AI ENHANCED RECOMMENDATION SYSTEM FOR TRAVEL, TOURISM AND HOSPITALITY

Mamidi Khushika Reddy[1]
[1]School of Computer Science and Engineering, VIT Chennai, India

ABSTRACT:

The travel industry is increasingly making use of the Machine Learning (ML) and Artificial Intelligence (AI) technologies to boost the functionality and user experience of their websites and apps. However, this evolution also involves challenges**.** This paper explores the key obstacles faced by the travel industry which is often overlooked while effectively implementing ML and AI solutions in their digital platforms. Challenges include the need for continuous adaptation to evolving user preferences and industry trends. Additionally, the complexity of integrating ML/AI into existing software and the requirement for specialized expertise pose significant hurdles. This project is an innovative AI Recommendation System designed to revolutionize personalized travel experiences ensuring that travel websites and apps simplify the travel experiences for the users by keeping it customer centric and it also promotes the organizations' growth by attracting more users. The system seamlessly integrates machine learning, collaborative based filtering to analyze user preferences and real-time trends. Incorporating natural language processing, the system extracts useful insights from user reviews, elevating recommendation accuracy to new heights. Furthermore, the inclusion of location-based services ensures the provision of context-aware suggestions, aligning recommendations with the user's geographical context. The evaluation of the recommendation system, conducted with a comprehensive dataset, showcases a marked improvement in recommendation quality. This significantly contributes to the field of AI applications in tourism, providing a robust tool for crafting personalized and memorable journeys as it focuses to navigate the complexities and unlock the full potential of ML and AI technologies in their digital offerings.

Keywords: Collaborative Filtering; Content based Filtering; Context Awareness; Geospatial Algorithm; KNN; Natural Language Processing (NLP); Recommendation system; Semantic Analysis

1. Introduction

The tourism industry thrives on personalized experiences, yet creating personalized recommendations for travelers poses significant challenges. Traditional methods often fall short in capturing the diverse preferences and dynamic trends of modern travelers. Hence, there is a persistent need for an innovative AI recommendation system that seamlessly integrates advanced technologies to reform personalized travel experiences. Such a system would not only enhance user satisfaction but also contribute to the advancement of AI applications in the tourism sector. This project introduces an innovative AI Recommendation System designed to enhance personalized travel experiences. The system combines machine learning algorithms such as collaborative filtering to analyze user preferences and real-time trends effectively. By incorporating natural language processing and semantic analysis, the system can extract detailed insights from user reviews, leading to more accurate recommendations. Additionally, the inclusion of location-based services allows for context-aware suggestions that consider the user's geographical context. Through evaluation using a comprehensive dataset, the system demonstrates significant improvements in recommendation

quality, making it a valuable tool for creating personalized and memorable journeys in the tourism sector. Using a web scraped data helps in gathering a vast amount of information from the latest information. This data is then processed and analyzed by the AI recommendation system to comprehend user preferences, trends, and sentiments accurately. By leveraging this diverse dataset, the system can offer recommendations personalized to each traveler's unique interests, preferences, and behavior patterns.

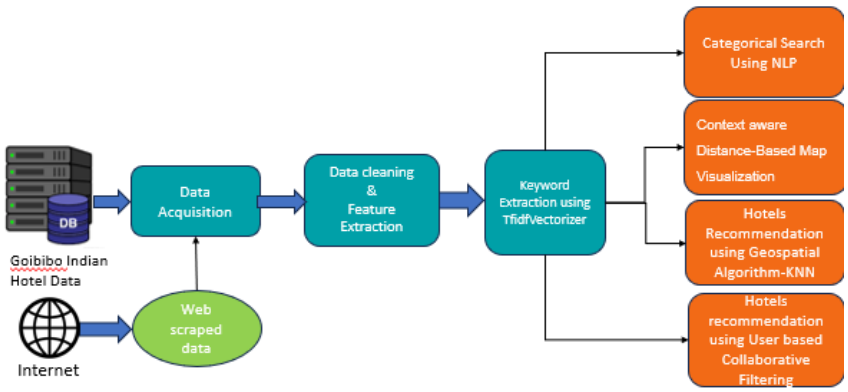
2. Related Work

[1] The study delineates a recommender system custom-made for tourist visits, offering practical understandings into system development and deployment within tourism management contexts. It highlights the significance of integrating collaborative filtering include collaborative filtering, content-based filtering techniques, thereby enhancing recommendation accuracy in tourism scenarios.[2] An intelligent recommendation model is presented, concentrating on tourist places and user preferences. The importance of collaborative filtering techniques in tourism recommendation systems is highlighted, emphasizing the necessity of aligning to user preferences for effective recommendations.[3] A recommendation model for travel destinations using Instagram photos and metadata. By combining object detection, similarity measures, classification, and data clustering, the model generates personalized suggestions. Evaluation shows enhanced performance, with 63% of users visiting recommended countries and 96% accuracy in matching visited countries. The automated, machine learning-based system holds potential for further advancements with metadata incorporation.[4] The study showcases a recommendation system for travel destinations based on geotagged data. It demonstrates the integration of geospatial algorithms to deliver context-aware suggestions, enhancing the significance of recommendations in tourism.[5] A tourism destination recommendation system using collaborative filtering and modified neural networks is proposed. Innovative approaches are emphasized to increase recommendation accuracy, predominantly within tourism settings.[6] Vis2Rec, a large-scale visual dataset for visit recommendation, is presented. The paper highlights the importance of visual data in enhancing the recommendation accuracy within tourism contexts.[7] A trip planner recommendation system employing big data analytics is proposed. The integration of big data techniques enables efficient trip planning, signifying the practical use cases in tourism recommendation systems.[8] A hybrid recommendation system for tourism, incorporating advanced algorithms and the TOPSIS model, is proposed. The study offers insights into algorithmic approaches, elevating recommendation methodologies for tourism scenarios.[9] A personalized recommender system for transportation. THOR ranks travel options based on individual preferences, employing contextual models to predict user engagement. Clustering algorithms addresses new user preferences. Experimental results validate THOR's efficacy in learning and ranking preferences.[10] Tourism destination recommendation based on association rule algorithms is introduced. The incorporation of association rule mining supports in identifying patterns among travel destinations, refining recommendation strategies.[11] The design and implementation of a personalized tourism recommendation system based on data mining and collaborative filtering algorithms is explained. Incorporation of multiple techniques boosts recommendation accuracy for personalized experiences.[12] The study focuses on the application of deep learning techniques in tourism recommendation systems, highlighting advancements in personalized travel recommendations through advanced and efficient algorithms.[13] A conceptual framework for a hybrid recommender system in tourism, integrating big data and AI methodologies, is introduced. The theoretical foundation laid focuses on the integration of diverse data sources and sophisticated algorithms for effective recommendations.[14] A systematic review of travel recommendation systems is shown, providing a comprehensive overview of present methodologies. Collaborative filtering, content-based filtering, NLP, and geospatial algorithms are among the methodologies studied.[15] TripRec, a recommender system for planning personalized city trips based on travel mobility analysis, is proposed. The study emphasizes on the employment of travel mobility data for personalized trip recommendations, providing enhanced travel experiences.

3. Proposed System

This project introduces an innovative AI Recommendation System designed to enhance personalized travel experiences. The system combines machine learning and collaborative filtering methods to analyze user preferences and real-time trends effectively. By incorporating natural language processing, the system can extract detailed insights from user reviews, leading to more accurate recommendations. Additionally, the inclusion of location-based services allows for context-aware suggestions that consider the user's geographical context. Through evaluation using a comprehensive dataset, the system demonstrates significant improvements in recommendation quality, making it a valuable tool for creating personalized and memorable journeys in the tourism sector. Several modules have been created in the recommendation system that are designed to improve user experience and to give personalized recommendations. The User location and category-based suggestion module using Goibibo hotel dataset employs Natural Language Processing (NLP) to make suggestions depending on where the user is located or his/her location preferences and the categories which differentiates the hotels which are also their main constraints in choosing a hotel. Besides, the Context-aware Distance-Based Map Visualization module on the same dataset will provide users with the map visualizations that contains information about hotels locations and a short summary which will help them to make better quick decisions. In Addition, a module focuses on the application of Geospatial Algorithm-K Nearest Neighbours (KNN) on web scraped data for recommending hotels based on the prices so that people can get the most affordable accommodations within their means. Finally, Hotels Recommendation module has used user-based collaborative filtering on web scraped data considering past user reviews and ratings to give specific recommendations based on personal preferences. This module also uses semantic analysis to segregate the hotel reviews based on their semantics, it allows users to easily view the segregated reviews thereby reducing the user's time and efforts in making travel decisions. This methodology is versatile as it uses different techniques as well as datasets to provide a seamless recommendation experience for travel enthusiasts such as location-based recommendations, contextual visualizations, affordable alternatives, and personalized suggestions influenced by feedback from users.

4. Architecture



5. Dataset Preparation

To acquire data, we collected the Goibibo Indian Hotel Dataset from Kaggle and scraped data about few hotels in Tamil Nadu along their user reviews from Google Maps. Then the data is cleaned to make sure it was accurate and consistent. Important features from the dataset were extracted for our recommendation system. The dataset is made better by adding more useful information. Data analysis approaches such as Correlation analysis, descriptive statistics, machine learning techniques, and clustering analysis are done to understand data better.

6. Modules

6.1.1 User Location and Category-Based Suggestion using NLP

The travellers or users interacting with the travel and tourism websites, seeking specific attributes in a hotel often encounter the inconvenience of sifting through extensive descriptions or details of every option available. Frequently, these desired attributes are not clearly specified in the filtering options provided. Current websites and applications lack the functionality to present users with tailored information, instead overwhelming them with all details simultaneously and necessitating manual search efforts. This not only results in a subpar user experience but also complicates the booking process, potentially leading to erroneous decisions and dissatisfaction among travellers. This module addresses this gap by enabling users to select and view only the hotel attributes that are of interest to them, streamlining the process of choosing accommodations with specific criteria. By presenting relevant information upfront, users can efficiently compare multiple hotels and make informed decisions, saving time and enhancing user satisfaction. Users can enter their location such as state or city and select a preferred category. Consequently, suggestions are generated based on both the user's location as well as the chosen category. The list of displayed hotel categories includes name, address, province/state, star rating or classification, other additional information. To ensure relevance, these results are sorted in the best to worst order according to the selected category. This can be later properly incorporated in the actual websites and apps where the results are specific and filtered enough to provide users with the only required information. Data preprocessing techniques like text mining is used in this module. Additionally, an NLP-based keyword search algorithm estimates distances from the user's location to hotels, filters places by state, and sorts them based on closeness. The algorithm also filters out all locations except hotels within a given state and generating them ordered by closest proximity first. Moreover, NumPy libraries along with IPython, widgets, pandas, folium, geopy and scikit-learn tools help process analyse and visualize data.

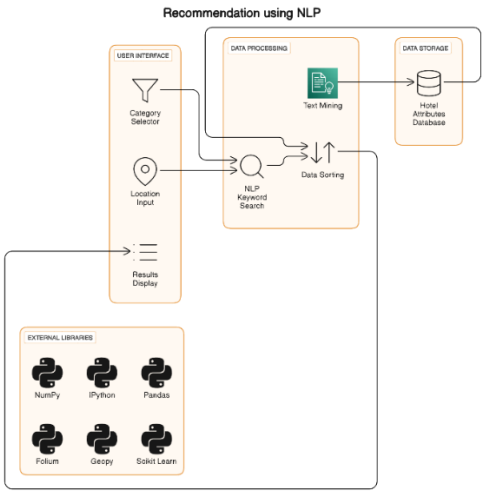


Figure 1 Recommendation using NLP

6.1.2 Contextual Sensitive Distance-Based Map Visualization

In contemporary travel and tourism websites, users typically navigate hotel options through search queries or form-based searches. However, locating hotels quickly that are nearest to their current position often proves challenging, as users must apply filters to refine their search results.

Consequently, both new users and seasoned travellers encounter difficulties in aligning their accommodation choices with their travel plans. Moreover, the process of viewing hotels on a separate platform such as Google Maps before booking through the website or app can prolong the booking process and potentially diminish user engagement. To address these challenges, Goibibo recently introduced a map visualization feature on their website, enabling users to view hotels alongside their respective distances. Nonetheless, the current implementation lacks the option for users to explore all available hotels directly on the map and select accommodations based on proximity. Instead, users are only presented with the map view after selecting a specific hotel, limiting their ability to swiftly search and book based on distance preference. The cluttered interface further complicates the user experience, as manually selecting each hotel for viewing becomes cumbersome. Thus, the primary objective of this module is to streamline and simplify the user decision-making process by enhancing accessibility and simplifying hotel selection based on distance criteria. This module uses the location of the user to provide personalized hotel recommendations. An interactive map is then displayed with an avatar showing the user's position and markers showing nearby hotels within the same state. Each marker shows relevant details like the name of the hotel, its physical address, how far it is from user's location and a rating as soon as it is clicked. It helps the users locate the hotels, compare hotels based on position and distance and make the decision process easy and quick. On the other hand, nearby facilities such as restaurants or hospitals can be chosen for ease. Data pre-processing techniques are employed in this system to handle missing values and combine text features for NLP-based keyword searches using TF-IDF vectorization. Geospatial calculations are used to determine distances between locations, while map visualization enabled by Folium library with color-coded ratings based on hotel clusters. Integration with Nominatim geocoding service converts textual places into geographical coordinates thereby increasing the accuracy. Through these ML algorithms and concepts the system provides effective and personalized travel recommendations directing towards individual's tastes, preferences.

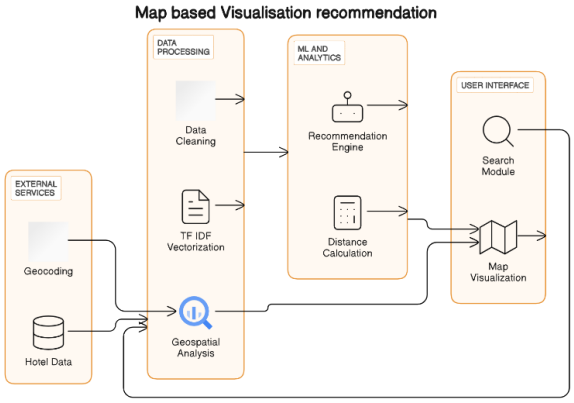


Figure 2 map-based recommendation

7.1.3 Hotels Recommendation using Geospatial Algorithm-KNN

The primary limitation for travellers often lies in their budgetary constraints. Some hotels thrive while others suffer financial losses due to a lack of insight into customer preferences. This module specifically targets pricing considerations, allowing users to propose prices for their preferred hotels. In cases where multiple price suggestions are submitted for a single hotel, the system calculates the average. This feature aids hotels and travel websites in adjusting prices to align with prevailing customer demand, facilitating the creation of attractive travel packages and plans aimed at drawing in more customers. This Hotels Recommendation feature uses a Geospatial Algorithm KNN (K Nearest Neighbours) and cosine similarity method to provide customized hotel suggestions based on price. By integrating price related data with factors, the algorithm identifies hotels that match the user's budget and preferences. Through KNN the feature evaluates the similarity, between hotels in terms of their price range and other key characteristics. K value taken here is 5 so the top 5 hotels

whose prices are closest to the user's price preference are displayed. By leveraging this algorithm, the feature ensures that users receive contextually appropriate hotel recommendations based on pricing considerations using the vast Goibibo Indian Hotel dataset.

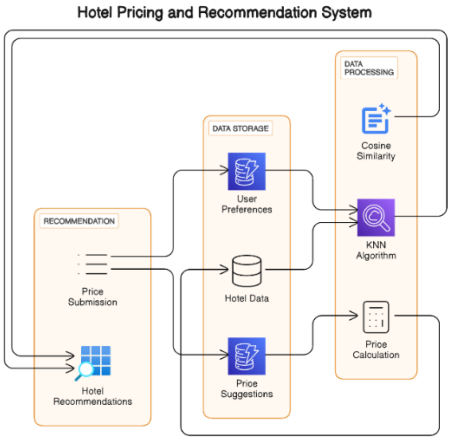


Figure 3 Recommendation using KNN

7.1.4 Hotel Recommendation using Collaborative Filtering

This module is designed to recommend hotels to users based on their search queries. It uses a combination of content-based filtering and collaborative filtering techniques. The module utilizes a dataset containing hotel reviews, along with associated information like hotel names, ratings, and prices. First, the dataset is cleaned, and any missing values are handled. The reviews are then tokenized into individual words using the nltk.tokenize module, and the words are converted to lowercase. This prepares the textual data for further analysis. The recommendation process starts with content-based filtering. A TF-IDF vectorizer is used to convert the tokenized reviews into numerical vectors. The cosine similarity between the user's query vector and the TF-IDF vectors of the hotel reviews is calculated. This helps identify hotels with similar keywords to the user's search. The top recommended hotels based on content similarity are then displayed to the user. Furthermore, user search preferences are assessed and rated, allowing for the suggestion of hotels frequented by users with similar preferences. This mechanism enables users to explore new options, thereby enriching the overall customer experience and enhancing satisfaction levels.

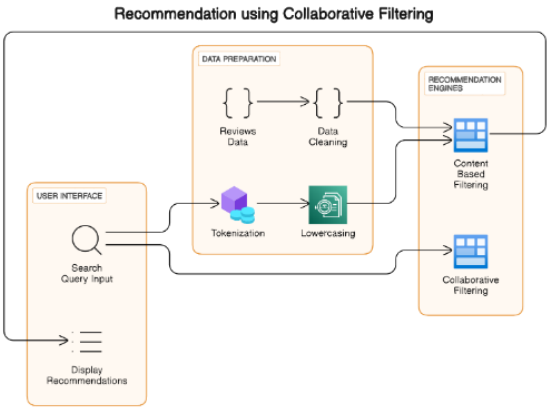
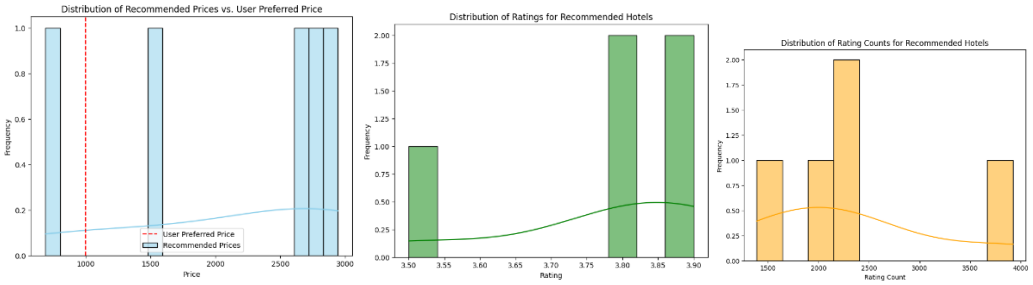


Figure 4 Recommendation using Collaborative Filtering

8 Results and Discussions

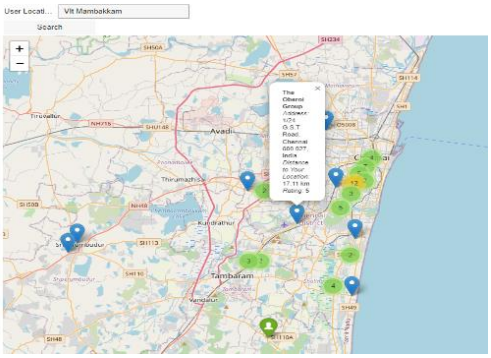


Here for the web scraped hotels are recommended in the most optimised way

Console interface:

Module1:

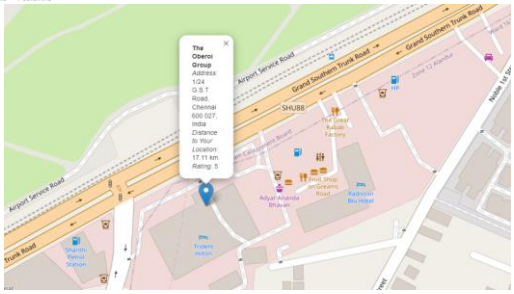
Module2:



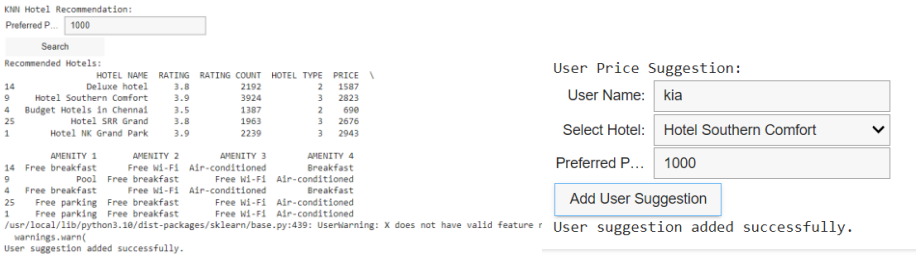
Recommended Places:

	hotel_brand	address	hotel_star_rating	distance_to_user_km
2454	Null2357	NO-208 A, velacherry Main Road, camp Road Junc...	2	8.943165
312	Null304	no.139 perumbakkam Tambaram Taluk (23 sholi...	0	9.138285
308	Null300	Plot No.2,Elcot Avenue,Rajiv Gandhi Road,(OMR)...	0	9.741355
325	Null315	No.17, Johnson Street, Behind Hindu Mission Ho...	0	10.010261
313	Null305	Near Infosys, Old Mahabalipuram Road, Sholinga...	0	10.221559
...	...	...	...	...
2167	Null2082	6/76A, Next to post office, Main Road	1	598.673549
1021	Null985	36, Main Road ,	0	598.764249
3307	Null3089	Near Seashore,Kovalam Road, Kanyakumari	3	598.868316
1025	Vedanta Wake up Group of Hotels	Building Viswa Residency, Anchukootuvilai Road...	0	598.939454
1023	Sparsa Group	6/112 B, Beach Road, Near Sunset point	0	599.274562

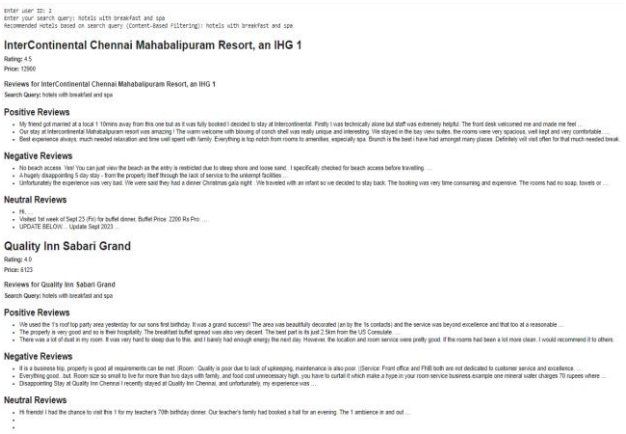
188 rows × 4 columns



Module 3:

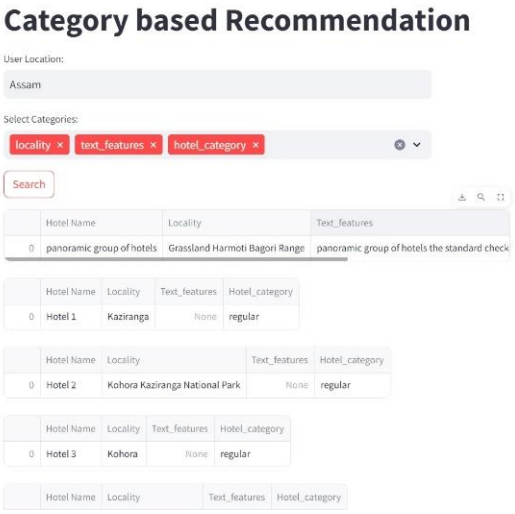


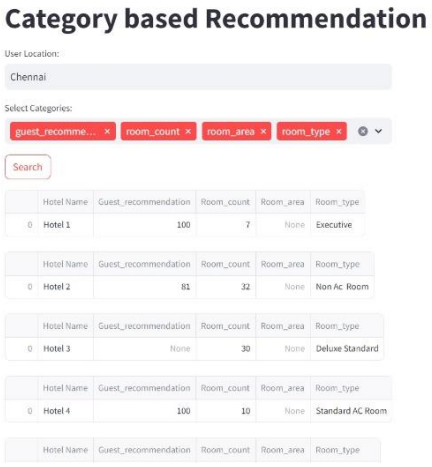
Module 4:



Web Interface:

Module 1:





Module 2:

	hotel_brand	address	hotel_star_rating	distance_to_user_km
2,451	Treebo Hotels	No. 2, 6th Cross Street, Lake Area, Nungambakkam, Chennai - 600034	2	4.2206
3,022	Treebo Hotels	No. 27, North Crescent Road, T.Nagar, Chennai	3	5.4737
3,015	FabHotels	No.29 and 31 Thanikachalam Road,Arcot Street, Pondi Bazar,T. Nagar	3	5.9564
3,023	Treebo Hotels	New No. 15, Old No. 9, Peters Road, Royapettah, Chennai 600014	4	6.8024
318	Executive Comfort Group of Hotels	3rd Floor,Block 2 #76/41 C.I.T Nagar 1st Main Road,Nandanam	0	7.5087
2,017	Executive Comfort Group of Hotels	9/1, Anandapuram (Near Dr. Ranga Road),Mylapore	1	7.6184
319	Executive Comfort Group of Hotels	5/2, North Mada Street,Srinagar Colony, Saidapet,	0	8.1649
3,017	FabHotels	South Canal Bank Road, Mandavelipakkam, Raja Annamalai Puram	3	8.8748
3,721	citrus hotels	Near Sunguvarchatram, Velankani Technology Park SEZ, Chennai-Bangalore Highway	4	32.5573
1,930	Leisure Hotels	Nagalore road Opp petrol bunk,	0	261.0956
[illegible]	Club Mahindra Group	19-49 Railway road, Off Ettines Road Ooty	4	425.9151
3,310	Country Club Group of Hotels	Prakasapuram Village, Shenbaganur, Kodaikanal	3	426.5347
[illegible]	Panoramic Group of Hotels	Vilpatty Road, Pachaimaruthodai, Kodaikanal	5	451.1992

Map-Based Visualization Using Geospatial Calculations

Enter Your Location (e.g., city name, address):

Anna Nagar

Search

Map

Recommended Hotels:

	hotel_brand	address
2,451	Treebo Hotels	No. 2, 6th Cross Street, Lake Area, Nungambakkam, Chennai - 600034
3,022	Treebo Hotels	No. 27, North Crescent Road, T.Nagar, Chennai
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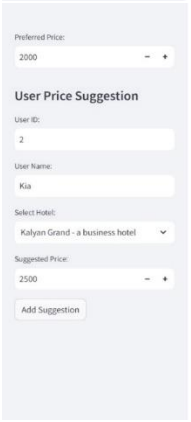
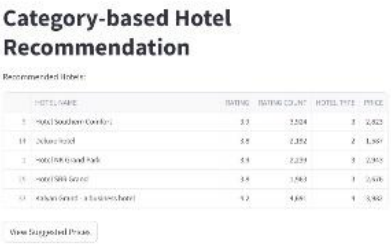
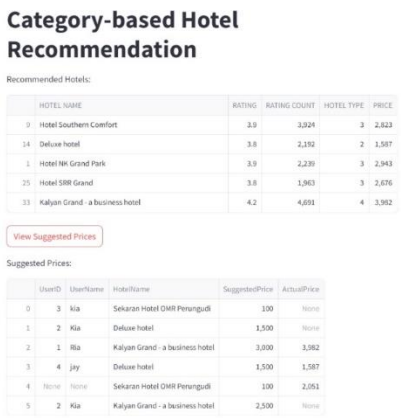
3,017	FabHotels	South Canal Bank Road, Mandavelipakkam, Raja Annamalai Puram
3,721	citrus hotels	Near Sunguvarchatram, Velankani Technology Park SEZ, Chennai-Bangal
1,930	Leisure Hotels	Nagalore road Opp petrol bunk,

Module 3:







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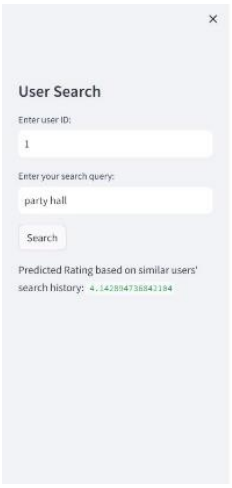

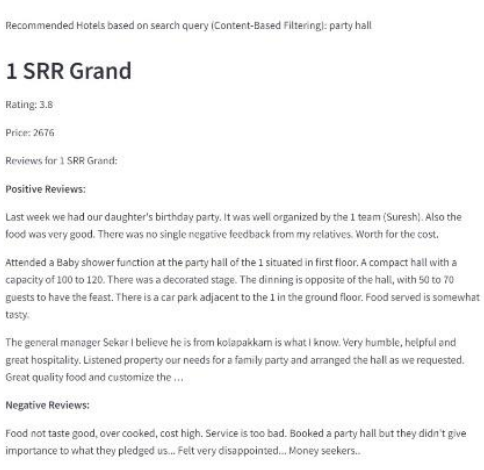

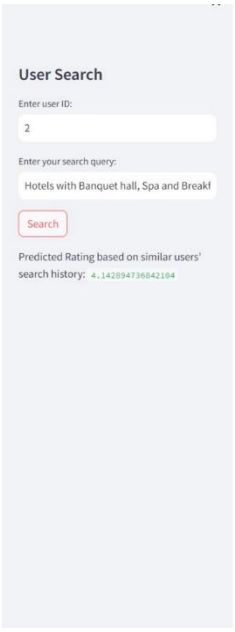

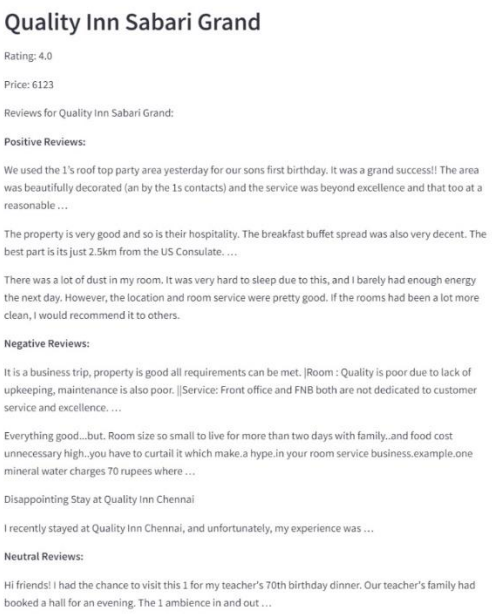

9 Conclusion

In this research, by using natural language processing, advanced machine learning algorithms, and location-based services, the system provides highly personalized travel recommendations that significantly enhance the user experience. The integration of collaborative filtering, semantic analysis, and geospatial calculations help in better understanding of user choices and behaviours, leading to more effective and relevant suggestions. The results show the system's accuracy in personalized recommendations, addressing the key challenges faced by travellers in planning their stays and travels. The system not only enhances the decision-making process through insightful recommendations but also helps in gaining overall satisfaction and engagement of users in the travel planning phase. Improving the system's ability to process and analyse real-time data could provide most timely and context-aware recommendations. By providing more personalized, accurate, and engaging travel planning experience, future of technology in travel is promising.

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