Restaurant Recommendation System

Prepared For
Smart-Internz
Applied Data Science Guided project

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Abstract

This project develops a personalized restaurant recommendation system based on user preferences, location, and dining history. It analyzes factors such as cuisine, price, and ratings to suggest suitable dining options. Machine learning techniques like collaborative and content-based filtering are used for accurate suggestions. The system enhances the dining experience by offering relevant and location-aware recommendations

Final Project Report

Contents

1 Introduction

1.1 Project overviews

The **Restaurant Recommendation System** is a smart, data-driven solution designed to help users efficiently discover restaurants that align with their unique preferences and situational contexts. As urbanization and mobile technologies continue to reshape consumer behavior, users are often overwhelmed by the sheer volume of available dining choices across platforms such as Google, Yelp, and Zomato. This leads to **decision fatigue** and suboptimal dining experiences. To solve this, the proposed system leverages a **hybrid recommendation model** combining collaborative filtering, content-based filtering, and geolocation-aware services.The **collaborative filtering component** analyzes historical user behavior, including past restaurant visits, ratings, and interaction patterns, to identify users with similar tastes and recommend restaurants favored by like-minded individuals. Meanwhile, the **content-based filtering module** evaluates restaurant attributes—such as cuisine type, price range, ambiance, and dietary offerings—to match them with explicit user preferences.
To enhance practicality, **geolocation data** is integrated using GPS APIs or IP-based location tracking. This allows the system to dynamically adapt its recommendations based on the user's current position or a specified location, ensuring that results are both **relevant and accessible**. For example, a user seeking budget-friendly vegan food in a new city would receive highly localized and personalized recommendations.

Furthermore, the system is designed with **adaptive learning capabilities**. Using techniques like reinforcement learning or preference feedback loops, the recommendation engine improves over time by understanding user behavior patterns, modifying weightage of features, and incorporating real-time feedback such as likes, bookmarks, or direct reviews.

1.2 **Objectives**

1. **To design and implement a recommendation engine** that effectively filters and ranks restaurants based on individual user preferences, including food type, cost, ambiance, and dietary needs.
2. **To apply machine learning models**, such as collaborative filtering (user-based and item-based) and content-based filtering, to identify patterns in user behavior and restaurant attributes.
3. **To incorporate location-aware features** using GPS or user-inputted location data, ensuring that recommended restaurants are conveniently accessible to the user.
4. **To gather and analyze restaurant reviews and ratings** from public sources (e.g., Yelp, Google Reviews, or internal datasets) to improve the trustworthiness and relevance of suggestions.
5. **To create a user-friendly interface** that allows users to input preferences, view recommended restaurants, and interact with the system seamlessly.
6. **To develop a feedback mechanism** that collects user satisfaction data post-visit to refine future recommendations and enhance personalization over time.
7. **To ensure scalability and adaptability** of the system for use in different geographic regions or for integration into existing food delivery or travel applications.

2 Project Initialization and Planning Phase

2.1 Define Problem Statement

2 Project Initialization and Planning Phase

Problem Statements (Restaurant Recommendation system):

PS No.	I am (Customer)	I'm trying to	But	Because	Which makes me feel
PS- 1	A tourist in a new city	Find good local restaurants	I don't know the area well	I lack local knowledge or reviews	Confused and unsure of where to eat
PS- 2	A vegetarian diner	Get recommendations for veg-only restaurants	Most apps show mixed cuisine places	I want strict dietary options	Frustrated and unsupported
PS- 3	A restaurant owner	Attract more customers through recommendation platforms	My restaurant is not being recommended often	The system doesn't promote new or small businesses	Invisible and discouraged
PS- 4	A student on a tight budget	Find affordable but tasty restaurants	Expensive options are shown first	Filters don't prioritize price or value	Overwhelmed and discouraged
PS- 5	A delivery app user	Get suggestions based on past orders	It doesn't adapt to my taste	The system lacks learning	Frustrated by repetition
PS- 6	A parent of young kids	Find kid-friendly and hygienic restaurants	No way to filter for child-friendly	Lack of safety and family-focused features amenities	Anxious about experience

PS-7	A small restaurant owner	Increase customer footfall via platforms	My business is buried under chain listings	Ranking algorithms favor large brands	Discouraged and invisibleguide

PS- 8	A new-in-town resident	Explore culturally diverse food options	Unaware of hidden gems in my area	No cultural/ethnic tags or user reviews	Disconnected and bored of same cuisine
PS- 9	A food delivery platform analyst	Monitor food safety and restaurant quality	Can'tverify ingredient safety from menus	Platforms lack AI food item scanners or trackers	Concerned about consumer trust
PS- 10	A data scientist	Analyze food trends from reviews	Datasets are messy, biased, or unavailable	Lack of structured sentimen and metadata	Blocked in model building and research
PS- 11	A foodie traveler	Find top-rated local restaurants in new cities	Recommendations don't match my taste or location	Generic, irrelevant suggestions	Frustrated and unsure where to eat
PS- 12	A restaurant owner	Improve my visibility on food apps	My reviews are outdated or low-rated	I can't easily respond or update info	Powerless and misrepresented
PS- 13	A health-conscious customer	Find healthy eating options nearby	Menus and calorie info are missing	I can't make informed decisions	Disconnected from my health goals

PS- 14	**A** healthconscious individual	Track the health benefits of different mushrooms	I can't identify what's in the store or dish	There's no easy app for instant scanning	Disappointed and disconnected from my health goals

1.1 Project Proposal (Proposed Solution)

Project Proposal (Proposed Solution)

This project proposal outlines a solution to address a specific problem. With a clear objective, defined scope, and a concise problem statement, the proposed solution details the approach, key features, and resource requirements, including hardware, software, and personnel

Project Overview	
Objective	To develop a system that provides personalized and efficient restaurant recommendations by analyzing user preferences, dietary requirements, location, and budget.
Scope	The project aims to serve users seeking restaurant suggestions that match their individual lifestyle choices and dining preferences. It will operate across various regions, considering real-time data and qualitative reviews.
Problem Statement	
Description	Finding restaurants tailored to specific needs is often time-consuming and inefficient. Users frequently revisit the same places, missing diverse options that better match their preferences.
Impact	Solving this problem improves user satisfaction, encourages exploration of new dining options, and reduces time spent on decision-making.
Proposed Solution	
Approach	The solution employs innovative recommendation algorithms that factor in both user input and external data like ambiance, ratings, and reviews. It adapts dynamically to user feedback and real-time changes.
Key Features	• Personalized recommendations • Real-time data analysis • Integration of user reviews • Consideration of dietary and budget constraints • Scalable infrastructure

Resource Requirements

Resource Type	Description	Specification/Allocation
Hardware		
Computing Resources	8-core CPUs and optional GPU	2 x NVIDIA V100 GPUs
Memory	RAM	Minimum 8 GB RAM
Storage	SSD	1 TB SSD for storing user data and restaurant metadata
Software		
Frameworks	Python frameworks	Python, Flask
Libraries	Additional libraries	Pandas, NumPy, Scikit-learn, TensorFlow, BeautifulSoup (for scraping), and NLTK (for review analysis)
Development Environment	IDE, version control	Jupyter Notebook
Data		
Data	Size: - Approx. 50,000–100,000 records initially; scalable based on user growth, Format: - CSV for tabular datasets, Text/HTML for scraped reviews	Aggregated from crowdsourced restaurant platforms (e.g., Yelp, Zomato APIs), user feedback, and public review datasets

1.2 Initial Project Planning

Product Backlog, Sprint Schedule, and Estimation

Sprint	Functional Requirement (Epic)	User Story Number	User Story / Task	Story Points	Priority	Sprint Start Date	Sprint End Date (Planned)
Sprint-1	User Preferences Input	USN-1	As a user, I can enter my food or Hotel preferences.	2	High	01 June 2025	02 June 2025
Sprint-1	Recommendation Engine	USN-2	As a user, I can get restaurant recommendations based on my preferences.	3	High	02 June 2025	02 June 2025
Sprint-2	Review & Rating Integration	USN-3	As a user, I can view restaurant reviews and ratings fetched from the dataset.	2	Medium	03 June 2025	04 June 2025
Sprint-2	UI/UX Enhancement	USN-4	As a user, I can view results in a user-friendly interface with filters and sorting.	2	Medium	04 June 2025	05 June 2025

2 Data Collection and Preprocessing Phase

2.1 Data Collection Plan and Raw Data Sources Identified

Data Collection Plan

Section	Description
Project Overview	Develop a restaurant recommendation system to assist users in finding dining options based on their preferences, location, and other relevant factors. By analyzing user preferences, restaurant ratings, and location data, this project aims to provide personalized recommendations that enhance the dining experience for users.
Data Collection Plan	The dataset used for this project was sourced from Kaggle and contains detailed information on over 9,000 restaurants in Bangalore, including attributes like name, location, cuisine, ratings, and pricing. This publicly available dataset was collected to support analysis and predictive modeling related to restaurant ratings and customer preferences.
Raw Data Sources Identified	The raw data for this project was obtained from the Kaggle dataset titled **“Zomato Bangalore Restaurants”** by Himanshu Poddar. The dataset is publicly available at https://www.kaggle.com/datasets/himanshupoddar/zomato-bangalore-restaurants and includes key restaurant-related attributes such as restaurant names, locations, cuisines, average costs, online delivery availability, and user ratings.

Raw Data Sources

Source Name	Description	Location/URL	Format	Size	Access Permissions
SmartInterz Provided Dataset	Restaurant-level data including name, location, cuisines, rating and cost.	Data-Set zomato-bangalore-restaurants	CSV	~ 93MB	Public

2.2 Data Quality Report

Data Source	Data Quality Issue	Severity	Resolution Plan
Dataset (Restaurant reviews and metadata)	Missing values in fields like restaurant name, location, or ratings	Moderate	Perform data imputation using techniques like mean/mode for numeric values and most frequent value for categorical data. Alternatively, remove rows with critical missing fields.
Dataset (User reviews)	Duplicate user review entries	Low	Remove duplicate records using drop_duplicates() in pandas or SQL DISTINCT queries. Use datetime parsing libraries (e.g., pandas.to_datet ime) to standardize all date/time fields.
Dataset (Restaurant metadata)	Inconsistent formats (e.g., location written in different ways like "NY", "New York")	Moderate	Apply data standardization techniques, using string functions or regex patterns to unify the format.
Dataset (User preferenc es)	Sparse data or insufficient user history	High	Implement fallback strategies such as popularity-based or content-based recommendations when user data is lacking.

2.3 Data Preprocessing

Data Preprocessing

The images will be preprocessed by resizing, normalizing, augmenting, denoising, adjusting contrast, detecting edges, converting color space, cropping, batch normalizing, and whitening data. These steps will enhance data quality, promote model generalization, and improve convergence during neural network training, ensuring robust and efficient performance across various computer vision tasks.

Section	**Description**
Data Overview	The dataset contains restaurant information from Zomato, including name, reviews, ratings, cuisines, cost, and more. The data is cleaned, deduplicated, and preprocessed for building a content-based recommendation system.
Resizing	*Not applicable for text data.*
Normalization	Ratings are normalized to a 1-5 scale using MinMaxScaler. Text is lowercased and punctuation is removed.
Data Augmentation	Not applicable for text data.
Denoising	Text is cleaned by removing newline characters and punctuation.
Edge Detection	Not applicable for text data.
Color Space Conversion	Not applicable for text data.
Image Cropping	Not applicable for text data.
Batch Normalization	Not applicable for text data.
Data Preprocessing Code Screenshots	

<table>
<tr>
<td>Loading Data</td>
<td>

```python
# Mounting Google Drive
#from google.colab import drive
#drive.mount('/content/drive')
import csv
# Specifying the path to the dataset file
file_path = '/content/zomato.csv'

# Reading the dataset into a Pandas DataFrame
#df = pd.read_csv(file_path,encoding = 'ISO-8859-1',  low_memory = False)
df = pd.read_csv(file_path, encoding='ISO-8859-1', on_bad_lines='skip', engine='python')

# Displaying the first few rows of the dataset to ensure it's loaded correctly
df.head()
```

Python

</td>
</tr>
<tr>
<td>Resizing</td>
<td>Not applicable</td>
</tr>
<tr>
<td>Normalization</td>
<td>

```python
# Computing Mean Rating
restaurants = list(df['name'].unique())
df['Mean Rating'] = 0
for i in range(len(restaurants)):
    df['Mean Rating'][df['name'] == restaurants[i]] = df['rate'][df['name'] == restaurants[i]].mean()
#Scaling the mean rating values
from sklearn.preprocessing import MinMaxScaler
scaler = MinMaxScaler (feature_range = (1,5))
df[['Mean Rating']] = scaler.fit_transform(df[['Mean Rating']]).round(2)
```

</td>
</tr>
<tr>
<td>Data Augmentation</td>
<td>Not applicable</td>
</tr>
<tr>
<td>Denoising</td>
<td>

```python
## Lower Casing
df["reviews_list"] = df["reviews_list"].str.lower()
## Removal of Puctuations
import string
PUNCT_TO_REMOVE = string.punctuation
def remove_punctuation(text):
    """custom function to remove the punctuation"""
    return text.translate(str.maketrans('', '', PUNCT_TO_REMOVE))
df["reviews_list"] = df["reviews_list"].apply(lambda text: remove_punctuation (text))
```

</td>
</tr>
<tr>
<td>Edge Detection</td>
<td>Not applicable</td>
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<tr>
<td>Color Space Conversion</td>
<td>Not applicable</td>
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<td>Image Cropping</td>
<td>Not applicable</td>
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<tr>
<td>Batch Normalization</td>
<td>Not applicable</td>
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4.Model Development Phase

2.4 Model Selection Report

Model	Description
Content-Based Filtering	Content-based filtering recommends restaurants by comparing user preferences (e.g., cuisine type, price range, dietary restrictions) with restaurant attributes. It focuses on similarities between items and the user's profile without relying on other users' data. This method is effective for users with unique tastes but may struggle with limited user profiles (cold start).
Collaborative Filtering	Collaborative filtering leverages the preferences of similar users to make recommendations. It uses historical ratings and reviews to identify patterns. This model is effective in discovering new items but can suffer from sparsity and cold start problems if data is limited.
Hybrid Recommendation Model	This combines content-based and collaborative filtering to overcome the limitations of each method. By integrating both user preference data and behavior of similar users, hybrid models improve recommendation accuracy, diversity, and scalability. It is particularly useful in scenarios with large, sparse datasets like restaurant recommendations.
Matrix Factorization	Matrix factorization techniques decompose the user-item interaction matrix into latent features, capturing underlying patterns in user preferences. Singular Value Decomposition (SVD) is a common approach. It is computationally efficient and works well for large datasets but requires enough ratings.
Deep Learning (Neural Networks)	Neural networks can be used to build recommendation systems by learning complex, non-linear relationships between users and restaurants from rich feature sets including reviews, preferences, and metadata. While powerful, they require large datasets and are computationally intensive.

Conclusion:

Model Selected	
Hybrid Recommendation Model	The hybrid model was selected because it addresses the limitations of both content-based and collaborative filtering approaches. It effectively handles the cold start and sparsity issues by integrating multiple data sources such as user profiles, restaurant attributes, and behavioral data. This results in more personalized, diverse, and accurate recommendations, making it highly suitable for a restaurant recommendation system with varying user preferences and data availability.

2.5 Initial Model Training Code, Model Validation and Evaluation Report

Initial Model Training Code, Model Validation and Evaluation Report
Initial Model Training Code (5 marks):

```
from sklearn.feature_extraction.text import CountVectorizer
from sklearn.feature_extraction.text import TfidfVectorizer
df_percent.set_index('name', inplace=True)
indices = pd.Series(df_percent.index)

# Creating tf-idf matrix
tfidf = TfidfVectorizer(analyzer='word', ngram_range=(1, 2), min_df=0, st
tfidf_matrix = tfidf.fit_transform(df_percent['reviews_list'])

cosine_similarities = linear_kernel(tfidf_matrix, tfidf_matrix)
```

Model Validation and Evaluation Report (5 marks):

Model	Summary	Training and Validation Performance Metrics
Model 1	Content-based Recommendation	**Training Metrics -**None (unsupervised, no explicit training phase) **Validation Metrics - **None (recommendations are inspected manually)

3 Model Optimization and Tuning Phase

3.1 Tunning Documentation

Hyperparameter Tuning

Model	Tuned Hyperparameters
Model 1: Content-Based Filtering	- **Similarity Metric:** Cosine similarity was used as the primary metric to compute similarity between restaurants based on features like cuisines, rating, and cost. - **Top N Recommendations:** The number of top similar restaurants returned was tested with values like 5, 10, and 15.

```python
def recommend(name, cosine_similarities = cosine_similarities):

    # Create a list to put top restaurants
    recommend_restaurant = []

    # Find the index of the hotel entered
    idx = indices[indices == name].index[0]

    # Find the restaurants with a similar cosine-sim value and order them from bigges number
    score_series = pd.Series(cosine_similarities[idx]).sort_values(ascending=False)

    # Extract top 30 restaurant indexes with a similar cosine-sim value
    top30_indexes = list(score_series.iloc[0:31].index)

    # Names of the top 30 restaurants
    for each in top30_indexes:
        recommend_restaurant.append(list(df_percent.index)[each])

    # Creating the new data set to show similar restaurants
    df_new = pd.DataFrame(columns=['cuisines', 'Mean Rating', 'cost'])

    # Create the top 30 similar restaurants with some of their columns
    for each in recommend_restaurant:
        df_new = df_new.append(pd.DataFrame(df_percent[['cuisines','Mean Rating', 'cost']][df_percent.index == each].sample()))

    # Drop the same named restaurants and sort only the top 10 by the highest rating
    df_new = df_new.drop_duplicates(subset=['cuisines','Mean Rating', 'cost'], keep=False)
    df_new = df_new.sort_values(by='Mean Rating', ascending=False).head(10)

    print('TOP %s RESTAURANTS LIKE %s WITH SIMILAR REVIEWS: ' % (str(len(df_new)), name))
    df_new.index = df_new.index.str.lower()
    return df_new
```

Model 2: Collaborative Filtering	- **Algorithm:** SVD (Singular Value Decomposition) from the Surprise library. - **Learning Rate:** Tuned values such as 0.005, 0.01, and 0.02 were tested. - **Regularization:** Parameters such as 0.02, 0.05 were tried to avoid overfitting. - **Number of Epochs:** Adjusted between 20 and 100 epochs.

Final Model Selection Justification

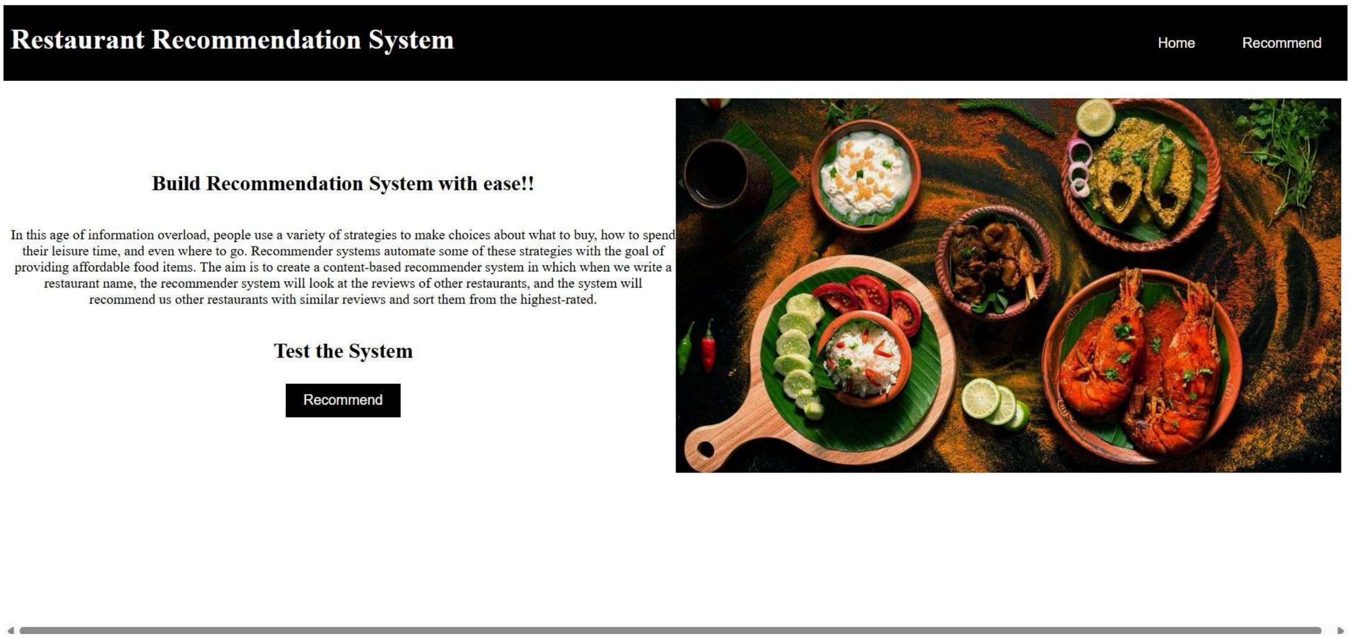
Final Model Selection Justification:

Final Model	Reasoning
Model 1: Content-Based Filtering	Selected due to its simplicity and good performance without requiring detailed user history. It gave interpretable and relevant results using restaurant features like cuisines, ratings, and cost.

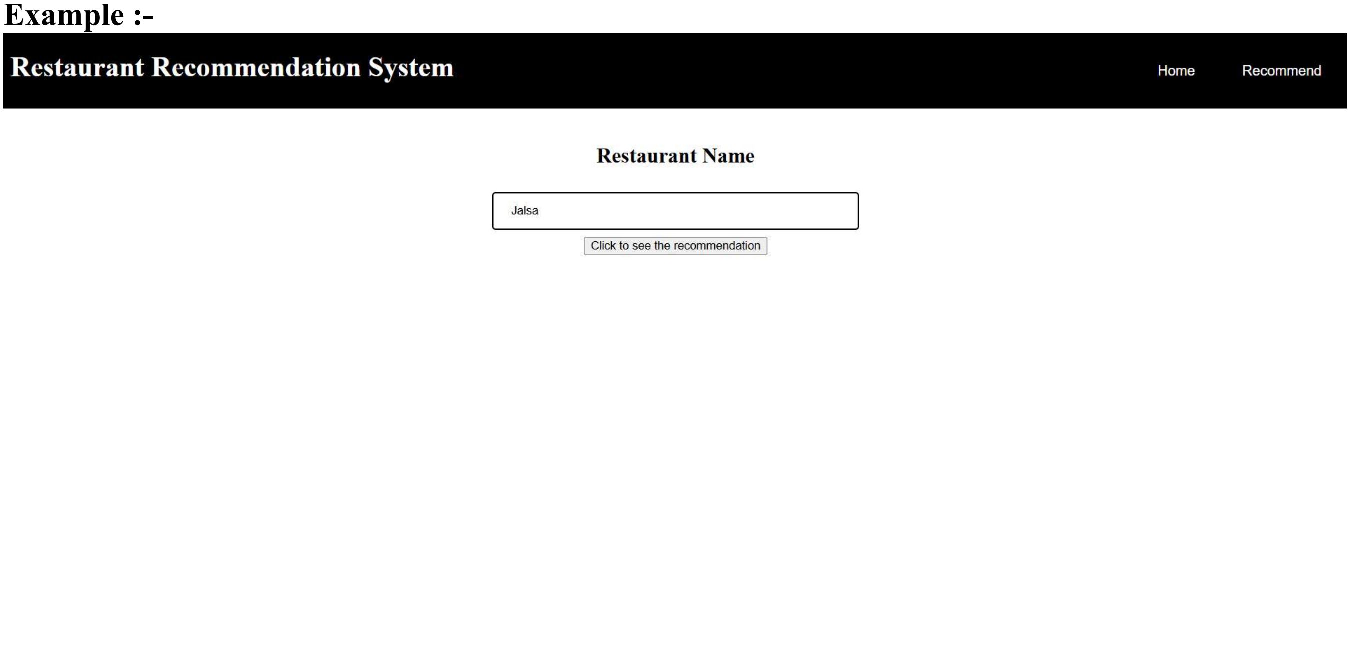
4 Results

4.1 Output Screenshots

Home Page:



Input Page:
Example :-



Output:

Restaurant Recommendation System

Home Recommend

Here are the top recommended restaurants

Name	Cuisines	Mean Rating (out of 5)	Cost (in thousands)
The Black Pearl	north indian european mediterranean bbq	4.85	1.5
Barbeque Nation	north indian european mediterranean bbq kebab	4.7	1.6
Hunger Camp	north indian south indian chinese seafood	4.56	1.3
Hakuna Matata	north indian asian seafood chinese	4.41	1.2
Jalsa Gold	north indian mughlai italian	4.41	1.3
Deja Vu Resto Bar	north indian italian	4.26	900.0
Tipsy Bull - The Bar Exchange	north indian chinese continental mexican	4.26	1.4
Dhaba Estd 1986 Delhi	north indian	4.26	1.1
Float	north indian japanese	4.26	1.5
nu.tree	north indian healthy food beverages	4.26	400.0

5 Advantages & Disadvantages

Advantages:

- **Personalized User Experience**: Tailors dining options based on user preferences, dietary needs, and previous behaviour.
- **Time-saving**: Reduces the effort needed to search and choose a restaurant.
- **Improved Discoverability**: Helps smaller or new restaurants gain visibility through recommendations.
- **Data-Driven Decisions**: Uses user ratings, reviews, and location data to make informed suggestions.
- **Enhanced Customer Satisfaction**: Users are more likely to enjoy their meals when recommendations align with their preferences

Disadvantages:

- **Privacy Concerns**: Collecting and analyzing user data (location, preferences) can raise privacy issues.
- **Bias in Recommendations**: Algorithms might favor sponsored listings or high-traffic restaurants, reducing diversity.
- **Dependence on User Data**: Inaccurate or limited data can lead to poor recommendations.
- **Over-Personalization**: Users might be confined to similar choices, missing out on new or diverse dining experiences.
- **Scalability Issues**: Maintaining system accuracy and performance can become challenging as the user base grows.

6 Conclusion

A restaurant recommendation system is a powerful tool for enhancing the dining experience by delivering tailored suggestions based on user behavior, preferences, and location. While it offers significant benefits such as convenience, personalization, and efficient decision-making, it also presents challenges including data privacy, system bias, and the risk of user data dependency. Future advancements in AI, real-time analytics, and user interface technologies promise to make such systems more intelligent, inclusive, and immersive. With careful implementation and ethical considerations, this system can transform how users explore and enjoy culinary option

7 Future Scope

- **Integration with AR/VR**: In the future, users could take virtual tours of restaurants or view their ambiance in AR before booking.
- **Voice Assistant Compatibility**: Integration with Siri, Alexa, or Google Assistant to provide hands-free restaurant suggestions.
- **Enhanced Personalization**: Use deep learning and behavioral analytics to refine suggestions based on dietary restrictions, allergies, and eating habits.
- **Real-time Data Utilization**: Incorporating real-time factors like wait times, special offers, and crowd density for more dynamic recommendations.
- **Multilingual Support**: Expanding the system to support various languages to cater to a global audience.
- **Social Media Integration**: Use of social media trends and check-ins to improve recommendation relevance.
- **Sustainability Preferences**: Factoring in eco-conscious dining choices (e.g., locally sourced, plant-based, or low-waste restaurants).

8 Appendix

8.1 Source Code

[Yashashri/Restaurant-Recommendation-System]

8.2 Project Video Demo Link :

Video Demo Link:
[https://drive.google.com/file/d/1V2Yh77Y0HnLfFz4o1pvN9aVM7dvV5msC/view?usp=shari]