Healthy Food Recommendations for User Communities through Trust and Popularity-Aware Aggregation

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Abstract. In recent years, food recommendation systems (FRS) have gained importance in inspiring healthy eating and supporting dietary decision-making. However, traditional methods focus on distinct users and tend to rank taste over nutrition, leading to unhealthy food suggestions. To overcome this, a Healthy Group Food Recommendation (HGFR) framework is proposed to balance health factors with cooperative user preferences. Initially, user–food interactions, ratings, and nutritional details were gathered from the Food.com dataset, which contains more than 178,000 recipes with comprehensive nutritional information and user reviews. Then, a graph-based model was created, where users were signified as nodes, and their similarities were computed using a time-aware rating mechanism. Next, a deep community detection method was employed for grouping similar users, and a trust network and popularity calculation confirmed that influential members had appropriate weights in group decisions. Furthermore, a health-aware prediction module compared nutrition values against World Health Organization (WHO) ranges, which produces normalized health scores that were combined with preference predictions. Finally, group aggregation was executed using a popularity-weighted average to recommend the top-k healthy foods. Experimental evaluation established that HGFR attained greater results in terms of Group Satisfaction Metric (GSM) with 93.0% when compared with the existing Group Preference Aggregation (GPA) method.

1 Introduction

In recent years, Deep Learning (DL) detection models have been used in numerous sectors for object detection and image recognition in health, finance, cyber security, and various automated vehicles [1]. DL algorithms integrate with some key applications such as computer vision, Natural Language Processing (NLP), and Speech Recognition. Moreover, these DL detection models help in the operation of self-driving cars, which helps cars to identify and classify pedestrians, other vehicles, traffic signals, and road signs [2]. Additionally, it helps in finance and cyber security by detecting fraud transactions and identifying security breaches to protect against fraud. However, these techniques are not accurate for detecting small objects with different viewpoints and lighting [3]. However, the existing food recommendation models typically recommend food to a single individual, and recommending food to multiple people or groups of people is a time-consuming process [4]. Therefore, it is a challenging task to suggest that unhealthy food leads to health problems and diseases. Furthermore, suggesting a narrow range of food across many people leads to missed opportunities to explore new nutritious food [4]. Moreover, categorizing different people's food preferences and evolving tastes in different cultural areas has become difficult. To overcome these challenges, a DL detection model called a Convolutional Neural Network (CNN) has been introduced for identification and classification [5]. The DL model will recognize the hidden patterns in compound data and recommend food based on user preferences and dietary restrictions [6]. Moreover, this model has the potential to capture diverse food items and classify them into clusters. Furthermore, these models have the ability to adapt easily when new metadata, such as different cultural cuisines, are added and partially categorized into their food type [7]. The state of art methods includes Convolutional Neural Network (CNN) model where it helps in extracting features from the visual data like images and videos. Moreover, this model has the potential to detect an image's color, shape, edges, and texture, which helps distinguish between different food dishes [8]. However, this model fails to detect complex dishes, such as salads or strews, which makes it difficult to recommend food for specific types of users. Simultaneously, Machine Learning (ML) unsupervised algorithm clustering methods, such as K means clustering and fuzzy c-clustering, help categorize different food items based on their type [9]. Moreover,

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this model cluster users if they belong to both healthy eaters and low protein and calorie consumers. However, this model struggles to categorize diverse amounts of food dishes across many parts of the world, leading to mis categorization [10].

The key contribution of the research:

- Healthy Group Food Recommendation (HGFR) framework is proposed to combine nutritional awareness with collaborative user preferences.
- A deep community detection method was employed for grouping similar users, whereas a trust network and popularity calculation confirmed that influential members had appropriate weights in group decisions.
- The health-aware prediction module compares nutrition values against the World Health Organization (WHO) ranges, which produce normalized health scores that are combined with preference predictions.

The remainder of this paper is structured as follows: Section 2 specifies the literature review, Section 3 demonstrates the proposed methodology, Section 4 explains the experimental results with corresponding discussion, and Section 5 presents the conclusion.

2 Literature review

Ahmad et al. [11] demonstrated a soil fertilization nutrient recommendation system based on evolutionary computation. Initially, data were collected from Ambedkar, India, a weather station, namely meteorological data of the Chhattisgarh dataset, which consists of features including temperature, humidity, rainfall, and values for the last ten years. First, data mining algorithm clustering-based fuzzy c-means was applied to the dataset to understand the hidden patterns in the dataset. Later, two machine learning (ML) models, Partial Least Square Regression (PLSR), the Group Preference Aggregation (GPA) method, and an optimization technique genetic algorithm were applied to manage integration in agriculture. Moreover, this model benefits farmers in predicting the water in an irrigation system that uses the soil, weather, and crop conditions. However, this model failed to predict the quality of the irrigation system when crops were treated with nitric acid fertilizers.

Zhao et al. [12] developed a healthy recommendation system using a heterogeneous graph-contrastive learning method. Initially, data were sourced from all recipe datasets, which consisted of 31,518 users, 25,683 food items, and 310,830 interaction records of food composition and nutrition information. First, the collected data were used to build a relational graph using the clustering method k-nearest neighbor algorithm (KNN) to cluster the nodes in the graph. Subsequently, cosine similarity was used to create a food similarity matrix. Moreover, this model has the ability to construct a food feature relation graph that helps users consume food based on diet preferences. However, this model suffers from a lack of diversity in recommendation results and fails to utilize collaborative information between users.

Fu et al. [13] demonstrated knowledge graphs for food recommendations based on gut microbiota and mental health. Initially, data were collected from the Food Data central (FDC) dataset, which consists of statistics regarding human food products and their associated nutrients. About 34,250 data samples were categorized into different food brands. First, the collected data were preprocessed using five principal dimensional analysis (PCA) components to reduce the dimensionality of the dataset while retaining essential information. Subsequently, an entity linking process was applied to the processed data to link entities for disambiguation. The processed data were then linked to the Kyoto Encyclopedia of Genes and Genomes (KEGG) database based on their labels. Therefore, to present the data graphically, three distinct relationships were applied to visualize the knowledge graph. Moreover, this model has the ability to recommend nutritional food and how food nutrition affects metal health. However, this model failed to ensure that particular foods affected mental health; however, further validation is required to recommend nutrient foods.

Pei-Min Lu and Zhaoyan Zhang [14] demonstrated Nutrition Feature Modeling and a personalized diet recommendation system based on neural networks and k-means clustering. Initially, data were sourced from the Kaggle website, which contains 8,790 data points and 54 features, including water content, food description name, carbohydrates, and sugars. First, the data were preprocessed using the standardization technique standard scalar function to normalize all the values uniformly. The preprocessed data were then fed through various algorithms such as k-means clustering, gradient boosting decision tree, Artificial Neural Network (ANN) and K Nearest neighbor algorithm (KNN). Therefore, these algorithms help the model improve the flexibility and accuracy of the recommended system. Moreover, this model has the potential to recommend nutritional foods based on dietary preferences. However, this model fails to recommend the right food for a particular individual based on their nutritional requirements.

Oyebode et al. [15] demonstrated personalized systems for health and wellness using machine learning techniques. Initially, data were collected from publicly available datasets, namely the Electronic Health Records (EHR) dataset, the Questionaries dataset, and the medical devices dataset. First the data was preprocessed for transformation using data imputation, normalization and standardization applied to normalize the data. Later, the preprocessed data were fed into Machine Learning (ML) and Deep Learning (DL) algorithms using Random Forest and Convolutional Neural Network (CNN) to process all the text and visual data for extracting the features for the recommendation. Moreover, this model has the ability to improve the mental well-being of an individual by recommending healthy eating guidelines. However, this model struggles to recognize nutritional food among rare chemical elements such as selenium in fish and iodine in seaweed.

3 Methodology

In this research, a Healthy Group Food Recommendation (HGFR) framework is proposed to join nutritional awareness with collaborative user preferences. Initially, user–food interactions and nutritional details were collected from the Food.com dataset, which consist of rich recipes and review information. Then, a graph-based representation is created, where users are nodes, and their similarities are evaluated utilizing a time-aware mechanism that highlights recent ratings. Next, deep community detection groups similar users into cohesive clusters, which are further enhanced by a trust network built from rating overlaps and community membership. Then, a popularity score is allocated to each user by incorporating trust and graph centrality, and recognizing influential members within groups. Following this, a health-aware prediction module estimates each food according to the World Health Organization (WHO) nutrition guidelines, making normalized health scores combined with preference predictions. Finally, group aggregation was achieved using a popularity-weighted averaging scheme to recommend the top-*k* healthy food items. A pictorial representation of the proposed HGFR framework is shown in Figure 1.

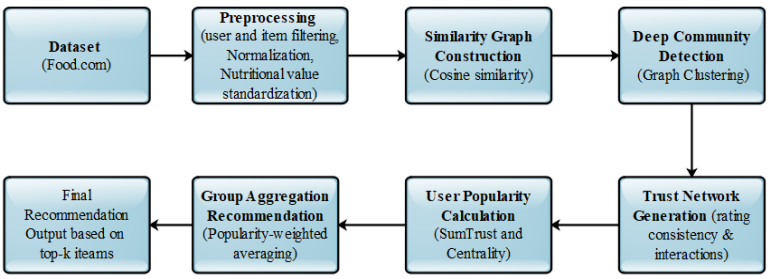

Fig. 1. Pictorial representation of the proposed HGFR framework.

3.1 Dataset

In this research, publicly available food preference datasets and nutrition-specific resources were applied to pretend real-world dietary recommendation environments. The main dataset consists of user–item interactions and ratings those available from open platforms such as Food.com [16], which provides authentic records of eating behaviors and preferences. To support health-aware modeling, nutritional datasets from the United States Department of Agriculture (USDA) and World Health Organization (WHO) rules were joint by delivering standardized nutrient profiles for food items. Furthermore, standard datasets such as FoodKG are used, as they deliver annotated ingredient structures and entity mappings. Each data instance was curated with user ratings, nutritional annotations, and hierarchical food concepts by confirming both semantic consistency and empirical grounding for building and estimating the Healthy Group Food Recommendation framework.

3.2 Preprocessing

Preprocessing plays an important role in making data for more effective recommendation modeling. Raw data often struggle with various issues including sparse ratings, variations in user rating behavior, and nutritional values recorded in dissimilar units. Without cleaning and standardization, these problems create bias and lead to reduced accuracy. To overcome this, filtering, normalization, and nutritional value standardization are applied, as explained in the following sections. These results confirmed that the dataset is reliable, consistent, and ready for health-aware recommendations.

3.2.1 User and item filtering

To address sparsity and noise. In this phase, users with less than a static number of ratings, such as (1-5) are deleted by user-based threshold filtering, as they lack enough history for reliable similarity computation. Similarly, items with very few interactions were excluded through item-based support filtering by ensuring that only current or sufficiently rated items were reserved. This technique improves the stability of the similarity graph and strengthens downstream recommendations.

3.2.2 Normalization

To address bias from different user rating behaviors, min–max normalization is employed to normalize the ratings from a 1 to 5 scale rescaled into a uniform 0–1 range. This adjustment eliminates discrepancies caused by users who reliably rate too high or too low. By applying linear scaling transformation, the system ensures that all ratings are directly comparable by allowing fairer similarity calculations and more accurate preference predictions across various users.

3.2.3 Nutritional value standardization

Nutritional attributes consist of calories, fat, and sugar, were recorded in inconsistent formats (per serving, per 100 g). To approve comparability, z-score standardization is employed to translate all the values into a common unit scale. This preprocessing stage permits reliable comparisons among the items and supports health-aware modeling by ensuring that

nutritional data reflect actual variances rather than measurement inconsistencies.

3.3 Graph representation of users

The starting point of the framework was to model the relationships between users based on their interactions with food items. Because food choices change over time, a time-aware graph representation was employed to capture these dynamics. Therefore, users are represented as nodes, while weighted edges signify their similarity, creating a graph $G = (V, E, W)$ where V states a set of users, E represents edges linking similar users, and the W matrix of edge weights denotes similarity scores. To estimate these weights, the time-aware similarity measure is used that highlights current ratings over older ratings. The comparison among users u and v is given in following Equation (1):

$$w_{u,v} = \frac{\sum_{f_i \in F_{u,v}} (r_{u,i} - \bar{r}_u)(r_{v,i} - \bar{r}_v) \times TW_{u,v,i}}{\sqrt{\sum_{f_i \in F_{u,v}} (r_{u,i} - \bar{r}_u)^2 \times TW_{u,v,i}} \sqrt{\sum_{f_i \in F_{u,v}} (r_{v,i} - \bar{r}_v)^2 \times TW_{u,v,i}}} \quad (1)$$

From (1), $F_{u,v}$ is the set of items rated by users, $r_{u,i}$ is the rating of food f_i by user u, and $\bar{r}_u$ is the average rating of user u. The time weight is defined by Equation (2):

$$TW_{u,v,i} = \sqrt{e^{-\lambda(T_L - t_{u,i})} \times e^{-\lambda(T_L - t_{v,i})}} \quad (2)$$

Where $t_{u,i}$ represents the timestamp of user u's rating for item f_i ,T_L is the modern timestamp in the dataset, and λ controls sensitivity to time. Moreover, higher λ highlights recent ratings, permitting the model to adapt to developing preferences. By incorporating time into similarity, this graph reflects real-world user behavior. Additionally, the developed similarity graph becomes the foundation for recognizing groups of like-minded users, which is attained through deep community detection, as explained in the next section.

3.4 Deep community detection

Following the user similarity graph, the next step is to recognize meaningful communities of users who share consistent preferences. Therefore, clustering users into communities improves recommendation accuracy because users within a similar group are more likely to exhibit common behaviors. To complete this task, a Deep Learning (DL) -based clustering approach that combines representation learning with community detection is proposed. Moreover, the similarity matrix attained in the graph representation of users is typically high dimensional, which makes traditional clustering methods less effective. Therefore, an autoencoder is utilized to learn the compact latent representations of users. The autoencoder decreases the rebuilding error among the input similarity matrix X and its reconstruction $\hat{X}$ expressed in Equation (3) below:

$$L_{Aut} = \frac{1}{2N} \|X - \hat{X}\|^2 \quad (3)$$

Where N denotes the number of users. These latent features are then passed to a clustering module that allocates users to the communities. The clustering process is shown by reducing the divergence between the predicted assignments and target distributions, as shown in Equation (4):

$$L_{Clu} = KL(Q \| P) \quad (4)$$

Where Q denotes soft cluster assignments and P is the target distribution intended to highlight high-confidence assignments. The joint optimization objective is expressed in Equation (5):

$$L = L_{Aut} + L_{Clu} \quad (5)$$

This process confirms that the latent representation preserves the structural similarity and forms cluster-friendly embeddings. By employing this method, users are categorized into coherent communities, where their preferences align more closely. These communities are grave for subsequent steps, because they permit the framework to develop trust relationships within and across user groups, as described in the following section.

3.5 Trust network generation

Trust plays an important role in collaborative decision making, particularly in food choices, where individuals often depend on trusted peers for recommendations. After detecting user communities, a trust network is introduced to support the connections between users with shared preferences. Moreover, the trust score between users u and v is derived from three components: the proportion of common foods rated, the connection of ingredients in their rated items, and their membership in the same community. The trust value is defined in Equation (6):

$$Trust(u, v) = \frac{1}{3}\left(\frac{|F_{u,v}|}{|F_u \cup F_v|} + \frac{|I_{u,v}|}{|I_u \cup I_v|} + Com(u, v)\right) \quad (6)$$

Here $F_{u,v}$ denotes a group of foods rated by users, $I_{u,v}$ is the set of common ingredients, and $\mathrm{Com}(u, v)$equals 1 if both users belong to the same community, and 0 otherwise. This symmetric trust score delivers a simple yet effective way to quantify the reliability among users. Therefore, the incorporation of both behavioral overlap and community membership confirms that trust is grounded in both preference parallel and structural groupings. The trust network now acts as the foundation for recognizing influential members whose opinions are more valuable in group recommendations. This leads to the next step in calculating user popularity, which plays a crucial role in recommendations.

3.6 User popularity calculation

In real-world group interactions, the impact of members is uneven. Certain users play a leading role in determining group choices owing to factors such as higher trust from peers, stronger central positioning within the network, or superior activity levels. To model this effect, a user popularity measure is presented that combines two key aspects, including SumTrust, which signifies the total amount of trust a user receives from other members of a similar community, reflecting how much their opinions are valued. Centrality captures the structural importance of a user in the similarity graph, which represents how accurately the nodes are connected within the network. By incorporating both SumTrust and Centrality, the proposed popularity degree effectively recognizes influential users, whose preferences should carry an improved weight in the recommendation process. The popularity of user u is defined in Equations (7) and (8):

$$Popularity(u) = \frac{2 \times SumTrust(u) \times Centrality(u)}{SumTrust(u) + Centrality(u)} \quad (7)$$

Where:

$$SumTrust(u) = \sum_{v \in G_c} Trust(u, v) \quad (8)$$

And $Centrality(u)$ is measured by Laplacian centrality, which estimates how much the total energy of the graph is reduced when the node is removed. This harmonic mean confirms that a user is considered popular only if both trust and centrality are high by avoiding cases where a user is central but not trusted, or trusted but peripheral. The intended popularity scores allocate diverse weights to users, which are subsequently utilized in group-level aggregation. Before that, however, we first predict how each user rates a food item by considering both preferences and health awareness, as explained in the following section.

3.7 User rating prediction

In traditional recommendation systems, ratings are mostly predicted based on user preference patterns. However, these methods often neglect nutritional considerations, which are important for food recommendations. To address this, the proposed framework establishes a health-aware prediction model that combines taste preference and nutritional balance. Therefore, the prediction depends on two complementary factors. Moreover, the preference factor is derived from collaborative filtering, where the system analyzes ratings given by alike users within the same community to calculate the extent to which a target user is like a particular food item. On the other hand, health factors estimate the nutritional quality of food based on the WHO guidelines. Additionally, each food item is assessed across main nutrients, such as proteins, fats, sugars, and sodium, and a health score is allocated by relying on whether the nutrient values fall within the recommended ranges. To balance these two aspects, the final predicted score for user u on food item f_i is expressed in Equation (9):

$$P_{u,f_i} = \alpha \times Health(f_i) + (1 - \alpha) \times Preference(u, f_i) \quad (9)$$

Where α is a tunable parameter that controls the trade-off between nutritional value and taste. This approach confirms that the system does not simply suggest popular but unhealthy foods, nor does it limit choices to highly nutritious but less interesting items. Instead, it provides a balanced recommendation that satisfies individual preferences and health requirements.

3.8 User group rating aggregation

This is the last phase of the proposed framework, which unites distinct user predictions into a collective group recommendation. In group settings, it is unrealistic to treat all members as having equal influence, as some users, owing to higher trust, stronger connectivity, or greater activity, play a more central role in decision-making. To capture this effect, a popularity-weighted averaging scheme was applied, in which the weight of each member's opinion was determined by the popularity score introduced in Section 3.4. Formally, for a group G_c and a food item f_i, the aggregated group prediction is calculated using Equation (10):

$$GPR_{G_c,f_i} = \frac{\sum_{u \in G_c} P_{u,f_i} \times Popularity(u)}{\sum_{u \in G_c} Popularity(u)} \quad (10)$$

Here, P_{u,f_i} signifies the health-aware prediction score for user u on item $f_i$derived in Section 3.5, whereas $(u)\text{Popularity}(u)\text{Popularity}(u)$ denotes the influence of user u within the group. By joining these two elements, the aggregation process confirms that the items are ordered not only according to how well they satisfy personal preferences and nutritional standards but also in a way that reflects the real-world influence of key group members. Finally, the top-k ranked items are presented as the group's recommendations, which confirm that the outcome is both nutritionally balanced and socially acceptable.

4 Experimented results

In this research, the DL detection Healthy Group Food Recommendation system (HGFR) is proposed to detect food images for healthy recommendations to user communities. For implementation, Python library keras and TensorFlow and cloud platforms such as Google Collab are used to run on Windows 10 pro, Intel i3 processor system with 8 GB RAM running speed at 3.70GHz. The evaluation metrics are considered and described in Equations (11)-(13):

$$Precision = \frac{|\{Recommended\ items\ that\ are\ relevant\}|}{L} \quad (11)$$

$$Recall = \frac{|\{Recommended\ items\ that\ are\ relevant\}|}{|\{all\ relevant\ items\}|} \quad (12)$$

$$GSM(G_c) = \frac{\sum u \in G_c (F_R \cap SF_u)}{(G_c \times L)} \quad (13)$$

Here, F_R denotes the group of recommended foods and SF_U refers foods list with ratings between 4 and 5. Additionally, G_C and L refer to length of the recommendation list as the users present in the Group c. The value of Group Satisfaction Metrics (GSM) should be in the range [0,1], where $GSM = 0$ indicates that none of the group members are satisfied with the suggested foods, whereas $GSM = 1$ indicates that all of the group members are satisfied

4.1 Performance analysis

Performance analysis metrics are used to measure the quality of food recommendations by calculating Precision, Recall and Group Satisfaction Metrics (GSM) using the above equations. By evaluating metrics with traditional methods such as integrated two-stage recommendations (ITGR), a GRGP to the proposed Healthy Group Food Recommendation system (HGFR) model. The performance results are represented in Figure 2.

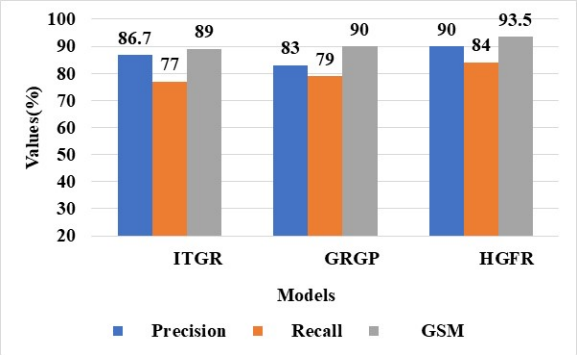

Fig. 2. Performance analysis of proposed HGFR.

From the above Figure 2, the proposed HGFR model attained with 90% precision ,84% recall, and 93.5% GSM metric values when compared to the traditional ITGR and GRGP models, respectively.

4.2 Comparative analysis

In the comparative analysis, the proposed HGFR model is compared with the existing model Group Performance Analysis (GPA) using metrics such as precision, recall, and GSM. The evolution metrics of the HGFR model compared with GPA [11] are listed in Table 1.

Table 1. Comparative analysis of proposed HGFR model.

Model	Precision (%)	Recall (%)	GSM (%)
GPA [11]	87	80	90
HGFR-Proposed Model	90	84	93.5

From the above Table 1, the proposed HGFR model attained greater GSM metrics with 94.5% than traditional GPA [11] model. Additionally, this model performed with precision 87%, 80% recall as well. Therefore, proposed HGFR model outperformed GPA in all aspects of metrics, with 87% precision, 80% recall, and 90% GSM respectively.

4.3 Discussion

The primary objective of this research paper is to develop a healthy food recommendation system to balance health factors according to user preferences. Simultaneously, food is popular and ensures that it is nutritious, especially for a group of people who want to eat healthy food. The results show that the proposed HGFR Model overcomes the challenges of the existing GPA [11] model and traditional ITGR and GRGP models in terms of developing an efficient healthy food recommendation system. The existing GPA model didn't find healthy foods, and it struggles to distinguish between popular food and healthy food, mostly relying on user ratings and recommendations. Thus, the proposed HGFR Model handles where it uses a health-aware prediction system that helps to integrate both nutritional profile and user rating, and suggests food accordingly. Moreover, this model has the potential to recognize the opinions of a group of people who eat the same kind of food; based on this, it identifies the popularity of the food majority of people. Similarly, the ITGR and GRGP models are not able to adapt to a situation where a user changes his diet over time because they work based on clustering techniques. In this research, the proposed HGFR Model comfortably adapts to any situation by using a time-similarity-aware measure that assigns weights to older ratings that help to understand user preferences accurately while balancing health as well. Furthermore, this method has the potential to understand common food and ingredient interests, which eventually makes the model more transparent and explainable. Finally, our proposed HGFR Model decisively outperforms the ITGR and GRGP models by developing a healthy food recommendation system while balancing both taste and nutrition for a group of people who want to eat healthy food.

5 Conclusion

This research developed an efficient healthy food recommendation system using the proposed HGFR model. The traditional ITGR and GRGP models struggle to adapt to a situation where a user changes his diet over time owing to their working based on clustering techniques. These challenges were resolved by the HGFR model, which comfortably adapts to any situation by using a time similarity aware technique to measure the weights of older ratings that help to understand the user preferences accurately while balancing health as well. Initially, user food choices, ratings, and nutrition details were gathered from the food.com website, which contains 178,000 recipes. First, the sourced data were preprocessed using normalization to standardize nutrient values, such as protein and sugar. Finally, the preprocessed data were fed into the HGFR Model, where the time-aware rating mechanism represents nodes in the graph and edges represent the similarity

among them. From The results HGFR model outperformed with 90% precision ,84% recall, and 93.5 % GSM metric values. In the future, the proposed model will further explore why a particular food was recommended to a user with a clear explanation by integrating Explainable Artificial Intelligence (XAI) models such as SHAP (SHapley Additive exPlanations) and Local Interpretable Model-Agnostic Explanations (LIME). In addition, XAI-based food recommendation systems will ensure health and taste preferences instead of blindly trusting the recommendations.

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