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MULTI-LAYER FOOD RECOMMENDATION SYSTEMS

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ABSTRACT

Recommendation Systems are one of the most popular applications of Machine Learning technology. They are information filtering systems that provide us with valuable suggestions based on our personal preferences and a variety of other factors. Finding one's favourite food from a variety of food items and dishes has become an important issue as one may not know what food to eat at that particular time or is unsure which item to prefer. So, this food recommendation system uses collaborative filtering and a Natural Language Processing algorithm to assist the user by recommending food items based on their previous preferences and ratings on various food items and suggests food items with low spice. There are numerous machine learning techniques available, such as collaborative-based filtering, content-based filtering, and a combination of content and collaborative based filtering known as hybrid filtering, knowledge-based filtering, and so forth, which can be used to implement the recommendation systems. Among all of these methods or technologies, we will be dealing with User-based filtering, which is a type of Collaborative based filtering in which we calculate the similarity coefficients of different users based on the inputs given, and then predictions are made. After the predictions, we will again make recommendations from the recommended list based on user preferences for the cuisine, and again from the recommended list, we will recommend the food items having low spice to the user. The main or primary aim of this proposed recommender system is to increase user satisfaction, and this application is expected to have a high accuracy of 90%.

Keywords- Recommendation systems, food recommendations, Natural Language Processing, predictions.

INTRODUCTION

Recommendation systems elicit the personal interests and preferences of an individual customers and make recommendations accordingly. So basically, these systems recommend things such as music, food, movies, books, videos, shopping items, and even people, and so on. This application is built to recommend food to users who prefer to eat food with little spice and has the potential to improve and support the quality of the decisions the user makes while searching for and selecting food through online websites. Due to their visibility and increased use on practically every platform, they have recently grown excessively popular. The most well-liked live recommendation systems can be found on websites like Amazon, Facebook, YouTube, Swiggy, Zomato, and others. The sheer magnitude of the people that these platforms serve has significantly increased their requirement. They essentially enhance user experience. A user, for example, would prefer not to go through the hassle of searching through Swiggy's or Zomato's massive inventory. So, it will be greatly appreciated if an item was recommended to him based on some criteria such as his rating of previously purchased food items, his favourite dish, and so on.

Food recommender systems are two-edged swords. They are beneficial to both the user and the provider. They keep the user engaged by recommending interesting food items, reducing the user's workload by reducing the number of options available. They allow for the exploration and discovery of items or dishes that the user may not be aware of or have never tried before.

Food delivery services such as Zomato, Swiggy, Domino's Pizza, and others operate in this fashion, where they recommend food items and, in some cases, a list of items is automatically generated. The important thing to remember here is that they are dynamic and change the recommendations based on the user's activity. They use machine learning algorithms to keep track of things so that they can evolve with each user rating of the recommendations.

There are four stages through which the data processes in recommendation system:

Data collection: Information is either explicit (like food reviews and ratings) or implicit (page views, order history, etc.).

Storing: Whether you should utilize a NoSQL database, object storage, or a regular SQL database for storage depends on the type of data used to generate the suggestions.

Analysing: After examination, the recommender system identifies products with comparable user interaction data.

Filtering: In the final stage, data is filtered to find the relevant data needed to give recommendations to the user. You must select an algorithm that works with the recommendation system in order to activate this.

Types of Recommendation system:

- **Content-based filtering:**

In this recommendation system we operate or deal with the similar content. If a customer/user consumes a specific food, then this system will look for other food items of similar taste or the same item with a different flavor that the user is consuming. When comparing similar content, several fundamental attributes are used to compute similarity.

The figure depicts the various flavors of chocolate ice cream. If a user is looking for chocolate ice cream, then butterscotch in the cone, choco bar, Kwality Walls, Gelato: Belgian Chocolate is recommended.

There are various metrics that can be used to calculate similarity. Among which one is Euclidean distance for computing numeric data related similarities, there is a cosine similarity for computing similarities related to textual data, and Jaccard similarity for computing similarities related to categorical data.

Euclidean distance:

$$\text{Inner}(x, y) = \sum_i x_i y i = (x, y)$$

Cosine Similarity:

$$\text{Similarity(X,Y)} = \frac{X.Y}{|X| \times |Y|}$$

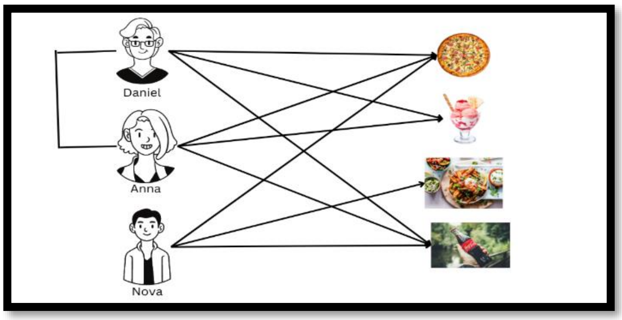
Jaccard Similarity:

$$J(A,B) = \frac{|A \cap B|}{|A \cup B|}$$

- **Collaborative based filtering:**

In this type of recommender system, we work on the similarities of different items as well as different users which are commonly used in e-commerce websites and in several online food delivery websites. This technique analyses the preferences of users based on their similarities and then makes recommendations. There are two approaches used in collaborative filtering- One is User-based and the other is Item-based.

User-User based collaborative filtering:



The figure depicts user-user based collaborative filtering with three users, Daniel, Anna, and Nova, and their interest in food. The system identifies users who have similar purchasing habits and computes the similarity between users based on purchase behavior. Daniel and Anna are alike because they bought similar items. We calculate the similarity coefficient using the formula:

$$sim(a,b) = \frac{\sum_{p \in P}(r_{a,p} - \bar{r}_a)(r_{b,p} - \bar{r}_b)}{\sqrt{\sum_{p \in P}(r_{a,p} - \bar{r}_a)^2} \sqrt{\sum_{p \in P}(r_{b,p} - \bar{r}_b)^2}}$$

And prediction formula:

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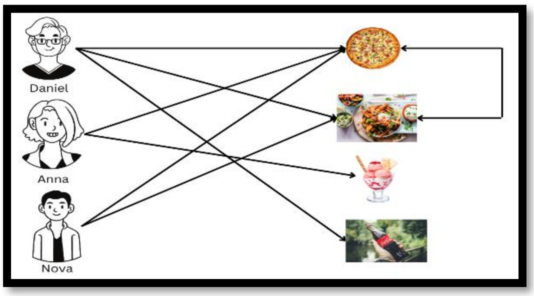
$$pred(a,p) = \overline{r_a} + \frac{\sum_{b \in N} sim(a,b) * (r_{b,p} - \overline{r_b})}{\sum_{b \in N} sim(a,b)}$$

It is the weighted average of the similarity scores combined with the rating for that specific food item.

Item-based Collaborative filtering:



The figures depict users Daniel, Anna, and Nova. The system looks for similar items that were purchased by the user. For predicting, we compute the similarities between different items rather than the users. Users Daniel and Nova both purchased pizza along with salad, indicating that they both have similar tastes.

- **Hybrid recommended system:**

Using both collaborative-based filtering and content-based filtering at the same time for suggesting a wider range of items to users/ customers is a Hybrid recommendation system. This new recommendation system is said to be more accurate in providing recommendations to the users than other recommender systems.

Natural Language Processing (NLP):

Natural Language Processing (NLP) is a branch of artificial intelligence. Machines use this technology to understand, analyze, manipulate, and interpret human languages. It assists developers in organizing knowledge for tasks like translation, automatic summarization, speech recognition, topic segmentation, etc.

There are many NLP tasks that break down human text or voice data to assist the computer in making sense of what it is ingesting. Some of the tasks are as follows:

- The task of reliably converting voice data into text data is known as speech recognition. Speech recognition is required for any application that responds to voice commands or questions.
- Sentiment analysis attempts to extract subjective qualities from text, such as emotions, attitudes, suspicion, confusion, and sarcasm.
- Part of speech tagging, also known as grammatical tagging, is the process of determining a words or piece of text's part of speech based on its use and context.
- NEM, or named entity recognition, recognizes words or phrases as useful entities. NEM recognizes Natural language generation is sometimes referred to as the inverse of speech recognition; it is the process of converting structured data into human language. 'Florida' as a place or 'Damon' as a man's name.

LITERATURE REVIEW

"A Systematic Study on the Recommender Systems in the E-Commerce" by Malekpours Alamdari, Hosseinzadeh, Jafari, Darwesh and Asghar. In 2020 of 16th June this journal was published, and 2020 of July 2nd is current version.

"The importance of trust in electronic commerce", by P. Ratnasingham, was published on 1998 of October. This describes that for a multitude of reasons E-commerce has become an inseparable part of business, such as its simplicity of use, is accessible universally, for its wide varieties, compassion for managing products from various vendors, secure and trusted payment methods, and the least amount of time is wasted as it is convenient for people to do shopping from home.

"The impact of cost, technology acceptance and employees' satisfaction on the effectiveness of the electronic customer relationship management systems", by authors Navimipour and Soltani, published on 2016 of February. Making payments, buying and selling goods and even physical products digitally, booking reservations for hotel online, booking tickets digitally, e-learning, registering online and a variety of other services of these applications are all widely available.

"Recommender systems", Commun. ACM, by authors Resnick and Varian, published in 1997. Recommender Systems (RS) learn from their customers' or users' behavior and then recommend products or items based on what they assume or believe are the most relevant among all the possible outcomes. They also offer tools for optimizing application adaptation for each user.

"Customer reviews analysis with DNN for e-commerce recommender systems", by authors Shoja and Tabrizi, in 2019. Recommender Systems (RSs) automate e-commerce personalization through combining both traditional and emerging technologies such as machine learning.

"Introduction to recommender systems handbook", by authors Rokach, Ricci, Kantor, and Shapira, in 2011. The enormous amount of data yielded through these websites makes it difficult for customers/users to take a decision on which products to purchase. Using RSs can significantly aid in the resolution of the problem. According to their reviews a large number of opted studies have mixed collaborative-based filtering with various methods, recurrently in a weighted manner. Furthermore, these studies asserted that the most significant issues were data sparsity and cold start.

"A systematic review of the state-of-the-art literature and recommendations for future research", by authors Charband and N. Jafari, in 2016 of December. The goal of this paper was to analyze recent publication journals in Recommender systems which focused on e-commerce and has shown how these systems' types, algorithms, methods, and implementations are evolving. Basic algorithms such as knowledge-based and Collaborative-based, content-based, and hybrid content-collaborative filtering's were studied. As a result, we gathered and analyzed numerous published research on Recommender systems which were used in e-commerce using a structured methodology.

PROBLEM IDENTIFICATION

With so many different food items and dishes to choose from, it is difficult for one to decide what to eat. Selecting an item from a large selection has become challenging because one may not know what food to eat at that time or is unsure which item to prefer. There are several items that the user is unaware of or has heard for the first time. Some people, such as patients, prefer to eat low-spice foods but are unsure which foods are spicy, medium, or low in spice.

As a result, this food recommendation system is proposed to assist customers or users by recommending foods that they might prefer. The food is recommended based on previous purchases, tastes, ratings for various items they have previously purchased. This application will recommend foods that are low in spice and non-spicy and also improves customer decision-making and maximizes user satisfaction.

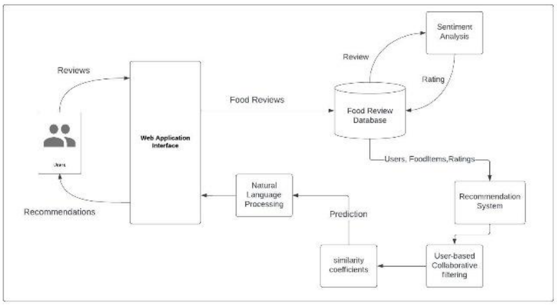
The problem with the recommendation system is predicting the users' opinions on various substances and being able to recommend the best items to each user. Another issue with recommendation systems is data sparsity, scalability, and grey sheep. Data sparsity indicates that the data is widely dispersed; it contains null and missing values. Scalability indicates that predicting a large number of rating items is difficult. Gray sheep denotes problems with time and memory.

Objectives:

- To enhance the accuracy of the proposed system.
- Reduce time complexity when compared to other applications.
- Enhance users' decision-making ability
- Maximize user satisfaction.

SYSTEM METHODOLOGY

A system architecture is created to depict the project's overall process flow:



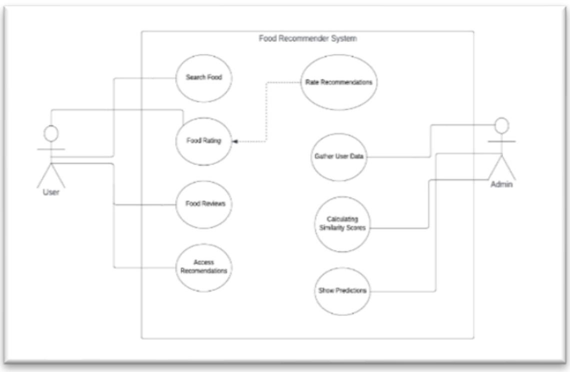
The diagram above depicts how this food recommendation system will function. The reviews provided by users via any web application interface are stored in the database; the reviews may be based on their taste or their preferred restaurants, cuisines, etc. Sentiment analysis will be performed based on the reviews, and ratings will be saved in the database.

The user ratings on various food items will be the input for the recommendation system, and we will calculate similarity coefficients between users using User-based collaborative filtering, and then the prediction will be made, and the recommended list will go through Natural language processing algorithm where the user can choose his preferred cuisine and food with low spice will be recommended to the user.

UML Diagram to depict the execution of project:

USE-CASE DIAGRAM:

The actors in this scenario are the admin and the user. Each use case includes actors, a description, pre/post conditions, and the control flow. The admin is responsible for maintaining the application up to date.



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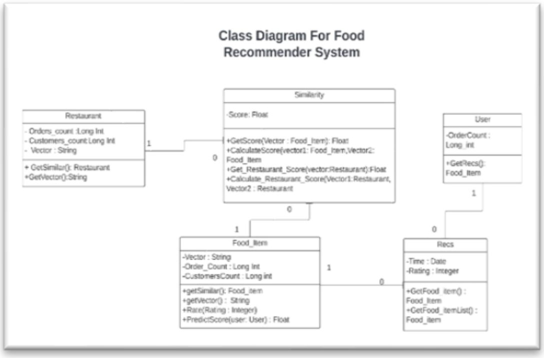
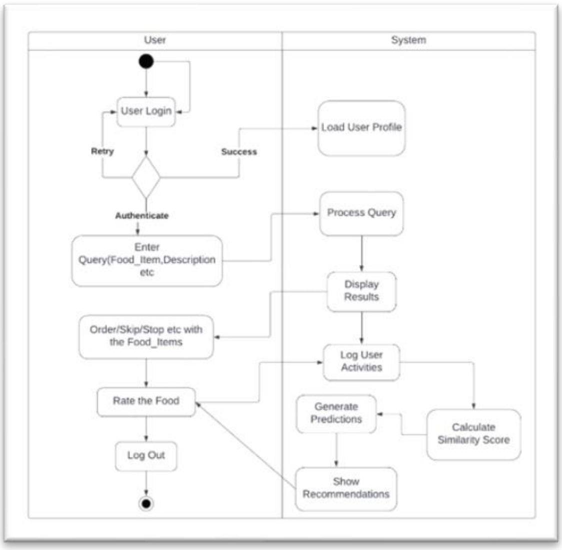
CLASS DIAGRAM:

The system's structure that is being modelled is described by the class diagrams. There are three main classes in the current food recommender system being developed: the User, the restaurant, and the food item. The additional two classes, Similarity and Recs, are used to calculate similarity scores and get food and restaurant recommendations.



ACTIVITY DIAGRAM:

An activity diagram describes the main activities for each service provided. These activity diagrams depict the recommender system's workflows. Workflows are illustrated sequentially, and control-flow lines are frequently used to specify conditions. The diagram is associated with a description, the initiator of the activity, and the workflow. When an activity begins, the initiator is typically a function module that is invoked.



OVERVIEW OF TECHNOLOGY

The technologies used for the implementation are:

Python libraries:

Pandas: Pandas is a popular open-source python library used for data analysis, and data manipulation and is primarily designed to work with relational or labelled datasets. It offers several data structures and operations for manipulating numerical data and matrix data. key features of Pandas are as follows:

- Pandas' primary data structure is a two-dimensional table with rows and columns called a data frame. Dataframes can store different types of data and handle missing data.
- Pandas include powerful data manipulation tools such as filtering, sorting, grouping, merging, and reshaping.
- Pandas include visualization capabilities that allow users to create various types of charts and graphs to explore their data.
- Pandas can read and write data from and to a wide range of file formats, such as Excel, CSV, SQL databases, and others.

NumPy: NumPy stands for Numerical Python which is an open-source python library used for scientific computing. This library contains multidimensional array objects as well as routines for processing those arrays. NumPy can perform logical and mathematical operations on arrays. key features of NumPy are as follows:

- NumPy includes a powerful N-dimensional array object that can be used to represent vectors, matrices, and higher-dimensional arrays. This makes it simple to perform mathematical operations on data arrays.
- NumPy offers optimised numerical functions for performing common mathematical operations like addition, multiplication, and trigonometric functions. These functions are intended to work with NumPy's N-dimensional arrays and are much faster than equivalent Python functions.
- NumPy includes a powerful linear algebra module that includes functions for performing matrix operations such as multiplication, inversion, and decomposition.

SciPy stats: SciPy stats is a module in SciPy, an open-source Python library used for scientific computing. The stats module includes a comprehensive set of statistical functions and distributions for various types of data analysis and modelling. Key features include:

- The stats module includes a number of statistical functions for analysing and summarising data, including mean, median, variance, and standard deviation.

- SciPy stats includes a large number of probability distributions, including normal, binomial, exponential, and others. These distributions can be used in a variety of applications to model and simulate random variables.

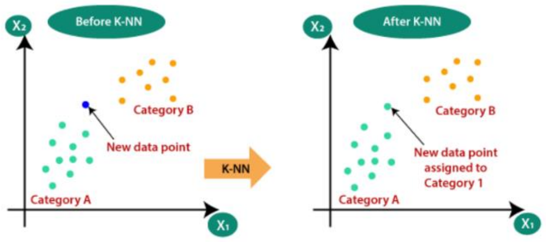
Seaborn: Seaborn is an open-source Python library used for data visualization that is built on Matplotlib. It includes a variety of functions and tools for creating informative and visually appealing statistical graphics, such as histograms, scatter plots, line plots, and bar plots. Seaborn offers a variety of statistical plots, including regression plots, categorical plots, and distribution plots, which can reveal underlying patterns in data and provide insights into variable relationships. It also supports the creation of interactive visualisations with tools like matplotlib widgets and plotly.

Sklearn: Scikit-learn (sklearn) is a popular open-source Python machine-learning library. It includes numerous algorithms and tools for tasks like classification, clustering, regression, and dimensionality reduction. Key features include:

- It is built on NumPy and SciPy and is optimized for speed and efficiency.
- It offers a large collection of algorithms for various machine learning tasks, such as support vector machines (SVMs), k-nearest neighbors (KNN), random forests, and others.
- It includes several tools for preprocessing and feature selection, including scaling, normalization, and feature extraction.
- It also provides tools for evaluating the performance of machine learning models, such as cross-validation and metrics like accuracy, precision, and recall.

KNN- k-nearest neighbors:

The k-nearest neighbors algorithm is a supervised learning non-parametric classifier that uses proximity to classify or predict the grouping of a single data point. While it can be used for either classification or regression problems, it is most commonly used as a classification algorithm, with the assumption that similar points are nearby. For classification problems, a class label is assigned by majority vote—that is, the label that is most frequently represented around a given data point is used. To determine which data points are closest to a given query point, the distance between the query point and the other data points must be calculated. The most commonly used distance measure is the Euclidean distance. In the k-NN algorithm, the k value specifies how many neighbours will be checked to classify a specific query point. If k=1, the instance is assigned to the same class as its single nearest neighbour.



Pearson correlation: In statistics, data analysis, and machine learning, the Pearson correlation is used for a variety of applications such as feature selection, data exploration, and model evaluation. It is a popular similarity metric in collaborative filtering, a recommendation system technique that predicts a user's rating or preference for an item based on the ratings and preferences of similar users or items. In user-based collaborative filtering, it is used to measure the similarity between users based on their ratings of items. Users who have rated similar items are thought to be more similar, and their ratings are used to make recommendations to other users. Pearson correlation is preferred over other similarity measures, such as cosine similarity because it considers the mean and variance of the ratings, which can be useful in situations where users have different rating scales or biases.

$$sim(a,b) = \frac{\sum_{p \in P}(r_{a,p} - \bar{r}_a)(r_{b,p} - \bar{r}_b)}{\sqrt{\sum_{p \in P}(r_{a,p} - \bar{r}_a)^2}\sqrt{\sum_{p \in P}(r_{b,p} - \bar{r}_b)^2}}$$

NLP libraries:

Spacy: Spacy is an open-source Python software library for natural language processing (NLP). Tokenization, part-of-speech tagging, named entity recognition, dependency parsing, and text classification are among the tools and features available for processing and analysing text data. Spacy is built to be efficient and quick, making it ideal for processing large amounts of text data. It also includes pre-trained models in English, French, Spanish, Portuguese, German, Italian, Dutch, and other languages. It also includes support for custom model training, integration with deep learning frameworks such as PyTorch and TensorFlow, and the ability to visualize and analyse text data using interactive visualizations and graphs.

nltk: The Natural Language Toolkit (NLTK) is a well-known open-source Python library for natural language processing (NLP). It includes tokenization, named entity recognition, part-of-speech tagging, sentiment analysis, and other tools and modules for processing and analysing text data. Key features include:

- Text processing tools and modules for a variety of NLP tasks.

- Languages supported include English, Spanish, Dutch, and others.
- A large corpus of corpora for training and testing natural language processing models.
- Custom corpus generation and text processing pipelines are supported.
- Integration with Python libraries like scikit-learn and TensorFlow.

IMPLEMENTATION

Food recommendation systems are based on the ratings of the user given on food they have tasted. So, first, we will be reading the dataset of both food and ratings dataset. The food dataset consists of information related to food such as food id, name, cuisine type, and description. Then we will be creating a user-food matrix. We will convert the dataset to a matrix format. The rows of the matrix represent users, and the columns represent food. The matrix's value is the user rating of the food item, if one exists. Otherwise, it displays 'NaN'. We normalize the rating by extracting the average rating of each user as some people tend to give higher ratings than others. After normalization, food with ratings lower than the user's average receives a negative value, while food with ratings higher than the user's average receives a positive value. Then we will be using Pearson correlation to compute the user similarity matrix. Now, let's look at a user ID to find similar users. We must first remove the picked user ID from the list of similar users and We will reduce the number of items in the pool by doing the following: Remove any food items that the target user has eaten. Only keep food items that similar users have eaten.We keep only the row for the picked User id in the user-item matrix and remove the items with missing values to remove the food item eaten by the target user. determine the number of similar users. The values in the user similarity matrix range from -1 to 1, with -1 indicating the opposite food preference and 1 indicating the same food preference. We need to set a positive threshold because user-based collaborative filtering makes recommendations based on users with similar tastes. In this case, we set the user similarity threshold to 0.3, which means that a user must have a Pearson correlation coefficient of at least 0.3 in order to be considered similar. After determining the number of similar users and the similarity threshold, we sort the user similarity value from highest to lowest, then print the ID and Pearson correlation value of the most similar users. We keep the user IDs in the top 10 similar user lists and remove the food items with all missing values to keep only the similar users' food. All missing values for a food item indicate that none of the similar users have eaten it. The food items that the picked user ID has eaten will then be removed from the similar user food list. errors='ignore' removes columns without displaying an error message. We will choose which food items to recommend to the target user. The weighted average of the user similarity score and food rating determines the recommended items. The similarity scores are used to weigh the food ratings, so users with higher similarity receive higher weights. This process will loop through items and users to determine the item score, rank the score from highest to lowest, and select the top ten food items to recommend to the picked user ID. Now we will recommend the food items to the target user based on their preferred cuisine type. For example, if the picked User ID wants to eat French cuisine type food, then we will recommend the top 10 of this type from the recommended list to the user. We will be using nltk library for specifications so that from the recommended list of preferred cuisine, we will again recommend food items having low spice or no spice at all.

CONCLUSION

The primary goal of this project is to provide recommendations to users with food items having low spice in an application using machine learning algorithms. We have designed and implemented the software using user-based collaborative filtering and natural language processing. The dataset under consideration contains ratings given by several users to specific food items, and based on the ratings provided by them we calculate the similarities between the users using the Pearson correlation coefficient, and we endeavour to recommend the food, and from that recommended list we again recommend food to our users based on their preferred cuisine and again from that list we recommend food having low spice. The system's efficiency is improved with the help of natural language processing, and the system is also capable of making appropriate recommendations to users and increasing user satisfaction. The accuracy of this food recommender system is expected to be more efficient.

FUTURE SCOPE

This recommendation system can also be programmed in such a way that it interacts with the user and ask questions to gain a better understanding of their food preferences and provide more accurate recommendations. And also, information like personal health data, such as body weight, height, age, medical history, and food allergies, can be used by this recommendation system to provide users with more personalized and healthy food recommendations. These systems should also be able to use real-time data such as location, weather, and time of day to provide users with context-based recommendations. For example, a user may receive recommendations for nearby restaurants that serve food appropriate for the current weather or time of day.

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