. 2022. Mealrec: a meal recommendation dataset. *arXiv preprint arXiv:2205.12133*.

Weiqing Min, Shuqiang Jiang, Linhu Liu, Yong Rui, and Ramesh Jain. 2019. A survey on food computing. *ACM Computing Surveys (CSUR)*, 52(5):1–36.

Md Kishor Morol, Md Shafaat Jamil Rokon, Ishra Binte Hasan, AM Saif, Rafid Hussain Khan, and Shuvra Smaran Das. 2022. Food recipe recommendation based on ingredients detection using deep learning. In *Proceedings of the 2nd International Conference on Computing Advancements*, pages 191–198.

Ole G Mouritsen, Rachel Edwards-Stuart, Yong-Yeol Ahn, and Sebastian E Ahnert. 2017. Data-driven methods for the study of food perception, preparation, consumption, and culture. *Frontiers in ICT*, 4:15.

Ferda Ofli, Yusuf Aytar, Ingmar Weber, Raggi Al Hammouri, and Antonio Torralba. 2017. Is saki# delicious? the food perception gap on instagram and its relation to health. In *Proceedings of the 26th International Conference on World Wide Web*, pages 509–518.

J Ben Schafer, Dan Frankowski, Jon Herlocker, and Shilad Sen. 2007. Collaborative filtering recommender systems. In *The adaptive web: methods and strategies of web personalization*, pages 291–324. Springer.

SK Shabanabegum, P Anusha, E Seethalakshmi, Meenakshi Shunmugam, K Vadivukkarasi, and P Vijayakumar. 2020. Withdrawn: Iot enabled food recommender with nir system.

Jagendra Singh. 2020. Collaborative filtering based hybrid music recommendation system. In *2020 3rd International Conference on Intelligent Sustainable Systems (ICISS)*, pages 186–190. IEEE.

Jieun Son and Seoung Bum Kim. 2017. Content-based filtering for recommendation systems using multiattribute networks. *Expert Systems with Applications*, 89:404–412.

Yaguang Song, Xiaoshan Yang, and Changsheng Xu. 2023. Self-supervised calorie-aware heterogeneous graph networks for food recommendation. *ACM Transactions on Multimedia Computing, Communications and Applications*, 19(1s):1–23.

Urvish Thakker, Ruhi Patel, and Manan Shah. 2021. A comprehensive analysis on movie recommendation system employing collaborative filtering. *Multimedia Tools and Applications*, 80(19):28647–28672.

Yijun Tian, Chuxu Zhang, Ronald Metoyer, and Nitesh V Chawla. 2021. Recipe representation learning with networks. In *Proceedings of the 30th ACM International Conference on Information & Knowledge Management*, pages 1824–1833.

Christoph Trattner and David Elsweiler. 2017a. Food recommender systems: important contributions, challenges and future research directions. *arXiv preprint arXiv:1711.02760*.

Christoph Trattner and David Elsweiler. 2017b. Investigating the healthiness of internet-sourced recipes: implications for meal planning and recommender systems. In *Proceedings of the 26th international conference on world wide web*, pages 489–498.

Wenjie Wang, Ling-Yu Duan, Hao Jiang, Peiguang Jing, Xuemeng Song, and Liqiang Nie. 2021a. Market2dish: health-aware food recommendation. *ACM Transactions on Multimedia Computing, Communications, and Applications (TOMM)*, 17(1):1–19.

Wenjie Wang, Fuli Feng, Xiangnan He, Liqiang Nie, and Tat-Seng Chua. 2021b. Denoising implicit feedback for recommendation. In *Proceedings of the 14th ACM international conference on web search and data mining*, pages 373–381.

Xiang Wang, Xiangnan He, Meng Wang, Fuli Feng, and Tat-Seng Chua. 2019. Neural graph collaborative filtering. In *Proceedings of the 42nd international ACM SIGIR conference on Research and development in Information Retrieval*, pages 165–174.

Xin Wang, Devinder Kumar, Nicolas Thome, Matthieu Cord, and Frederic Precioso. 2015. Recipe recognition with large multimodal food dataset. In *2015 IEEE International Conference on Multimedia & Expo Workshops (ICMEW)*, pages 1–6. IEEE.

A Data Description

More information about attributes in the proposed datasets is provided in Table 6. The attributes cover various aspects of Vietnamese dishes, such as ingredients, cooking methods, or nutrition amounts, providing a comprehensive overview of

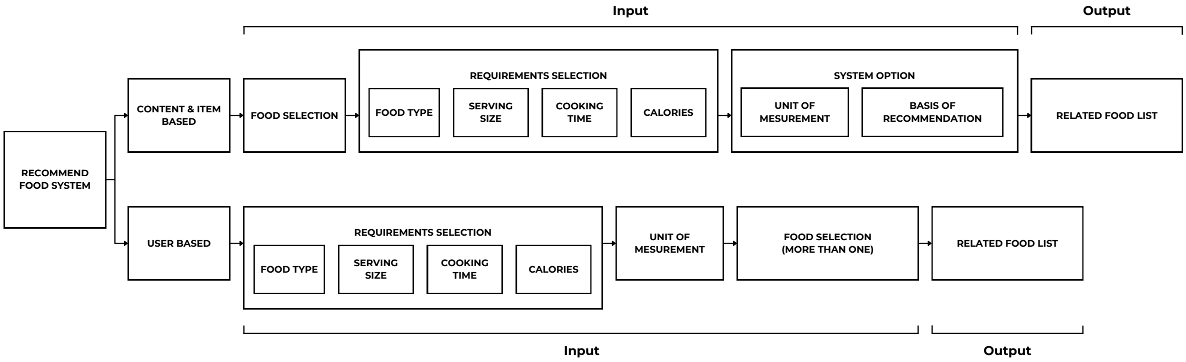

Figure 6: Food Recommendation System.

Vietnamese cuisine. This detailed dataset aims to support further research in culinary arts, cultural studies, and nutritional analysis by offering a structured and extensive collection of data on traditional and contemporary Vietnamese dishes.

B Visualization

We utilized Streamlit, a popular framework known for its powerful capabilities and ease of converting projects into web applications, to optimize our system development process. The application features two separate pages for the Content-based and Item-based Collaborative Filtering methods, distinct from the User-user Collaborative Filtering approach, allowing for tailored user interactions. For Content-based and Item-based methods, users input their preferred food item; the system then assesses similarity with other items using six different metrics and filters results based on serving size, cooking time, calorie content, and food type. For User-based recommendations, users select any number of liked food items; the system calculates and visualizes ratings between 4 to 5 points to facilitate ease of use and maintain a clean interface. Further details and system interface specifics are available on our Github page ([6]). More specific details about the system distribution are presented in Figure 6.

[6]https://github.com/QuocAn55/DS300

Table 6: Description of the data

File name	Attribute	Description	Example
foods.csv	food_id	dish identifier	1839
	dish_name	the name of the dish	Khoai lang chiên *(Fried sweet potatoes)*
	description	brief information describing	Khoai lang chiên ăn kèm tương ớt. *(Fried sweet potatoes served with chili sauce.)*
	dish_type	non-vegetarian or vegetarian dish	Món mặn *(Non-vegetarian dish)*
	serving_size	the number of people the dish serves	4 người *(4 people)*
	cooking_time	the time needed to prepare (minutes)	45
	ingredients	the necessary ingredients to cook the dish	500g khoai lang, 100 muỗngl sữa tươi có đường, 50g đường, 100g bột mì *(500g sweet potatoes, 100ml sweetened milk, 50g sugar, 100g flour.)*
	cooking_method	Detailed instructions on how to cook the dish	500 khoai lang đem luộc chín, bỏ vỏ nghiền nhuyễn, Cho 50g đường, 100 bột mì, Tạo hình theo ý muốn rồi chiên vàng giòn đều. *(Boil 500g of sweet potatoes until cooked, peel and mash them. Add 50g of sugar and 100g of flour. Shape as desired, then fry until golden and crispy.)*
	dish_tags	keywords related to the dish	khoai lang chiên *(Fried sweet potatoes)*
	calories	the amount of calories (kcal)	369
	fat	the amount of fat (grams)	11
	fiber	the amount of fiber (grams)	8
	sugar	the amount of sugar (grams)	26
	protein	the amount of protein (grams)	38
	image_link	link leading to the image	https://image.cooky.vn/recipe/g6/53055/s640/4434382e-8a0b-435d-8fa1-963ebe8bd70c.jpeg
	nutrient_content	aggregate content of nutrients	369, 11, 8, 26, 38
ratings.csv	user_id	user identifier	76
	food_id	dish identifier	168
	rating	user ratings for the dish	4