Tourist Spot Recommendation Algorithm using Heuristics

Kapil Soni[1], Rigved Desai[2], Aman Sahu[3], Dr. Vijaya J[4]
[1,2,3]B.Tech, Data Science & Artificial Technology
IIIT Naya Raipur
[4]Department of Data Science & Artificial Technology
IIIT Naya Raipur
Raipur, India
[1]kapil21102@iiitnr.edu.in, [2]rigved21102@iiitnr.edu.in, [3]aman21102@iiitnr.edu.in, [4]vijaya@iiitnr.edu.in

***Abstract*—This project introduces a Tourist Spot Recommendation Algorithm utilizing Heuristics, incorporating clustering, mathematical algorithms, and geolocation-based techniques. The aim is to offer personalized tourist spot recommendations, considering factors like annual visitors and user ratings. The goal is to revolutionize travel experiences by providing efficient and personalized journeys through an AI-powered tourism management app.**

Artificial intelligence (AI) has emerged as a catalyst in reshaping travel planning and exploration. Recognizing the need for tailored experiences, the project addresses this gap by employing cutting-edge recommendation algorithms within the app. These algorithms generate customized suggestions based on user preferences and current location, enhancing user satisfaction and simplifying the travel planning in the digital age marked by information overload.

The app's key contributions encompass advanced personalization, improved user experience, and the integration of location-based services. The paper incorporates a thorough literature review on AI-based tourism management, identifying research gaps and challenges. The proposed framework encompasses data preprocessing, leveraging clustering algorithms like K-means, Fuzzy C-Means, and K-medoids, and determining optimal recommendations through a novel evaluation metric.

Promising results conclude the study, showcasing the application's functionality in creating personalized itineraries. The proposed framework combines clustering, visitability scoring, and penalization to deliver efficient and highly personalized travel recommendations. Future directions involve data expansion, feedback-driven hyperparameter tuning, algorithm refinement, and adding functionalities for an enriched user experience. The commitment to ongoing improvement underscores the app's evolution, ensuring its sustained relevance in the dynamic landscape of AI-driven tourism management.

***Index Terms*—Tourism Management, Recommendation Systems, User Personalization, Location-based Services, Travel Planning, Clustering Algorithms, and Heuristics.**

I. Introduction

This work introduces an innovative solution for Tourist Spot Recommendation using Heuristics. As artificial intelligence (AI) continues to reshape the travel industry, we aim to provide more personalized and efficient travel experiences [1]. Compared to traditional tourism applications that often fail to deliver tailored experiences, our app harnesses cutting-edge AI technologies to transform how individuals plan, explore, and enjoy their journeys.

The unique proposition of our Tourist Spot Recommendation app lies in its utilization of AI-powered recommendation algorithms driven by heuristics. The app seeks to elevate user satisfaction and streamline the travel planning process by offering users customized suggestions based on their preferences and current location. In an era saturated with information, choosing the ideal tourist destinations has become a daunting task. Our solution addresses this challenge as a personalized AI-driven tourism management tool.

Tailored to individual tastes and specific states of interest, our app focuses on recommending the most enticing travel spots in India. It facilitates seamless and personalized travel experiences by suggesting top attractions within the user's selected state, complete with precise location details. This proves invaluable for travelers seeking to uncover hidden gems and well-known landmarks in their chosen location.

The primary objective of this paper is to introduce an innovative approach to tourist spot recommendation using heuristics. Our app simplifies vacation planning, making it personalized and effortless by streamlining the time-consuming travel planning process through its exceptional features and capabilities. Our Tourist Spot Recommendation app aims to provide users with more relaxed and cost-effective travel experiences by creating tailored itineraries and optimizing transportation.

II. Motivation

The motivation for developing a Tourist Spot Recommendation Algorithm stems from the evolving landscape of the travel industry. Travelers' expectations have shifted, demanding more personalized, seamless, and enjoyable travel experiences. Traditional tourism apps have struggled to meet these changing needs, creating innovation opportunities. The motivation for this endeavor arises from several key factors:

A. Contributions

The significant contributions of this Tourist Spot Recommendation Algorithm include:

1. Advanced Personalization: We introduce an advanced personalization system that utilizes AI and machine learning

to provide travelers with tailored recommendations based on their unique preferences and real-time location data.

2. Enhanced User Experience: The app prioritizes user satisfaction by offering an intuitive and user-friendly interface, real-time updates, and seamless navigation to improve travel experience.

3. Recommendation Algorithms: Our recommendation algorithms consider many factors, including user preferences, ratings, reviews, historical popularity, and geographic location, resulting in highly relevant and contextual travel recommendations.

4. Location-Based Services: The app harnesses location-based services to deliver real-time information on nearby tourist attractions, activities, and events, encouraging spontaneous exploration.

5. Cross-Platform Applicability: The app will be designed for cross-platform use, ensuring accessibility across various devices and operating systems.

The organization of our work is as follows: -
Section III: Literature Review: This section comprehensively reviews existing literature on the Tourist Spot Recommendation Algorithm, highlighting the latest advancements and research trends.
Section IV: Tourist Spot Recommendation Algorithm: In this section, we present the architecture, features, and underlying technologies of our innovative app.
Section V: Proposed Framework: Here, we share the framework of how to build the project from scratch and the outcomes of each step.
Section VI: Experimental Results and Analysis: We share the results of extensive experimentation and analysis, which validate the effectiveness of our recommendation algorithms and user satisfaction enhancements.
Section VII: Conclusion and Future Directions: In the final section, we conclude the article by summarizing our research contributions and discussing the potential impact of our AI-based tourism management app on the travel industry and user experiences.

III. Literature Review

In recent years, the application of artificial intelligence (AI) in the tourism industry has gained significant attention. AI-based tourism management apps have emerged as powerful tools for enhancing traveler experiences and optimizing travel planning. This literature review explores relevant studies that have contributed to developing AI-driven solutions in tourism.

A. Research Gap, Issues, and Challenges

Smart Tourism and Personalization::

- Buhalis and Amaranggana (2015) discuss enhancing tourism experiences through the personalization of services in smart tourism destinations. This involves leveraging information and communication technologies to tailor services to individual preferences. [1]

Foundations of Smart Tourism::

- Gretzel et al. (2015) lay the foundations for smart tourism, highlighting its development and impact on the electronic markets. The paper discusses the key elements contributing to the evolution of smart tourism. [2]

AI and ML in Tourism and Hospitality::

- Minazzi et al. (Year) provide a state-of-the-art review of Artificial Intelligence (AI) and Machine Learning (ML) applications in the tourism and hospitality sector, showcasing the latest advancements and potential areas of growth. [3]

Social Media Analytics in Hospitality::

- Xiang et al. (2017) conduct a comparative analysis of major online review platforms, emphasizing the implications for social media analytics in the hospitality and tourism industry. [4]

Deep Learning for Sentiment Analysis::

- Dinh et al. (2019) present a survey on deep learning for sentiment analysis, exploring the application of advanced neural network techniques to analyze and understand sentiment in textual data. [5]

Privacy-Preserving Deep Learning::

- Khan and Cao (2019) review privacy-preserving techniques in deep learning, highlighting the challenges and solutions for protecting sensitive information in AI models. [6]

Content-Based Recommendation Systems::

- Luo et al. (2019) provide a comprehensive review of content-based recommendation systems, discussing the methodologies and technologies involved in suggesting items based on their features. [7]

Sentiment Analysis of Web Services::

- Wang et al. (2018) offer a review and comparative analysis of sentiment analysis techniques applied to web services, focusing on understanding public opinions and perceptions. [8]

Matrix Factorization for Recommendation::

- Shi et al. (2019) augment matrix factorization with user and item features for recommendation systems, improving the accuracy of predictions in collaborative filtering. [9]

Leveraging Ranking Models in Recommendation::

- Zhong et al. (2016) explore the integration of ranking models in recommendation systems, providing insights into improving the relevance and effectiveness of recommendations. [10]

Wide & Deep Learning for Recommender Systems::

- Cheng et al. (2016) introduce wide & deep learning techniques for recommender systems, combining the strengths of both memorization and generalization to enhance recommendation performance. [11]

Based on the observations and analysis of the literature [12]–[16], several research gaps, issues, and challenges can

TABLE I: References, Technique Used, and System's Goal

References	Technique Used	System's Goal
Iswandhani and Muhajir (2018)	K-means cluster analysis	Identification of three tourist destination clusters based on social media popularity, providing insights into destination popularity.
CURUMIM: A Serendipitous Recommender System for Tourism Based on Human Curiosity	Content-Based (CB) and Collaborative Filtering (CF) techniques	Personalized tourism recommendations based on Facebook data to surprise users positively.
Fundeanu, D.D.	Innovative regional cluster model	Leveraging various databases for identifying and supporting the development of successful tourism clusters, offering a comprehensive framework for tourism development.
AI Based Tour Management Assistant	Chatbots controlled by artificial intelligence	Addressing customer needs by offering timely information on key factors such as infrastructure facilities and destination tourism infrastructure facilities.
Personalized Museum Exploration by Mobile Devices	Deep Learning and Fuzzy Logic techniques	Implicitly detecting users' preferences based on the geolocation of social media photos.

be identified in the context of Tourist Spot Recommendation Algorithms:

- Limited Integration of AI: While there is a growing interest in AI in the tourism industry, there is a need for more comprehensive and integrated AI solutions. Many existing studies [3], [4] focus on specific aspects, such as clustering or vendor evaluation, without considering the broader spectrum of travel management.
- Data Sources and Quality: The accuracy and quality of data from social media and tourism databases still need to be improved [5]. Ensuring the reliability of data used for clustering and recommendations is vital for the success of Tourist Spot Recommendation Algorithm.
- Personalization: Most literature focuses on the general clustering of tourist destinations but needs more in-depth personalization [6]. AI can offer highly personalized recommendations, and further research is needed to harness this potential to enhance user satisfaction.
- Scalability and Adaptability: AI models' scalability and adaptability to various tourism environments are challenging [7]. The ability to apply AI solutions to different regions and travel preferences requires further exploration.
- User Trust and Privacy: Ensuring user trust and privacy when collecting and using data for personalized recommendations is critical [8], [9]. Striking a balance between personalization and user privacy is a continuous challenge.

B. *Clustering Algorithms:*

- Bezdek et al. (1984), Ghosh and Dubey (2013), Cannon et al. (1986), Kaur et al. (2014), Harikumar and Surya (2015), Anwar et al. (2021), Murtagh and Contreras (2012, 2017), and Sisodia et al. (2012) collectively provide an overview of clustering algorithms, including fuzzy c-means and k-medoid methods, offering insights into their efficiency and application domains. [17]–[25]

Addressing these gaps and challenges is essential for the continued development and improvement of the Tourist Spot Recommendation Algorithm, ultimately enhancing the travel experience for users.

IV. Problem Definition

The existing AI-based tourism management applications need comprehensive integration, accurate and reliable data sources, and the ability to provide highly personalized travel recommendations [10], [11]. Furthermore, the scalability and adaptability of these applications to diverse tourism environments still need to be improved. The challenge is to develop an AI-driven tourism management app that overcomes these limitations, ensuring user trust, privacy, and satisfaction. This problem definition encapsulates the challenge of developing a Tourist Spot Recommendation Algorithm using Heuristics is an AI-based tourism management app that leverages high-quality data, offers personalization, and scales to various tourism scenarios while safeguarding user privacy and trust. The goal is to maximize user satisfaction by addressing the identified research gaps and challenges.

V. Proposed Framework

In developing the AI-based tourism management app, we have structured our framework to address the identified challenges and achieve a highly efficient and personalized tourism recommendation system. This framework explains the following steps and components in detail:

1) Data Preprocessing: The first step involves preprocessing the data to ensure its quality and readiness for analysis. It includes data cleaning, the removal of duplicates, and appropriate data type conversions.
2) K Means Clustering: We utilize the K-means clustering algorithm to group data points based on geographical coordinates. The primary features for clustering are latitude and longitude, representing the locations' geographical positions. We employ the elbow method to determine the optimal number of clusters (K), which calculates the Within-Cluster-Sum of Squared Errors (WSS) for different K values. Euclidean Distance: It measures the shortest distance between two locations (x1,y1) and (x2,y2).

$$\text{Distance} = \sqrt{(x_2 - x_1)^2 + (y_2 - y_1)^2}$$

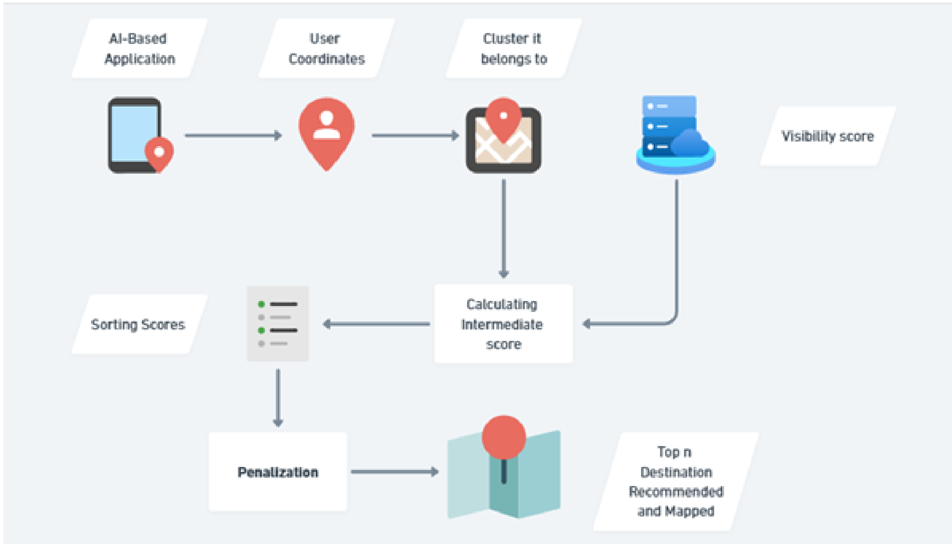

Fig. 1: Flowchart of the Framework

Algorithm 1: K-Means(data, K, max_iterations)

```
Data: data, K, max_iterations
Result: centroids, cluster_assignments
centroids = randomly_initialize_centroids(data, K);
cluster_assignments = initialize_empty_clusters(K);
for iteration in range(max_iterations) do
    for i in range(len(data)) do
        data_point = data[i];
        nearest_centroid =
          find_nearest_centroid(data_point, centroids);
        cluster_assignments[nearest_centroid].append(data_point);
    new_centroids =
      calculate_new_centroids(cluster_assignments);
    if new_centroids are close to centroids then
        break;
    centroids = new_centroids;
return centroids, cluster_assignments;
```

3) Calculation of Optimal Recommendations: Our recommendation system employs a novel evaluation metric that consists of three steps: Visitability Score, Intermediate Score, and Penalization.

- Visitability Score(λ): This metric assesses the popularity and visitability of a tourist spot to potential visitors. It calculates a weighted average of normalized ratings and visitor counts. Initially, weights for ratings and visitors are set arbitrarily, but these can be fine-tuned based on data collected from the user and the model's performance.

$$\lambda = (w_R \cdot n_R) + (w_V \cdot n_V) \tag{1}$$

where:

λ is the Visitability score
w_R is the weight of rating
n_R is the normalized rating
w_V is the weight of visitors visited
n_V is the normalized visitors

- Intermediate Score (κ): This metric considers several crucial factors, including the destination's Visitability Score, which gauges its popularity and prominence, and the user's Personalization preferences, ensuring tailored recommendations. Additionally, it considers the Distance factor to provide recommendations within the user's preferred proximity. By harmonizing these factors and their respective weights, the Intermediate Score offers a balanced assessment of potential destinations. It empowers travelers to explore places that align with their interests and cater to their convenience, resulting in a more satisfying and personalized travel experience.

$$\kappa = (w_\lambda \cdot n_\lambda) + (w_\rho \cdot \rho) - (w_D \cdot n_D) \tag{2}$$

where:

κ is the Intermediate Score
w_λ is the weight of Visitability Score
n_λ is the normalized Visitability Score
w_ρ is the weight of Personalization score
ρ is the Personalization Score
w_D is the weight of distance
n_D is the normalized distance

- Personalization Score (ρ) is a binary value(0 or 1) if the category of the place lies in the interest of the use, then 1; otherwise, 0.
  Penalization: If a category has already been recommended to the user, it is penalized to prevent recommending the same type repeatedly. A new table is created, and the intermediate score is adjusted for previously recommended categories in the same category as the following recommendation. The data is then sorted again to provide updated results.

$$\psi = \kappa + \delta \tag{3}$$
$$\delta = (i_c - 1)^2 \cdot \alpha \tag{4}$$

where:

ψ is the final score
δ is the penalty
i_c is the ith tourist spot in the category list c
α is penalty factor constant

A. Additional Components

- Clustering: The geographical coordinates of locations in India are clustered to identify nearby places for tourists. Clustering techniques such as K-means clustering are used to group the locations effectively. Definitions:
- Visitability Score: A metric used to measure the popularity and visitability of a tourist spot or destination to potential visitors. Intermediate Score: A metric to determine how prominent a specific tourist spot is to a particular visitor based on location and personalization. .
- Penalty: A mechanism for reducing the intermediate score of categories that have already been recommended to avoid repetitive recommendations.
- Final Score: The final score of a tourist spot is used to determine whether it will be recommended to the user.

This model framework combines clustering, visitability scoring, and penalization to offer tourists highly personalized and efficient recommendations for their travel itineraries, taking into account popularity and location. Weight adjustments and iterative processes enhance the accuracy and relevance of submissions.

B. Clustering Methods

- K-Means Clusting : K-means clustering is a popular unsupervised machine learning algorithm used for partitioning a dataset into K distinct, non-overlapping subsets (clusters). The goal of the K-means algorithm is to group data points that are similar to each other while keeping the clusters as distinct as possible. It is widely used in various fields, including data analysis, image processing, and pattern recognition.
  By using the elbow method, which is used to determine the optimal number of clusters in a dataset for clustering, we can conclude that k=15 was the elbow point.
- Fuzzy C-Means (FCM): Fuzzy C-Means clustering is a soft clustering algorithm that allows data points to belong to multiple clusters simultaneously, assigning a degree of membership to each point for each cluster. FCM is an extension of the traditional K-Means clustering algorithm, providing a more flexible approach for cases where data points may have ambiguous cluster assignments.
  The objective function for Fuzzy C-Means clustering is given by:

$$J_m(U, V) = \sum_{i=1}^{N} \sum_{j=1}^{C} u_{ij}^m \|x_i - v_j\|^2 \tag{5}$$

subject to the constraints:

$$\sum_{j=1}^{C} u_{ij} = 1 \quad \text{for } i = 1, 2, \ldots, N \tag{6}$$
$$u_{ij} \in [0, 1] \quad \text{for } i = 1, 2, \ldots, N,\ j = 1, 2, \ldots, C \tag{7}$$

where:

$J_m(U, V)$ is the fuzzy objective function
N is the number of data points
C is the number of clusters
u_{ij} is the membership degree of data point x_i to cluster v_j
m is a fuzziness parameter
$V = \{v_1, v_2, \ldots, v_C\}$ is the set of cluster centroids

- K-medoids Clustering: K-medoids is a partitioning method used in cluster analysis. In k-medoids clustering, the goal is to partition a dataset into k clusters, where each cluster is represented by one of the data points called a ”medoid.” A medoid is the most centrally located point within a cluster, minimizing the sum of dissimilarities (or distances) between itself and the other cluster's other points.
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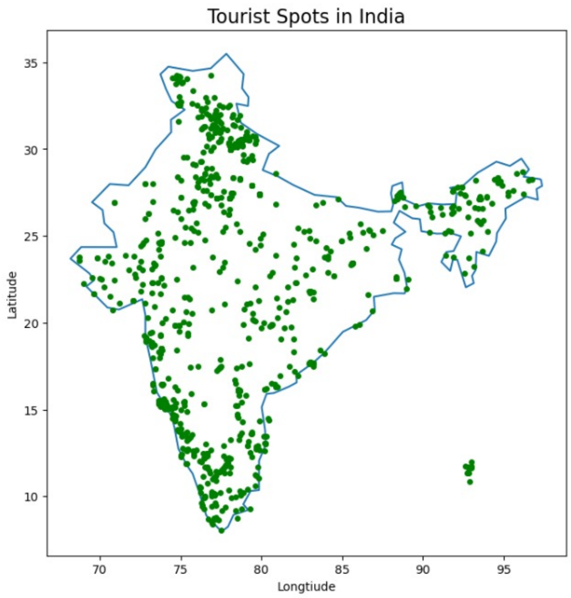
  The formula for k-medoids clustering is given by:

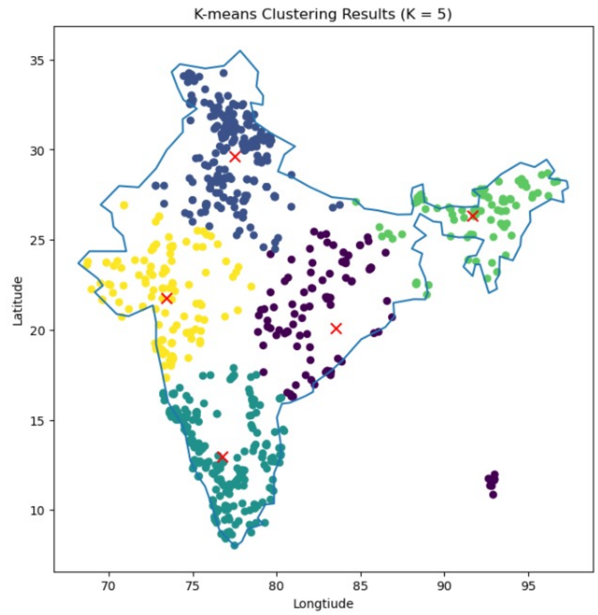
$$D(I, j) = \sum_{i=1}^{k} \sum_{l \in C_i} d(j, l) \tag{8}$$

where $D(I, j)$ is the total dissimilarity of cluster C_I with medoid j, and $d(j, l)$ represents the dissimilarity (distance metric) between medoid j and data point l in cluster C_i.

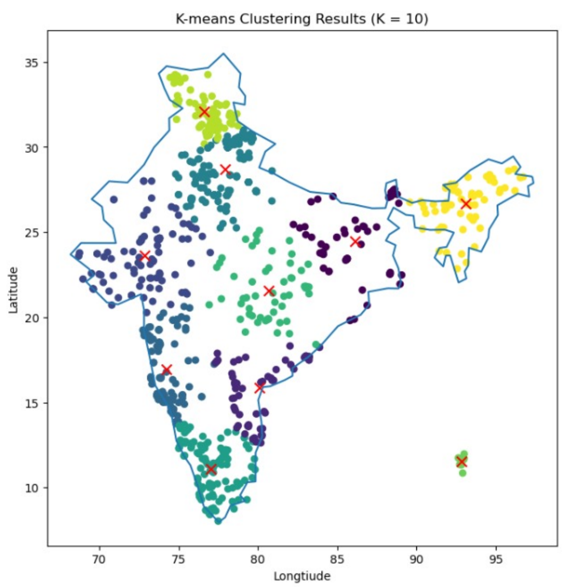
- Hierarchical clustering: Hierarchical clustering is a type of cluster analysis that builds a hierarchy of clusters. It can be visualized as a tree structure, called a dendrogram, where each node represents a cluster. The leaves of the



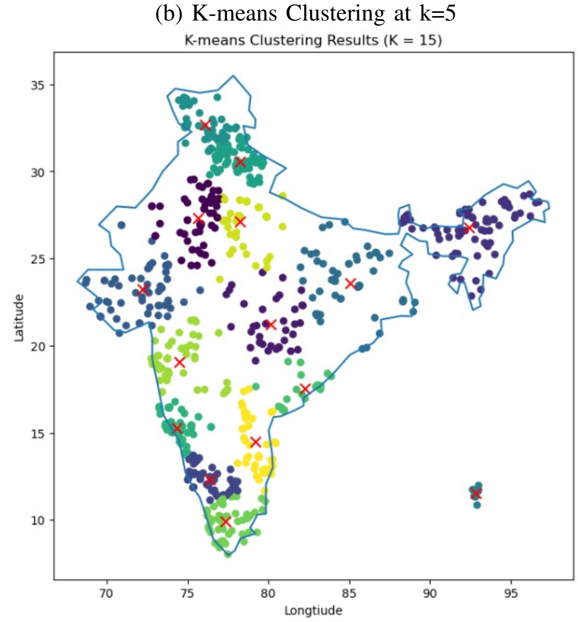
(a) K-Mean Clustering



(b) K-means Clustering at k=5



(c) K-Mean Clustering at k=10



(d) K-Mean Clustering at k=15

tree are the individual data points, and as you move up the tree, clusters are formed by merging or splitting existing clusters.

Hierarchical clustering can be represented by the following formula:

$$d_{ij} = \text{some function}(C_i, C_j) \tag{9}$$

where d_{ij} is the distance between clusters C_i and C_j. The function used to calculate the distance may vary based on the linkage method, such as single linkage, complete linkage, or average linkage.

C. Sum of squared error(SSE):

SSE is a metric describing how dispersed or spread data points are inside a cluster. It is frequently utilized to evaluate the quality of the clustering solution as a component of an objective function or assessment measure. Depending on the clustering technique being utilized, the precise formula could change. The sum of squared error (SSE) is used to assess how well clustering algorithms perform, especially in partitioning techniques like k-means clustering. SSE measures the degree of variance or dispersion inside a cluster. Often, the objective of clustering is to reduce the SSE. A tighter and more cohesive cluster is suggested when the SSE is smaller since it shows that

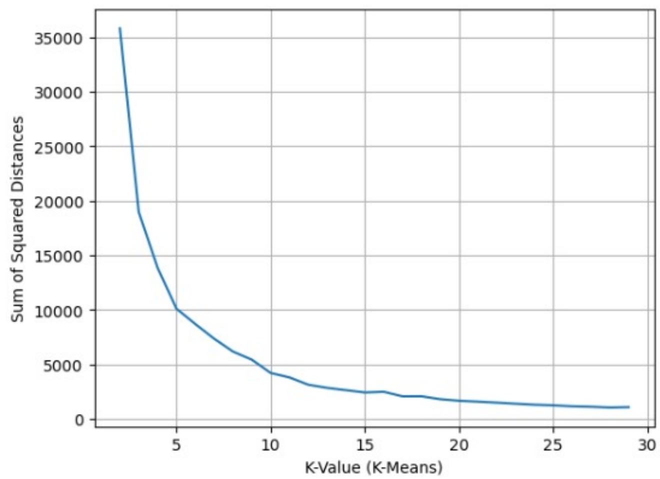


Fig. 3: Determination of the best cluster using the Elbow method

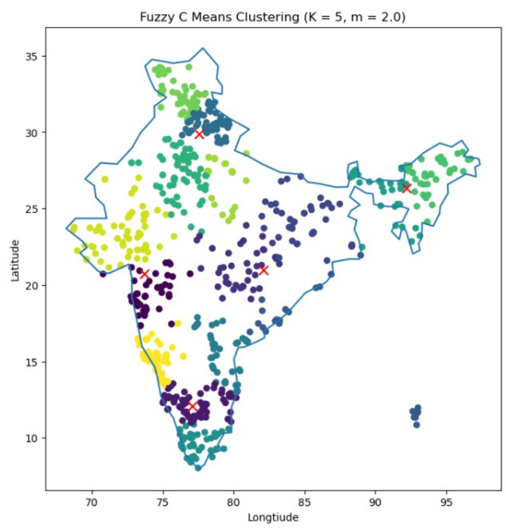


Fig. 4: Fuzzy C-Means Clustering at k=5

the data points inside each cluster are closer to their centroid.

The Sum of Squared Error (SSE) in clustering is given by:

$$SSE = \sum_{i=1}^{k} \sum_{j=1}^{n_i} \|x_{ij} - c_i\|^2$$

k is the number of clusters. n_i is the number of data points in cluster i. x_{ij} is the j-th data point in cluster i. c_i is the centroid of cluster i.

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TABLE II: Sum of Squared Error Values for Different Clustering Methods

Clustering Method	**Sum of Squared Error**
K-medoids	13941.76
K-means	13118.28
Hierarchical Clustering	12374.69
Fuzzy C-Means (FCM)	12981.59

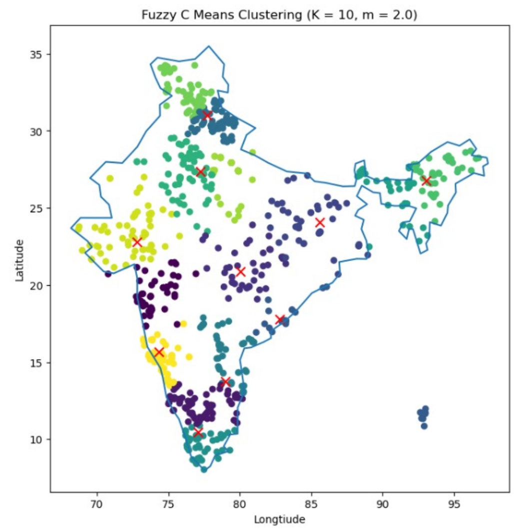


Fig. 5: Fuzzy C-Means Clustering at k=10

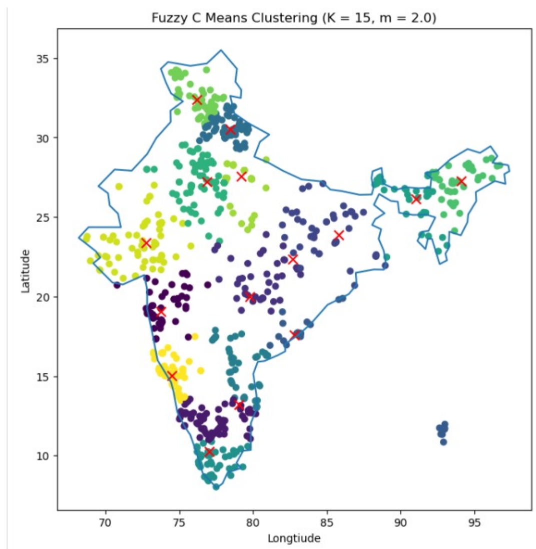


Fig. 6: Fuzzy C-Means Clustering at k=15

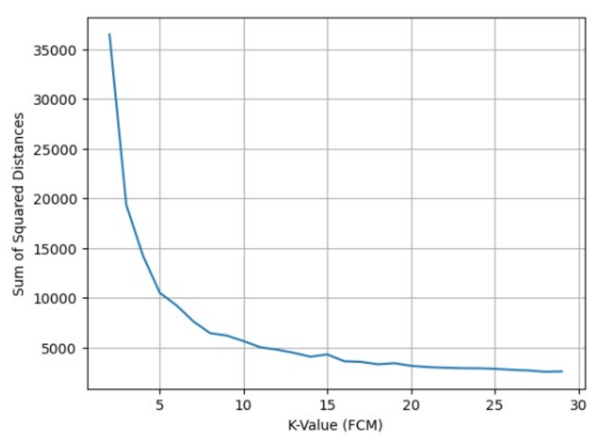


Fig. 7: Determination of the best cluster using the Elbow method for Fuzzy C-Means

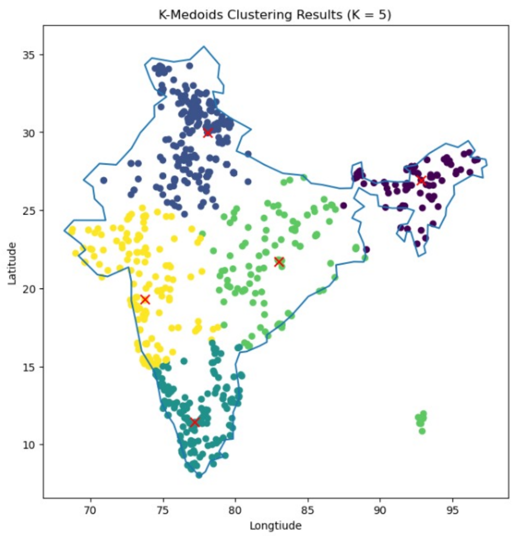


Fig. 8: K-medoids Clustering at k=5

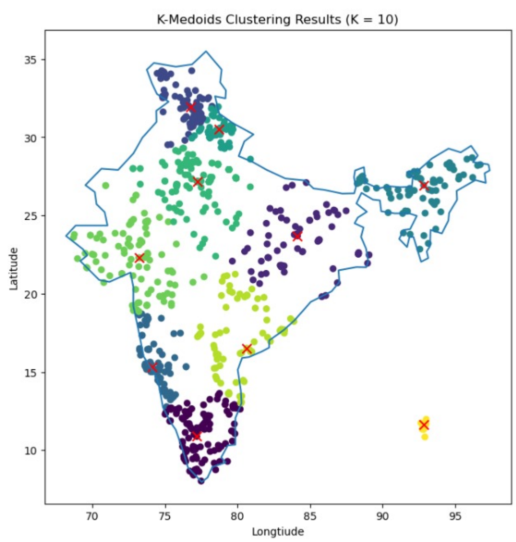


Fig. 9: K-medoids Clustering at k=10

VI. Results

The outcomes demonstrate the functionality of the application, showcasing a seamless process from the initial selection of the starting location to the generation of a comprehensive itinerary. Users are guided through a user-friendly experience, starting with the choice of their location and culminating in the efficient formation of a personalized travel plan. The application effectively navigates users through each step, ensuring a smooth and intuitive journey from location selection to the completion of a well-structured itinerary. As of now, the application encompasses a diverse array of 13 distinct destination categories. These categories provide users with a wide range of options, allowing for varied and personalized travel experiences based on their preferences and interest

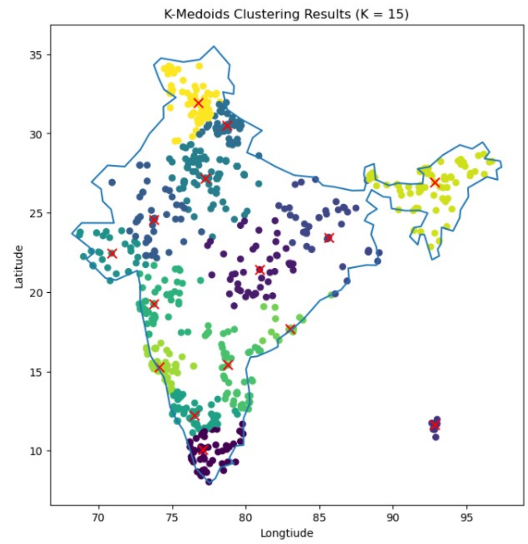


Fig. 10: K-medoids Clustering at k=15

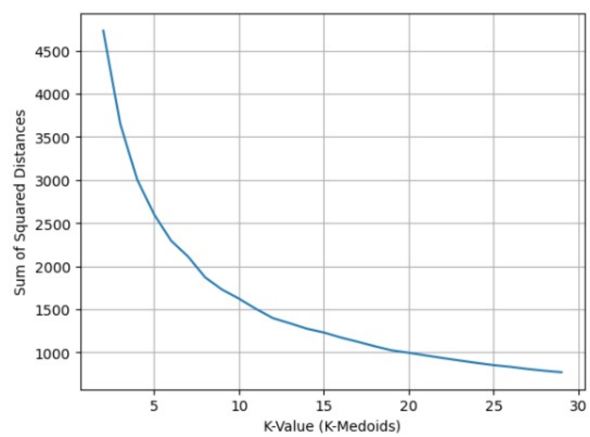


Fig. 11: Determination of the best cluster using the Elbow method for K-medoids

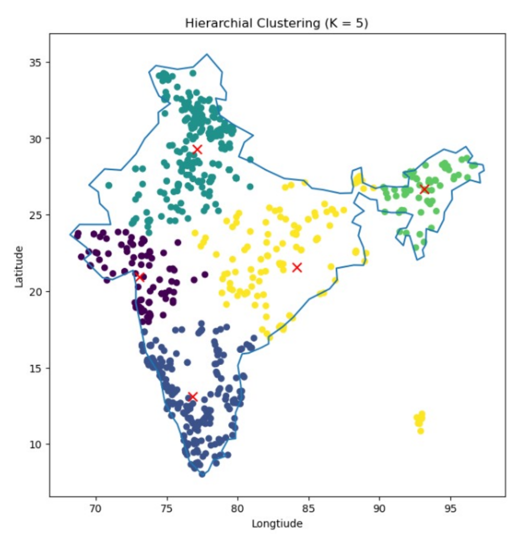


Fig. 12: Hierarchical Clustering at k=5

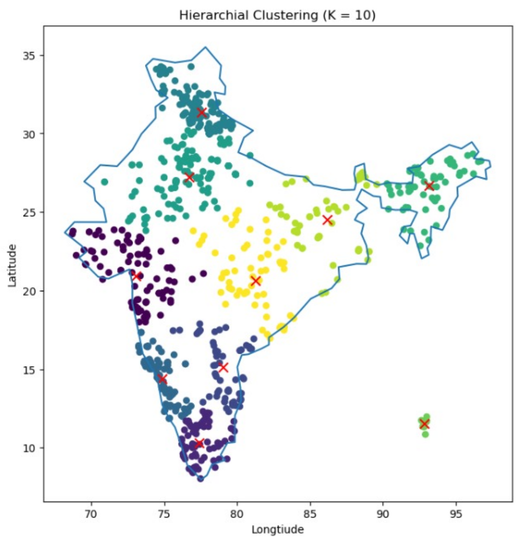


Fig. 13: Hierarchical Clustering at k=10

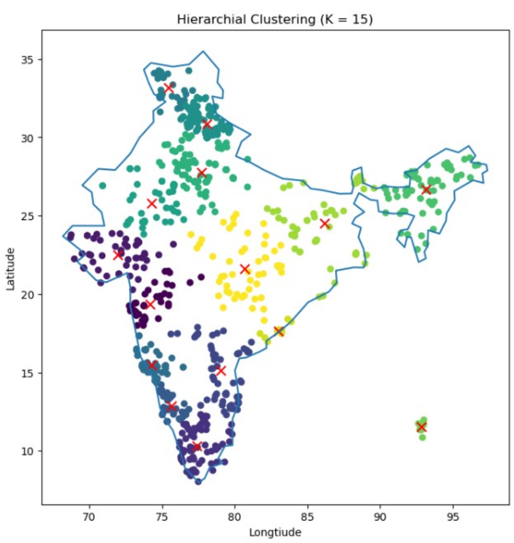


Fig. 14: Hierarchical Clustering at k=15

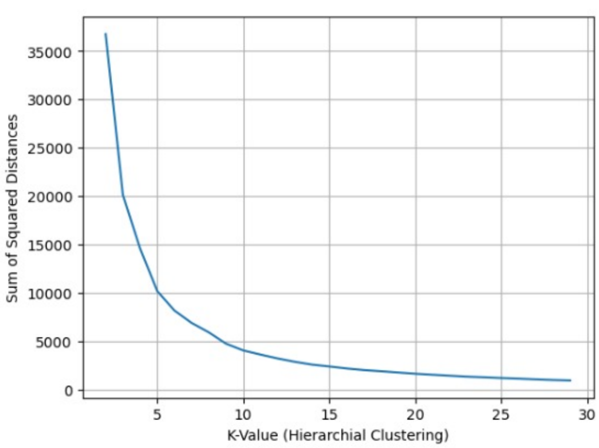
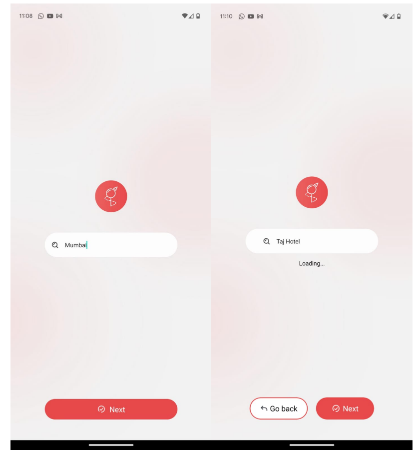
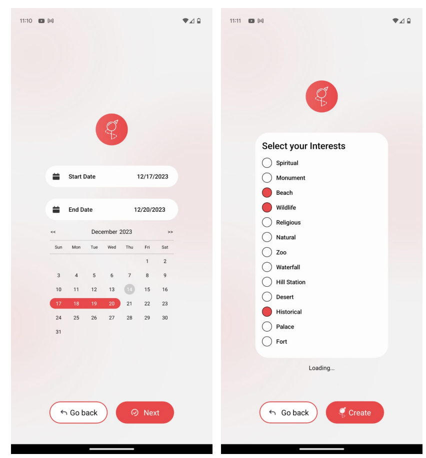


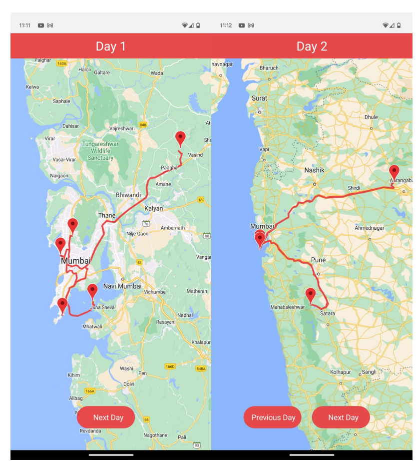
Fig. 15: Determination of the best cluster using the Elbow method for Hierarchical Clustering



(a) FIGURE 1 (b) FIGURE 2



(c) FIGURE 3 (d) FIGURE 4



(a) DAY 1 (b) DAY 2

VII. Conclusion and Future Directions

In conclusion, our Tourist Spot Recommendation Algorithm using Heuristics project has made remarkable strides in optimizing the recommendation system for travelers. Through the implementation of K-means clustering with an optimal K value of 15, we have successfully grouped tourist destinations based on geographical proximity, resulting in more coherent and efficient itineraries for users. The Visitability Score, which integrates normalized ratings and visitor data, represents a significant advancement in tailoring user recommendations. To further enhance the precision and relevance of our recommendations, we actively refine the weights assigned to different factors within the model. Through trial and error, we are fine-tuning the importance of various scores to ensure an accurate representation of places. Currently, our weight adjustments prioritize a Visitability Score with a weight of 0.25, a Personalization Score with a weight of 0.5, a Normalized Distance with a weight of 0.25, and a Penalty Factor Constant set at 0.25. This model framework combines clustering, visitability scoring, and penalization to offer tourists highly personalized and efficient recommendations for their travel itineraries, taking into account popularity and location. Weight adjustments and iterative processes enhance the accuracy and relevance of submissions.

1) Data Expansion: Our goal is to accumulate more comprehensive datasets. This includes the collection of online social community data to uncover hidden gems in specific areas, particularly focusing on tourist destinations. This process entails gathering additional information such as precise geographical coordinates, user ratings, and visitor statistics. The acquisition of a more expansive and diverse dataset will empower us to deliver more nuanced and refined recommendations.
2) Feedback based hyperparameter tuning: User reviews will serve as a data-driven approach to improve our model's performance by informing both dataset augmentation and hyperparameter tuning, specifically considering interest alignment, distance constraints, and rating-based weighting.
3) Improve the algorithm via introducing new formulas and algorithms.
4) Add more functionalities: Add more features in the app. Includes Hotel dataset and budget and various more parameters to improve user experience.

By focusing on these future directions, we anticipate that our AI-based tourism management app will continue to evolve, providing users with an even more tailored, efficient, and enjoyable travel experience. This commitment to ongoing improvement ensures that our system remains at the forefront of AI-driven tourism management.

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