ISSN No:-2456-2165 https://doi.org/10.38124/ijisrt/IJISRT24MAR717

Devoloping a Robust and Accurate Food Recommendation System Using a Hybrid Filtering Approach

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Abstract:- With the increase of fame for online food platforms as well as a broad range of culinary choices, there has been a need for stronger and more correct food recommendation systems that can help users in discovering new and fascinating foods that are tailored to their individual tastes. This paper presents an innovative design of constructing a recommendation system by utilizing both content-based approach and collaborative filtering techniques. Our system applies machine learning algorithms to examine user preferences as well as dish attributes with personalized recommendations based on it thereby increasing satisfaction levels and overall engagement rates. The experimental results we provide herein demonstrate the efficacy and accuracy of our hybrid filtering method and prove its ability to transform how individuals find pleasure in eating.

***Keywords*:-** *User-Item Matrix, Vectorization, Cosine Similarity Matrix.*

I. INTRODUCTION

The plethora of food choices in the ever-evolving world of cuisines nowadays may be overwhelming for those who prefer restaurants with personalized services. One breakthrough that solves this is the emergence of Food Recommendation Systems which combines technology with cuisine. These are huge databases, where advanced algorithms and data analysis sift through culinary knowledge, user preferences and contextual factors to give recommendations that are tailor-made. As a result, these systems will offer consumers new and pleasurable experiences as well as simplifying them in their decision making. The Food Recommendation System acts as a culinary compass by connecting people to rich mosaic of global foods, flavours and dietary requirements hence improving dining experiences.

A. User-Item Matrix

The basis of collaborative filtering based recommendation systems lies in the user-item matrix, which captures information about how users interact with our items. It represents users as rows and items as columns. Each cell contains a numerical value that corresponds to either the rating or interaction that a user has with an item. Using patterns and correlations in this matrix, recommendation systems model user preferences and item similarities. Through matrix factorization methods or nearest neighbour techniques, these systems mine insights from the user-item matrix that are then used to make personalized recommendations for users.

B. Vectorization

In the case of recommendation systems, vectorization is an important step in making recommendation algorithms more efficient and accurate. The transformation of text-based attributes like food names or user preferences into numerical forms is made possible by vectorization techniques that are compatible with machine learning models. By changing textual information into high-dimensional feature vectors, vectorization makes it easy to compare and analyse similarities among various items or users within a recommendation system. Hence, this change enables recommendation algorithms to utilize advanced mathematical methods for pattern recognition and similarity measures, thereby improving the relevance of recommendations given to users.

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C. Cosine Similarity

Cosine similarity is one of the main metrics employed in recommender systems for measuring the degree of similarity between two vectors by calculating the cosine of their angle. It is often used as a measure to determine how close user-item vectors are to each other or rather item-item vectors in a recommendation context. Recommendation systems can find the most similar items to each other or a given user's preferences by calculating the cosine similarity between feature vectors representing users or items. This similarity measure is at the heart of collaborative filtering and content-based recommendation approaches, which allows for accurate and relevant recommendations to be produced by utilizing text and numeric attributes of items/users.

II. RELATED WORK

Jiangpeng He et al. Estimation [1]. According to this paper's proposal, deep learning-based techniques have shown amazing outcomes in a variety of image-based nutrition assessment applications, including food categorization and portion size estimate. When many tasks need to be processed simultaneously in real life, it might be challenging to apply conventional approaches, which only focus on one work at a time. Multi-task learning, on the other hand, employs L2-norm based soft parameter sharing to train the classification and regression tasks concurrently. To further enhance the accuracy of food portion size prediction, we further suggest combining normalization with cross-domain feature adaption. picture-based nutritional portion estimate may be greatly advanced by utilizing our results, which surpass baseline techniques in terms of classification accuracy and mean absolute error. One of the most prevalent jobs in computer vision is picture classification. For the purpose of preventing disease, it is critical to track and document food consumption in image-based dietary evaluation. But determining the portion size of an object is a difficult undertaking. The numerical number that is directly proportional to the item's spatial amount in world coordinates is known as the part size of an object.

Xinyue Pan and others [2]. As suggested in this article, food image categorization facilitates the study of nutrient consumption from collected food photos and is a basic and crucial step in image-based dietary evaluation. Nevertheless, the majority of the work that has already been done on food categorization is on predicting "food types," which do not directly provide information about nutritional makeup. This constraint results from the intrinsic inconsistencies in nutrition databases, which are responsible for linking every "food item" to its corresponding data. Consequently, the goal of this effort is to classify food products in accordance with nutrition databases. In order to do this, we first present the VFN-nutrient dataset by adding a food item with nutritional composition information to each food image in VFN. Because food item annotation is more discriminative than food type annotation, the dataset takes on a hierarchical structure as a result. However, the food item annotations only display visual associations with each other based on the nutritional composition information, which presents a major barrier when using deep learning-based approaches for categorization. Food image classification, which aims to predict the food consumed in an eating occasion image, is a crucial component of image-based dietary assessment. To address this issue, we then propose a multi-stage hierarchical framework for food item classification by iteratively clustering and merging food items during the training process. This allows the deep model to extract image features that are discriminative across labels. In this study, we demonstrate that, as shown in Figure 1, a food may be annotated using both its food category and individual meal elements.

Wang Guo-Hua [3] and others. As suggested by this technique, the teacher network's SoftMax output was utilized in the initial KD research as additional supervisory data to train the student network. A high-capacity network's output, however, does not deviate appreciably from ground truth labels. Additionally, the SoftMax output has less information than the representation in the penultimate layer because of the classifier layer. A student model's performance is hampered by these problems. Furthermore, KD finds it challenging to condense instructor models that have been through self- or unsupervised-supervised learning. However, prior works only concentrated on distilling features in the middle layers or transforming the features. Few have addressed the issue of forcing the student to directly mimic the teacher's feature in the penultimate layer. Feature distillation has gained increasing attention in recent years. The various architectures between the instructor and the student cause problems when distilling features in the intervening layers, and when changing features, some information about the teacher may be lost. We think that mimicking the feature just in the penultimate layer is a superior technique to directly replicate the feature for knowledge distillation. In contrast to KD, it can learn a classifier from the teacher without the student model. When the teacher and student have distinct architectures, feature mimicking may be simply applied to a teacher taught via unsupervised, metric, or self-supervised learning. Second, trouble comes when teacher and student characteristics have different dimensionalities.

Park Seulki[4] et al. The absence of data from minority classes causes the classifier's generalization performance to worsen, which is the problem of class unbalanced data that has been proposed in this system. In this work, leverage of the rich context of the majority classes as background pictures to offer a unique minority over-sampling technique to enhance varied minority samples. The main concept is to use rich-context photographs from a majority class as background images and then paste an image from a minority class on top of them to diversity the minority samples. The approach is straightforward and readily integrable with the current long-tailed recognition techniques. Through comprehensive experiments and ablation studies, we empirically demonstrate

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the efficiency of the suggested oversampling strategy. Real-world data are likely to be naturally unbalanced, with a significant variation in the number of samples per class. Oversampling the minority is a simple and basic way to solve the class imbalance issue. If models are trained on an unbalanced dataset, they can be easily biased toward majority classes and likely to have a poor generalization ability on detecting minority classes.

et al., Jiangpeng He [5]. Has suggested in this system: To forecast the sorts of foods in each input image, food classification is the fundamental stage in image-based dietary assessment. Foods in real-world situations, however, are usually long tail distributed, meaning that some food kinds are taken more frequently than others. This results in a serious problem with class imbalance and impairs performance overall. Furthermore, food data is not the subject of any long-tailed classification approach now in use, which makes things more difficult because food pictures vary within and across classes. Two new benchmark datasets for long-tailed food categorization are presented in this work: Food101-LT and VFN-LT, where the long-tailed food distribution in real life is reflected in the number of samples in VFN-LT. In order to address the issue of class imbalance, a novel two-phase framework is then proposed, which consists of (1) under sampling the head classes in order to eliminate redundant samples while maintaining the learned information through knowledge distillation, and (2) oversampling the tail classes in order to perform visually aware data augmentation. Through a comparative analysis between our approach and the most advanced long-tailed classification algorithms currently available, we demonstrate the efficacy of the suggested framework, achieving optimal results on the Food101-LT and VFN-LT datasets. The findings show the potential for applying the suggested method to relevant real-world applications.

III. EXISTING SYSTEM

It has been assumed that food recommender systems can be useful for changing people's eating habits and encouraging them to adopt a healthier diet. The aim of this study was to create a new hybrid food recommender system which addresses the drawbacks of previous systems including lack of consideration for aspects such as food components, time, cold start users, cold start food items, and community. There are two stages in the suggested strategy: user-based recommendations and content-based recommendations for food. In the first step, clustering is done through graph clustering on users and foods, whereas in the second step, deep learning based method will be utilized. Furthermore, an inclusive technique was used to account for temporal as well as user-community factors thereby improving the quality of suggestions given to users. Five different evaluation metrics – precision, recall, F1 score, area under curve (AUC) and normalized discounted cumulative gain (NDCG) – were employed to compare our model with existing state-of-the-art recommendation algorithms on "Allrecipes.com" dataset. Finally; the designed food recommender system was tested using data obtained from Allrecipes.com used by different models; hence validating its effectiveness when compared with other approaches.

IV. PROPOSED SYSTEM

The method we propose is novel as it seeks to boost the performance of food recommendation systems through its adoption of hybrid filtering. The proposed system integrates content-based and collaborative filtering methods in order words; it aims at providing more accurate recommendations which are personalized for users. This paper therefore intends to mitigate these shortcomings by incorporating both user-item attributes and user-user interactions to generate recommendation lists that match individual tastes unlike previous research (Adomavicius & Tuzhilin, 2005). Moreover, our system uses dynamic learning schemes that update themselves as per fluctuations of consumers' tastes in various kinds of foods over time. Its recommendations will remain valid due to constant updating and refining based on new data inputs. Finally, users will have an easy way of getting their choice options or exploring some items they never thought existed via an intuitive interface provided by the recommended dishes list.

V. SCHEMATIC DIAGRAM

In Figure 1, the use of these datasets is demonstrated. In this research effort, datasets from Kaggle were used to build a model and create item- and rating-based suggestions.

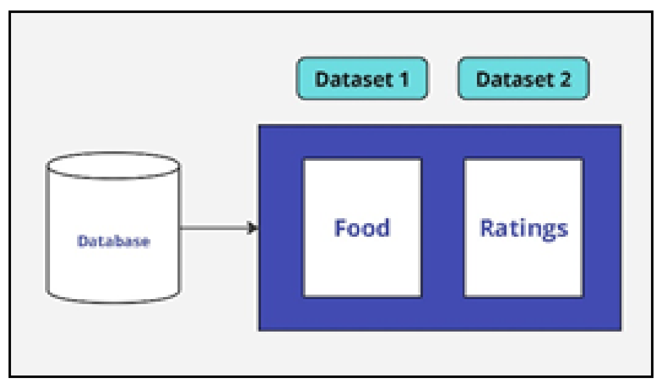

Fig. 1. Food Dataset

The recommender model's performance has been evaluated using two datasets. The dataset is composed of two files which were "food.csv" and "ratings.csv". These datasets were designed to enhance the functionality of the recommendation systems. The "food.csv" dataset consisted of 401 samples having features such as Food id, Name, C type, veg non and description. These attributes were selected one by one and employed to make the recommenders better than they were before. The data set contained detailed information

ISSN No:-2456-2165 https://doi.org/10.38124/ijisrt/IJISRT24MAR717

about many different food items along with their characteristics. The "ratings.csv" file included a total of 512 samples involving User ID, Food ID, and Rating among other things. All relevant variables necessary for building a recommendation system and constructing the model were carefully chosen from both these datasets. To enhance the accuracy and effectiveness of this recommendation system, this selection methodology ensured that only the most appropriate features with optimal explanatory power have been considered and used in modeling it into an operational tool for decision making purposes. Figure 2 is a visual representation of the ratings.csv dataset.

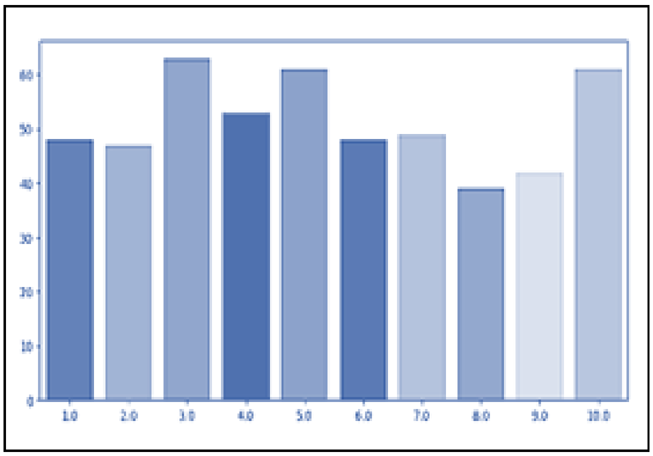

Fig. 2. Rating Distribution

This research aimed at optimizing recommendations thereby leading to a more accurate and personalized suggestion system for users through merging variables from both databases with respect to choosing meaningful attributes for them. Figure 3 depicts the main block design of the proposed system.

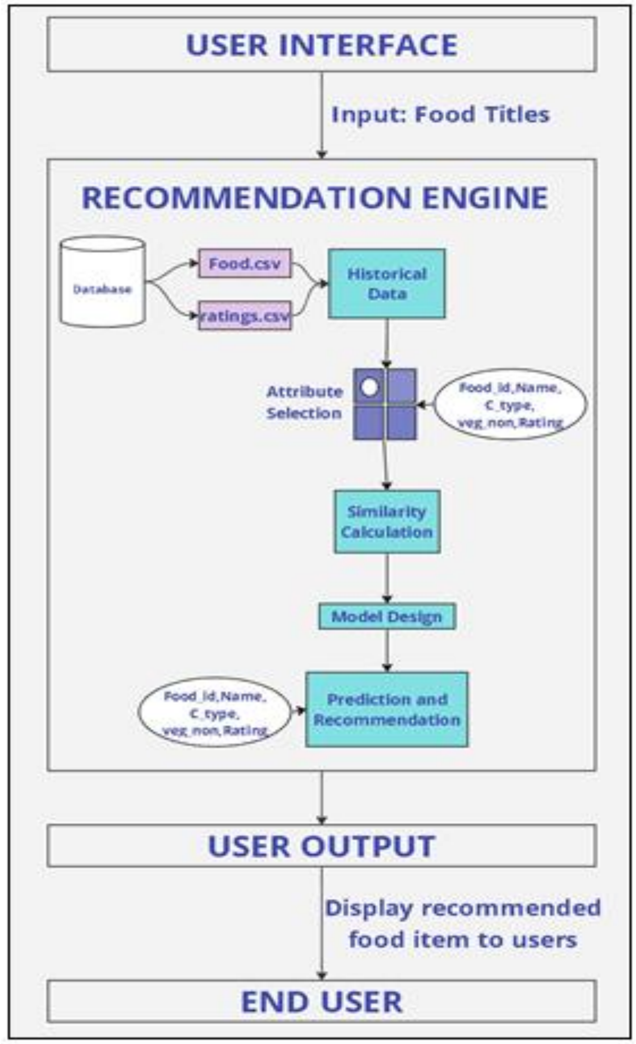

Fig. 3. Block Diagram

It incorporates an overall discussion that touches on various aspects including but not limited to technological development focusing on streamlit, interaction design, objective oriented design for our system as well as others that are related.

VI. METHODOLOGY

A. Collection and Preprocessing of Data

➢ *Dataset Acquisition:*

The first stage was to get a complete dataset with various food items, such as their names, descriptions, cuisine types and whether they are vegetarian or non-vegetarian.

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➢ *Data Cleaning:*

The process invloved detailed cleansing of the data set to eliminate any inconsistencies, duplicates or missing values that could have affected the quality and integrity of information used in analysis.

➢ *Feature Engineering:*

Further analysis as well as recommendation model development was based on relevant features like description and cuisine type chosen.

B. Content-Based Filtering to Recommend Food

On food recommendation using content-based filtering, we have come up with a model for tailoring recommendations to user's tastes through a comprehensive process that is based on user-specific attributes and textual similarity. Initially, we collected detailed attributes for all food items such as name, ID, cuisine type, and vegetarian/non-vegetarian classification. Afterwards, the textual data associated with the food items were processed by applying string matching algorithms which included steps like removing stop words, converting text to lower case and omitting punctuation marks. We employed cosine similarity distance algorithm to calculate the similarities among texts of different foods thereby creating feature vectors representing their attributes and textual properties. By combining features that are specific to each user with those that resulted from string matching results, we calculated similarity scores which ranked food items. The foods that could suit the needs of these users best would therefore be recommended first before others in this category. Thus, we were able to sort them according to how they matched what the user wanted. This significantly improved the capability of content-based filtering algorithms in giving precise personalized recommendations leading to better user satisfaction.

➢ *Text Processing:*

Tokenization, stemming and stop-word removal were some of the techniques employed to pre-process the food items' descriptions in order to extract meaningful information from them.

➢ *Vectorization:*

Processed text data including words were transformed into numerical vectors using CountVectorizer technique that treats every food item as a vector within n-dimensional space.

➢ *Similarity Calculation:*

The computations relied upon cosine similarity for assessing how similar two foods are considering their vectorized forms. By employing this similarity measure, it was possible to identify foods having similar descriptions.Equation 1 illustrates the formula used to determine the cosine similarity between two vectors, A and B. The dot product of vectors A and B, or A.B, is the result of multiplying each of their respective components by itself elementwise.

$$cosine\ similarity(A, B) = \frac{A \cdot B}{||A||\ ||B||} \tag{1}$$

C. Food Recommendation via Collaborative filtering

In this approach to recommending food items, tailored suggestions are based on user ratings and associated textual information about food products. Beginning by extracting data such as user and food IDs, we also collected the names of the foods that were being referred for the recommendation process to get more meaning. Using this information, we created a matrix showing how users related with items and their preferences hence calculating their cosine similarity with respect to users' ids and food item's id. To identify the nearest neighbors for any given user using both numerical evaluations as well as text provided in vector representation for instance feature vectors contained within textual information. The closest neighbors were identified regarding rating patterns and food preferences by considering both ratings and text in terms of feature vectors. These people's ratings coupled with their food names helped us generate individual recommendations accounting for both numerical evaluations as well as text characteristics. Thereafter, these recommendations were ranked according to their mean score so that the most relevant ones could appear first. This collaborative filtering approach has advanced our ability to provide users with personalized, context-aware food recommendations by closing the gap between numeric scores and written words appended towards food items.

➢ *User-Item Matrix:*

It was constructed a user-item matrix that was sparse where rows stand for users, columns represent food items, and the matrix elements show user ratings for various food items.

➢ *Nearest Neighbor Search:*

Based on user ratings, the k-nearest neighbors algorithm has been applied to locate similar food items. The algorithm identifies popular foods among similar users by finding those with similar tastes. Figure 4 depicts the k-nearest neighbor.

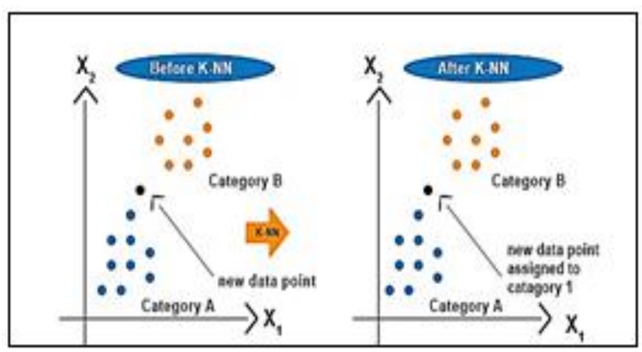

Fig. 4. k-Nearest Neighbor

ISSN No:-2456-2165 https://doi.org/10.38124/ijisrt/IJISRT24MAR717

D. Development of User Interface

➢ *Streamlit Integration:*

Adopting the Streamlit framework in order to develop a web interface that is simple to use and will communicate with the food recommendation system.

➢ *Interactive Features*:

Building interactive input tools like text boxes and selection buttons, which allow users to give information for personalized recommendations.

➢ *Real-Time Updates:*

Making real-time updates possible and allowing Streamlit to create dynamic contents; which can improve the user experience and responsiveness of the application.Including Streamlit in the methodology section allows transparency on the technology used in developing the user interface as well as emphasizes on the interactivity and user-centeredness of the system. It also demonstrates how important user experience is in making sure that there is successful implementation of a food recommendation system.

VII. CONCLUSION

The presented research concludes by introducing a new and effective method of improving food recommendation systems by combining content-based filtering with collaborative based filtering techniques. The system employs advanced text processing techniques such as Count Vectorizer and TF-IDF to obtain meaningful numerical representations from textual descriptions, thereby enhancing the accuracy of recommendations. Additionally, the system applies collaborative filtering algorithms like k-nearest neighbors that improve recommendations according to user preferences. Figure 5 represents the user interface of the proposed system.

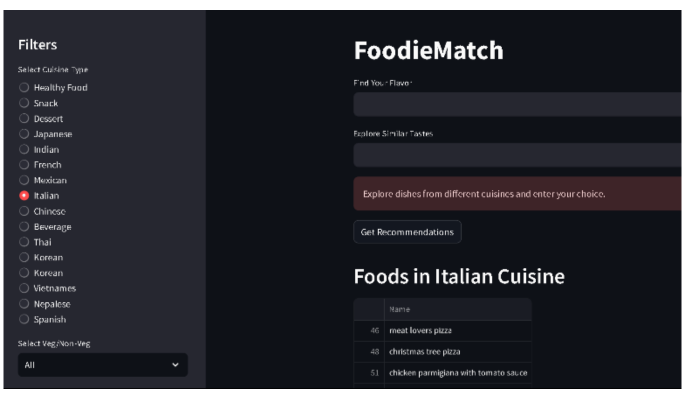

Fig. 5. User Interface in Streamlit App

Figure 6 depicts the user interface after the recommended food is displayed from both content-based and collaborative filtering as a hybrid approach.

Fig. 6. End Result After Food is Recommended

VIII. FUTURE WORK

The future work in this area could involve integrating machine learning advances such as deep learning models to improve the accuracy and sophistication of food recommendation systems even further. Furthermore, real-time user feedback should be included so that the system can adapt dynamically while recommendations can change according to developing preferences, hence optimizing user experiences. In addition, location or time-contextual information may be considered in favor of context-awareness in recommendations.

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