A NOVEL TIME-AWARE FOOD RECOMMENDER-SYSTEM BASED ON DEEP LEARNING AND GRAPH CLUSTERING

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ABSTRACT- It is generally agreed that food recommender systems can change people's eating habits and help them adopt better ones. The main goal of this project is to come up with a new and better way to suggest meals than the ones that have been used before. This includes not thinking about the food's nutritional value, not thinking about what the community wants, not thinking about time limits, and not thinking about special food items. The suggested system has two separate parts: meal ideas based on content and dinner suggestions made by users. At first, graph clustering is used to put food items and consumers into groups. In the next step, a method called machine learning is used. In addition, a careful method is used to evaluate temporal and user-community factors, which raises the quality of the plan sent to the client. The "Allrecipes.com" data analysis showed that the method for making cooking suggestions was working perfectly.

***KEYWORDS*:** Food ingredients, Time factor, cold start usersand food items, Community aspects

1. INTRODUCTION

As a result of sophisticated technology, the internet has evolved into a vast network of interconnected computer systems that enable data transfer and alteration. These systems have grown in popularity among online shoppers because they enable users to produce more personalized product recommendations. These algorithms assess a customer's probable interest in goods by examining their profile information and present interests. The basic goal of using a suggestion system is to present people with useful and actionable ideas. Compounding the problem, users must wade through massive amounts of food-related data on the internet in order to find the information they seek. Locating certain gourmet meals might be difficult due to the volume of information available on many platforms, such as cooking websites and social media. Internet-based meal enhancement solutions are growing, while food recommender systems (RS) are becoming increasingly popular. These systems offer a wide range of options, including food for takeaway and merchandise for sale in actual stores.

The importance of meal recommendations in the food sector is growing since they allow customers to quickly select items that match their interests. According to Elahi, Lim, and Zaveri (2023), RS is widely used in a variety of industries, including online retail platforms, social networking sites, online content providers, and music and video streaming services. These systems search for and pick the most relevant content based on the user's interests and choices.

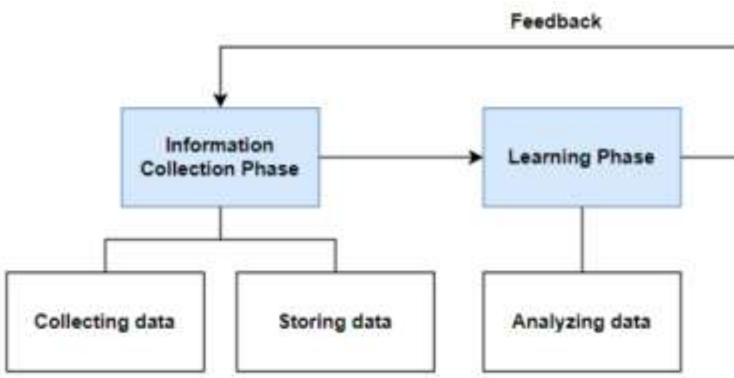
Recognizing the relationship between the client and the product allows the customer to identify shared traits, helping the production of ideas that are relevant to them. Alibaba, Amazon, and eBay were among the first companies to adopt recommendation systems (RS), which are sophisticated technologies used in the realm of electronic commerce. The rapid spread of the COVID-19 virus needs expanded use of e-commerce recommendation algorithms to extract large amounts of client data for the purpose of providing personalised product recommendations. According to a 2020 study by Oyebode and Orji, RS can not only recommend previously unpurchased products to clients, but also speed up the process of identifying specific products that consumers are looking for. A sizable proportion of the population is trying to adjust to their new lives as a result of quick changes in their food and behavioral habits.

Gao et al. (2020) and Li et al. (2023) found that food recommender systems (FRS) can help people adopt healthier lifestyle choices. Individuals in the health and food industries use recommendation systems to efficiently organize and categorize large amounts of data. These systems can encourage healthy eating, produce new recipes, and provide tailored meal ideas to each user. Food recommendation systems can uncover potential health issues and promote healthy living by tracking the frequency with which certain meals are consumed.

2. SECTIONS OF THE RECOMMENDATION PROCEDURE

The process of developing a recommendation system includes obtaining information, deriving knowledge from it, receiving both explicit and implicit feedback, and lastly formulating suggestions.

Fig. 1 The steps of creating a tip are as follows.



Information gathering involves the collection and archiving of data so that recommendations can be made. Acquiring relevant data is the first and most crucial step in developing a suggestion system. The explicit, implicit, and hybrid approaches are the three primary methods for obtaining knowledge from users. It may be difficult to obtain the information you require if people refuse to provide you with explicit input data, such as reviews, comments, and ratings. However, because it can provide unique insight into the preferences and viewpoints of the user, this type of data is highly appreciated and believed to be more accurate once it is gathered (Kumar et al., 2019).

The system routinely gathers implicit input data such as browser logs, clickstream data, and transaction data.

This information is readily available in the system, making it straightforward to obtain. In all fairness, though, ratings and views may not be as reliable as precise input data because they are not derived from actual people. This type of feedback could expedite the data gathering process and simplify things for users (Isinkaye et al., 2015).

Feedback comes in two flavors: direct and indirect. One kind of feedback that makes use of both is hybrid feedback. Because the ranking system integrates user input with easily accessible statistics, it is more accurate and valuable. The system can create better recommendations by integrating data from several sources to gain a better understanding of the user's preferences, behavior, and dislikes (Kumar et al., 2019).

Suggestions can be made in three primary ways: hybrid-based, content-based, and collaborative filtering (CF/CB). The recommendations are restricted by the person's current reading selections and past reading experiences. Consider the situation. The distinct approach The attributes of an item are used by the CB filtering process to generate predictions. It is a good source of ideas for papers, blogs, and articles. According to Isinkaye et al. (2015), the content-based (CB) technique generates recommendations based on user profiles and attributes derived from their evaluations of an item's content.

Content-based (CB) filtering technologies, such as PRES, make selections based on how closely the content adheres to the user's preferences. Conversely, when people who share similar interests utilize collaborative filtering, their selections are matched. Personalized ideas can be created by carefully matching the papers in the collection with the user's profile. The level of accuracy of the ideas will vary based on the number of notes and suggestions provided by users. Users receive tailored suggestions because they all have unique histories. The pages are arranged according to the following criteria: new, close, comparable, and relevant. On this page, the most significant articles are displayed as links. CB use a variety of techniques to determine the degree of similarity between two papers before providing insightful recommendations.

To display the relationships between words in a collection, many vector space models can be applied. These models employ a variety of statistical techniques, including Decision Trees, Neural Networks, Term Frequency Inverse Document Frequency (TF/IDF), and Naive Bayes algorithms. These techniques extract data from the underlying model and provide recommendations using machine learning or statistical analysis. Textual data can be transformed into numerical representations using the TF-IDF approach (Zhang et al., 2020), which can then be utilized to train machine learning models for prediction.

The system focuses on two primary areas: data from previous user-RS encounters and a methodical approach based on the user's selections. According to Zhang et al. (2020), collaborative filtering (CF) is a technique that uses the ratings and comments of users who are similar to the user to predict what the user would like. CF's core tenet is that judgments need to be made on the basis of what the majority of people are aware of. Numerous studies have previously been conducted to support this theory. If they don't express it, customers tend to pick particular items from a display automatically. According to Tran et al. (2018), the recommendation system identifies clients with comparable tastes and proximity to one another. Next, it makes recommendations based on what these customers have already tried and enjoyed.

According to Tran et al. (2018), a number of individuals employed item-based, matrix factorization, model-based, and user-based joint filters in 2018. A novel method is used to item-based recommender system challenges, with the goal of increasing the precision of user suggestions and the scalability of collaborative filtering methods on big datasets. Selecting close friends from a vast pool of potential neighbors is one of the main issues with traditional collaborative filtering methods.

To circumvent this issue, item-based algorithms prioritize product correlations above consumer ties. In order to determine what they like best, customers search for alternatives to the items they previously enjoyed. Item-based algorithms can perform as well as user-based algorithms with less computer resources, according to Andika et al. (2022). The relationships between objects remain constant for the most part.

The following phase is called Mathematical Factorization (MF). It is applied to recommendation systems to address issues arising from limited number of ratings per user and low number of ratings in the matrix. Matrix factorization is an effective method for handling these issues. Matrix factorization (MF) methods have attracted a lot of attention due to their ability to reduce the number of dimensions, separate implicit elements, and learn on their own. Text mining and spectral data analysis are effective when combined. The majority of matrix factorization models are based on this hidden factor model. The latent component model consists of an item factor matrix and a user factor matrix. They create a score matrix when combined. The research conducted by Bokde and colleagues. The majority of people concur that the most effective and precise method for handling the sparsity issue in recommendation system databases is matrix factorization (MF).

The collaborative filtering process is carried out using the model-based method. Most of the time, this takes up less room than methods that use close elements. Also, the thoroughness of the model that was constructed during the preparation portion speed up the training and execution of predictions by a substantial amount. It could also make it harder for items to line up appropriately. Methods that use models, such controlled or unsupervised machine learning, offer the data a complete structure before it is collected. The prediction phase is different from both the training phase and the model-building phase because of this. There are many types of machine learning methods, such as rule-based algorithms, neural networks, decision trees, support vector machines, regression models, and Bayes classifiers (Aggarwal, 2016).

3. BACKGROUND WORK

Food Recommender Systems

According to Meng et al. (2020) and Trang Tran et al. (2018), FRS are computational models that propose food items according to specific characteristics or dietary requirements. These prejudices may be revealed by the way users interact with the system (Xie & Lou, 2022). (Meng et al., 2020). It is possible to propose foods based on learnt preferences using either pre-made or freshly-prepared ingredients. To this end, it is helpful to establish a connection between how food tastes and factors such ingredients, cooking techniques, and nutritional content (Meng et al., 2020). It is common practice to compare data submitted to the FRS with a specific database. The concept is evaluated, either rationally or subjectively.

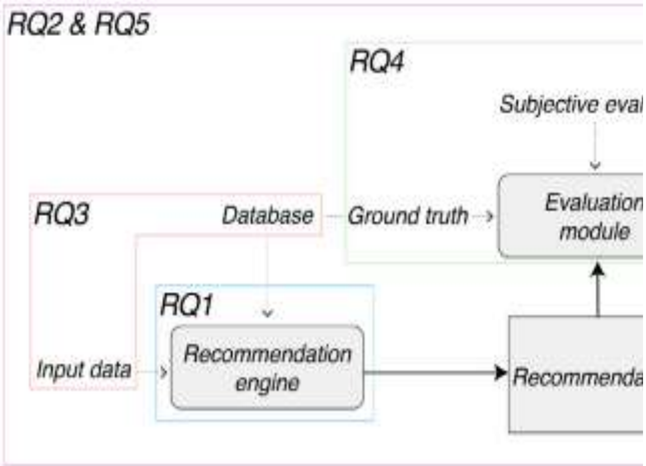


Fig. 2. The FRS employs a comprehensive design, as illustrated Connections between RQs and key components of the system are established.

See Figure 2 for an illustration of the primary framework. There are essentially two categories into which FRS fall at the most fundamental level. The overall design of the building is depicted in Figure 2. In its recommendations, the FRS falls into two categories: those with obvious benefits and those without. There is a well-known first group. Customers' wants and needs form the basis for inferential thinking. The processing level of these traits is such that they resemble food items. Recipe evaluations, historical facts, and location details are just a few of the highlights. After a similarity metric is computed, the user is presented with related food products that are highlighted.

Since it adapts to the preferences of each user, this implicit assistance is effectively tailored to their needs. The second kind of FRS uses food attributes alone to recommend meal items. The computer retrieves these attributes directly from a query when you choose this strategy. Assuming you have sufficient data to generate ideas, it is not necessary to understand the user's needs. The technology can either acquire the same foods or create new ones according to the user's instructions. Even if they aren't strictly necessary for personalization, these systems might still consider user preferences. Every individual receives a unique set of recommendations from the identical questions when this occurs.

RECOMMENDATION METHODS

The recommendation process of an FRS entails the utilization of logical reasoning to generate ideas or recipes and the identification of characteristics. The methods may be classified based on the characteristics that are employed during the recommendation generation process. The techniques are categorized into four distinct classifications in accordance with the taxonomy that Bai et al. (2019) and Ghannadrad, Arezoumandan, Candela, and Castelli (2022) proposed. A variety of advanced techniques are covered in the courses, including collaborative filtering, content-based filtering, graph-based methods, and collaborative filtering.

Content-based filtering

Content-based filtering compares the contents of two entities in order to identify similarities between them. The analysis may encompass two objects, the user profile, or both. The objects are assessed in accordance with the user profile preferences in the provided scenario (Amami, Pasi, Stella, & Faiz, 2016; Ghannadrad et al., 2022). In order to determine user preferences, one may employ two methods: direct inquiries or indirect reference to prior interactions (Pazzani&Billsus, 2007).

Consistencies were noted in both the consumer profile and the culinary products. This is founded on the assumption that people have a tendency to seek out recommendations that are similar to well-known things. In this particular instance, shared attributes are discerned between the two objects under scrutiny. This is based on the logical deduction that interchangeable use is possible for objects that share similar attributes. The

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final recommendation is ascertained through the comparison of these characteristics (Lops et al., 2011). The criteria employed to assess similarity exhibit substantial variation across diverse FRS and encompass an extensive array of components, including photographs of the finished product and its constituent parts. Bai et al. (2019) introduced an essential and widely employed methodology within the domain of recommender systems.

Collaborative-filtering

By comparing two user profiles for similarities, collaborative filtering algorithms generate suggestions (Bai et al., 2019; Zhang, Liu, Guo, Bai, & Gan, 2021). Individuals who share similar interests and inclinations are more likely to be attracted to the same products, according to these strategies (Ghannadrad et al., 2022). For this purpose, collaborative filtering-based FRS employ a variety of methods to assess user similarity. Through the utilization of user profiles, it becomes feasible to propose novel items to a specific user on the basis of similarities detected with a multitude of other users (Bai et al., 2019).

Graph-based methods

The main objective of graph-based techniques is to generate graphs that visually depict both the item and the user. Graph-based techniques are primarily employed to generate graphical depictions of the interconnections between users and items (Bai et al., 2019; Ghannadrad et al., 2022). Vertices are utilized in these systems to represent both commodities and users. By connecting nodes and edges, the relationships between products and customers are illustrated (Bai et al., 2019). The capability of this recommendation system to integrate data from various sources has been demonstrated (Bai et al., 2019). When assessing meal recommendations, one can infer their correlation from the coexistence of particular ingredients in those meals. Additionally, the structural details concerning the relationships between users and recipes may be considered. In addition, a number of Meal Recommendation Systems (MRS) utilize bidirectional links between human-generated recipes and concurrently consider the availability of ingredients to propose meal options. Furthermore, the relationships between users can be identified by evaluating specific attributes. This facilitates the implementation of collaborative filtering as a recommendation generation technique. The process of graph recommendation, according to Bai et al. (2019), consists of two primary phases: proposal generation and graph construction.

Hybrid methods

"Hybrid recommendation systems" are a collection of recommendation approaches that combine the distinct benefits of multiple recommendation systems. Hybrid solutions possess the capability to surmount and exceed the limitations of diverse methodologies through the utilization of a diversified implementation (Bai et al., 2019). By implementing this procedure, the accuracy and effectiveness of the suggestions can be enhanced (Bai et al., 2019; Ghannadrad et al., 2022). Nevertheless, the enhanced effectiveness is contingent upon the manner in which the techniques are amalgamated (Bai et al., 2019). The reference "Bai and others, 2019" pertains to a publication authored by Bai and several collaborators in the year 2019. Recommendations can be acquired by utilizing multiple sources of information using this technique. Consequently, this system possesses the capacity to furnish consumers with precise and all-encompassing counsel.

RECOMMENDATION ALGORITHMS

The algorithm defines the procedure for calculating and retrieving individual recommendations, while being firmly based on the core concepts and characteristics used

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in recommendation systems. Within the domain of algorithms, the main categorizations consist of machine learning, statistics, and querying.

Machine learning

These algorithms are used to create suggestions by applying machine learning approaches. To do this, a machine learning technique is employed to forecast the unique attributes of individuals or food products. The aspects refer to a user's assessment of a food and a recipe's exclusion of a certain item.

Statistics

Diverse statistical measures are utilized in the field of statistics to compute similarities. The degree of resemblance between a user and a food item, or between two users, or between two food products, can be quantified using the chosen recommendation technique. Afterwards, the statistic that is collected is used to choose suggestions, and subsequently, the user is given the recommendations.

Query

The recommendations are generated by an algorithm that depends on queries and directly obtains data from a food product database. The queries are built based on established parameters to guarantee accurate data organization and filtering. Furthermore, a query can predict several associations between individuals, culinary items, or both by utilizing sophisticated database techniques.

Evaluation

The procedure of assessing the degree of excellence of the recommendations. When analyzing the FRS, it is essential to take into account two prominent attributes. Prior to proceeding, it is essential to choose the assessment approach to be employed. Furthermore, the selection of appropriate assessment criteria is of paramount significance. The metrics specify the precise characteristics of the system that are assessed, whereas the method outlines the sequential process for executing the evaluation. Ghannadrad et al. (2022) categorized evaluation approaches into three distinct groups: online, offline, and hybrid, based on their taxonomy. The online assessment procedure collects recommendations and assesses the user's engagement with the system. The user's experience is determined by their interactions with the system and can be assessed by surveys or interviews (Vrijenhoek et al., 2021). The evaluation approach mentioned above is highly desirable since it has the ability to produce precise results in real-life scenarios (Silveira, Zhang, Lin, Liu, & Ma, 2019).

The accuracy of the suggestions is evaluated by utilizing a particular dataset in a controlled offline environment (Ghannadrad et al., 2022). Silvara et al. (2019) divided the dataset into two sections: one for training the algorithm and another for evaluation. Recommendation evaluations typically entail a comparison utilizing precise quantitative measurements. This evaluation method is both economical and automated, but it necessitates the utilization of certain assessment metrics. Recent research has categorized evaluation markers into three major groups. This set includes classifications based on errors, rankings, and accuracy. Metrics that do not fall within the aforementioned categories are identified and categorized as miscellaneous.

Accuracy-based metrics evaluate the extent to which the recommended values align with the true values. Therefore, it is frequently used in projects that necessitate classification (Gallo, Landro, La Grassa, &Turconi, 2022). Metrics like as F1, recall, accuracy, and precision are commonly used. Within the scope of recommendations, recall measures the exact number of suggestions that were successfully retrieved (Ghannadrad et al., 2022; Ng & Jin, 2017; Powers, 2016; Rostami, Oussalah, &Farrahi, 2022). Precision is the measure of the ratio of accurate and advantageous recommendations. The F1 metric is computed by taking the harmonic mean of precision and recall, as outlined by Powers (2016), Wang, Li, Pavlu, & Aslam (2018), and Ghannadrad et al. (2022).

Collectively, these indications offer a thorough evaluation of the caliber of the proposals. Recipe ranking measures evaluate the frequency at which a certain recipe appears within a designated set of top recommendations or forecasts (Ghannadrad et al., 2022). Mean Reciprocal Rank, Average Precision, and Normalized Discounted Cumulative Gain are metrics that evaluate the ranking of items. All measurements has the universal ability to precisely understand the process of finding the most efficient recipe, as demonstrated by Chen, Ngo, and Chua (2017) and Chen, Pang, and Ngo (2017). Error-based measurements are used to quantify the difference between expected values and the actual ground truth values. The goal of these metrics is to assess performance, as stated by Ghannadrad et al. (2022). These measures are useful for FRS tasks that require predicting numerical features and are suitable to issues like regression (Gallo et al., 2022). These features include the amount of chemicals (Li et al., 2021) and the associated evaluations of similarity (Park, Kim, Park, Shin, & Kang, 2019). Furthermore, this area can be evaluated using quantifiable measures such as the percentage of relevant recommendations and the ratings given to those recommendations.

4. EXPERIMENTAL RESULTS

We conducted a thorough investigation to determine the efficacy of the developed EHFRS. To determine the efficiency of our plan, we methodically gathered data from the culinary-focused online community www.Allrecipes.com. The data collected ranges from 2000 to 2018 and contains information on 52,821 food items sold through the website. Gao et al. (2019) gather time stamps, nutritional information, and user comments for each food product. Client satisfaction with various food items can be measured based on their ranking order. A total of 68,768 persons, 1,093,845 evaluations, and 45,630 food items were collected. F1, AUC, NDCG, Precision, and Recall are five metrics commonly used to assess the efficacy of a newly constructed meal recommendation system. Evaluating the memory and accuracy of recommender systems is difficult due to the subjective nature of user ratings, which define the relative value of various objects.

Experimental Setup

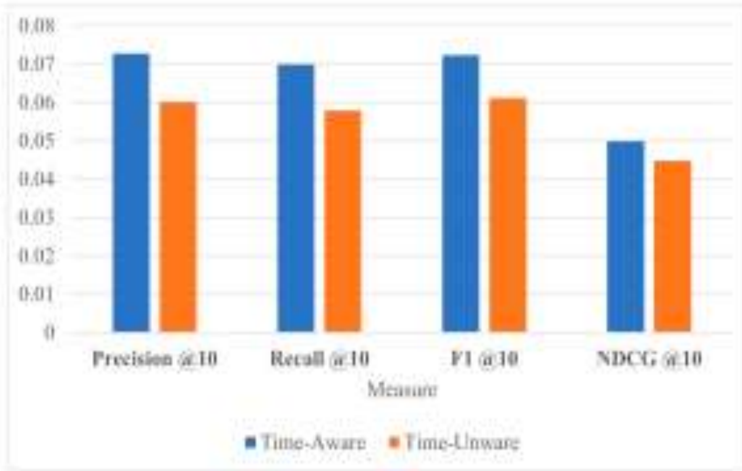

Figure 3: An analysis of performance that concentrated on temporal characteristics..

Performance Comparison

We undertake extensive studies to validate the effectiveness of the EHFRS model that we designed. The We do comprehensive research to ensure the effectiveness of the EHFRS model we created. The results are then evaluated and presented using the pre-established evaluation criteria. We chose four cutting-edge meal suggestion techniques as benchmarks to ease comparisons. The following food recommendation models are used: Graph Convolutional Network (FGCN) (Gao et al., 2022), Hierarchical Attention Food Recommendation (HAFR) (Gao et al., 2019),

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and Collaborative Filtering Recipe Recommendations (CFRR) (HGAT) (Tian et al., 2022). During the first phase of our inquiry, we will look at how integrating timestamps in our existing meal suggestion system affects the accuracy of user rating forecasts.

Figure 3 compares the efficiency of suggested food selections with and without timestamps during the suggestion process. The figure clearly shows that the proposed time-aware meal recommender system surpasses the time-agnostic equivalent in terms of rating accuracy. The measures NDCG@10, Precision@10, Recall@10, and F1@10 improved by 21.13%, 20.72%, 18.13%, and 11.38%, respectively. This test used precision@10, recall@10, F1@10, AUC, and NDCG@10 to evaluate the performance of numerous meal recommendation systems.

Table 1 compares the efficacy of several techniques to restaurant recommendation. The newly created food recommendation model (EHFRS) surpassed all previous cutting-edge algorithms across all evaluation metrics. A closer look at these numbers reveals that the proposed method surpasses the second-best food recommender system (FGCN) by 4.08%, 3.23%, 3.16%, 3.69%, and 10.82% in terms of Precision@10, Recall@10, F1@10, AUC, and NDCG@10, respectively. This test yields a result of 0.2 for the γ parameter in the EHFRS. This parameter controls the effect of nutritional parameters on the recommendations.

This study investigates the influence of changing a few parameters on the efficacy of the suggestion list. The studies included analyzing the performance of many meal recommender systems utilizing lists of 10, 15, and 20 items. Figures 4–6 show the effect of the recommendation list's size on NDCG, recall, and precision. Increasing the length of the concept list has been shown to increase NDCG and recall results.

Method	Precision	Recall	F1	AUC	NDCG
HAFR	0.0692	0.0671	0.0687	0.6439	0.0451
CFRR	0.0671	0.0647	0.0637	0.6421	0.0431
HGAT	0.0672	0.0649	0.0638	0.6431	0.0436
FGCN	0.0710	0.0681	0.0695	0.6639	0.0462
EHFRS	**0.0739**	**0.0703**	**0.0717**	**0.6884**	**0.0512**

Table 1: The effectiveness of different meal ideas.

The following study investigates the effect of changing the capacity of the recommendation list on many metrics. The study used suggestion lists of 10, 15, and 20 items to evaluate the effectiveness of several meal recommender systems. Figures 4-6 show the effect of idea list size on the NDCG, Precision, and Recall parameters. Expanding the number of thoughts available has been shown to improve memory and NDCG.

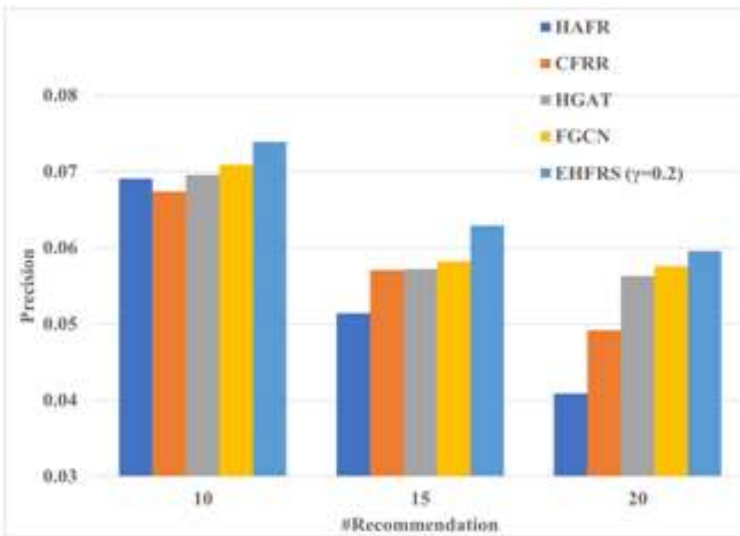

Figure 4: The accuracy of Top-N's dietary recommendations.

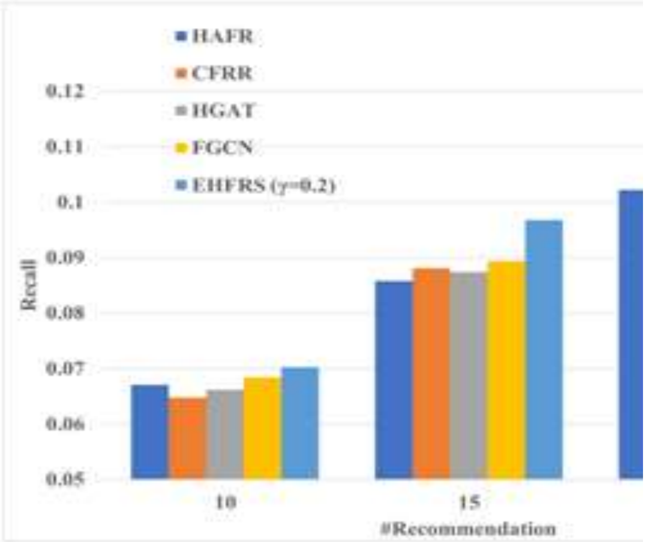

Figure 5: Remember the recommendations made by Top-N.

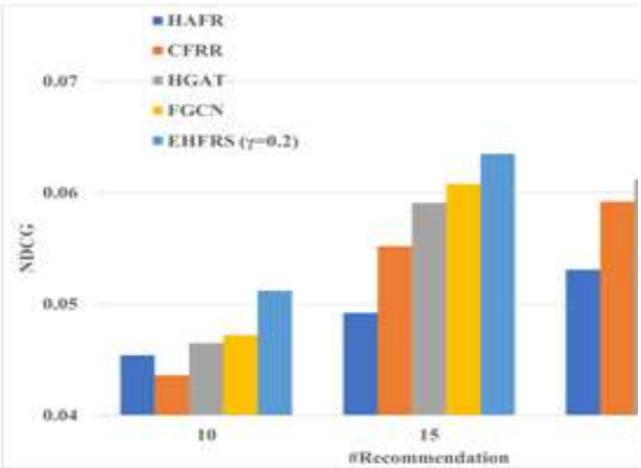

Figure 6: The NDCG gives a list of suggested foods, sorted by NDCG score.

Utilizing measures reduces accuracy. In tests, the meal recommender system consistently outperformed other comparison systems. When choosing a meal, consider the health controllable element ³ to calculate the right amount of healthy food to ingest. You have the power to change this configuration to assure the safety of the food. Increasing the value may cause unhappiness among individuals if the meal suggestion approach prioritizes health. Increases in this value may result in decreased accuracy, memory capacity, speed, and the recommender system's ability to uncover new information. As γ grows from 0 to 0.8, the suggested system measures in Figure 7 alter. When the Delta parameter was increased from 0 to 0.8, the NDCG@10, Precision@10, Recall@10, and F1@10 measures all fell by 40.09%, 52.02%, 37.73%, and 45.58%, respectively.

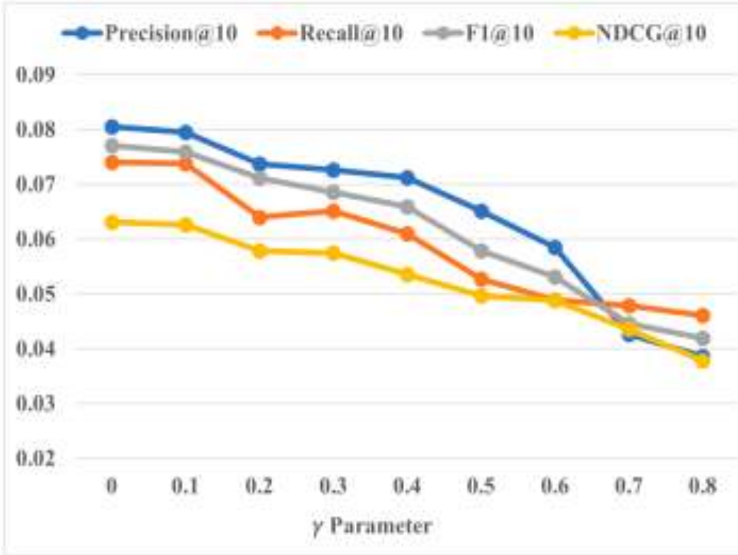

Figure 7: Health-related success review.

Sample code

```
#!/usr/bin/env python
"""Django's command-line utility for administrative tasks."""
import os
import sys


def main():
    """Run administrative tasks."""
    os.environ.setdefault('DJANGO_SETTINGS_MODULE', 'a_novel_time_aware_food_reco
    try:
        from django.core.management import execute_from_command_line
    except ImportError as exc:
        raise ImportError(
            "Couldn't import Django. Are you sure it's installed and "
            "available on your PYTHONPATH environment variable? Did you "
            "forget to activate a virtual environment?"
        ) from exc
    execute_from_command_line(sys.argv)


if __name__ == '__main__':
    main()
```


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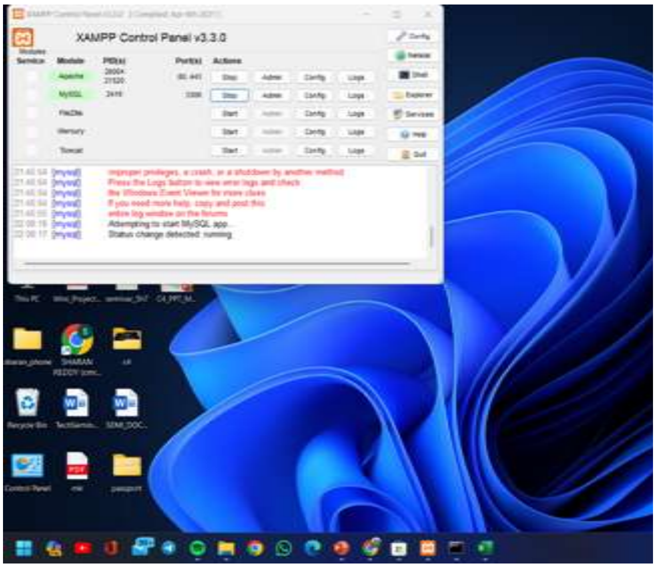

Figure 8:XAMPP control Panel

Figure 9: Home page

Figure 10:user login

Figure 10: User details

Figure 11: Food Prediction

Figure 12: View Food details

Figure 13:Prediction accuracy

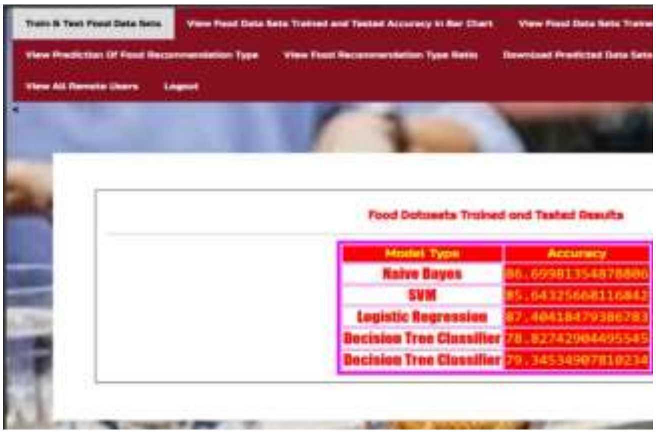

Figure 14:Trained and tested results

5. CONCLUSION

Because of the expanding number of Internet users and its popularity, many people are purchasing goods that have been recommended to them as useful. Food recommendation systems are an essential component of many lifestyle services and can be used in a variety of ways. This study suggests a unique and superior technique to recommending blended meal options. It addresses earlier system concerns by taking into account food ingredients, time stamps, new users, goods, and user classifications. All four concerns are addressed simultaneously by the proposed solution. The use of temporal data, trust networks, user groups, and both content- and user-based models improves the recommender system's performance. Adopting a nutritious diet may reduce the intensity of symptoms linked with noncommunicable diseases. Our goal is to use the nutritional makeup of each dish to deliver tailored meal suggestions to individuals while taking into account their existing and potential health issues.

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