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A Novel Time-Aware Food Recommender-System

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ABSTRACT

This paper presents a unique hybrid food recommender system designed to address shortcomings found in earlier versions. Critical elements including food components, time constraints, cold start situations for users and food products, and community dynamics were frequently disregarded by previous systems. The suggested method is divided into two stages: user-based and content-based recommendations for meals. Graph clustering is used in the first stage to classify users and food items, and a deep learning technique is used in the second stage for additional refinement. Moreover, an all-encompassing approach is employed to tackle temporal and user-community issues, finally improving the quality of recommendations. Five performance indicators are used for evaluation versus the most advanced recommender systems: NDCG, F1, AUC, Precision, and Recall.

Keywords: Food recommender systems, User-based recommendations, Deep learning, Precision, NDCG.

1. INTRODUCTION

The internet has become an indispensable part of everyday life, fulfilling a wide range of purposes from professional endeavors like accessing materials for professional growth to leisure activities like socializing and shopping [1-4]. But users may become overwhelmed by the abundance of information available online, which can cause confusion and cause them to lose focus on their original goal [5]–[7]. Search engines have made an attempt to reduce repetition, but customizing results is still difficult and frequently produces the same results regardless of user profiles [8, 9]. Recommender systems are becoming more and more popular as powerful tools for online customization [10]–[12], helping users find relevant services, handling information overload, and providing individualized experiences [13]–[15].

Food recommendations have a significant role in encouraging healthy behaviors, especially in the context of lifestyle choices [13]–[15]. Food recommendation research has long trailed other leisure domains despite its importance, possibly because of cultural constraints and the intrinsic difficulties of food choice prediction [19]. However, the necessity for efficient food recommendation systems is highlighted by lifestyle-related illnesses such diabetes and obesity [19], [20], and [21]. When considering the process as a machine learning challenge, it is important to precisely comprehend the dietary preferences of users in order to construct suggestions that work, particularly in situations that are health-related [22]–[25].

Many recommender systems have developed in recent decades to forecast user preferences and aid in decision-making [15], [19], [26]–[30]. Although prior food recommender systems have demonstrated potential in acquiring user preferences from past experiences with recipes and food products, there is continuous interest in improving these systems to better meet the demands of users. These systems continue to have the same issues:

Food ingredients: The majority of earlier food recommender systems [29], [30], mostly depend on user ratings to generate food recommendations using a collaborative filtering method that ignores food components. This is because it has been observed that people typically favor a certain dish since it has elements they would find appetizing. This can ignore a few crucial recommendation points. For instance, someone may love anything with chicken wings as their favorite cuisine, but they may be sensitive to certain spices that are used in food preparation. As a result, it's possible that collaborative filtering recommender systems fall short in taking into consideration the preferences and limitations of such users.

2) Time factor: The foundation of traditional recommender systems [19], [26]–[28] is the idea that consumers who have shown similar preferences in the past will continue to do so in the future. As a result, many recommender systems rely on static data and overlook possible changes in a user's diet, lifestyle, or dietary preferences that might arise over time in practical situations.

3) Cold-start food items and users: Traditional collaborative filtering-based food recommender

systems struggle to identify related foods or active user neighbors because users typically score a small number of items. As a result, people who have rated a sufficient number of foods can only receive recommendations from collaborative filtering-based food recommendation systems. Foods that haven't received enough user ratings are also disregarded by this kind of cooperative screening.

4) User group: The user's community or area is another problem that current recommender systems overlook. It makes intuitive sense to leverage the community feature to extrapolate from the actions of active users in the neighborhood to forecast the success chances of a specific diet and the rating of unseen food items. Generally, models based on clustering may be used to manage community aspects. However, research has also demonstrated that this strategy has a number of additional issues that are inextricably linked to the clustering techniques used (e.g., ideal number of clusters, effectiveness of similarity metrics applied).

In this research, a novel collaborative filtering-based and content-based recommender system that addresses all four of the aforementioned problems at once is created in order to overcome the aforementioned drawbacks. In particular, the concept considers the similarity between users and the similarity of dishes based on their components, while also accounting for the time factor and the features of the user's community. A time-aware food recommendation system based on deep learning and graph clustering (TDLGC) is the name of the technique. To put it briefly, TDLGC uses two stages to suggest the user's favorite foods: (1) user-based rating prediction and (2) food-based rating prediction. The user-based rates are anticipated in the first phase by taking into account the users' similarity matrix and community. Using a deep learning based clustering algorithm.

Following the first food grouping into many clusters, the rating of the items that are not visible is estimated. It is advised to consume the Top N meals after these two stages. The suggested approach differs from earlier food recommendation systems in the following ways:

1) Ingredient-aware food recommender system: Our model incorporates both content-based (food-based phase) and collaborative filtering-based (user-based phase) models, in contrast to conventional collaborative-based food recommender systems. Consequently, a selection of dishes that take into account the user's past ratings as well as their tastes is suggested.

2) Time-aware food recommender system: This work develops a unique time-aware similarity measure that accounts for changes in diet or food preferences over time. Because of this, the proposal can effectively manage situations in which consumers gradually modify their ratings or preferences.

3) Trust-aware food recommender system: Developed to address the issues with cold start foods and cold start users, this system replaces the conventional collaborative filtering-based food recommender systems. In order to effectively forecast user ratings, our suggested model creates a trust network of users based on trust (follower-following) assertions. The creation of trust networks is crucial to solving the neighbor selection issue. Because there is a strong association between user ratings-based similarity measures and trust statements, trust statements may be used to forecast how unknown products would be rated in food recommendation systems. In this study, knowledge that is kept outside of the user's local neighborhood of similarity is used to overcome the data sparsity problem by integrating the user's ratings-based similarity and trust network.

4) A meal recommendation system with community awareness: In contrast to earlier research that did not take users' communities into consideration while making meal recommendations, our algorithm specifically takes these factors into account. The ideal user cluster count is computed automatically. Furthermore, the suggested approach takes into account sparse datasets by employing a graphical representation in which edge weights are determined based on user ratings-based similarity and trust networks.

The structure of this document is as follows: Section 2 goes over the food recommender system models that have been employed in the past. The issue formulation and specifics of our constructed model are covered in Section 3. Section 4 discusses the experimental findings and a comparison with the most advanced food recommendation systems. Section 5 concludes and provides an overview of future work perspectives.

2. RESEARCH METHODOLOGY

In the current study's sequel, we'll assume the following: (i) that there is a user community with members who communicate a minimum level of trust; (ii) that each user has ratings about a set of food items (each item is made up of several ingredients) that represent his or her own diet preference(s); and (iii) that users' preferences

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may change over time and that these changes are fully documented.

The aforementioned three presumptions should thus be taken into consideration by the constructed recommender system. Our TDLGC recommender-system's core principle is to integrate the ideas of Deep Learning (DL) and Graph Clustering (GC) in a way that considers both the user's trust network and timely ratings from previous users.

All told, there are two main stages to the created model's conceptual framework that are shown in Figure 1: Two methods of rating prediction are available: (1) user-based, and (2) food-based. The user-user similarity matrix and the users' trust network are created in the first phase (i) by employing both the user rating and the follower-following network. Next, (ii) the supplied user set is mapped onto a weighted graph based on the trust network and user similarities. The third stage, (iii), involves proposing a unique time-aware graph clustering technique to cluster users into various groups based on their behavior. Lastly, (iv) predicts new user-based ratings by using users' clusters from the previous phase, user similarity, and past ratings. Using a deep learning-based method, the food ingredients are incorporated in the second phase (i). The similarities between various cuisines are then evaluated (ii) using the corresponding embedding vectors. Lastly, (iii) predicts the rating of foods that have not yet been seen using the food similarities. Following these two stages, (iv) the food that ranks highest will be recommended to the user based on both the food-based and user-based predictions. The issue formulation is given in the remaining portion of this part, followed by an explanation of each stage of
the suggested food recommender system.

A. Formulation of Problems

Think of a meal recommendation system that has M food items and N users. Let the sets of users and food items be U = {u1, u2, u3,..., uN } and F = {f1, f2, f3,..., fM }, respectively. Let R be the user-food matrix, including the ratings that users have given to specific food products. It is assumed that the Like rt-scale is used, with each rating having a value in {1, 2, 3, 4, 5}. Moreover, a profile with various attributes, like age, gender, height, weight, location, and so on, may be assigned to each element uj of U that represents a particular person. In this instance, we limit ourselves to a base situation in which the user profile has a single unique element (the user ID). In a similar vein, a collection of characteristics, including ingredients, calories, sugar, fat, and so forth, may be attributed to each constituent of F. Each food item fi in our formulation is defined solely by its ingredients; that is, if the set of all known ingredients is represented by IngSet = {ing1, ing2, ing3,..., ingm}, then the set of ingredients of fi is represented by Ii = {ingσ (1), ingσ (2), ingσ (3),..., ingσ (ki)}, where ki is the number of ingredients in food fi and σ is some permutation of integers {1, 2, 3,..., m}.

A follower-following network Follower (U, E, W) is used to describe the interaction between users; E and W represent the set of network edges and their related weights, respectively. This follower-following network creates an aggregate users network G(U, E, W) and a trust network Trust G(U, Tr) that take into consideration the similarities between users based on their rating.

Lastly, we can regularly track the network's progress thanks to the time stamps that are available on user ratings. We utilized a monthly sample in this instance, therefore t (uj, i) displays the time stamp of user uj's recorded rating of food fi. We utilized monthly intervals in our analysis since all evaluations were retrieved between 2000 and 2018, which resulted in 132 monthly periods. Thus, for recorded ratings from the first month of 2000, the t (uj, i) value will be 1, and for recorded ratings from the last month of 2018, it will be 132.

Our meal recommender system's primary job is to forecast the user's rating of the food. We've outlined the notations used below:

Inputs:

- User set: U = {u1, u2, u3, . . . , uN }
- Food set: F = {f1, f2, f3, . . . , fM }
- Set of all ingredients in all foods:

IngSet = {ing1, ing2, ing3, . . . , ingm}

- Ingredients of food fi:

Ii = {ingσ (1), ingσ (2), ingσ (3), . . . , ingσ (ki)}, where σ is some permutation of integers {1, 2, 3, . . . , m}.

Rating given to food fi by user uj at time t: ri(uj, t)

- User-Food rating matrix: R = {1, 2, 3, 4, 5}N ×M
- Follower-following network Follower(U , E, W)

Output:

- Rating Prediction Function:ˆpi(uj) = f (U , F, I , R)
- Recommendation: ˆF ={ˆf1, ˆf2, ˆf3, . . . , ˆfL}.

B. PERSON-BASED ESTIMATION

The rating (with respect to each user) of an unseen food item (with a given set of ingredients) is predicted during the user-based prediction phase using timely previous ratings (as in matrix R) and knowledge about user networks and trust relationships (through a new clustering-based strategy that uses a new user-similarity metric). This helps to resolve the issue with the cold start. The fundamental layout of the suggested user-based rating prediction approach for a straightforward dataset with nine users is shown in Figure 2. The specifics of the created user-based

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prediction are described in the remaining sections of this subsection.

1) SIMILARITY CALCULATION OF USERS

The time-aware similarities between various users are determined using a novel Time-Aware-based similarity measure in the first phase of the suggested technique.

where rk (ui) is the average score that user ui has rated, and rk (ui) is the rating that user ui has assigned to food fk. Similar to this, Aui,uj is the collection of meals that have been reviewed by both ui and uj users. The term TW (ui,uj,k) refers to the total weight of user-submitted ui and uj ratings to food fi, taking into account the ratings' time stamp. The weight is determined as follows: The formula for TW (ui,uj,k) is

where t (ui, k) is the duration of the user's recorded evaluation of food fk. The variable λ denotes a user control parameter that modifies the influence of the time factor, while TP represents the maximum Time Periods.

An elevated (against decreased) value of λ signifies a growing (vs declining) significance of time in the similarity score. We will remember that due to the sparsity of the 18-year-old ratings gathered, user ratings are divided into monthly time intervals (TP is set to 132). Weekly or even daily time periods might be viable, dependable alternatives in the case of denser user-food ratings.

2) CREATE A NETWORK OF TRUST

In classic recommender systems, the nearby selection problem is addressed in part by the trust network. Prior research [55]– demonstrated that individuals with mutual trust frequently have a similar rating profile. Therefore, in conventional collaborative filtering systems, trust relationships—if they exist—can be utilized as an extra layer of information to forecast things that are not observed.

The follower-following network that is now accessible in our situation can be used to establish trust connections. Basically, it's presumed that user ui trusts user uj if user ui follows user uj. As a result, the trust network of users is represented as TrustG(U, Tr), an unweighted and undirected graph where U is the set of users and Tr is the set of connections connecting them. This may also be expressed equivalently as a weighted graph, where the edge weight between users ui and uj is set to 1 in the event that user ui trusts user uj, and set to zero otherwise.

3) USER REPRESENTATION IN GRAPHS

The user set U is now mapped into a weighted graph, G(U, E, W), where W is the computed similarity between various users in U and E is the set of edges among all users. The trust connection and Pearson correlation coefficient are used in the user-based prediction model to determine the edge weights between various users in the following manner: where Tr(ui, uj) is the users' explicit trust score. and uj are determined during the creation of the trust network, while sim(ui, uj) represents the user similarity determined by using the suggested time-aware-based similarity metric. In the unit interval, α represents a control parameter that modifies the trust and user similarity component distributions.

4) USER CLUSTERING

Selecting a neighborhood that is suitable for the intended user is one of the most crucial issues for any recommender system. In fact, the recommender system finds suitable neighbors for a specific target user, which helps it anticipate ratings with accuracy. The best strategies to address the limitations of collaborative filtering and enhance the neighborhood selection process's general quality entail using a recommender system based on clustering. We found the following drawbacks in the user clustering techniques currently used in recommender systems:

- Before executing user clustering, the number of clusters must be specified. One of the most crucial factors in user clustering, the density of users in a cluster, often overlooked.
- While every user is treated equally, certain powerful users ought to exert more influence on the clustering process. The recently released graph clustering-based technique is used in the suggested method to divide the users into many groups in order to overcome these drawbacks.

This approach gets around the equal treatment of nodes in earlier techniques by iteratively merging nodes to create a compact network. This approach detects communities in a big graph using a fast parallel model. The approach is demonstrated to be quicker than earlier techniques, such as , , for user clustering, and it has the ability to automatically calculate the number of clusters.

5) PREDICTION OF USER-BASED RATINGS

When it comes to user-based rating prediction, user ui's rating of food fk is predicted as follows:

where w(ui, uj) denotes the edge weight, determined by Eq (3), between user uj and user uj. Ci is equivalent to the user community that the user ui is a part of.

C. PREDICTION BASED ON FOOD

Food similarities and past ratings are used to forecast the rating of unknown foods in the food-based prediction phase. This stage of the suggested system's goal is to use the cluster structure amongst meals to tackle the cold start issue. When specific goods have no past ratings

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recorded, a challenging and frequent issue in classic recommender systems is known as the "item cold start problem." Item clustering techniques are frequently used in recommender systems to overcome this problem. In this study, we propose an ingredient-based food clustering. As a result, the method used in the suggested framework turns food constituents into embedding vectors. The created food-based rating prediction for a basic dataset containing seven items is shown in Figure 3. Additionally, the specifics of the suggested food-based prediction model are described in the remaining portion of this paragraph.

1) INTERNAL FOOD EMBEDDING

Every meal is mapped to an n-dimensional real valued vector in this stage. The Bidirectional Encoder Representations from Transformer-Large (BERT-Large) [61] model is used in our suggested food clustering methodology to map the foods to contextualized embedding. Strictly speaking, by the end of 2018, BERT had proven itself as a pioneer in a number of NLP tasks [62], where it was able to pretrain deep bidirectional representations from unlabeled text beyond the capabilities of conventional language representation models by conditioning on both left and right context in all layers. The pretrained BERT model may be used for a variety of purposes with only one extra output layer. Each meal fi is seen as a sentence when using Natural Language Processing (NLP) techniques for food clustering, and the components of that food Ii = {ingσ(1), ingσ(2), ingσ(3),..., ingσ(ki)} are regarded as words of that sentence. Sentences (i.e. meals) and tokens (i.e. ingredients) are the inputs used in the feature extraction process. The output is a JSON file that contains simulated embeddings from various BERT layers. Tokens are n-dimensional vectors that depict the scene in which they occur. To create a contextualized representation, the last step is to average all of the token representations that are part of the phrase. Figure 4 provides an overview of our BERT-based food embedding technique.

2) THE CALCULATION OF FOOD SIMILARITY

It is possible to capture food components by using contextualized embeddings. Thus, we employed the closeness of meals in vector space as a measure of similarity in our food clustering algorithm. Foods that have vectors close by are likely to have certain components in common. A clustering phase is included in the suggested food-based rating prediction model to create groupings of related foods based on how far apart their vector space representations are from one another. To assess how similar the meals were to one another, Euclidean distance was employed. Formally, the contextualized representation vectors of food fi and food fj are fi = {fi1, fi2, fi3,..., fiL} and fj = {fj1, fj2, fj3,..., fjL}, respectively. Next, we compute the similarity between food fi and food fj using the formula:

Sim(fi, fj) = 1-√(∑_(l=1)^L(fil - fjl)^2).

where the l-th dimension of the contextualized representations vector of the food fi is indicated by the symbol fi.

3) FOOD CLUSTERING

The Deep Embedded Clustering (DEC) approach [63], which shortens the distance between comparable embedding vectors in the embedding space, is used by the food clustering algorithm described in this study. Kullback-Leibler (KL) divergence and AutoEncoders (AE) are used by DEC to improve the embedding vector representation and reduce the dimensionality of the data. In particular, the AE predicts the class label of the input data in an unsupervised mode by utilizing both feedforward and backpropagation to ascertain the encoder and decoder weight values. Essentially, DEC uses a stacked AE to recast the food embedding space as a Z-space. The latter transfers the food vector fi onto Z-space and is composed of several deep neural networks.

The pre-training and fine-tuning phases of the greedy layer-wise training phase are used by the stacked AE. It improves the training performance of the deeper neural network by solving the vanishing gradient problem while conducting unsupervised learning for every layer of the neural network. This can increase the input data's (si) network capabilities so that different vectors can be represented. The encoder and decoder are concatenated to carry out a fine-tuned learning process after the pre-training phase. Furthermore, all layers in our method—aside from the encoder and decoder's initial hidden layers—use the non-linear SeLU function [64]. Additionally, the dropout technique is used in this strategy to lower the likelihood of overfitting.

The encoder zi's latent space layer is the first Z-space representation that is created following the fine-tuning stage. Moreover, zi will be updated repeatedly in order to refine the cluster centroid . Using Kullback-Leibler divergence, the fitness function in this clustering approach minimizes the difference between the soft assignment qij and the target distribution pij. Thus, the following formula may be used to determine the probability, qij, of allocating the point zi to j:

Moreover, qij may be repeatedly improved in the following ways to enhance the clustering coupling:

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where CFk stands for cluster j's soft cluster frequencies, which are computed as follows:

Lastly, the following formula is used to determine the Kullback Leibler divergence objective function:

4) FOOD-BASED RATING PREDICTION

Regarding the food-based prediction, the following is the anticipated rating of food fi for user u: The formula is

where rj(u) is the user u's rating of food fj. In the same way, the average food rating is denoted by r̄i. The similarity score between food fi and fj, which may be computed by (5), is represented by sim(fi, fj), and Cfi indicates the collection of foods that are part of the cluster to which food fi also belongs.

D. TOP-N RECOMMENDATION

The final food prediction for user u is defined as a convex combination of the user-based and food-based forecasts after the user-based and food-based predictions have been computed:

where the user-based and food-based predictions on food fi for user u are denoted by pu-based_i(u) and pf-based_i(u), respectively. The trade-off between forecasts based on food and those based on the user is managed by the parameter β.

3. RESULTS AND DISCUSSION

System Provider:

In the above screen, algorithms showcase their training and testing accuracies through a bar chart visualization. This graphical representation offers insights into the performance of the system across different algorithms, aiding in the evaluation of its effectiveness.

View Food Recommend Prediction Type Details !!!

FoodId	UserId	Following_Users	Followers	Rating	Time	Review	Prediction
B004E4EBMG	A3TIACCF9FM8PB	1	2	5	1306627200	I like it, easy to carry,does not taste	Recommended
B004E4EBMG	A240FRPD4MEXND	0	1	1	1327881600	What a great tasting drink mix! It's by	Not Recommended
B004E4EBMG	A2P739KOM4U5JB	0	1	5	1327536000	I really like the MIO mango peach. I add	Recommended
B004E4EBMG	A2K89ROB2OLYHB	0	2	1	1340841600	I have become more conscious of products	Not Recommended
B004E4EBMG	ANEEEFP4BL7ZX	3	4	1	1325462400	Other than a bit of natural fruit flavor,	Not Recommended
B004E4EBMG	A1YS7LL4403XNR	0	0	5	1336953600	Peach Mango Mio is my water flavoring agent	Not Recommended
B004E4EBMG	A311KBQDJQNIZE	0	1	4	1326240000	My local grocery has four different	Recommended
B005IOXR1M	A29SL4BB5VFHF3	0	0	5	1327363200	I was hoping this would taste wonderful	Recommended
B004E4EBMG	ARYSDAZNRXN6G	2	4	1	1322870400	I tried this in water, and it took a lot more	Not Recommended
B001EPQNCO	A33U6HUGLKZIWY	0	0	5	1.346E+09	My title says it all. The coffee is our	Recommended

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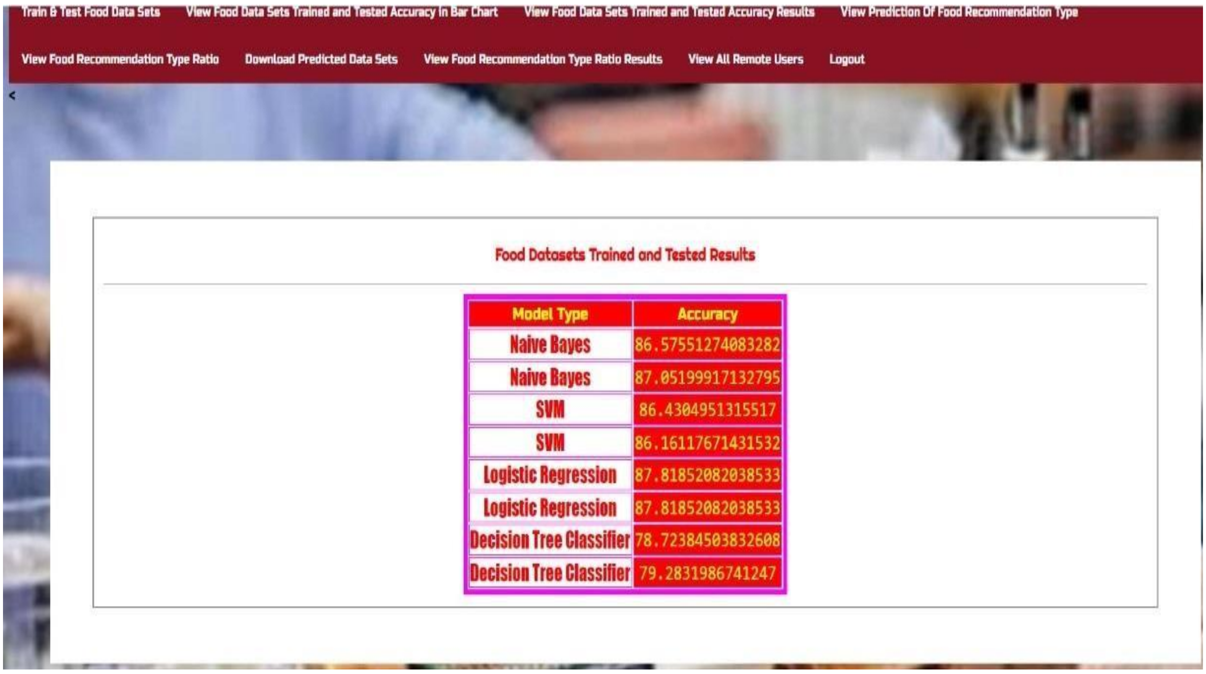
In the above screen, we display detailed information about the prediction types utilized in food recommendation. This overview offers insights into how the system generates recommendations, enhancing understanding of its functionality and predictive capabilities.

In addition to model type and accuracy ratios, this interface enables users to make informed decisions about the efficacy of different algorithms in predicting food recommendations, ensuring optimal performance and user satisfaction.



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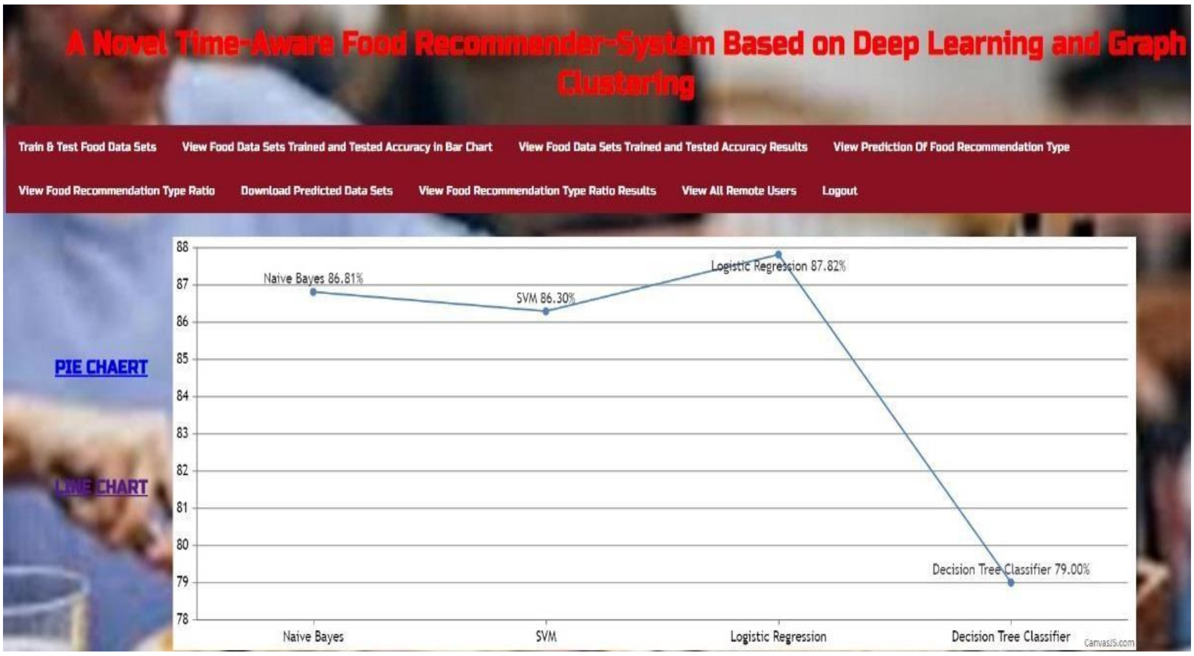
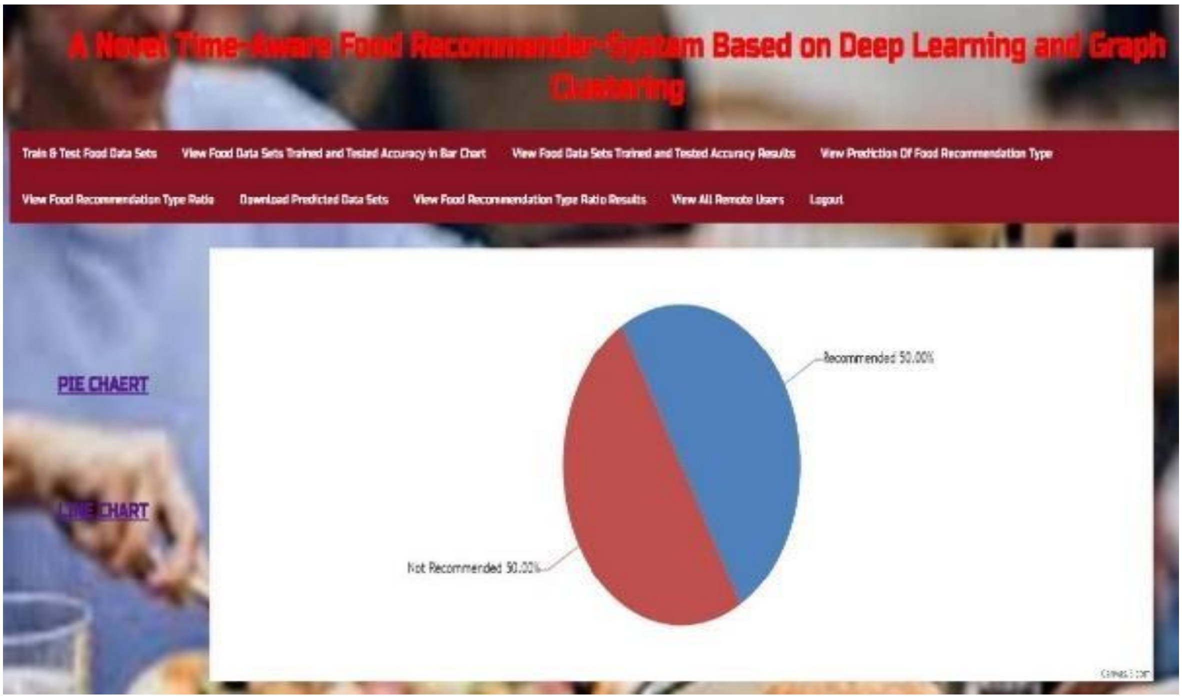
In this comparison, we analyze the trained and tested results of food datasets, focusing on model type and accuracy represented in decimal values. The visualization facilitates a comprehensive understanding of the performance of various models in predicting food recommendations, thereby informing decisions regarding the selection of optimal algorithms for enhanced user satisfaction.



This interface employs a line graph to visualize the performance metrics of various models across trained and tested food datasets. By presenting this data in a graphical format, users can easily analyze trends and make informed decisions regarding model selection and optimization.



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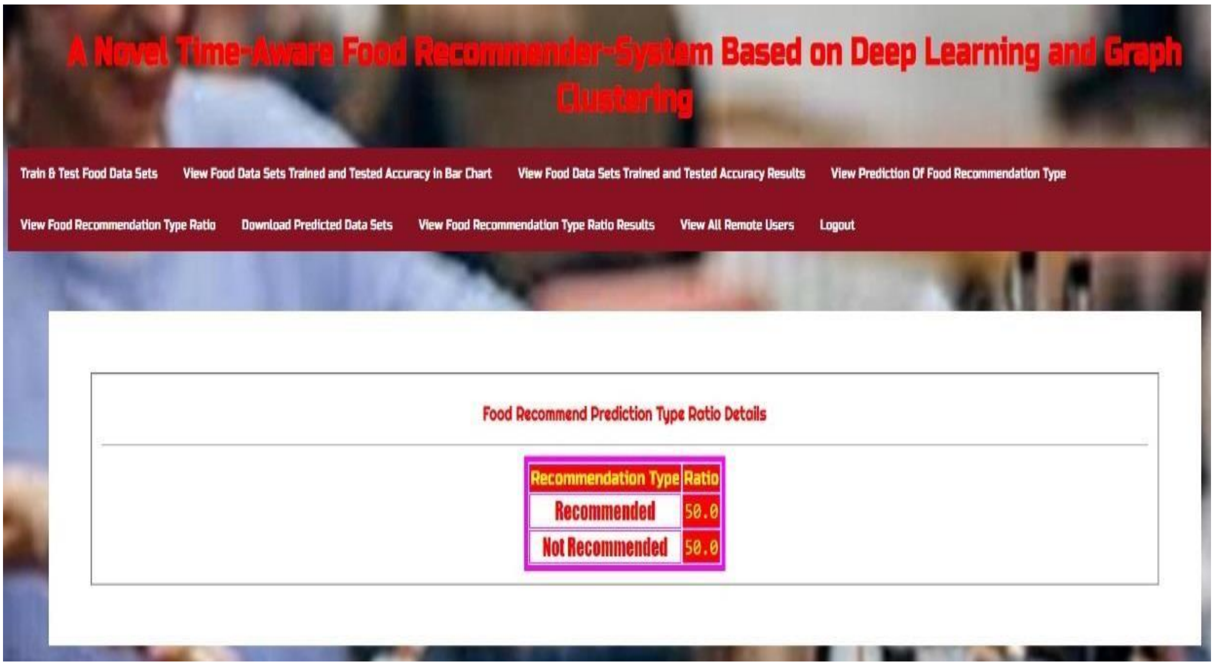
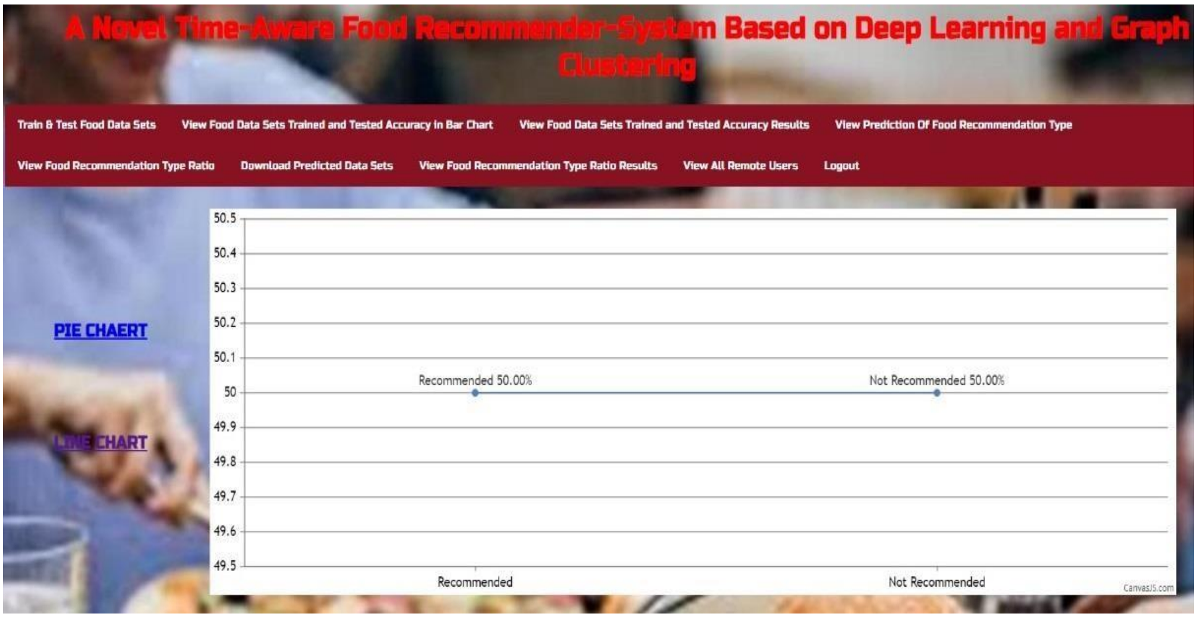
This interface displays a pie chart visualizing the distribution of recommended and non-recommended data within the food datasets. By depicting the proportion of recommended and non-recommended items, users can quickly grasp the balance between the two categories, aiding in decision-making for the recommendation system.



This interface offers insights into the distribution of recommended and non-recommended items within the food recommendation prediction type. It provides valuable data on the proportion of recommended versus non-recommended items in the dataset.



This interface presents a line graph representation illustrating the distribution of recommended and non-recommended items within the food recommendation prediction type.

4. CONCLUSION

Increasingly, recommender systems that choose goods that are reasonably acceptable for users' demands are becoming more common as a result of the Internet's expansion, popularity, and user base growth. Food recommender systems are essential components of many lifestyle services and are used in a wide range of lifestyle applications. In order to address the drawbacks of earlier food recommender systems—such as their disregard for food components, time stamps, cold start users and cold start items, as well as user communities—a unique hybrid system is built in this work. The suggested approach uses user-based and content-based models, temporal information, trust networks, and user communities to solve all four problems at once and enhance the recommender system's ultimate accuracy. User-based and content-based recommendations for food are the two stages of the suggested strategy. In the first phase, users and food items are clustered using graph clustering; in the second phase, a deep-learning based technique is employed. Five distinct metrics have been used to compare the model to the most recent food recommender system that has been developed, including the LDA, HAFR, and FGCN methods: precision, recall, F1, AUC, and NDCG. The created food recommender system surpasses the most advanced food recommender systems by a significant margin, according to the trial findings. It also attained the best performance. In order to further enhance the ultimate performance of the meal suggestion, we plan to add user-provided side information (such as gender, age, height, weight, location, and culture) into the framework in future works. Furthermore, healthy eating practices can reduce the intensity of symptoms related to non-infectious disorders. In further research, we hope to incorporate the nutritional properties of every product as supplementary data and provide dietary recommendations based on the illnesses and general health of each individual.

REFERENCES

[1] S. Wang, L. Cao, Y. Wang, Q. Z. Sheng, M. A. Orgun, and D. Lian, "A survey on session-based recommender systems," ACM Comput. Surv., vol. 54, no. 7, pp. 1–38, Sep. 2022.

[2] P. Wang, Y. Wang, L. Y. Zhang, and H. Zhu, "An effective and efficient fuzzy approach for managing natural noise in recommender systems," Inf. Sci., vol. 570, pp. 623–637, Sep. 2021.

[3] A. D. Viniski, J. P. Barddal, A. D. S. Britto, Jr., F. Enembreck, and H. V. A. D. Campos, "A case study of batch and incremental recommender systems in supermarket data under concept drifts and cold start," Expert Syst. Appl., vol. 176, Aug. 2021, Art. no. 114890.

[4] X. Yu, Y. Chu, F. Jiang, Y. Guo, and D. Gong, "SVMs classification based two-side cross domain collaborative filtering by inferring intrinsic user and item features," Knowl.-Based Syst., vol. 141, pp. 80–91, Feb. 2018.

[5] N. Hazrati and F. Ricci, "Recommender systems effect on the evolution of users' choices distribution," Inf. Process. Manage., vol. 59, no. 1, Jan. 2022, Art. no. 102766.

[6] L. Xie, Z. Hu, X. Cai, W. Zhang, and J. Chen, "Explainable recommendation based on knowledge graph and multi-objective optimization," Complex Intell. Syst., vol. 7, no. 3, pp. 1241–1252, Jun. 2021.

[7] M. Wasid and R. Ali, "A frequency count approach to multi-criteria recommender system based on criteria weighting using particle swarm optimization," Appl. Soft Comput., vol. 112, Nov. 2021, Art. no. 107782.

[8] S. Forouzandeh, M. Rostami, and K. Berahmand, "A hybrid method for recommendation systems based on tourism with an evolutionary algorithm and topsis model," Fuzzy Inf. Eng., vol. 14, no. 1, pp. 26–50, 2022.

[9] S. Forouzandeh, M. Rostami, and K. Berahmand, "Presentation a trust Walker for rating prediction in recommender system with biased random walk: Effects of H-index centrality, similarity in items and friends," Eng. Appl. Artif. Intell., vol. 104, Sep. 2021, Art. no. 104325.

[10] T. N. T. Tran, A. Felfernig, and N. Tintarev, "Humanized recommender systems: State-of-the-art and research issues," ACM Trans. Interact. Intell. Syst., vol. 11, no. 2, pp. 1–41, Jul. 2021.

[11] M. Slokom, A. Hanjalic, and M. Larson, "Towards user-oriented privacy for recommender system data: A personalization-based approach to gender obfuscation for user profiles," Inf. Process. Manage., vol. 58, no. 6, Nov. 2021, Art. no. 102722.

[12] X. Yu, F. Jiang, J. Du, and D. Gong, "A cross-domain collaborative filtering algorithm with

expanding user and item features via the latent factor space of auxiliary domains," Pattern Recognit., vol. 94, pp. 96–109, Oct. 2019.

[13] M. Ge, F. Ricci, and D. Massimo, "Health-aware food recommender system," in Proc. 9th ACM Conf. Recommender Syst., Sep. 2015, pp. 333–334.

[14] D. Bianchini, V. De Antonellis, N. De Franceschi, and M. Melchiori, "PREFer: A prescription-based food recommender system," Comput. Standards Interfaces, vol. 54, pp. 64–75, Nov. 2017.

[15] M. B. Vivek, N. Manju, and M. N. Vijay, "Machine learning based food recipe recommendation system," in Proc. Int. Conf. Cogn. Recognit. Singapore: Springer, 2018, pp. 11–19.

[16] T. N. T. Tran, A. Felfernig, C. Trattner, and A. Holzinger, "Recommender systems in the healthcare domain: State-of-the-art and research issues," J. Intell. Inf. Syst., vol. 57, no. 1, pp. 171–201, Aug. 2021.

[17] M. Premasundari and C. Yamini, "Food and therapy recommendation system for autistic syndrome using machine learning techniques," in Proc. IEEE Int. Conf. Electr., Comput. Commun. Technol. (ICECCT), Feb. 2019, pp. 1–6.

[18] J.-C. Kim and K. Chung, "Knowledge-based hybrid decision model using neural network for nutrition management," Inf. Technol. Manage., vol. 21, no. 1, pp. 29–39, Mar. 2020.

[19] R. Y. Toledo, A. A. Alzahrani, and L. Martinez, "A food recommender system considering nutritional information and user preferences," IEEE Access, vol. 7, pp. 96695–96711, 2019.

[20] S. Barko-Sherif, D. Elsweiler, and M. Harvey, "Conversational agents for recipe recommendation," in Proc. Conf. Hum. Inf. Interact. Retr., Mar. 2020, pp. 73–82.

[21] Z. Li, J. Hu, J. Shen, and Y. Xu, "A scalable recipe recommendation system for mobile application," in Proc. 3rd Int. Conf. Inf. Sci. Control Eng. (ICISCE), Jul. 2016, pp. 91–94.

[22] H. I. Lee, I. Y. Choi, H. S. Moon, and J. K. Kim, "A multi-period product recommender system in online food market based on recurrent neural networks," Sustainability, vol. 12, no. 3, p. 969, Jan. 2020.

[23] W.-Y. Chao and Z. Hass, "Choice-based user interface design of a smart healthy food recommender system for nudging eating behavior of older adult patients with newly diagnosed type II diabetes," in Proc. Int. Conf. Hum.-Comput. Interact. Cham, Switzerland: Springer, 2020, pp. 221–234.

[24] V. S. Vairale and S. Shukla, "Recommendation framework for diet and exercise based on clinical data: A systematic review," in Data Science and Big Data Analytics. Singapore: Springer, 2019, pp. 333–346.

[25] A. Kale and N. Auti, "Automated menu planning algorithm for children: Food recommendation by dietary management system using ID3 for Indian food database," Proc. Comput. Sci., vol. 50, pp. 197–202, Jan. 2015.

[26] X. Gao, F. Feng, H. Huang, X.-L. Mao, T. Lan, and Z. Chi, "Food recommendation with graph convolutional network," Inf. Sci., vol. 584, pp. 170–183, Jan. 2022.

[27] 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 Trans. Multimedia, vol. 22, no. 6, pp. 1647–1659, Jun. 2020.

[28] 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 Proc. 28th ACM Int. Conf. Multimedia, Oct. 2020, pp. 34–3468.

[29] C. Trattner and D. Elsweiler, "Investigating the healthiness of internet-sourced recipes: Implications for meal planning and recommender systems," in Proc. 26th Int. Conf. World Wide Web, Apr. 2017, pp. 489–498.

[30] F. Pecune, L. Callebert, and S. Marsella, "A recommender system for healthy and personalized recipes recommendations," in Proc. HealthRecSys@RecSys, 2020, pp. 15–20.

[31] Q. Shambour, "A deep learning based algorithm for multi-criteria recommender systems," Knowl.-Based Syst., vol. 211, Jan. 2021, Art. no. 106545.

[32] Y. Deldjoo, A. Bellogin, and T. Di Noia, "Explaining recommender systems fairness and accuracy through the lens of data characteristics," Inf. Process. Manage., vol. 58, no. 5, Sep. 2021, Art. no. 102662.

[33] Q. Zhang, J. Lu, and Y. Jin, "Artificial intelligence in recommender systems," Complex Intell. Syst., vol. 7, no. 1, pp. 439–457, 2021.

[34] M. F. Dacrema, S. Boglio, P. Cremonesi, and D. Jannach, "A troubling analysis of reproducibility and progress in recommender systems research," ACM Trans. Inf. Syst., vol. 39, no. 2, pp. 1–49, 2021.

[35] Q. Guo, F. Zhuang, C. Qin, H. Zhu, X. Xie, H. Xiong, and Q. He, "A survey on knowledge graph-based recommender systems," IEEE Trans. Knowl. Data Eng., early access, Oct. 7, 2020, doi: 10.1109/TKDE.2020.3028705.