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Research Article

Designing an Efficient Restaurant Recommendation System Based on Customer Review Comments by Augmenting Hybrid Filtering Techniques

Mauparna Nandan[1*], Pourush Gupta[2]

[1]Department of Computer Applications, Techno Main Saltlake, Kolkata, India
[2]Department of Mathematics, National Institute of Technology, Durgapur, India
E-mail: mauparna2011@gmail.com

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Abstract: Recommendation systems are being widely employed in order to provide users with a tailored set of services. They are primarily designed to generate advice or ideas (like restaurants, tourist places, medicines, movies, etc.) that address user concerns and can be efficiently utilized in a variety of industries. In today's world, where we have a plethora of dining options available, choosing the right restaurant that matches our preferences can be a daunting task. To simplify this process and provide personalized recommendations, restaurant recommendation systems have emerged as a valuable tool. By leveraging the power of natural language processing (NLP), these systems can analyze textual data, such as user reviews and restaurant descriptions, to generate tailored suggestions for users. NLP is one of the machine learning techniques for intelligently and effectively analyzing, comprehending, and extracting meaning from human language. By utilizing techniques like sentiment analysis and named entity recognition, the system can understand user queries and match them with relevant restaurant attributes. It can consider factors such as cuisine type, price range, location, ambiance, and customer reviews to generate accurate and relevant recommendations. In the current study, the evaluation's findings reveal that the suggested ExtraTreeRegressor algorithm outperforms other algorithms in terms of performance. The novelty of this research lies in the fact that here hybrid filtering is employed, which is not yet implemented in similar studies. The goal of this research article is to provide a more accurate and reachable list of suggested eateries. The results and conclusion show that the suggested approach produces good accuracy.

***Keywords*:** recommendation system, NLP, content-based filtering, collaborative filtering, cosine similarity

1. Introduction

A recommendation system is a technology that analyzes user data and provides personalized suggestions or recommendations for items or content that are likely to be of interest to the user. These systems are widely used in various domains, including e-commerce, streaming platforms, social media, news aggregators, and more. In various fields, recommendation systems have gained significant popularity in recent times. These systems are composed of algorithms that can learn from input data and provide customers with the recommendations they require after processing it. Recommendation systems are a type of information filtering system that enhances the quality of search outcomes by

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suggesting items that are more relevant to the search query or related to the user's search history. The main objective of a recommendation system is to assist users in finding relevant items from a large pool of options. By leveraging algorithms and machine learning techniques, these systems process user data, such as browsing history, purchase behavior, ratings, and preferences, to generate recommendations that align with individual tastes and needs.

As a rule, recommendation tools suggest products to customers by analyzing factors such as search history, user similarities, patterns, and ratings. Real-time examples of such systems include YouTube, Amazon, Facebook, and others. These systems work primarily on historical data, ranking available items and recommending the most relevant ones to customers based on their preferences. Recommendation systems are commonly used to suggest movies, products, restaurants, tourist destinations, and other items of interest. Recommendation systems also contribute to business growth by increasing customer satisfaction, retention, and conversion rates. Personalized recommendations can lead to higher customer engagement, repeat purchases, and increased customer loyalty. Additionally, these systems can help businesses uncover patterns and insights from user data, enabling them to make data-driven decisions, optimize marketing strategies, and improve their product or service offerings. Recommendation systems also play a vital role in modern service operations systems by leveraging user data and algorithms to provide personalized recommendations. They enhance the customer experience, increase sales and revenue, improve conversion rates, support inventory management, and facilitate content and service personalization. By integrating recommendation systems into their operations, businesses can deliver more relevant and targeted experiences to their users, leading to improved satisfaction and loyalty.

As time passes, people are increasingly using the reviews of others to make decisions about what products to purchase, what movies to watch, what books to read, and where to eat. In the past, people relied on recommendations from peers, such as word of mouth, blog posts, and reviews, or sought out expert advice from sources like columnists or librarians. Nowadays, crowd-sourced review platforms like Yelp, TripAdvisor, and Google are extremely common, providing a wealth of information about local businesses, especially restaurants. With so many options available, people often feel overwhelmed and have difficulty making informed choices that meet their specific desires and needs. A potential solution to this problem is a personalized recommender system that can offer accurate suggestions. This saves a lot of time and effort, as well as helping users discover relevant items and content, thereby leading to increased satisfaction and engagement.

A restaurant recommendation system is an intelligent technology that helps users discover and select suitable dining establishments based on their preferences and requirements. It leverages data analysis, machine learning algorithms, and user feedback to provide personalized suggestions and enhance the dining experience. The primary goal of a restaurant recommendation system is to assist users in navigating the vast array of dining options available, saving them time and effort while ensuring they have a satisfying culinary experience. By considering various factors such as cuisine type, location, price range, ambiance, dietary restrictions, and user preferences, these systems generate tailored recommendations that align with individual tastes.

User feedback and reviews play a crucial role in restaurant recommendation systems. By considering ratings, reviews, and feedback from previous diners, these systems gather valuable insights about the quality, service, and overall dining experience at various establishments. This feedback loop enables continuous learning and improvement, both for the recommendation system itself and the restaurants it recommends. Restaurant recommendation systems bring several benefits to both users and restaurant owners. For users, these systems simplify the process of selecting a restaurant by presenting them with a curated list of options tailored to their preferences. Users can explore new dining experiences, discover local favorites, and save time in the decision-making process. For restaurant owners, recommendation systems help attract a larger customer base by promoting their offerings to relevant customers and enabling them to understand customer preferences better.

In recent times, comments posted on websites and social networks have been recognized as a valuable and implicit source of information. Within this context, it is possible to extract the user's food preferences by analyzing these comments and examining the sentiments expressed within them. To achieve this, the utilization of natural language processing (NLP) techniques can be employed to effectively analyze and uncover the underlying emotions concealed within the user's comments. The recommender system being proposed aims to initially extract the users' preferences from the text-based comments they provide. Subsequently, it provides tailored restaurant recommendations based on these preferences. By transforming both the user's preferences and the restaurant's menu into vectors and evaluating the similarity between them, it becomes possible to determine the compatibility of the restaurant with the user. Ultimately, the system suggests restaurants that have menus most closely aligned with the user's preferences.

The paper presents the following contributions:

- The personalized system proposed in this study extracts user preferences by analyzing their opinions and improves the obtained list through sentiment analysis. The accuracy of extracting user preferences by analyzing individual comments surpasses methods such as term frequency (TF) and inverse document frequency (IDF).
- To enhance accuracy, a semantic approach is employed to cluster the names mentioned in the comments when extracting user preferences.
- A suitable dataset is collected from the Zomato website, as it is considered to be one of the best food delivery apps, in order to evaluate the effectiveness of the proposed system in real-world scenarios. Ratings and reviews are widely regarded as critical factors that significantly influence the perception of a restaurant's quality.

2. Related literature

By using the users' current geographical position, Habib et al. (2016) presented a novel location, preference, and time-based restaurant recommendation system. The method examines check-in records of specific users to examine their visitation patterns, cuisine preferences, and restaurant popularity. Four main factors are used to calculate recommendation scores. These are: 1) user preference score; 2) restaurants' separation; 3) the hour of the day; 4) the popularity ratings of the eatery, etc. To demonstrate the recommendation technique, an open dataset is being used.

Saha and Santra (2017) suggested using textual comments while rating restaurants. By retrieving the textual feedback of the patrons, restaurants in Kolkata are taken into consideration for ranking purposes. The user's emotional state is first assessed, and then his attitude toward a particular food item is determined. The accuracy factor is increased by performing a performance assessment of the findings using the collaborative filtering approach.

Aye and Aung (2017) suggested developing a sentiment lexicon for Myanmar that is specific to the restaurant and food industries and applying sentiment analysis to lexicon-related recommendation studies for customer text feedback in Myanmar. The suggested method has effectively interpreted data for Myanmar's language supply, providing a total precision of 96% based on feedback from 500 consumers in the restaurant and food industries. The analysis of 500 customers' reviews has produced results that are very accurate.

To mine user-political (Pol) relationship features, Yang and Züfle (2016) suggest only using spatiotemporal trajectory data. The results show that characteristics derived from spatiotemporal data accurately predict the popularity of the Pol using ground truth data from FourSquare as the base.

A robust and scalable commendation system is what Gandhi and Gheewala (2017) propose. It combines recommendation system techniques like collaborative filtering with a massive data association rule mining approach to provide high precision. By using the user's prior behavior, the result produces solid and improved recommendations linked to tailored movie recommendations.

Techniques for food recommendations are suggested by Utama et al. (2017). The three filtering strategies that are being suggested — content-based, collaborative, and hybrid — compare different recommendation systems based on their advantages and disadvantages. The hybrid recommendation technique results in improved system functionality; more study in this area can produce improved algorithms and noticeably better recommendation systems.

According to Jalan and Gawande (2017), the purpose of the research is to recommend hotel names to travelers based on their preferences by incorporating input from other travelers along with the rating value to improve prediction accuracy. The context-aware hybrid strategy is used to provide customized hotel recommendations by combining the collaborative filtering approach with sentiment analysis. Consequently, the recommendation results are expanded by using a context-based technique.

By utilizing the method of supervised machine learning, Hossain et al. (2017) suggested a wonderful strategy for the prediction of customer sentiment based on their online evaluations provided for a specific organization. This suggested model helps restaurant operators understand their place in the industry and the opinions of their customers. The model also predicts whether a particular kind of user review will be favorable or unfavorable. When compared to star ratings, textual content predicts user sentiments more accurately and increases reliability.

By using aggregated data from the text-based properties linked with audio things, Xing et al. (2016) suggested creating latent embedding for podcast items. The embedding for podcast items that denotes content similarity between other podcast items of a similar nature is produced using NLP. Cross-validation results in improved categorization control of the expected content, according to the findings.

A restaurant is a common gathering place that serves one or more dishes. Currently, many applications include details about restaurants, such as the name of the eatery, its menu, and the cost of its meal. Recommender systems are frequently employed in restaurant applications (Gupta & Singh, 2013).

There have been numerous studies done on recommender systems. A recommender system is a useful tool for assisting users in finding content that is pertinent to their interests (Zeng et al., 2016). Recommender systems are able to quickly address the issues brought on by growing amounts of information on the internet (Baizal et al., 2016; Jonnalagedda et al., 2016). Examples of programs that make use of recommender systems include Facebook, Netflix, Amazon, and YouTube.

Recommender systems are used in some research to implement different domains, including travel products, books, movies, etc. (Baizal et al., 2016). The user-based collaborative filtering method utilized for tourism is described in the study (Arigi et al., 2018; Baizal et al., 2018; Jia et al., 2015). Three steps make up the recommendation process: 1) information representation of users or tourists; 2) creation of user neighbors; and 3) production of recommendations for tourist attractions.

In the paper (Wang et al., 2015), user-based and item-based methods of collaborative filtering are merged to increase the capacity of the information that is provided. Combining these two approaches will increase recommendation accuracy and decrease cold-start issues. The paper (Baizal et al., 2016) discussed knowledge-based recommender systems as a means of resolving the cold-start issue. In the study (Li et al., 2016), the user-based collaborative filtering method was described. Performance and accuracy were increased by applying weighted similarity computations. The weighted similarities hierarchy has two examples: (1) one-tier weighting and (2) two-tier weighting.

For a better understanding, the related works have been presented in Table 1.

Table 1. Comparative analysis of various literatures on restaurant recommendation system

Title	Authors	Year	Methodology	Key findings
"Location based personalized restaurant recommendation system for mobile environments"	Gupta et al.	2013	Recommendation system in mobile environment	The paper introduces a personalized, location-based recommendation system integrated into mobile technology, employing a machine learning (ML) algorithm to analyze user behavioral patterns and proposing methods to address and rectify challenges faced by contemporary recommendation systems.
"A collaborative filtering recommendation algorithm based on user clustering and Slope One scheme"	Wang et al.	2013	Collaborative filtering	The proposed method involves clustering users based on their item ratings, filtering out irrelevant information, and subsequently applying the Slope One scheme for predicting item ratings.
"Context-aware restaurant recommendation system using location-based services"	Li et al.	2014	Contextual recommendation	Integrated location-based information to provide context-aware restaurant recommendations, enhancing user relevance and satisfaction.
"Collaborative filtering based simple restaurant recommender"	Farooque et al.	2014	Collaborative filtering based on user attributes and user ratings	The paper introduces a recommender system design incorporating collaborative filtering (user-based), partitioning, and clustering of data for the development of a highly accurate restaurant recommendation system.
"A hybrid recommendation system for restaurants"	Narwani et al.	2020	Hybrid recommender	Combined collaborative filtering and content-based methods to offer more accurate and diverse restaurant suggestions.
"Comparing filtering techniques in restaurant recommendation system"	Koetphrom et al.	2018	Recommendation system based on real data	The study aims to provide insights into the effectiveness of various filtering methods for enhancing restaurant recommendations.
"Personalized food recommendation using deep neural network"	Mokdara et al.	2018	Deep learning	The research suggests integrating a deep neural network into a recommendation system focused on Thai food, achieving a high precision of 90% in predicting user profiles and an 89% accuracy in hit ratio.
"Context-aware group-oriented location recommendation in location-based social networks"	Khazaei and Alimohammadi	2019	Social media mining	The study introduces a context-aware group-oriented location recommendation system using a random walk algorithm to enhance restaurant recommendations, achieving better user satisfaction.

Table 1. *Continued*

Title	Authors	Year	Methodology	Key findings
"Sentiment analysis and classification of restaurant reviews using machine learning"	Zahoor et al.	2020	Sentiment analysis	The paper concentrates on the impact of sentiment analysis on restaurant recommendations by analyzing customer reviews from various restaurants in Karachi, finding that sentiment-enhanced models can better capture user preferences.
"A DeepFM model-based personalized restaurant recommendation system"	Xu	2021	Deep learning	Investigated the application of deep learning techniques, such as neural collaborative filtering, for personalized restaurant recommendations, achieving high accuracy.

A few influential papers that can serve as a starting point for the current research work are cited below:

- "Evaluating collaborative filtering recommender systems" by Herlocker et al. (2004): This paper compares different collaborative filtering algorithms, including user-based and item-based approaches. It evaluates the algorithms based on the Movielens dataset and provides insights into their strengths and weaknesses.
- "Content-based recommendation systems" by Pazzani and Billsus (2007): This survey paper explores various content-based recommendation techniques, including their application to restaurant recommendations. It discusses feature extraction, similarity measures, and the challenges of content-based approaches.
- "Matrix factorization techniques for recommender systems" by Koren et al. (2009): This seminal paper introduces the use of matrix factorization for collaborative filtering in recommendation systems. It discusses the basic principles and provides insights into the application of matrix factorization to restaurant recommendations.
- "A restaurant recommendation system by analyzing ratings and aspects in reviews" by Gao et al. (2015): This paper provides an overview of existing restaurant recommendation systems, categorizes them into different approaches (collaborative filtering, content-based, knowledge-based, etc.), and discusses their advantages and limitations. It also highlights the challenges and future research directions in this domain.
- "Deep neural networks for YouTube recommendations" by Covington et al. (2016): This paper presents the YouTube recommendation system, which employs deep neural networks for personalized video recommendations. Although focused on videos, the principles discussed can be relevant to restaurant recommendation systems as well.

3. Recommendation systems

Recently, recommendation systems have been enjoying a meteoric rise in popularity due to their widespread application. A recommendation system is a collection of specialized algorithms and machine learning solutions that learn from the input and, after being processed, are able to recommend the required items to clients. In general, it is a tool that recommends products to clients based on a variety of characteristics, such as their search history, user similarities, and comparable patterns, as determined by their ratings. Real-world examples include websites like YouTube and Amazon, as well as social networking sites like Facebook. Their operational methods rely heavily on past data. On the basis of the available data, products are sorted, and the most pertinent are sent to clients. It allows marketers to increase conversion rates and average order value. With the use of various effective tools, recommender systems can predict user ratings even before the user has submitted one. Primarily, a recommendation system processes data through the following four phases:

- Collection: The information that is gathered may be apparent (such as ratings and comments on products) or it may be implicit (page views, order history, etc.).
- Storing: The kind of data that is used to generate recommendation systems can be either a regular SQL database, an object storage system, or a NoSQL database, among other possible options.
- Analyzing: After investigation, the recommender system identifies goods with similar user engagement data.
- Filtering: The data are filtered one last time in order to collect the relevant information necessary to provide the user with recommendations at this stage, which is the final step in the process. To enable this feature, an appropriate algorithm that is compatible with the recommendation system has to be chosen.

3.1 *Types of recommendation systems*

The most well-known application of machine learning is creating product recommendations, through which it solves numerous problems. Recommendation systems are primarily classified into three categories. The various types of recommendation systems are displayed in Figure 1.

- Content-based filtering: Content-based filtering (CBF) methods recommend items based on their features or attributes. In restaurant recommendation systems, CBF approaches analyze restaurant characteristics such as cuisine, price range, location, and user preferences. By modeling user preferences and matching them with restaurant attributes, CBF methods can offer personalized recommendations. However, they may struggle to capture diverse user tastes and preferences beyond the provided attributes.
- Collaborative filtering: Collaborative filtering (CF) is a popular technique used in recommendation systems. It analyzes user behavior and preferences to recommend items. In the context of restaurant recommendations, CF methods typically rely on user ratings or feedback to generate recommendations. CF-based systems can provide personalized recommendations based on similarities between users' preferences. However, they often suffer from the cold-start problem (lack of initial data for new users) and sparsity issues (limited user feedback).

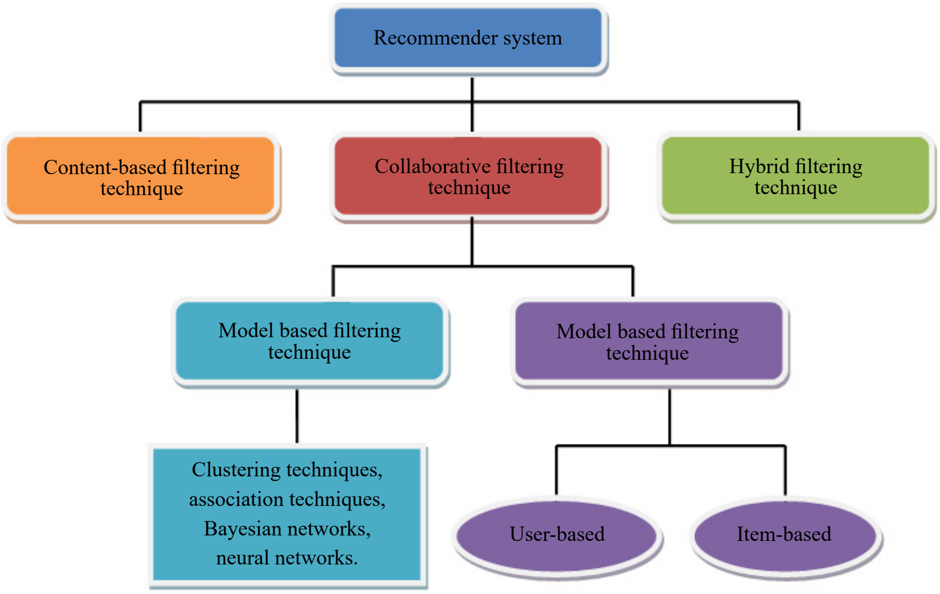

Figure 1. Different types of recommendation systems

- Hybrid filtering: Hybrid recommendation systems combine multiple techniques to overcome the limitations of individual methods. For restaurant recommendations, a hybrid approach might integrate collaborative filtering and content-based filtering. By leveraging the strengths of both methods, hybrid systems can provide more accurate and diverse recommendations. They can handle the cold-start problem, exploit item attributes, and incorporate user preferences effectively.

3.2 *Impact of restaurant recommendation systems from users aspect*

Restaurant recommendation systems can have a profound impact on customers or users. These systems are designed to enhance the dining experience, provide personalized suggestions, and improve customer satisfaction. The key impacts of restaurant recommendation systems on customers are:

- Personalization: One of the most significant benefits of recommendation systems is personalized dining recommendations. By analyzing user preferences, past orders, and behavior, the system can suggest dishes that align with individual tastes. This personalization makes customers feel valued and understood, leading to higher levels of satisfaction.

- Discovery of new dishes: Recommendation systems expose users to new and diverse menu items they might not have tried otherwise. Customers can discover hidden gems, unique dishes, or even items from different cuisines that match their preferences.
- Time efficiency: These systems help customers make quicker decisions about what to order. Instead of browsing through an extensive menu, users are presented with relevant options, saving time and reducing decision fatigue.
- Enhanced user experience: With personalized recommendations, customers feel more engaged with the restaurant's offerings. This improved user experience can lead to a stronger emotional connection to the brand and increase the likelihood of repeat visits.
- Increased satisfaction: When customers receive recommendations that align with their tastes and preferences, they are more likely to enjoy their meals. Higher satisfaction levels lead to positive reviews, increased loyalty, and potential word-of-mouth recommendations.
- Feedback and user engagement: Some recommendation systems allow customers to provide feedback on their dining experience and rate the suggested dishes. This engagement fosters a sense of involvement and helps the restaurant further refine their recommendations.
- Seamless online ordering: For restaurants with online ordering platforms, recommendation systems can facilitate smoother transactions by suggesting dishes customers are likely to enjoy, leading to a higher conversion rate.

It's essential for restaurants to strike a balance between personalization and privacy concerns. While customers often appreciate tailored suggestions, they may also be sensitive about the use of their data. Implementing clear and transparent data policies can help mitigate potential privacy issues and build trust with users. Overall, restaurant recommendation systems can significantly improve the dining experience for customers by providing personalized, relevant, and engaging suggestions, ultimately benefiting both customers and the restaurants themselves.

3.3 *Impact of restaurant recommendation systems from managerial aspect*

Restaurant recommendation systems can have a significant impact on restaurant operations managers or managers. These systems use data and algorithms to suggest personalized recommendations to customers, enhancing their dining experience. Here are some of the ways restaurant recommendation systems can influence restaurant managers:

- Improved customer experience: Recommendation systems can help managers deliver personalized suggestions to customers based on their preferences, past orders, and reviews. This personalization can lead to higher customer satisfaction, as guests are more likely to find dishes they enjoy, leading to repeat business and positive word-of-mouth.
- Increased revenue: By suggesting popular or high-margin menu items, recommendation systems can influence customers' choices and increase the average check size. This can boost revenue for the restaurant, as guests may be more inclined to try new dishes or add extras based on the system's recommendations.
- Efficient inventory management: With access to data on popular dishes and customer preferences, managers can optimize inventory management. They can adjust ingredient orders based on actual demand, reducing food waste and lowering costs.
- Staffing optimization: Recommendation systems can provide insights into peak times and popular dishes, allowing managers to schedule staff more effectively. They can align staffing levels with demand, ensuring excellent service during busy periods and reducing labor costs during slower times.
- Menu engineering: Managers can use recommendation system data to fine-tune their menu offerings. They can identify underperforming dishes or explore the possibility of introducing new items that align with customer preferences.
- Data-driven decision-making: Restaurant managers can use the data collected by the recommendation system to make informed decisions. They can analyze customer preferences, order patterns, and feedback to adapt their strategies and improve the overall dining experience.
- Marketing and promotion: Recommendation systems can support targeted marketing efforts. Managers can run promotions or discounts on specific dishes that the system identifies as less popular to boost their sales.
- Customer feedback and reviews: Recommendation systems can encourage customers to leave reviews and

feedback, providing valuable insights for managers to gauge customer satisfaction and address any potential issues.

Overall, restaurant recommendation systems can be a valuable tool for restaurant managers to optimize their operations, enhance customer satisfaction, and make data-driven decisions to improve their business's overall performance. However, it's crucial for managers to interpret the data with care and maintain a balance between automation and the human touch to provide a unique and welcoming dining experience.

4. Proposed system methodology

As new restaurants continue to emerge on a regular basis, the industry still remains unsaturated, but demand is steadily rising. Despite this increasing demand, it has become challenging for new establishments to compete with well-established restaurants, especially when many of them offer similar food options. With such an overwhelming demand for restaurants, it has become crucial to consider several other factors, such as the demographic characteristics of a specific location as diverse categories of people reside in different localities, the approximate food price, the restaurant theme, the preferences and requirements of individuals within a particular neighborhood, etc., in order to design a suitable and appropriate restaurant recommendation system for a locality. The proposed system primarily comprises two parts: extracting user preferences and, secondly, designing a recommendation system, which are described in detail in this section. The control flow diagram of the proposed system methodology is depicted in Figure 2.

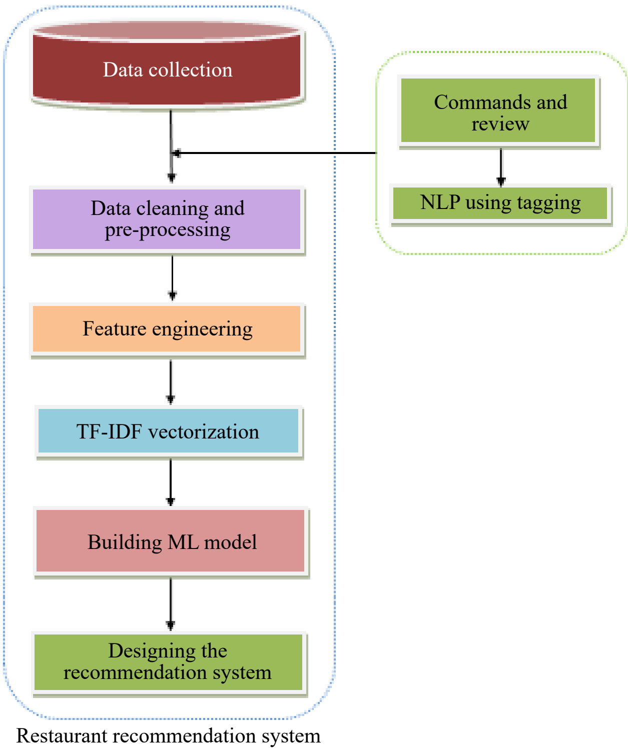

Figure 2. Control flow diagram of the proposed methodology

The workflow of the current study is illustrated as follows:

A. Data collection: The dataset employed for this research work has been fetched from Kaggle. The dataset comprises of columns like URL, address, name, rate, phone, location, cuisines, rest_type, dish_liked, menu_item, approx._cost(for two people), etc.

B. Data cleaning and pre-processing: The subsequent stage involves data cleaning and feature engineering, which entails performing various tasks on the data, including:

1. Removing unnecessary columns from the dataset.
2. Eliminating duplicate entries.
3. Handling any missing values (NaN) by removing or imputing them.
4. Modifying column names to ensure clarity and consistency.
5. Conducting data transformations as required.
6. Adjusting the column names to align with the desired format.

The data preprocessing mainly comprises of the following steps:

1. Converting text to lowercase.
2. Removing punctuation marks.
3. Eliminating stopwords (commonly used words with little semantic meaning).
4. Removing URLs from the text.
5. Correcting any spelling errors.

C. Feature engineering: This refers to the process of analyzing and visualizing data to gain insights, discover patterns, and understand the underlying structure of the dataset. It involves examining the data from various angles, summarizing its main characteristics, and identifying any relationships or trends present in the data. It is typically conducted before performing more advanced statistical modeling or machine learning tasks to represent the underlying information in the data and improve model performance.

D. TF-IDF vectorization: TF-IDF vectorization is a technique used to represent text documents as numerical feature vectors. It is widely employed in NLP and information retrieval tasks. TF-IDF vectorization aims to capture the importance of a term within a document and across a collection of documents. It consists of two main components:

1. TF: The term frequency of a term (word) within a document is calculated as the number of times the term appears divided by the total number of terms in the document. It reflects the relative importance of the term within the specific document.
2. IDF: The inverse document frequency of a term is calculated as the logarithm of the total number of documents divided by the number of documents containing the term. It measures how rare or unique a term is across the entire document collection.

The TF-IDF value for a term within a document is obtained by multiplying its TF by its IDF. A higher TF-IDF value indicates that a term is more important within a specific document compared to the overall collection. TF-IDF vectorization helps capture the uniqueness and significance of terms in individual documents while considering their frequency and distribution across the document collection. It is commonly used for tasks such as text classification, information retrieval, text clustering, and document similarity analysis.

E. Building ML model: Building the ML model mainly consists of choosing appropriate ML algorithms or models based on the problem type (e.g., classification, regression, clustering) and the characteristics of the data. Consider factors such as model complexity, interpretability, and scalability. The chosen models are then trained with the training data by optimizing their parameters, and finally, their performance is evaluated through various evaluation metrics. The following ML models have been implemented in the current study:

1. Linear regression: A linear regression model is a statistical modeling technique used to establish a relationship between a dependent variable and one or more independent variables. It assumes a linear relationship between the variables, aiming to predict the value of the dependent variable based on the independent variables. In a simple linear regression model, there is one independent variable, and the relationship is described by a straight line. The model equation can be represented as:

$$Y = \beta_0 + \beta_1 X + \varepsilon \tag{1}$$

where:

- Y represents the dependent variable or the variable being predicted.
- X represents the independent variable, or the variable used to make predictions.
- β_0 and β_1 are the coefficients or parameters that represent the intercept and slope of the line, respectively.
- ε represents the error term or residual, accounting for the variability not explained by the model.

The goal of a linear regression model is to estimate the coefficients β_0 and β_1 that minimize the sum of squared residuals and provide the best fit to the data. This estimation is typically achieved using methods like ordinary least squares (OLS), which find the coefficients that minimize the difference between the predicted values and the actual values in the training data.

2. Random forest: A random forest model is an ensemble learning method that combines multiple decision trees to make predictions. It is a powerful and popular machine learning algorithm used for both classification and regression tasks. The random forest algorithm operates by constructing a multitude of decision trees during the training phase. Each decision tree is built on a different subset of the training data, randomly sampled with replacement (known as bootstrapping), and considering a random subset of features at each split.

Given an input sample with features X, the random forest predicts the class label Y by aggregating the predictions of all the decision trees in the forest. For a regression problem, the random forest predicts the target variable Y by averaging the predictions of all the decision trees. Again, given an input sample with features X, the random forest calculates the predicted value Y by averaging the predictions from each decision tree in the forest. Overall, random forest models are widely used in various domains, including finance, healthcare, marketing, and natural language processing, due to their robustness, accuracy, and interpretability.

3. ExtraTreesRegressor: The ExtraTreesRegressor model, also known as the extremely randomized trees model, is a variant of the random forest algorithm. It is used for regression tasks, aiming to predict continuous target variables based on input features. Similar to the random forest algorithm, the ExtraTreesRegressor builds an ensemble of decision trees. However, it has two key differences:

- Randomized feature selection: In ExtraTreesRegressor, feature splitting is performed randomly rather than considering the best possible split at each node of the decision trees. This randomness enhances the diversity among the trees in the ensemble and can lead to improved generalization performance.
- Randomized threshold selection: The splitting thresholds for each feature are also chosen randomly, rather than being determined based on the best possible split point. This additional randomness further increases the diversity among the decision trees.

These randomizations make the ExtraTreesRegressor algorithm computationally efficient as it avoids the need to search for optimal splits at each node. However, it may also lead to increased variance in the model's predictions. The ExtraTreesRegressor model is widely used for regression tasks, especially when dealing with large datasets and high-dimensional feature spaces. It can handle noisy data, nonlinear relationships, and outliers relatively well.

F. Designing the recommendation system: The suggested hybrid recommendation system combines CBF and item-to-item CF techniques. It analyzes user-written comments to extract preferences and recommends restaurants based on the similarity between their menus and the user's extracted preferences. Additionally, by considering the user's past food choices, the system suggests restaurants with similar menus. This approach leverages item-to-item collaborative filtering to offer personalized recommendations. Hence, the proposed system operates as a hybrid filtering system by incorporating both content-based and collaborative filtering methods.

4.1 *Cosine similarity*

Cosine similarity is a commonly used similarity metric in recommendation systems, particularly in CBF approaches. It measures the cosine of the angle between two vectors, representing the similarity between their directions or orientations in a high-dimensional space. In the context of recommendation systems, cosine similarity is used to quantify the similarity between user preferences and item features.

Cosine similarity is typically applied in recommendation systems for the following reasons:

- Representing user preferences and item features: In content-based recommendation systems, user preferences and item features are often represented as high-dimensional vectors. Each dimension corresponds to a specific attribute or characteristic (e.g., genre, price, location) that describes the items. Similarly, user preferences are represented as vectors, where each dimension represents the user's preference for a particular attribute.

- Calculating cosine similarity: To determine the similarity between a user's preferences and an item's features, the cosine similarity is computed. This involves taking the dot product of the user preference vector and the item feature vector and dividing it by the product of their magnitudes. This filter employs two distinct types of data. First, the user's preferences and interests, personal information such as age, and occasionally the user's history represent the user vector. And secondly, the product-related information serves as the item vector. The item vector contains the characteristics of all objects that can be utilized to calculate their similarity. Cosine similarity is used to compute the recommendations. If '*A*' is the user vector and '*B*' is an item vector, then the formula for cosine similarity is given below:

$$\text{Cosine similarity} = (A \bullet B) / (\|A\| * \|B\|) = \Sigma(A_i * B_i) / \left(\sqrt{\left(\Sigma(A_i)^2\right)}\right) * \sqrt{\left(\Sigma(B_i)^2\right)} \quad (2)$$

- Ranking and recommendations: Once the cosine similarity values are calculated between user preferences and item features, the items are ranked based on their similarity scores. Higher cosine similarity values indicate greater similarity between the user's preferences and the item's features. The top-ranked items are then recommended to the user.

The advantage of using cosine similarity in recommendation systems is that it captures the orientation or direction of the vectors rather than their magnitudes. It is particularly useful when the magnitude of the vectors (e.g., user preferences) is not relevant and the focus is on the relative similarity between the vectors.

5. Results and discussions

In the current research work, a hybrid-based filtering technique has been implemented to develop a restaurant recommendation system. This technique employs both the CBF technique and the CF technique to design a recommender system based upon customer review comments. The hybrid recommendation system employs a variety of techniques, including the combination of independent recommenders, the addition of content-based characteristics to collaborative models employing multiple criteria, etc. The entire process is discussed below:

1. Data collection: The dataset employed in the current study comprises of 51,717 rows and 17 columns and has been sourced from Kaggle as already mentioned earlier. A snapshot of the dataset is displayed in Figure 3.

	address	name	online_order	book_table	rate	votes	location	rest_type	dish_liked	cuisines	approx_cost(for two people)	reviews_list	menu_item	listed_in(type)
0	942, 21st Main Road, 2nd Stage, Banashankari, ...	Jalsa	Yes	Yes	4.1/5	775	Banashankari	Casual Dining	Pasta, Lunch Buffet, Masala Papad, Paneer Laja...	North Indian, Mughlai, Chinese	800	[('Rated 4.0', 'RATED\n A beautiful place to ...	[]	Buffet
1	2nd Floor, 80 Feet Road, Near Big Bazaar, 6th ...	Spice Elephant	Yes	No	4.1/5	787	Banashankari	Casual Dining	Momos, Lunch Buffet, Chocolate Nirvana, Thai G...	Chinese, North Indian, Thai	800	[('Rated 4.0', 'RATED\n Had been here for din...	[]	Buffet
2	1112, Next to KIMS Medical College, 17th Cross...	San Churro Cafe	Yes	No	3.8/5	918	Banashankari	Cafe, Casual Dining	Churros, Cannelloni, Minestrone Soup, Hot Choc...	Cafe, Mexican, Italian	800	[('Rated 3.0', "RATED\n Ambience is not that ...	[]	Buffet
3	1st Floor, Annakuteera, 3rd Stage, Banashankar...	Addhuri Udupi Bhojana	No	No	3.7/5	88	Banashankari	Quick Bites	Masala Dosa	South Indian, North Indian	300	[('Rated 4.0', "RATED\n Great food and proper...	[]	Buffet

Figure 3. Snapshot of the dataset

2. Feature engineering and visualizations: Once all the data cleaning and pre-processing has been completed, we attempt to discover some relevant data insights. Figure 4 depicts the top 10 most famous restaurant chains in a city, along with the number of outlets for each restaurant.

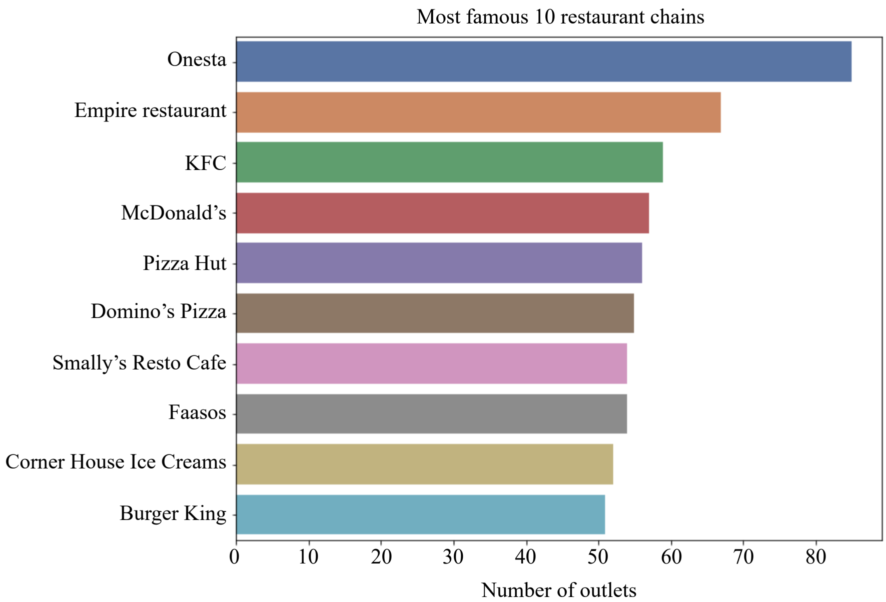

Figure 4. Top 10 restaurants

The rating given by the customers to the restaurant on every order is illustrated in Figure 5, whether the restaurants deliver online orders or not is displayed in Figure 6, and the delivery distance in km for every order is depicted in Figure 7, respectively.

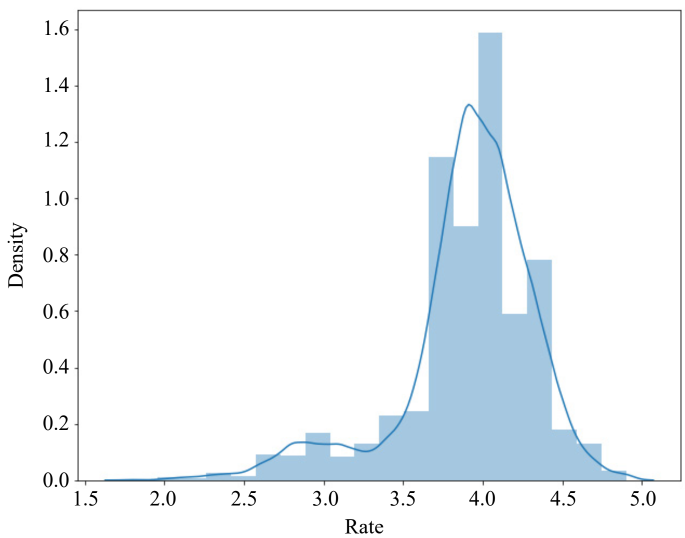

Figure 5. Ratings by customers

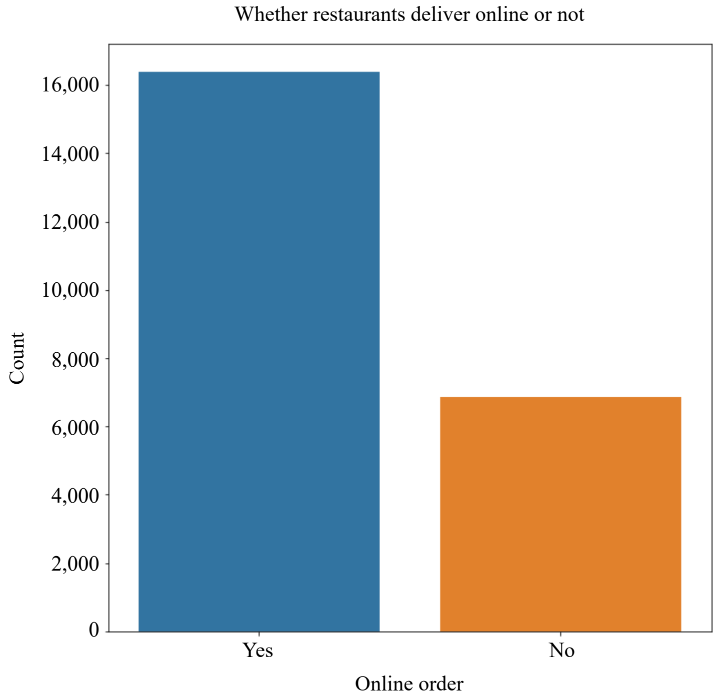

Figure 6. Online vs offline orders

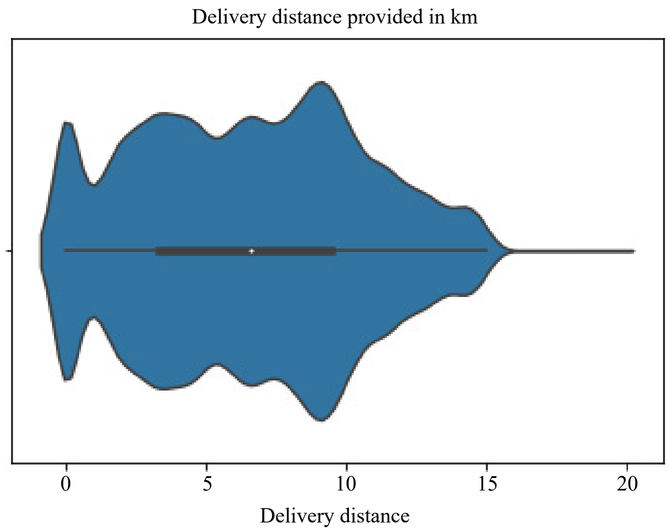

Figure 7. Delivery distance in km

Figure 5 indicates that the majority of vendors are rated between 3.5 and 4.5 on average, and no vendor possesses a rating lower than 2.5. Figure 6 displays that the majority of restaurants offer options for both online orders and delivery. Figure 7 indicates that the median delivery distance is around 6 km, with the 25th percentile around 3 km and the 75th percentile around 10 km, thereby indicating that the majority of orders are delivered within 10 km.

In order to explore further information regarding the percentage of restaurants based on their ratings, Figure 8 and Figure 9 display the number of restaurants that offer table booking or not.

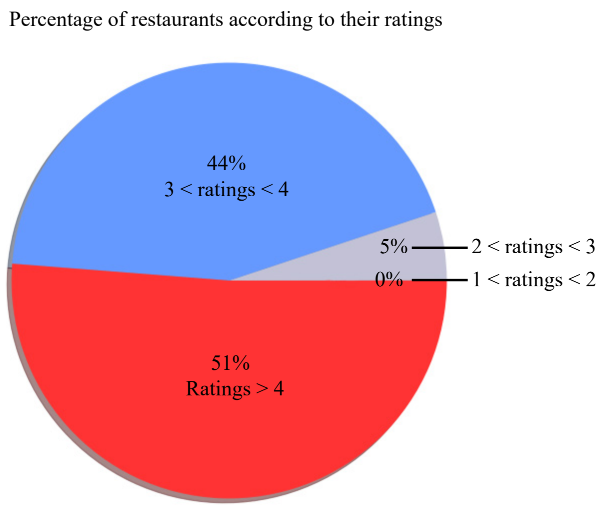

Figure 8. Percentage of restaurants based on their ratings

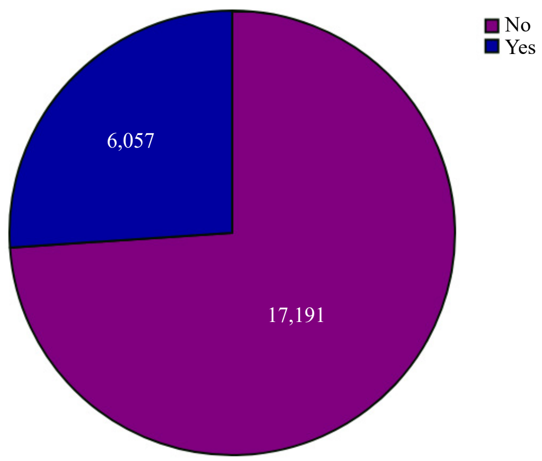

Figure 9. Table booking of restaurants

From Figure 8, it can be observed that 51% of restaurants have ratings greater than 4.0 and 44% of restaurants have ratings between 3 and 4. From Figure 9, it can be observed that most of the restaurants do not offer table booking. They serve customers on a first-come, first-served basis.

Furthermore, Figure 10 displays the types of services provided by different restaurants, and Figure 11 represents the distribution of dining food costs for two people.

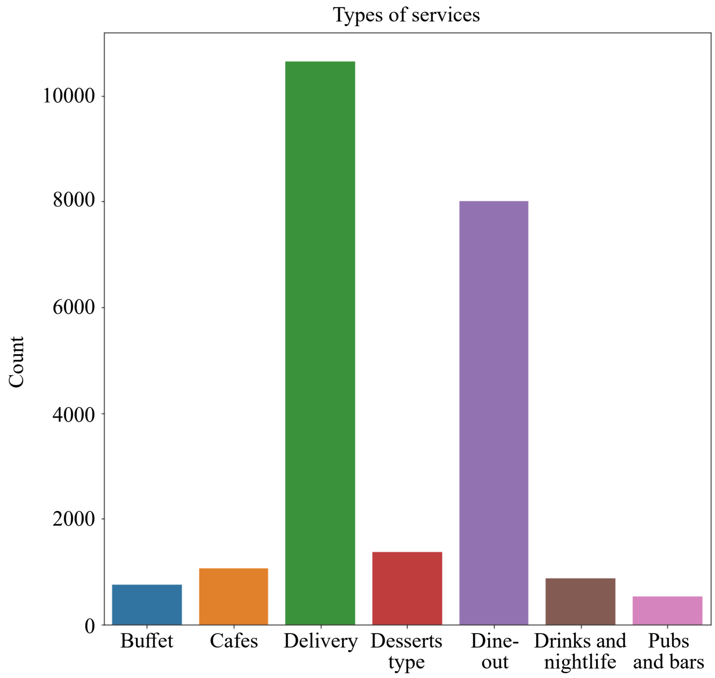

Figure 10. Types of services by restaurants

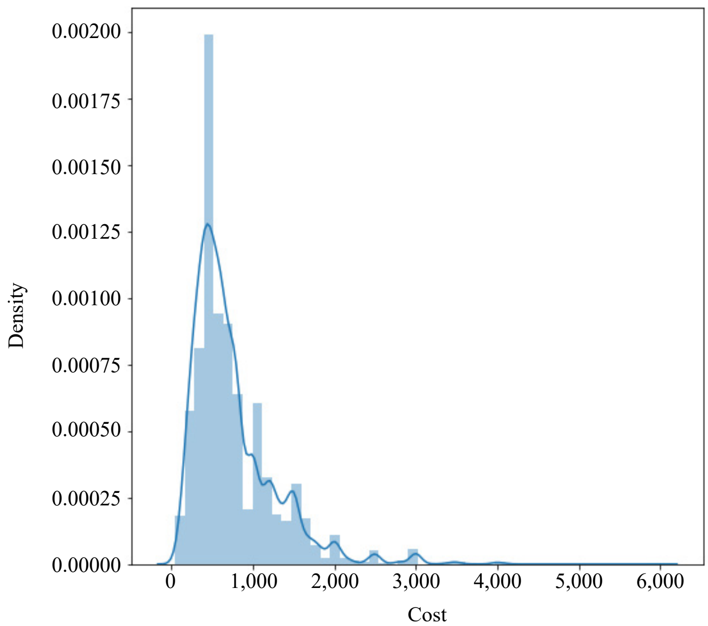

Figure 11. Distribution of dining costs

Figure 10 represents the different types of services provided by restaurants in general, and from Figure 11, it can be concluded that the average cost of dining for two people ranges from 0 to 2,000 rupees.

The top 30 food dishes of various restaurants are depicted in Figure 12, and Figure 13 displays the different categories of restaurants available.

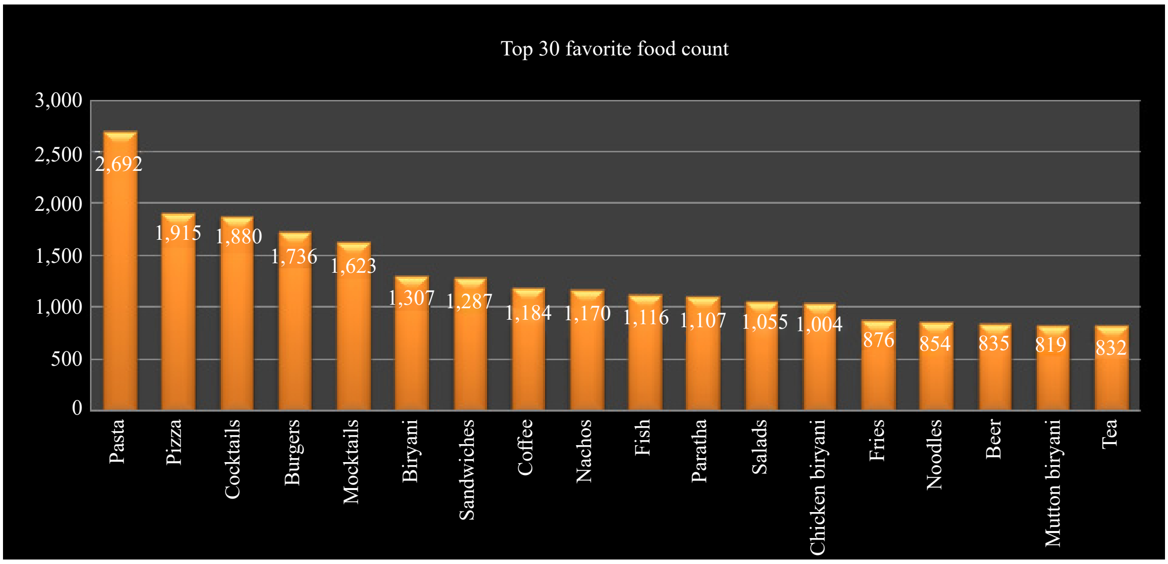

Figure 12. Types of food at restaurants

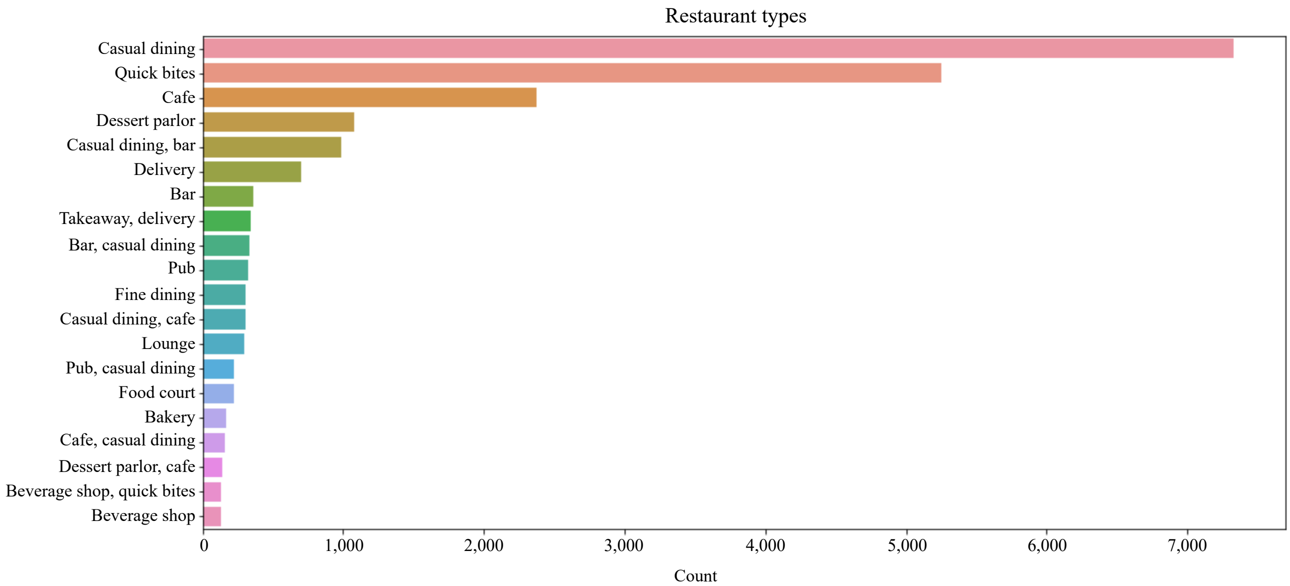

Figure 13. Different categories of restaurants

From Figure 12, it can be inferred after analysis that the 5 most liked dishes are pasta, pizza, cocktails, burgers, and mocktails, respectively. Figure 13 reveals that casual dining, quick bites, and cafes are the three most common types of restaurants that are highly preferred by customers.

3. ML model building and evaluation: It will be better to choose regression models, as they offer a robust and interpretable framework for predicting continuous variables. They also provide insights into relationships, statistical inference, and transparent decision-making, thereby making them valuable tools in various domains such as finance, economics, healthcare, and the social sciences. Since the dimensions here are not too large, boosting algorithms or linear regression models can be implemented. In the current study, three regression models, namely linear regression, RandomForestRegressor and ExtraTreesRegressor models have been trained with the training data and then implemented and tested with the testing data.

Regression models have well-established evaluation metrics, such as mean squared error (MSE), root mean squared error (RMSE), and R-squared (coefficient of determination), which allow for quantitative assessment of model performance. These metrics provide a benchmark for comparing different models and selecting the best one. In the current study, in order to assess the performance of the ML models, the R-squared metrics have been evaluated for all three regression models.

R-squared, also known as the coefficient of determination, is a commonly used metric to evaluate the performance of regression models in machine learning. It measures the proportion of the variance in the dependent variable (target) that is predictable from the independent variables (features) used in the model. The R-squared value ranges from 0 to 1, with 1 indicating a perfect fit where the model explains all the variability in the target variable and 0 indicating that the model does not explain any of the variability. However, negative values can occur if the model performs worse than a horizontal line (the average of the target variable). The R-squared values obtained for the 3 models are depicted in Table 2.

Table 2. Evaluation metrics of ML models

ML model	R-squared value
Linear regression	0.21980
RandomForestRegressor	0.91762
ExtraTreesRegressor	0.93631

From the above table, it can be inferred that the ExtraTreesRegressor outperforms the other models and gives us the best model.

4. Designing a recommendation system: The last step is to design a restaurant recommendation system that will recommend restaurants depending on the customer's choice. This is achieved by applying the cosine-similarity algorithm, by which customers can make customized choices about their favorite restaurants according to their own preferences. Cosine similarity involves utilizing the concept of vector space representation to measure the similarity between restaurants and user preferences. Cosine similarity is a metric used to measure the similarity between two vectors in a multi-dimensional space. It calculates the cosine of the angle between the vectors, indicating their orientation or similarity in direction.

To compute the cosine similarity between two vectors A and B, the formula is as follows:

$$\text{cosine\_similarity}(A, B) = (A \bullet B) / (||A|| * ||B||)$$

where:

- $A \bullet B$ represents the dot product of vectors A and B, which is the sum of the element-wise products.
- $||A||$ and $||B||$ represent the Euclidean norms (also known as magnitudes or lengths) of vectors A and B, respectively.

The cosine similarity value ranges from -1 to 1, with:

- 1 indicating that the vectors are perfectly similar or parallel.
- 0 indicating that the vectors are orthogonal or completely dissimilar.
- -1 indicating that the vectors are perfectly dissimilar or pointing in opposite directions.

Cosine similarity is commonly used in recommendation systems, natural language processing, information retrieval, and clustering tasks. In recommendation systems, cosine similarity is often applied to measure the similarity between user preferences and item attributes to provide personalized recommendations. It helps identify items (e.g., movies, products, or restaurants) that are most similar to a user's preferences based on their past behavior or stated preferences.

By applying content-based filtering, the top 10 restaurants in Delhi similar to Pizza Hut are displayed in Figure 14.

Restaurants Name	Cuisines	Aggregate Rating	Cosine Similarity
Pizza Hut	Italian, Pizza, Fast Food	3.5	1.00
Domino's Pizza	Pizza, Fast Food	3.7	0.90
Ovenstory Pizza	Pizza, Fast Food	0.0	0.90
Sbarro	Pizza, Italian	3.5	0.86
Caffe Tonino	Pizza, Italian, Cafe	3.9	0.68
The Rolling Joint	Fast Food	3.9	0.52
Indian Coffee House	Fast Food	3.3	0.52
Nizam's Kathi Kabab	North Indian, Fast Food	3.8	0.45
The Luggage Room Kitchen And Bar	North Indian, Continental, Fast Food	3.6	0.36
Life Caffe	Cafe, North Indian, Italian, Japanese, Fast Food	3.6	0.36

Figure 14. Top 10 restaurants similar to Pizza Hut

Similarly, the top 10 restaurants that are similar to Barbeque Nation by applying CBF are depicted in Figure 15.

Restaurants Name	Cuisines	Aggregate Rating	Cosine Similarity
Barbeque Nation	North Indian, Chinese	4.1	1.00
Delhi Darbar Dhaba	North Indian, Chinese	3.2	1.00
Fa Yian	Chinese	4.0	0.90
China Garden	Chinese	3.9	0.84
Cafe Hawkers	Chinese, Continental, North Indian	3.7	0.77
Playboy Cafe	North Indian, Chinese, Continental	3.7	0.77
Parikrama – The Revolving Restaurant	North Indian, Chinese, Mughlai	3.8	0.69
My Bar Headquarters	North Indian, Mughlai, Chinese	3.7	0.69
SSKY Bar & Lounge	Mughlai, North Indian, Chinese	3.5	0.69
Amber	North Indian, Chinese, Mughlai	2.6	0.69

Figure 15. Top 10 restaurants similar to Barbeque Nation

In a similar manner, the recommendations for the top 10 restaurants by choosing any random restaurant based on CF are displayed in Figure 16.

```
Recommendations for Restaurant "The Peppermill Restaurant & Fireside Lounge" on priority basis

1: "Hash House A Go Go"
2: "Capriotti's Sandwich Shop"
3: "In-N-Out Burger"
4: "Yard House"
5: "Firefly"
6: "Secret Pizza"
7: "Earl of Sandwich"
8: "Grimaldi's Pizzeria"
9: "Mon Ami Gabi"
10: "Grand Lux Café"
```

Figure 16. Top 10 restaurants similar to The Peppermill Restaurant & Fireside Lounge

Another example of top 10 restaurant recommendations based on collaborative filtering similar to Domino's Pizza is depicted in Figure 17.

```
Recommendations for Restaurant "Domino's Pizza" on priority basis

1: "Pizza Hut"
2: "Subway"
3: "McDonald's"
4: "Taco Bell"
5: "Walmart Supercenter"
6: "Panda Express"
7: "Starbucks"
8: "Smashburger"
9: "Wendy's"
10: "Walgreens"
```

Figure 17. Top 10 restaurants similar to Domino's Pizza

6. Conclusion and future scope

A restaurant recommendation system is a valuable tool for assisting users in discovering and selecting suitable dining options. By leveraging various techniques such as CBF, CF, and machine learning algorithms, a restaurant recommendation system can provide personalized and relevant recommendations to users based on their preferences, past behavior, and other relevant factors. The implementation of a restaurant recommendation system involves collecting and preprocessing data, performing feature engineering, and applying algorithms such as cosine similarity, collaborative filtering, or hybrid approaches.

A well-designed restaurant recommendation system offers several benefits. It enhances the user experience by reducing the effort and time required to find suitable dining options. It helps users discover new restaurants, explore diverse cuisines, and make informed decisions based on their preferences and requirements. For restaurant owners, the recommendation system can increase customer engagement, improve customer satisfaction, and potentially drive more business to their establishments.

The future scope of restaurant recommendation systems is promising, with several potential areas for improvement and advancement. Recommendation systems can be enhanced by incorporating contextual information such as user location, time of day, weather conditions, and social context. By considering these factors, recommendations can be more personalized and relevant to the specific context in which the user is seeking restaurant suggestions. Incorporating fine-grained preferences to capture and utilize more detailed and fine-grained user preferences can lead to more tailored and accurate recommendations. The current study encompasses only the user's preference for designing a restaurant recommendation system. It does not entail the restaurant recommendation system from the point of view of the system manager, which may be considered in a future study. By exploring the use of advanced machine learning techniques, such as deep learning, reinforcement learning, or hybrid models, recommendation accuracy can be improved in order to overcome the limitations of traditional methods. These approaches have the potential to extract more complex patterns and uncover hidden relationships in restaurant data. Thus, as technology advances and user expectations evolve, recommendation systems have the potential to play a crucial role in shaping the way people explore, discover, and enjoy the personalized world of dining.

Conflict of interest

There is no conflict of interest for this study.

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