Tourism Data Exploration: Analysis and Visualization for Impactful Insights

A PROJECT REPORT

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CERTIFICATE

This is to certify that the Project report **"TOURISM DATA EXPLORATION: ANALYSIS AND VISUALIZATION FOR IMPACTFUL INSIGHTS"** being submitted by VAISHNAVI C, SHRUTHI V AND RUTHIKA S SHETTY bearing roll number(s) 20211CSE0846, 20211CSE0298 AND 20211CSE0308 in partial fulfillment of the requirement for the award of the degree of Bachelor of Technology in Computer Science and Engineering is a bonafide work carried out under my supervision.

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DECLARATION

We hereby declare that the work, which is being presented in the project report entitled **TOURISM DATA EXPLORATION: ANALYSIS AND VISUALIZATION FOR IMPACTFUL INSIGHTS** in partial fulfillment for the award of Degree of **Bachelor of Technology** in **Computer Science and Engineering**, is a record of our own investigations carried under the guidance of **MS. SREELATHA P.K, Assistant Professor, School of Computer Science Engineering & Information Science, Presidency University, Bengaluru.**

We have not submitted the matter presented in this report anywhere for the award of any other Degree.

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ABSTRACT

Tourism happens to be a dynamic and fast-evolving sector, which is largely significant to economic development and cultural exchange. The project aims at improving the Indian tourism industry with an application of Artificial Intelligence and Machine Learning (AIML) techniques, providing insights and solutions to the industry through an analysis of varied datasets concerning Indian tourism-clustering, predictive modelling, and trend analysis to find useful patterns and insights within travel behavior, regional performance, and socio-economic impacts.

Clustering models assign clusters of tourist spots on aspects such as geographic characteristics, popularity, and preferences of visitors to create possible configurations of travel options. Predictive models predict the travel patterns with which tourism authorities plan their domestic circuit tours and better allocation of resources. This project will specify seasonal trends through historical and demographic data analyses and preferences that are region-specific to enable stakeholders to promote sustainable tourism practices. Advanced algorithms like K-Means clustering include data pre-processing, exploratory analysis, and generation of data visualizations to drive insightful decision-making. Such results include identification of highly-rated landmarks, overcrowded tourist destinations, and performance statistics on tourism for regions, which are necessary for the right managing of the marketing strategy, planning of infrastructure, and optimization of resources.

This project builds a comprehensive framework with AI/ML-driven technique-based approaches alongside holistic datasets toward thinking about and acting in the complex world of the tourism ecosystem, which also points to the transformational power of data-driven decision-making toward a sustainable future.

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INTRODUCTION

1.1 Overview

Tourism is a vital industry, contributing significantly to global GDP and fostering cultural exchange. India, with its rich cultural and geographic diversity, attracts millions of travellers annually. However, evolving traveller preferences and increasing data availability demand advanced analytical approaches for better tourism management. Traditional methods of managing tourism lack the precision and scalability offered by modern data-driven techniques.

This project leverages Artificial Intelligence (AI) and Machine Learning (ML) to analyse tourist data. Using clustering and predictive modelling, the study identifies trends, segments destinations, and provides actionable insights for improved tourism planning. By employing algorithms such as K-Means for clustering and Principal Component Analysis(PCA) for predictive modelling, the project aims to revolutionize tourism management by offering sustainable, personalized, and efficient solutions.

1.1.1 Significance of Tourism Analytics

Tourism analytics helps stakeholders make data-driven decisions to optimize resources, improve traveller experiences, and promote sustainability. Key benefits include:

- **Resource Optimization**: Grouping destinations based on shared characteristics to manage resources effectively.
- **Personalized Travel Experiences**: Predicting traveler preferences for designing customized tour packages.
- **Marketing Strategies**: Targeting specific demographics through insights from tourism data.
- **Sustainability**: Promoting balanced tourism to prevent over-tourism and conserve resources.

By analysing patterns in the data, this project provides actionable recommendations for tourism boards and travel agencies.

1.2 Motivation

The project is driven by the need to address challenges in the tourism sector, such as seasonality, resource mismanagement, and lack of personalized services. The primary motivations include:

- **Enhancing Data Utilization**: Addressing the gap in using existing data to extract actionable insights.
- **Improving Traveler Experiences**: Understanding tourist preferences for tailored services.
- **Supporting Sustainability**: Developing data-driven solutions to promote eco-friendly practices.
- **Fostering Regional Development**: Identifying underexplored regions with high tourism potential.

This project aims to use AI/ML techniques to unlock the full potential of tourism analytics, fostering economic growth and sustainable practices.

1.3 Scope of the Project

The project focuses on utilizing a dataset of Indian tourist destinations to explore patterns and predict trends. The major areas covered include:

- **Data Preprocessing**: Cleaning and transforming data for analysis.
- **Clustering Analysis**: Using K-Means to group destinations based on similarities.
- **Predictive Modeling**: Employing Principal Component Analysis(PCA) to predict destination significance.
- **Actionable Recommendations**: Providing insights to stakeholders for resource planning and marketing strategies.
- **Visualization**: Presenting clear visualizations of results using tools like PCA.

CHAPTER-2

LITERATURE SURVEY

The study by Jiantao Wu et al [1] explores the impact of climate change on the tourism economy, a topic not yet fully realized despite increasing climate concerns. Using knowledge graph techniques, including weather data, the study aims to deepen understanding of the relationship between climate and tourism. Findings suggest that organizing climate and tourism data through knowledge graphs can provide valuable insights, potentially enhancing both quality of life and the resilience of the tourism industry. Method includes importing CSV datasets into a Neo4j knowledge graph (KG) using Cypher's load CSV command. Entities like "Airport" and relationships between "City" and "Weather Station" were mapped, with intermediate CSV files linking "Station" IDs to city names. Key properties, such as geodesic distances, were added to enhance data utility and calculation efficiency within the KG. The data was collected from various resources like NOAA GHCND, AviationStack, Climateq, Simplemaps.

This study by Olimpia Alcaraz et al [2] investigates the intersection of physical and digital realms in tourism, introducing smart tourism destinations (STDs) that leverage technology and open data to enhance visitor experiences and inform decision-making. It demonstrates how integrating open data with local business campaign data can innovate tourism management and foster smart ecosystems through public-private collaboration. An AI-based search engine using word embeddings was developed to identify relevant open data, improving traditional data retrieval. The findings highlight the potential of this integration to enrich tourist experiences and support destination management strategies, contributing insights on combining retail and open data in a real case study.

The initial internal data used in this study are derived from local campaigns known as *bono consumo* (consumer voucher), a promotional campaign resulting from the health crisis caused by COVID-19. The initial private dataset was compiled by APYMECO, the local traders' association, which gathered data on the usage of consumer vouchers in the four editions of the campaign: October 2021, June 2022, September 2022, and November 2022. This dataset comprises more than 300,000 entries.

This paper by Saman Forouzandeh et al [3] introduces a novel approach to travel recommendation systems in the tourism industry, combining the Artificial Bee Colony (ABC) algorithm with Fuzzy TOPSIS. The Techniques for Order of Preference by Similarity to Ideal Solution (TOPSIS) is utilized as a multi-criteria decision-making method to optimize recommendations. Data were collected through an online questionnaire from 1,015 respondents on Facebook. In the first stage, the TOPSIS model identifies a positive ideal solution based on four key factors. In the second stage, the ABC algorithm searches for destinations to recommend the best tourist spot to users, enhancing the decision-making process for tourists. The data was gathered through questionnaires provided to self-driven travelers. The authors distributed a survey to hotel visitors to gather data on the level of service. The data gathered by questionnaires, the exploration of popular topics, and the difficulty of materials were valued.

This paper by Tao Peng et al [4] aims to enhance tourism demand forecasting accuracy by integrating social network data with traditional data sources. Using a web crawler, the authors collect social network data and apply sentiment analysis using the BERT model. The study builds a forecasting model based on Gradient Boosting Regression Trees, incorporating structured variables such as weather and holidays. Using Huang Shan as a case study, the authors conduct an empirical analysis comparing the model's performance against existing models, supported by an ablation study. Results indicate that incorporating social network data significantly improves forecasting accuracy for tourism demand.
Social network data acquisition is mainly achieved through web crawlers, which can collect and organize data on the Internet in accordance with established rules.

This study by İbrahim Topal and Muhammed Kürşad Uçar [5] explores the growing importance of the tourism and travel sector in the global economy, emphasizing the influence of social media on consumer purchasing decisions. By analyzing historical user data from TripAdvisor, the research aims to employ artificial intelligence methods to identify profiles of consumers likely to prefer Turkey as a travel destination. This approach enables businesses to target the right audience and enhance the effectiveness of their promotional activities. Methods like F-Score Feature Selection Algorithm, classifiers such as Decision trees (DT), k Nearest Neighbors Classification Algorithm (KNN), Multilayer Feedforward Artificial Neural Networks (MLFFNN), Probabilistic Neural Networks (PNN), and Support Vector Machines

(SVMs) were used. The study used the travel data history of Chinese tourists taken from TripAdvisor. The data belong to a total of 624 users. The acquisition of historical data took place between 27 April and 11 May 2018.

Nesreen K. Ahmed et al [6] used models like MLP (Multilayer Perceptron) for classification/regression, RBF (Radial Basis Function) with Gaussian functions, GRNN (Generalized Regression Neural Network) using a Gaussian kernel, KNN (K-Nearest Neighbors) based on nearest neighbors, CART (Classification and Regression Trees) with decision trees, SVR (Support Vector Regression) using support vectors, and GP (Gaussian Processes) modeling data as a Gaussian process. This study explores machine learning methods for tourism demand forecasting, traditionally dominated by models like ARIMA and exponential smoothing. It evaluates the performance of seven machine learning models on Hong Kong's inbound travel data and examines the impact of adding the time index as an input variable, comparing these models' effectiveness against conventional approaches. In this study, data published in the study made by Law and Pine to forecast inbound travel demand for Hong Kong was used.

The study by Ram Krishn Mishra et al [7] shows the use of SVR and Random Forest Regressor. SVR (Support Vector Regression), adapted from Support Vector Machines, is used for predicting real-number data, offering infinite possible solutions for continuous outputs. Random Forest Regressor is a tree-based model that splits data into nodes, with predictions made by averaging responses in terminal nodes for regression tasks. It improves prediction accuracy and reduces overfitting by constructing multiple decision trees on different sub-samples of the dataset, making it more robust than a single decision tree, which is prone to overfitting due to random noise. This study examines international tourist data from 2010 to 2020, analyzing multiple dimensions to identify valuable features for forecasting. Using Support Vector Regression (SVR) and Random Forest Regression (RFR), the research predicts global tourist arrivals, achieving forecasting accuracies of 99.4% and 84.7%, respectively. The study also addresses the impact of COVID-19 lockdowns on forecasting accuracy. A substantial amount of data gathered by the government or other public entities is made available. These data sets are referred to as public data since they do not require specific authorization to use them.

The study by Noelyn M. De Jesus et al [8] used time series data of tourist arrivals, particularly around the COVID-19 pandemic, splitting the dataset into three partitions for model training and testing. These partitions were based on key events like the first COVID-19 case (January 2020), travel suspensions (March 2020), and stricter entry restrictions (December 2020). The dataset was loaded into the Orange Data Mining tool, and a Multilayer Perceptron (MLP) neural network was used for time series prediction. The model's performance was evaluated using metrics like MSE, RMSE, MAE, MAPE, and R^2. The best model was selected based on the highest R^2 and lowest MAPE, indicating how well the predictions matched the actual values. This research evaluates the predictive power of an artificial neural network (ANN) model for forecasting tourist arrivals, using tourism data from the Philippines spanning 2008-2022. The ANN was trained on three distinct data compositions and assessed with various time series evaluation metrics, achieving an R-squared value of 0.926 and a MAPE of 13.9%. The study found that including data from unexpected events, like the COVID-19 pandemic, improved model accuracy. The findings suggest that ANN can be a valuable tool for government and tourism stakeholders to support strategic and investment decisions. The researchers collected the actual inbound tourist arrivals to Philippines between 2008-2022 from the Department of Tourism's official website.

This article reviews machine learning techniques for predicting tourism, specifically analyzing prior studies in this domain. Bilal Sultan Abdualgalil et al [9] discuss various machine learning techniques applied to tourism data analysis, focusing on two primary activities: association learning and classification learning. Key techniques include Logistic Regression and Linear Regression for predicting binary and continuous outcomes, respectively; Decision Trees and Random Forests for supervised classification and regression; Support Vector Machines for binary classification; and Naive Bayes for fast and effective classification. Additionally, KNN is highlighted for its simplicity in classifying data based on nearest neighbors, while K-Means Clustering is used for unsupervised grouping of data. Other methods like Dimensionality Reduction (e.g., PCA) simplify datasets, and Gradient Boosting and AdaBoost improve model accuracy through iterative refinement. The results showed higher prediction accuracy when using the first-quarter dataset, demonstrating its effectiveness for forecasting tourist numbers. The dataset obtained from www.kaggel.com website was used.

This study by Dinda Thalia Andariesta et al [10] presents machine learning models for predicting international tourist arrivals in Indonesia during the COVID-19 pandemic using multisource Internet data. In this study, data from the Indonesian Statistical Bureau, TripAdvisor, and Google Trends were used to develop prediction models for international tourist arrivals. The process involved data preprocessing, feature extraction, and forecasting model development using ANN, SVR, and Random Forest. These models were evaluated using RMSE, MAE, and MAPE to ensure accuracy. The ANN model used previous tourist data, online posts, and search volumes as predictors. The RF model, known for its reliability, averaged predictions from multiple decision trees to improve forecasting performance. First, the researchers collected tourism data from the Indonesian Statistical Bureau Indonesia or BPS from January 2017 until June 2021. Next, we collect the data from a global online tourism platform, TripAdvisor.

CHAPTER-3

RESEARCH GAPS OF EXISTING METHODS

1. Scalability and Data Integration Challenges

Many studies encounter scalability issues, particularly when integrating multi-source data. For example, integrating diverse climate and tourism datasets to build knowledge graphs faces challenges as more data sources are added, limiting the model's efficiency in handling large-scale applications. Additionally, augmenting retail data with open datasets encounters compatibility issues, as open data is not always readily available or uniformly structured, further complicating integration efforts.

2. Limitations in Real-Time Application

Several existing methods rely heavily on historical data, which limits their applicability in real-time scenarios. For instance, models focusing on climate data and tourism relationships fail to address real-time decision-making needs due to their dependence on past datasets. Similarly, high computational demands in hybrid recommendation systems and AI-based forecasting approaches hinder their ability to deliver quick and actionable insights in real-time.

3. Privacy and Data Access Issues

The utilization of consumer and open data raises significant privacy concerns. Studies leveraging retail and open data for smarter tourism often face ethical and regulatory challenges, making it difficult to use consumer data without breaching privacy norms. Furthermore, accessing and pre-processing such data can be time-intensive and may not always yield consistent results.

4. High Computational Requirements

Many state-of-the-art methods require extensive computational resources, which may not be feasible for widespread adoption. For example, hybrid models that use evolutionary algorithms, TOPSIS, or artificial neural networks (ANNs) demand significant computational power, especially for processing and analysing complex data patterns. This limitation is particularly pronounced in real-time or resource-constrained environments.

5. Dependence on Specific Data Sources

Several models are overly reliant on specific platforms or types of data. For example, methods predicting tourist preferences for Chinese tourists depend heavily on TripAdvisor data, limiting the generalizability of insights across diverse tourist populations. Similarly, models

leveraging social media data or Google Trends are vulnerable to biases inherent in these platforms, which may not always reflect actual demand or tourist behaviour.

6. Scalability and Adaptability Challenges

Existing tourism systems struggle to scale during periods of high demand, such as peak travel seasons or major events, leading to server crashes, delays in processing, and reduced functionality. Additionally, they lack adaptability to integrate emerging technologies like augmented reality (AR) or virtual reality (VR) to enrich the tourism experience. These systems also fail to incorporate data from new sources, such as social media trends or real-time environmental changes, making them less responsive to tourists' evolving needs.

7. Limited Data Interoperability and Analytics

Tourism data is often dispersed across multiple entities—hotels, airlines, local businesses, and government agencies—with little to no interoperability between them. This results in missed opportunities for leveraging big data to generate actionable insights. For instance, platforms could use predictive analytics to anticipate peak travel periods, optimize pricing strategies, or recommend alternative destinations. However, the absence of unified data standards prevents stakeholders from collaborating effectively to enhance the tourist experience.

8. Environmental and Sustainability Concerns

Modern tourism systems seldom prioritize sustainability. There is limited integration of environmental monitoring or eco-friendly practices into tourism solutions. Platforms rarely provide tourists with real-time updates on environmental conditions, carbon footprints of their travel choices, or recommendations for sustainable alternatives. This gap prevents the tourism industry from aligning with global sustainability goals and addressing climate change impacts.

9. Inadequate Support for Multilingual and Diverse Cultural Needs

Many existing platforms offer limited support for multilingual users or fail to cater to diverse cultural needs. For international travellers, language barriers remain a significant challenge when navigating foreign destinations. Similarly, recommendations often fail to consider cultural preferences, dietary restrictions, or local customs, leading to suboptimal experiences for tourists from different backgrounds.

10. Weak Crisis Management Capabilities

Current tourism platforms are ill-equipped to handle unexpected disruptions, such as natural disasters, pandemics, or political instability. This makes it difficult for tourists to adapt to sudden changes or for service providers to mitigate the impact of crises on their operations.

CHAPTER-4

PROPOSED METHODOLOGY

4.1 Data Collection

Data collection is the foundational step of the process, focusing on gathering diverse and comprehensive datasets.

- **Sources of Data**: Data is sourced from social media platforms (e.g., Twitter, Instagram, and Facebook), travel review platforms (e.g., TripAdvisor, Google Reviews), and user interaction logs from tourism-related websites or apps. Social media data provides insights into public sentiment, trending destinations, and real-time updates on tourist behavior. Travel platforms contribute structured reviews, ratings, and destination-specific information, while user interaction data captures personalized preferences, search patterns, and booking behaviors.
- **Purpose**: Collecting data from multiple sources ensures diversity, enabling a holistic analysis of tourism trends and preferences. It also allows the model to capture dynamic factors such as seasonal shifts, sudden changes in demand, or emerging trends in the tourism sector.

4.2 Data Pre-Processing

The raw data collected is often incomplete, noisy, or inconsistent, necessitating pre-processing before it can be used for analysis.

- **Data Cleaning**: This step removes inconsistencies such as duplicate records, missing values, and irrelevant data. For example, irrelevant social media posts or incomplete reviews are filtered out to maintain dataset quality.
- **Normalization**: Data is standardized to ensure uniformity. For instance, varying formats for dates, currencies, or location names are normalized to ensure compatibility across all datasets.
- **Feature Extraction**: Relevant features are identified and extracted for analysis. Key features may include traveler demographics (age, nationality), destination attributes (location, cost, activities).
- **Purpose**: Effective data pre-processing reduces noise and ensures that the models receive clean, structured data for better performance and accuracy.

4.3 Machine Learning

- **Recommendation Models**: Using collaborative filtering, content-based filtering, or hybrid methods, these models offer personalized suggestions to users. For example, based on a user's past searches and preferences, the system can recommend destinations, accommodations, or activities tailored to their interests.
- **Predictive Models**: These models use historical data and patterns to forecast future trends. For instance, regression models or time series analysis can predict peak tourist seasons, the demand for specific destinations, or the impact of external factors like weather or global events.
- **Clustering Models**: Clustering algorithms such as K-Means or destinations based on shared attributes. For example, tourists can be segmented into clusters based on travel preferences, budget ranges, or preferred activities, enabling targeted marketing and customized packages.
- **Purpose**: Machine learning enables the system to derive actionable insights from data, offering accurate and user-focused analytics for both tourists and industry stakeholders.

4.4 Visualization

Graphs were created using Python libraries such as **Matplotlib** and **Seaborn** to visualize key metrics, trends, and predictions. Examples include:

- **Top Destinations**: Bar charts showcasing the most popular tourist spots based on Google reviews or visitor numbers.
- **Seasonal Demand Fluctuations**: Line graphs depicting patterns in tourism demand during different times of the year.

- **Features**: Graphs are designed to be intuitive, with clear labels, legends, and color schemes for easy interpretation. Real-time data updates and drill-down capabilities provide deeper insights for stakeholders.
- **Purpose**: Visualization bridges the gap between technical analysis and practical decision-making, enabling stakeholders to identify trends, evaluate performance, and implement data-driven strategies effectively.

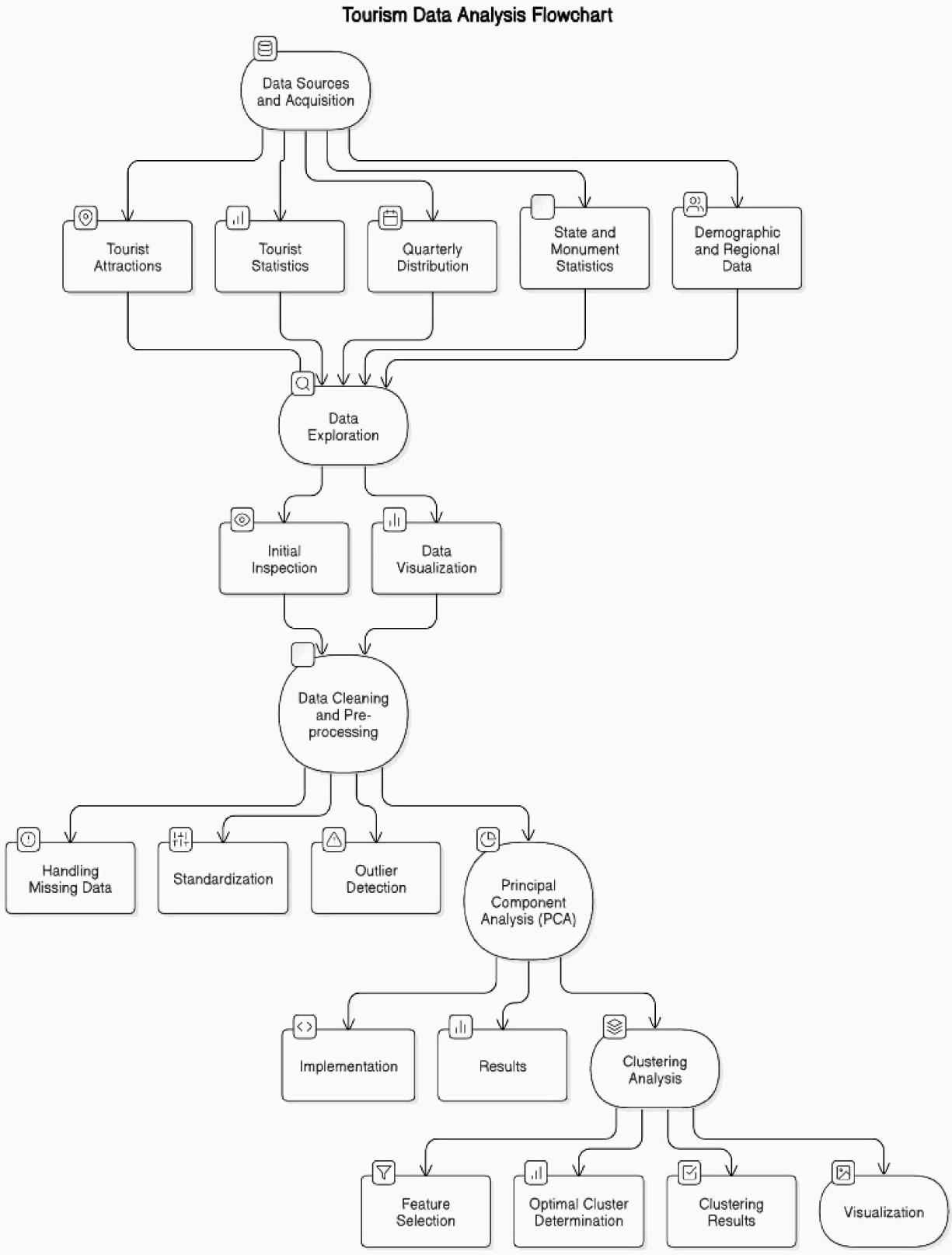

Figure 4.1: Tourism Data Analysis Flowchart

This flowchart outlines the journey of analysing tourism data, starting with gathering various sources like tourist attractions, demographics, seasonal trends, and state-specific statistics. The collected data is then explored to uncover patterns through initial inspection and visualization. Afterward, it's cleaned and pre-processed by handling missing values, detecting outliers, and standardizing formats. Key features are extracted using techniques like PCA (Principal Component Analysis) to simplify the data. Next, clustering methods are implemented to group similar patterns, with steps to select the best features, determine the ideal number of clusters, and interpret the results. Finally, the findings are visualized to offer insights into tourism trends, helping drive better decisions for the industry.

CHAPTER-5

OBJECTIVES

1. Develop a Robust Clustering Algorithm for Tourist Data Segmentation

Segmentation of tourist data is essential for understanding the diverse needs and preferences of travelers. This objective involves exploring and implementing a variety of clustering algorithms, such as K-Means to categorize tourists into distinct groups based on relevant attributes.

- **Attributes for Segmentation**: Demographics (e.g., age, gender, nationality), travel preferences (e.g., adventure, luxury, budget-friendly), and behavioral patterns (e.g., frequency of travel, spending habits) will serve as key features for clustering.
- **Algorithm Selection**: Each clustering algorithm will be evaluated for its ability to handle large, diverse datasets. For instance, K-Means is ideal for well-defined clusters, hierarchical clustering provides insights into relationships between clusters.
- **Outcome**: The clustering process will help tourism stakeholders identify distinct groups of tourists, enabling the design of personalized experiences and targeted marketing strategies.

2. Construct Predictive Models for Forecasting Tourist Travel Clusters

Accurate forecasting of tourist trends is crucial for proactive decision-making. This step focuses on developing and evaluating predictive models such as time series analysis, regression models, and classification models to predict how tourist clusters evolve over time.

- **Time Series Analysis**: This will be used to understand seasonal and temporal trends, such as peak travel periods and off-season dynamics.
- **Regression Models**: These will identify key factors influencing changes in tourist clusters, such as economic shifts, political events, or natural disasters.
- **Classification Models**: These will help categorize future tourists into pre-defined clusters, ensuring predictive accuracy for tailored service offerings.
- **Outcome**: These predictive models will empower tourism authorities and businesses to anticipate changes, optimize resources, and plan effectively for varying levels of demand.

3. Analyze and Interpret Results from Clustering and Predictive Models

Once the clustering and predictive models are implemented, a thorough analysis of the results is essential to derive meaningful insights.

- **Cluster Characteristics**: Key attributes and behavioral patterns of each cluster will be identified. For example, one cluster might represent budget travelers who prefer off-season travel, while another could consist of luxury tourists seeking high-end services.
- **Trends and Patterns**: By analyzing predictive results, emerging trends—such as an increasing interest in eco-tourism or shifts in travel preferences post-pandemic—can be identified.
- **Outcome**: This step provides a deeper understanding of tourist behaviors and market dynamics, forming the foundation for strategic planning and innovation in tourism services.

4. Develop Actionable Recommendations for Tourism Authorities

Using insights derived from clustering and predictive models, actionable recommendations will be provided to tourism authorities to enhance their planning and service delivery.

- **Optimizing Resource Allocation**: Authorities can allocate resources efficiently, such as enhancing infrastructure in popular destinations or preparing for peak seasons.
- **Targeted Marketing Campaigns**: Specific clusters can be targeted with tailored marketing strategies. For instance, promoting cultural festivals to tourists interested in heritage or adventure packages to thrill-seekers.
- **Improving Service Offerings**: Insights can guide the development of new services, such as family-friendly amenities, eco-friendly travel options, or luxury accommodations based on identified demand.
- **Outcome**: These recommendations aim to boost tourist satisfaction, increase revenue, and ensure sustainable tourism growth.

CHAPTER-6

IMPLEMENTATION

6.1 Dataset Description

The project uses a wide range of datasets to analyse tourism patterns and trends in India. These datasets include:

1. **India-Tourism-Statistics-1981-2020-fta_nri_ita**:
    - Historical data on Foreign Tourist Arrivals (FTAs), Non-Resident Indians (NRIs), and Indian Tourist Arrivals (ITAs) from 1981 to 2020.
    - Used for trend analysis and forecasting.
2. **India-Tourism-Statistics-2001-2019-agegroup**:
    - Distribution of tourists by age groups between 2001 and 2019.
    - Helpful for understanding demographic trends in tourism.
3. **India-Tourism-Statistics-2001-2019-quaterly**:
    - Quarterly distribution of tourists from 2001 to 2019.
    - Used to analyze seasonality and peak tourist periods.
4. **India-Tourism-Statistics-2001-2019-worldvsindia**:
    - Comparative data showing international vs. domestic tourism from 2001 to 2019.
5. **India-Tourism-Statistics-2019_region-and-reason**:
    - Region-wise data categorized by reasons for travel (e.g., leisure, business).
    - Used to identify regional tourism trends and purposes.
6. **India-Tourism-Statistics-2021-monuments**:
    - Visitor data for major monuments in India in 2021.
    - Helps assess the popularity of historical sites.
7. **India-Tourism-Statistics-region-2017-2019**:
    - Regional tourist trends from 2017 to 2019.
    - Analyzed to study fluctuations and preferences.
8. **India-Tourism-Statistics-statewise_2019-2020_domestic_foreign**:
    - State-wise statistics for domestic and foreign visitors from 2019 to 2020.
    - Enables comparisons between states and identifies popular destinations.

9. **Top Indian Places to Visit**:
    - Details on tourist attractions, including location, type, significance, ratings, and accessibility.
    - Used for clustering and destination analysis.

6.2 Pre-Processing and Integration

Each dataset was pre-processed and integrated into the analysis pipeline:

- **Standardization:** Numerical values were scaled using Min-Max normalization to facilitate clustering. Textual inconsistencies in columns like Zone and State were resolved using regex-based cleaning.
- **Feature Engineering:** Creating new attributes (e.g., Cost per Hour = Entrance Fee / Visit Duration) to enhance clustering and PCA. Consolidating categories, such as combining similar significance values (Historical, Cultural).
- **Outlier Detection:** Outliers in attributes like entrance fees and visitor ratings were identified using interquartile range (IQR) and treated accordingly.

6.3 Principal Component Analysis (PCA)

To reduce dimensionality and highlight underlying trends, PCA was performed:

Objective:

- Simplify high-dimensional data into fewer components while preserving variance.
- Identify key attributes influencing tourist behavior and destination popularity.

Implementation:

- Numerical attributes (Entrance Fee, Google Review Rating, Number of Reviews, etc.) were scaled and fed into PCA.
- The explained variance ratio was analyzed to determine how much information each component retained.

Results:

- The first two principal components explained a significant portion of the variance, representing combined influences of destination features (e.g., cost, significance, and reviews).

6.4 Clustering Analysis

Clustering was employed to group similar tourist destinations based on shared characteristics. The methodology involved:

- **Choice of Algorithm:** K-Means Clustering: Chosen for its simplicity and efficiency in handling structured data.
- **Feature Selection:** Features like Google Review Rating, cost per hour, and PCA-transformed dimensions were used to define clusters.
- **Optimal Cluster Determination:**
  - The Elbow Method was used to determine the optimal number of clusters (k) for K-Means. The value of k was selected where the inertia curve showed a "knee."
  - The silhouette score evaluated the quality of clustering by measuring cohesion (within-cluster closeness) and separation (distance between clusters). Higher silhouette scores indicated better cluster separability and compactness.
- **Clustering Results:** Destinations were grouped into clusters reflecting shared traits, such as affordability, cultural significance, or visitor ratings.
- **Insights and Metrics:**
  - Cluster Analysis: The mean of numerical features for each cluster was calculated to understand the characteristics of each group.
  - Insights were derived from these means, such as identifying high-rated premium destinations, budget-friendly spots, or eco-tourism potentials.

Clustering, an unsupervised learning approach, focuses on identifying patterns in unlabeled data, where conventional metrics like accuracy and precision are not applicable due to the absence of ground truth labels. Instead, methods such as the Elbow Method (to determine optimal cluster count), Silhouette Score (for evaluating cluster compactness and separability), and dimensionality reduction techniques like PCA (for visual interpretation) are employed to assess the effectiveness of clustering models like K-means.

6.5 Visualization

Effective visualization was key to communicating the findings. Specific techniques included:

- **Cluster Profiles:** Bar charts and radar plots depicted cluster-specific attributes, such as average ratings or entrance fees.
- **Temporal Trends:** Line graphs illustrated changes in FTAs and DTAs over decades.

6.6 Tools and Libraries

The study leveraged a robust data analysis pipeline built on Python:

Libraries:

- pandas and numpy: Data manipulation and numerical computations.
- sklearn: PCA, clustering, and evaluation metrics.
- matplotlib and seaborn: Visualization.

6.7 Development Environment: Google Colab for interactive exploration.

CHAPTER-7

TIMELINE FOR EXECUTION OF PROJECT

(GANTT CHART)

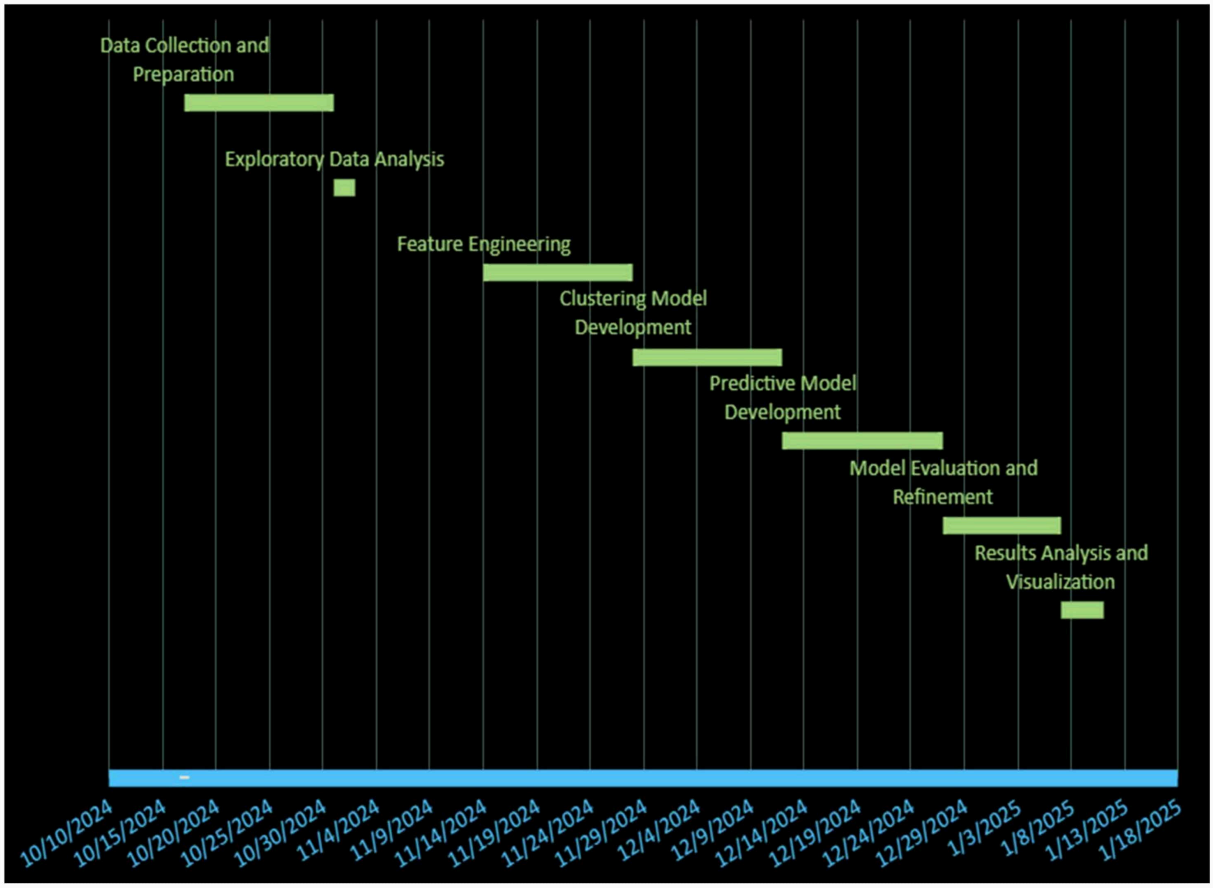

Figure 7.1: Gantt Chart

The Gantt chart outlines the timeline for our project, starting with Data Collection and Preparation from October 10, 2024, followed by a brief phase of Exploratory Data Analysis to uncover initial insights. Feature Engineering overlaps with Clustering Model Development, enhancing data for better performance. Subsequently, Predictive Model Development runs parallel, refining forecasting capabilities. The final stages, from late December 2024 to mid-January 2025, include Model Evaluation and Refinement and Results Analysis and Visualization to present actionable insights and outcomes.

CHAPTER-8

OUTCOMES

1. Accurate Tourist Segmentation:

- The clustering model is expected to segment tourists based on demographics, preferences, and behaviors effectively. This will allow tourism authorities and companies to better understand different tourist groups and cater to their needs.

2. Improved Forecasting of Tourist Travel Patterns:

- Predictive models developed will help forecast future tourist behaviors and travel preferences, enabling tourism operators to plan more efficiently and anticipate the needs of tourists in real-time.

3. Optimized Tour Package Scheduling:

- By forecasting tourist travel clusters, the project aims to optimize the scheduling and customization of domestic tour packages, increasing efficiency in resource allocation and improving tourist satisfaction.

4. Actionable Insights for Tourism Authorities:

- The analysis of the clusters and predictions will provide tourism authorities with actionable insights, such as how to allocate resources, design targeted marketing campaigns, and improve service offerings.

5. Contribution to Sustainable Tourism:

- The project will contribute to sustainable tourism practices by optimizing travel routes and packages, reducing unnecessary travel, and promoting eco-friendly options aligned with sustainability goals.

CHAPTER-9

RESULTS AND DISCUSSIONS

The objective of this project was to categorize top Indian tourist destinations into meaningful clusters based on their characteristics, such as ratings, entrance fees, and visiting time, to derive actionable insights for improving tourism strategies. By leveraging machine learning techniques, we identified patterns within the dataset and proposed recommendations tailored to the needs of each cluster.

The dataset was pre-processed to ensure compatibility with clustering algorithms. Irrelevant columns, such as names and text-based descriptions, were removed. Categorical features, including "Zone" and "Best Time to Visit," were label-encoded, while numerical features, like "Google Review Ratings" and "Entrance Fees," were normalized using standard scaling. These steps ensured the dataset was uniformly prepared for analysis.

To determine the optimal number of clusters, the Elbow Method and Silhouette Scores were applied to assess cluster quality for values of k ranging from 2 to 10. The Elbow Method revealed an inflection point at k=4, suggesting three distinct groups of destinations. Subsequently, the K-Means algorithm was implemented with three clusters, and each destination was assigned to one of these clusters based on its features.

We have categorized Indian tourist destinations into four clusters: Premium Destinations, Budget-Friendly Spots, Eco-Tourism Potentials, and Underrated Destinations. Each cluster represents distinct characteristics, target audiences, and development needs, offering valuable insights into the tourism landscape.

1. Premium Destinations: These destinations are well-established and cater to affluent, high-paying tourists, including international travellers. They are characterized by high Google review ratings, reflecting visitor satisfaction, and higher entrance fees, indicating exclusivity. DSLR cameras are typically allowed, showing less restrictive policies, and the destinations often offer premium experiences such as luxury accommodations and guided tours. To maintain their appeal, these destinations can focus on enhancing high-end amenities, personalized services, and exclusive packages to continue attracting affluent visitors.

2. Budget-Friendly Spots: Budget-friendly destinations are known for their affordability and accessibility, making them ideal for families, students, and large groups. These spots are characterized by low entrance fees and moderate Google review ratings, indicating decent satisfaction levels but room for improvement. Developing basic infrastructure and promoting family-friendly activities would enhance their appeal. Cost-effective promotional strategies can also help these destinations gain more visibility among their target audience.

3. Eco-Tourism Potentials: Eco-tourism destinations hold significant natural or ecological importance, appealing to eco-conscious travellers. These spots often have moderate entrance fees, which are typically used for conservation efforts. While they have high to moderate Google review ratings, DSLR restrictions may be in place to protect the environment. Developing eco-friendly infrastructure, such as nature trails and sustainable accommodations, can enhance their appeal. Additionally, targeted campaigns that highlight the ecological significance and sustainability of these destinations can attract environmentally aware tourists.

4. Underrated Destinations: This cluster consists of lesser-known and unexplored destinations with untapped potential. These destinations often have minimal or no entrance fees and lower Google review ratings, which could be attributed to a lack of awareness or inadequate infrastructure. However, they offer significant opportunities for development. Improving accessibility, infrastructure, and amenities, combined with targeted marketing efforts, can transform these destinations into attractive tourist spots. Collaborating with local communities and leveraging social media influencers can further boost their visibility and reputation.

Comparative Analysis of Clusters: When comparing the clusters, Premium Destinations stand out with the highest Google review ratings and entrance fees, targeting affluent tourists. Budget-Friendly Spots, in contrast, attract cost-conscious travellers with low fees and moderate ratings. Eco-Tourism Potentials offer a niche appeal to eco-conscious individuals, with fees often tied to conservation efforts. Underrated Destinations, though lagging in ratings and development, hold immense potential for growth with the right investments in infrastructure and promotion.

The clusters also vary in terms of DSLR policies and tourism potential. Premium and eco-tourism destinations are more DSLR-friendly, emphasizing their scenic and cultural significance. Meanwhile, underrated destinations need awareness campaigns to build their

reputation and attract visitors. Each cluster represents a unique segment of the tourism market, providing actionable insights to tailor strategies for growth.

To visualize the clustering results, Principal Component Analysis (PCA) was used to reduce the dataset dimensions to two components. A scatterplot of the PCA-transformed data provided a clear visual representation of the clusters, showing well-separated groups. These clusters reflected distinct characteristics: destinations with high ratings and entrance fees formed one group, while budget-friendly and moderately rated destinations constituted the other two.

A deeper analysis of the clusters revealed significant insights. The first cluster primarily included destinations with high ratings, premium entrance fees, and longer visiting times, making them ideal for international and affluent travellers. The second cluster featured budget-friendly destinations with moderate ratings and shorter visiting times, appealing to local and family travellers. The third cluster contained emerging or underrated destinations with average ratings and minimal fees, showcasing potential for eco-tourism and niche campaigns.

Actionable recommendations were derived for each cluster. For premium destinations, enhancing luxury amenities and targeted marketing were suggested. Budget-friendly locations could benefit from infrastructure improvements and promotional campaigns. Emerging destinations were recommended to focus on sustainable tourism initiatives and partnerships with local communities to create unique experiences.

Overall, the project demonstrated the value of clustering techniques in uncovering hidden patterns within the dataset and providing insights for strategic decision-making in tourism. Future enhancements could include incorporating additional features, such as seasonal trends or proximity to other attractions, to refine the clustering model further. These findings underscore the potential of data-driven approaches in shaping effective tourism policies.

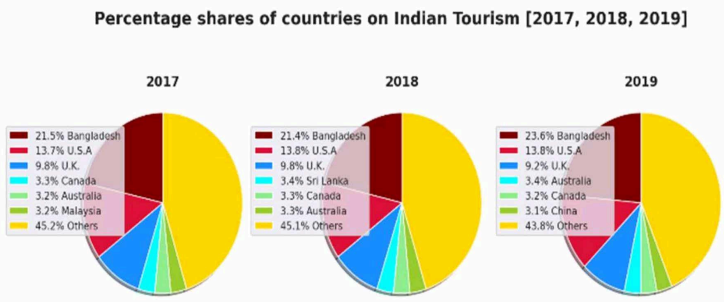

Figure 9.1: Percentage shares of countries on Indian Tourism [2017, 2018,2019]

In Figure 3 the chart illustrates the percentage share of countries in Indian tourism from 2017 to 2019. Bangladesh consistently leads, contributing over 21%, followed by the USA and UK with smaller shares. Other countries make up the majority, exceeding 45% annually, showcasing a diverse range of contributors. The data highlights stable trends in international tourism sources for India.

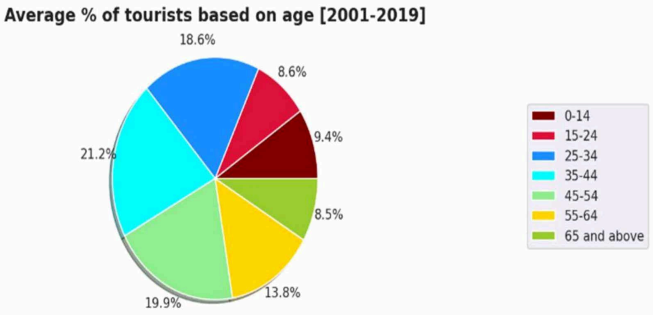

Figure 9.2: Average % of tourists based on age [2001-2019]

In Figure 4 the chart shows the average percentage of tourists by age group from 2001 to 2019. The largest share is from the 45 – 54 age group (21.2%), followed by 35 – 44 (19.9%) and 55–64 (18.6%), indicating a higher participation of middle-aged and older adults. Younger age groups (0–34) collectively contribute less than half, highlighting tourism's appeal to older demographics.

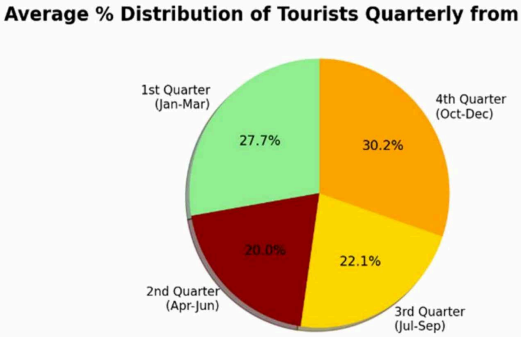

Figure 9.3: Average % Distribution of Tourists Quarterly from 2001-2019

In Figure 5 the pie chart illustrates the average percentage distribution of tourists across four quarters from 2001 to 2019. The highest percentage of tourists (30.2%) visited during the 4th quarter (October to December), followed by 27.7% in the 1st quarter (January to March). The 3rd quarter (July to September) accounted for 22.1% of tourist visits, while the 2nd quarter (April to June) had the lowest share at 20.0%. The chart highlights seasonal variations in tourist activities over the years.

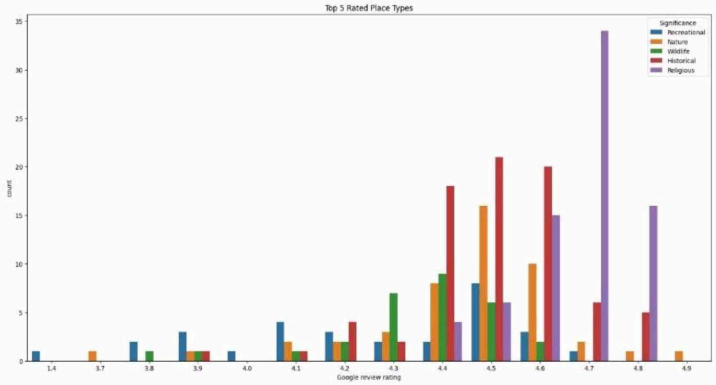

Figure 9.4: Top 5 Rated Place Types

In Figure 6 the bar chart displays the top 5 rated place types based on Google review ratings. Categories include recreational, natural, historic, religious, and other places, with their counts distributed across ratings from 1.4 to 4.9. Religious places dominate higher ratings (4.7-4.9), while recreational and natural sites have a balanced spread, peaking around 4.5. Historic places exhibit a more even distribution with moderate counts, highlighting variations in how different place types are rated by visitors.

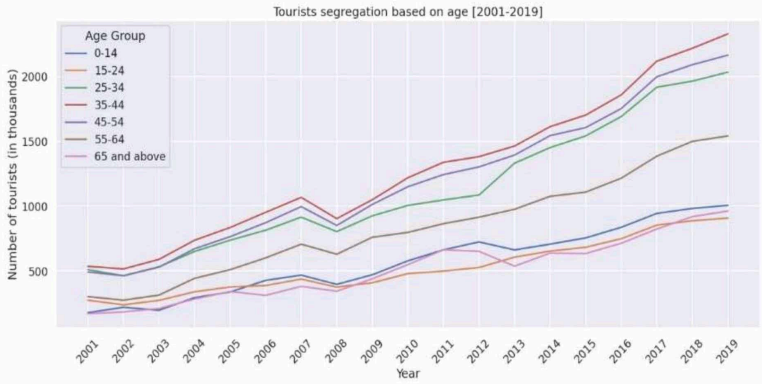

Figure 9.5: Tourists segregation based on age [2001-2019]

In Figure 7 the line chart shows tourist segregation by age group from 2001 to 2019, measured in thousands. Across the years, all age groups exhibit a steady increase in tourist numbers, with a notable dip around 2009, likely due to global events. The 25-34 and 35-44 age groups consistently have the highest counts, while the 65 and above group shows gradual growth. The 0-14 group remains the lowest throughout, reflecting age-related travel preferences.

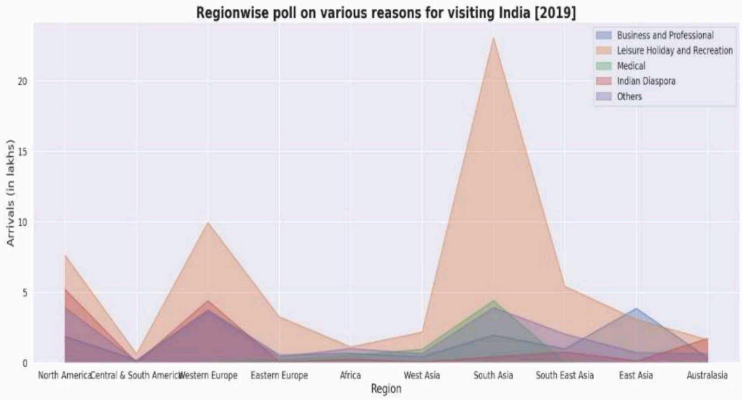

Figure 9.6: Region-wise poll on various reasons for visiting India [2019]

In Figure 8 the chart shows region-wise arrivals to India in 2019, segmented by reasons for visiting. South Asia leads with the highest visitors, driven by Indian Diaspora and leisure tourism. Western Europe follows, contributing significantly to business and leisure trips. Other regions, like North America and Southeast Asia, show moderate arrivals, while medical tourism remains less prominent but visible in South and West Asia. Overall, the chart highlights India's strong pull for leisure and diaspora visits, with potential growth in medical tourism.

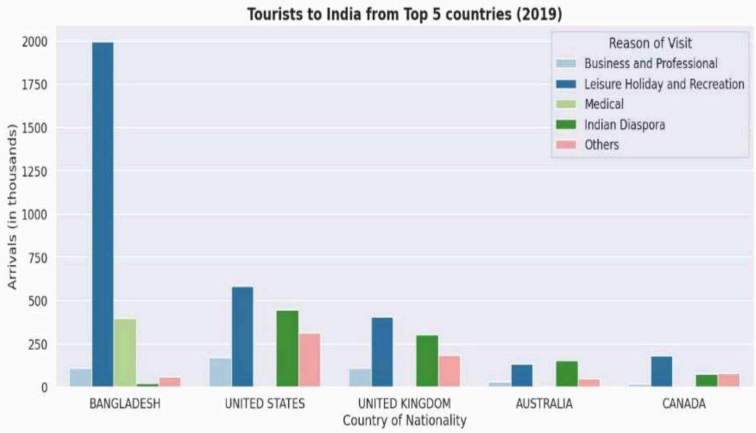

Figure 9.7: Tourists to India from Top 5 countries (2019)

In Figure 9 the chart highlights tourist arrivals to India from the top 5 countries in 2019. Bangladesh leads significantly, driven by leisure tourism and medical visits. The United States and the United Kingdom follow, with balanced contributions from business, leisure, and diaspora visits. Australia and Canada show lower but consistent tourist flows, primarily for leisure and diaspora purposes.

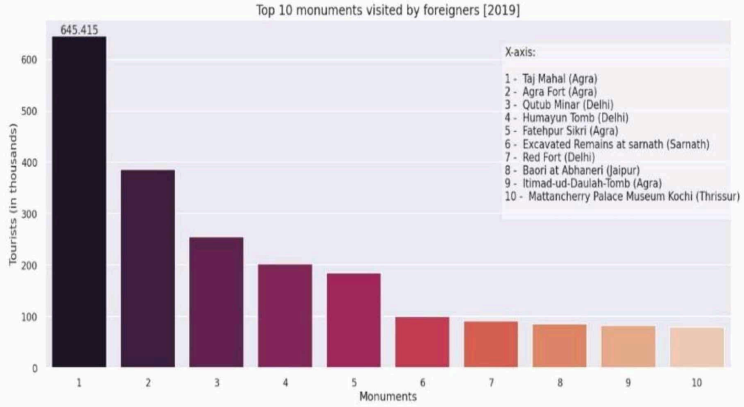

Figure 9.8: Top 10 monuments visited by foreigners [2019]

In Figure 10 the chart shows the top 10 monuments visited by foreign tourists in India in 2019. The Taj Mahal in Agra leads with over 645,000 visitors, followed by Agra Fort and Qutub Minar in Delhi. Other popular attractions include Humayun's Tomb, Fatehpur Sikri, and the Red Fort. The list highlights a strong preference for iconic historical and architectural sites, primarily concentrated in Agra, Delhi, and Jaipur.

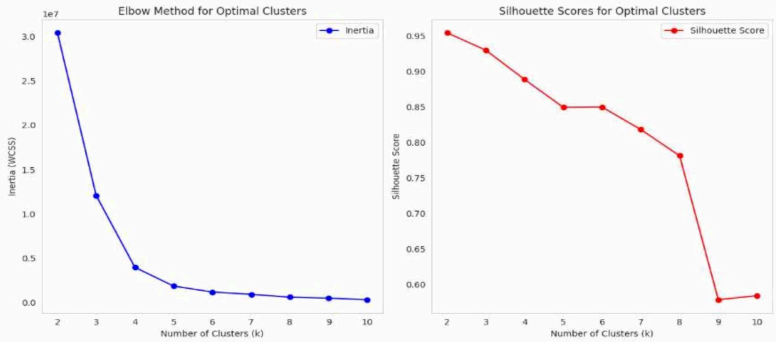

Figure 9.9: Elbow Method for Optimal Clusters and Silhouette for Optimal Clusters

In Figure 11 the image uses two methods to determine the optimal number of clusters (k) for clustering analysis. In the Elbow Method (left plot), the inertia (WCSS) decreases sharply as k increases but levels off around k=4, indicating the optimal number of clusters where adding more clusters doesn't significantly reduce WCSS. In the Silhouette Score (right plot), higher scores indicate better cluster cohesion and separation. The scores decrease as k increases, with the highest values at k=2 or 3, suggesting these clusters are more well-defined. Together, these methods help balance compactness and interpretability when selecting k.

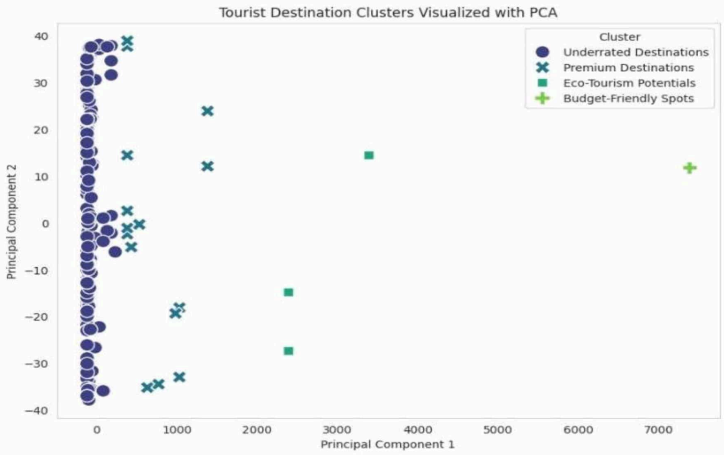

Figure 9.10: Tourist Destination Clusters Visualized with PCA

In Figure 12 the plot visualizes clusters of tourist destinations using Principal Component Analysis (PCA) for dimensionality reduction. Four clusters are shown: Underrated Destinations (dense cluster near the origin), Premium Destinations (spread out, marked by crosses), Eco-Tourism Potentials (squares with moderate spread), and Budget-Friendly Spots (plus signs, further apart). PCA simplifies the data into two principal components, highlighting distinctions between clusters based on key features of the destinations.

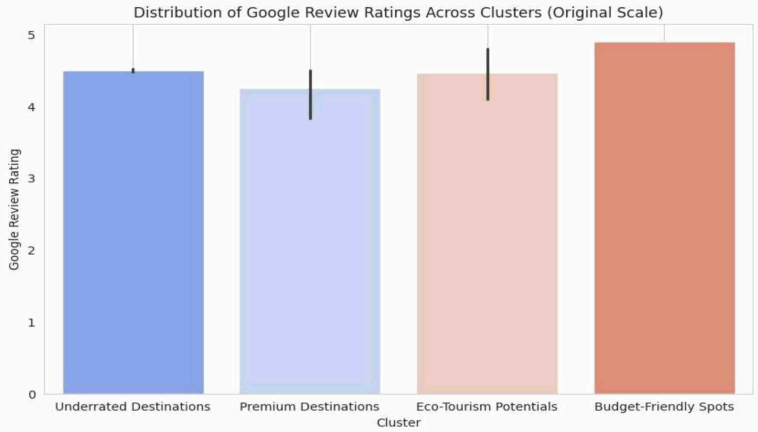

Figure 9.11: Distribution of Google Review Ratings Across Clusters (Original Scale)

In Figure 13 the bar chart compares the average Google Review ratings across four tourist destination clusters: Underrated Destinations, Premium Destinations, Eco-Tourism Potentials, and Budget-Friendly Spots. The highest ratings are observed for Budget-Friendly Spots, followed by Underrated Destinations and Eco-Tourism Potentials, while Premium Destinations have slightly lower average ratings. Error bars indicate the variability in ratings within each cluster.

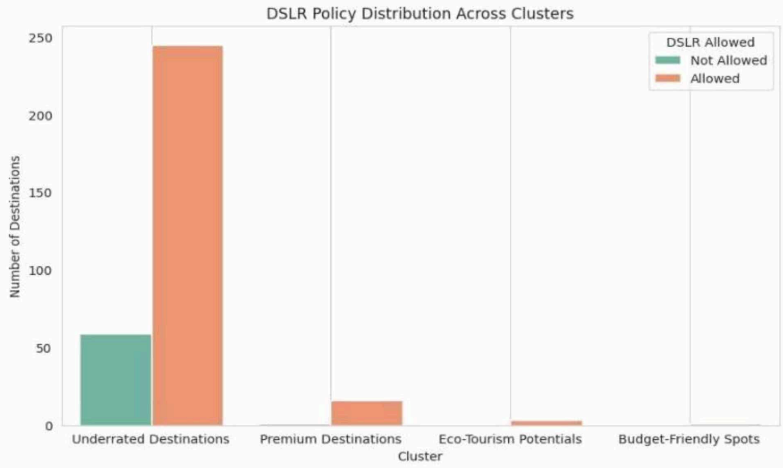

Figure 9.12: DSLR Policy Distribution Across Clusters

In Figure 14 the bar chart presents the DSLR policy distribution across various clusters of tourist destinations. The "Underrated Destinations" cluster dominates with a high number of destinations allowing DSLR use, while a smaller fraction restricts it. In contrast, the other clusters ("Premium Destinations," "Eco-Tourism Potentials," and "Budget-Friendly Spots") show a minimal representation, with negligible destinations allowing or restricting DSLR usage. This indicates that DSLR policies are primarily relevant to the "Underrated Destinations" category.

CHAPTER-10

CONCLUSION

This project effectively harnesses the power of AI/ML techniques and diverse datasets to analyse, predict, and optimize trends in the Indian tourism sector. By integrating clustering, predictive modelling, and trend analysis, the study provided valuable insights for tourism authorities, stakeholders, and decision-makers.

The clustering model grouped tourist destinations into distinct categories based on attributes such as visit duration, review ratings, and entrance fees. These clusters offered actionable insights into traveller preferences, identifying budget-friendly destinations, high-rated landmarks, and locations suited for time-constrained travellers. The use of Principal Component Analysis (PCA) further enhanced interpretability by visualizing these clusters in reduced dimensions, enabling stakeholders to make informed decisions regarding resource allocation and marketing strategies.

Predictive models, such as the Principal Component Analysis(PCA), were used to classify destinations based on their significance, leveraging features like regional importance, ratings, and accessibility. These models also provided accurate forecasts of travel patterns, empowering authorities to design better domestic tour packages and manage tourist inflows effectively. By splitting data into training and testing sets, the model was rigorously evaluated using performance metrics such as accuracy, precision, recall, and F1-score, ensuring its reliability in real-world applications.

Seasonal trends and demographic analysis added depth to the study by highlighting key factors influencing tourist behaviour. For instance, quarterly tourist distributions revealed peak seasons for travel, while age group trends showcased evolving demographic preferences over time. Historical data, such as Foreign Tourist Arrivals (FTAs) from 1981-2020, was analysed to forecast future trends and assess the impact of external factors like the COVID-19 pandemic on tourism.

The integration of multiple datasets—including region-wise statistics, state-wise tourist distributions, and monument visitor data—allowed for a comprehensive analysis. Advanced

visualizations, such as pie charts, line charts for trends, and bar plots for state-wise comparisons, ensured that findings were both accessible and impactful for stakeholders.

By leveraging historical and real-time data, this project demonstrated how AI/ML techniques can promote sustainable tourism practices. These include reducing overcrowding at popular destinations, managing seasonal fluctuations, and directing tourists to underexplored regions. Additionally, actionable recommendations derived from the study support targeted marketing campaigns, efficient resource allocation, and eco-friendly tourism initiatives.

In conclusion, this project highlights the critical role of data-driven decision-making in addressing modern challenges in the tourism industry. It showcases the potential of AI/ML to foster growth, sustainability, and enriched traveller experiences, paving the way for a more efficient and responsive tourism ecosystem in India.

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APPENDIX-A

PSUEDOCODE

Step 1: Import Necessary Libraries

import libraries:

- Pandas, NumPy for data manipulation and computation
- Matplotlib, Seaborn for data visualization
- sklearn: StandardScaler, LabelEncoder for preprocessing
  KMeans, PCA for clustering
  train_test_split, classification_report for modeling and evaluation

Step 2: Load and Explore Datasets

LOAD datasets:

- "India-Tourism-Statistics-1981-2020-fta_nri_ita"
- "India-Tourism-Statistics-2001-2019-agegroup"
- "India-Tourism-Statistics-2001-2019-quaterly"
- "India-Tourism-Statistics-2001-2019-worldvsindia"
- "India-Tourism-Statistics-2019_region-and-reason"
- "India-Tourism-Statistics-2021-monuments"
- "India-Tourism-Statistics-region-2017-2019"
- "India-Tourism-Statistics-statewise_2019-2020_domestic_foreign"
- "Top Indian Places to Visit"

INSPECT data:

- Check for missing values using isnull()
- Display basic statistics using describe()
- Identify categorical and numerical columns

Step 3: Data Preprocessing

FOR each dataset:

- Handle missing values:
  IF values are missing:
  Fill missing numerical values with mean/median

Fill missing categorical values using forward fill or placeholder

- Label encode categorical columns (e.g., Region, Zone, Type)
- Scale numerical columns (e.g., Entrance Fees, Ratings) using StandardScaler

INTEGRATE datasets:

- Merge datasets to create a unified table for analysis

Step 4: Exploratory Data Analysis (EDA)

CALCULATE correlation matrix:

- Identify relationships between numerical columns

VISUALIZE:

- Plot bar charts for state-wise domestic and foreign visitors
- Plot pie charts for quarterly tourist distributions
- Create line plots for age group trends over time

Step 5: Clustering Analysis

DEFINE features for clustering:

- Select columns like "Ratings," "Entrance Fees," and "Time Needed to Visit"

PERFORM K-Means clustering:

- Use the Elbow Method to find the optimal number of clusters (1 to 10)
- The silhouette score evaluated the quality of clustering by measuring cohesion (within-cluster closeness) and separation (distance between clusters).
- Assign each data point to a cluster

VISUALIZE clusters:

- Apply PCA to reduce dimensions
- Plot PCA-based scatter plots with clusters

Step 6: Trend Analysis

LOAD historical tourist data:

- Use "India-Tourism-Statistics-1981-2020-fta_nri_ita"

ANALYZE foreign and domestic tourist trends:

- Calculate yearly growth or decline in arrivals
- Plot line charts for visual representation

FORECAST future trends using time series analysis:

- Predict tourist arrivals for the next few years

Step 7: Visualization and Insights

VISUALIZE findings:

- PCA scatter plots for clusters
- Bar charts for regional and state-level trends
- Line plots for quarterly and yearly trends

PROVIDE insights:

- Identify highly rated, budget-friendly destinations
- Highlight seasonal peaks in tourism
- Suggest underperforming regions with potential for growth

APPENDIX-B

ENCLOSURES

Project work mapping with the Sustainable Development Goals (SDGs)

Figure AB.1: Sustainable Development Goals (SDGs)

The figure AB.1 represents the United Nations Sustainable Development Goals (SDGs), a set of 17 global objectives designed to address social, economic, and environmental challenges. These goals aim to eradicate poverty, promote health, education, and gender equality, ensure clean water and energy, and drive sustainable economic growth. They also focus on reducing inequalities, building sustainable cities, combating climate change, and preserving life on land and water. Additionally, the SDGs emphasize peace, justice, and strong institutions while fostering global partnerships for sustainable development. Together, these goals provide a roadmap for a more inclusive, equitable, and sustainable future.

1. SDG 8: Decent Work and Economic Growth

Our project enhances the tourism industry by leveraging technology to optimize resources and promote underutilized regions, thereby creating new job opportunities and fostering sustainable economic growth.

2. **SDG 11: Sustainable Cities and Communities**

   Our project contributes to building sustainable communities by implementing data-driven insights for better urban infrastructure around tourist destinations, promoting eco-friendly and sustainable tourism practices.

3. **SDG 12: Responsible Consumption and Production**

   Our project ensures responsible tourism by recommending balanced tourist distribution across regions, reducing the environmental strain on over-visited areas and promoting eco-tourism alternatives.

4. **SDG 17: Partnerships for the Goals**

   Our project fosters collaboration among stakeholders, such as tourism boards, businesses, and data platforms, ensuring a unified effort toward achieving sustainable development goals.

Sreelatha P K

Report

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