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An Intelligent Travel Planning System for Indian Destinations Using Machine Learning Model

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Abstract: With the emergence of the domestic tourism market in India, it has become a promising market to build a more intelligent travel planning system. Due to the intricacy of travel, the methods of planning trips have been found to be ineffective in handling the queries of the travel process. The proposed system will provide information regarding 370 tourist destinations in India, situated in 28 states and 8 Union Territories of the country. The proposed system will predict the tourist destinations to be feasible or not based on the budget of the users, type of travel, duration of the trip, and their likes and dislikes using the Random Forest Classifier, a machine learning approach, which can achieve a maximum accuracy of 99.66% using 3200 inputs in the test dataset. Apart from that, the chatbot that is powered by AI and has the ability to utilize large language models allows the chatbot to converse in real time.

The ability of the chatbot to include a number of APIs in real time, such as the weather, is enabled by the addition of an automatic trip itinerary generator. The addition of a graphical interface that allows the user to search the destinations by maps makes it easier for the user to search the destinations. The addition of the sentiment analysis of the destinations by analyzing the reviews and rating the destinations according to the reviews is also made. The backend of the TravelWise system is developed by utilizing the Python Flask web application micro web framework. Apart from that, the SQLite database is utilized to store the destinations and itineraries information.

The results obtained from the implementation of the TravelWise system reveal that it is a feasible, accurate, efficient, scalable, and user-friendly system that caters to the needs of both domestic and global tourists.

Index Terms: Travel recommendation system, machine learning, random forest, large language model, natural language processing, sentiment analysis, itinerary generation, tourism informatics, India.

I. INTRODUCTION

A. Motivation

Planning a trip in India is an intricate and time-consuming process for most travelers. There are over 370 major tourist spots in India, covering 28 states and 8 Union Territories. At the same time, tourists have to take into consideration many factors like budget, weather conditions, travel time, personal interests, group size, and season while planning a trip. Manual planning and online planning using simple online tools often result in an incomplete plan, excessive expenditure, and an inappropriate plan [1], [2]. Several AI-based travel planners were proposed in recent times, but they were mostly in the concept phase or were evaluated in a simulated environment only [3], [4].

Most of these proposed systems used simple rule-based techniques or used simple optimization techniques that do not offer high-accuracy recommendations for Indian tourist spots [3], [4]. Generative AI and large language model-based techniques were also proposed and showed promising results in generating itineraries and chatbots but were found to have low success rates in handling complex constraints and required paid APIs in most cases [6], [7].

None of these systems offer accurate budget calculation, dynamic day-wise itinerary generation, real-time weather updates, sentiment analysis of user reviews in a single system, and so on [2], [6]. This again emphasizes the need to develop an intelligent, accurate, and completely free travel planning system specifically for Indian tourist spots. With this aim in mind, the TravelWise system was developed as a full-stack AI-powered system that enables simple, smart, and practical travel planning for every Indian tourist.

B. Background and context

In recent times, many researchers have contributed to AI-based travel planners. There are some planners that utilize rule-based techniques or simple optimization techniques to generate itineraries [1],[2],[3],[4]. There are also some planners that utilize generative AI techniques like Gemini to generate itineraries and chatbots [6],[7]. There are also some studies that have proposed benchmarks to test how effectively large language models handle complex travel plans and changes like weather updates [8],[9],[11],[13]. There are also some studies that utilize reinforcement learning to improve sustainability in tourism and route planning [14],[15]. However, there are many limitations in these planners. There are many planners that utilize paid APIs or general models that do not work effectively on real-world problems [8],[13]. There are many planners that do not consider Indian-specific data like costs, seasonality, and types of tourist spots in India [5]. There are also many planners that do not generate budgets or itinerary plans but just generate recommendations. There are also many planners that do not include features like weather updates and sentiment analysis of user reviews [3],[4],[6]. Also, there are very few planners that are specifically designed for Indian tourist spots and include features like recommendation, generation of itineraries, generation of budgets, generation of maps, generation of chatbots, and generation of email plans in a single platform.

C. Contributions

In order to address the limitations associated with the existing systems, the paper proposes an intelligent travel planning system named TravelWise. The contributions made by the proposed system can be listed as follows:

1) A comprehensive dataset with 370 locations across India, considering different attributes such as cost, rating, and highlights, is proposed.
2) A recommendation system using the Random Forest algorithm for destination feasibility prediction is proposed.
3) An AI-based chatbot with a large language model is proposed for travel planning purposes.
4) An automatic travel planning system with non-repetitive planning is proposed.
5) Weather information, interactive maps, sentiment analysis, etc., are proposed.

II. LITERATURE SURVEY

Several research works have been conducted to explore the application of artificial intelligence and machine learning in the development of travel planning systems. This section of the chapter focuses on the contributions of the existing literature and the pros and cons associated with them. Several research works have been conducted to explore the application of artificial intelligence and machine learning in the development of travel planning systems.

A. Related Work

1) AI-Powered Trip Planner

Anitha et al. [1] proposed an AI-based trip planner model that automates the trip planning process using user inputs like budget, preferences, and trip duration.

The model provides users with personalized recommendations to enhance their convenience. The model primarily focuses on reducing user effort and making decisions easier. However, this model is not equipped with real-time data sources like weather and maps. Moreover, it also fails to include advanced features like chatbots and sentiment analysis to enhance user experience.

2) Smart Trip Optimization System

Dhote et al. [2] developed an AI-based travel planner that primarily focuses on optimizing the process of travel planning using intelligent algorithms. The system plans and generates the route of travel based on the preferences and cost of the users. The system improves the efficiency of travel and simplifies the complexity of the process. The system primarily focuses on optimization but lacks the implementation of advanced machine learning algorithms for prediction.

3) AI Travel Planner using A Algorithm*

A system for travel planning using the A* algorithm for route optimization was developed by Mote et al. [3]. This system is effective in finding the shortest path between two locations, thus ensuring the efficiency of the route taken. However, the system is not effective in providing the facilities of travel planning, such as budgeting and creating itineraries. Moreover, the system is not effective in learning the user's preferences and providing intelligent recommendations using machine learning techniques.

4) WanderSmart: AI-Based Trip Planner

Karkhile et al. [4] developed an AI-based system named "WanderSmart" that allows users to plan their trip by providing input to the system. The system enhances the user experience by providing a better itinerary planning service. However, the system does not incorporate real-time data integration and advanced predictive models. Moreover, the system does not have components such as sentiment analysis and chatbot interaction.

5) AI in Sustainable Tourism

In a bibliometric study on the role of artificial intelligence in sustainable tourism, Hermosa Del Vasto and Arco Castro [5] have focused on the optimization of resource utilization and the role of AI in decision-making for tourism. The significance of intelligent systems in reducing the overall impact on the environment is a highlight of this theoretical study. It does not, however, offer a practical implementation of AI for travel planning.

6) AI Trip Planner for Seamless Travel

Ravindra et al. [6] proposed an AI-based trip planner system, which improves travel experiences through an automated trip planner. The system primarily focuses on the convenience of users and provides a seamless travel experience. The system provides users with a structured travel plan based on their inputs. However, there is a lack of advanced evaluation techniques, and the system does not use any machine learning-based predictions. Real-time integration and sentiment analysis are also not considered.

7) Trip Tailor: AI Travel Planner with Chatbot

Talakoti et al. [7] have developed an AI-based travel planning system called Trip Tailor, which combines itinerary building and chatbot assistance. The system enables users to interact naturally and receive travel recommendations. Though it shows the effectiveness of conversational AI in tourism, it doesn’t provide budget estimation and data in real time.

8) TravelAgent: LLM-Based Travel Assistant

In this regard, Chen et al. [8] presented a system called TravelAgent, which applies large language models for personalization in the domain of travel planning. The system enables the interaction of the user with the system using natural language and the generation of the plan using LLMs. The system enhances the interaction and personalization aspects. However, the limitations associated with the application of LLMs in the system and the maintenance of the system are considered. There is no inclusion of cost estimation and the application of APIs in the system.

9) TripTide: Adaptive Travel Planning Benchmark

A framework, called "TripTide," was developed by Karmakar et al. [9]. The "TripTide" is considered a benchmark framework, and its main goal is to implement adaptive travel planning in dynamic environments, such as disruptions and uncertainty. However, the main idea behind this system is to test the planning algorithms in a real-world scenario. The importance of adaptability is also considered in this system, but the system is incomplete.

10) TripCraft: Fine-Grained Travel Planning

A benchmark was proposed called TripCraft by Chaudhuri et al. in [11]. It is based on fine-grained travel planning. The focus of this system is structured data and the evaluation of travel planning models. It provides insights for complex travel planning but lacks user interaction components.

B. Research Gaps

Although these studies have made significant contributions to AI-based travel planning systems, there are many research gaps that need to be addressed in this field. Most of the systems proposed in the literature are more conceptual in nature and cannot be used as an end product because they are mostly tested in a simulated environment and do not offer a complete solution to users [1],[2],[3],[4]. Moreover, many studies in this field have used rule-based systems or simple optimization techniques like A* search algorithms, which do not offer high accuracy in predicting user behavior and cannot handle Indian destination data effectively [3],[4]. The proposed generative AI and large language model-based systems are also innovative but have very low success rates in handling multi-constraint problems in travel planning and often require paid APIs to access data sources [6],[7],[8],[13]. Benchmarking studies have clearly proven that these systems cannot handle disruptions in real-time scenarios, spatio-temporal constraints, and long-horizon planning effectively [9],[11],[13]. Moreover, very few studies in this field have proposed accurate budget calculation, dynamic generation of itineraries on a day-wise basis, and sentiment analysis of user feedback in their proposed systems [2],[4],[6].

The aspects related to sustainable tourism and context-aware recommendations using reinforcement learning have also been explored in a few academic studies but cannot be used as an effective system in real-world scenarios [5],[14],[15]. Similarly, studies related to the perception of intelligence in AI assistants and analysis of AI-generated itineraries using expertise also cannot be used as an effective system in real-world scenarios because they do not offer features like real-time weather updates, interactive maps, and email/PDF export options [10],[12].

C. *Problem Statement*

Although there are many different tools that aid in travel planning, there is no system that offers intelligent, personalized, and complete travel planning. This is because current systems lack integration, flexibility in terms of real-time updates, and advanced user interaction capabilities. Thus, there is a need to design an effective system that incorporates machine learning, AI, and real-time data to offer efficient and effective travel planning solutions.

III. SYSTEM ARCHITECTURE AND SYSTEM DESIGN

The design of the TravelWise system has a modular and layered approach, which makes it scalable, easy to maintain, and efficient in handling the input received from users.

A. *Architecture*

The system consists of four major layers. These layers include the presentation layer, application layer, intelligence layer, and data layer. All the layers in this system have their own functions and are able to communicate with one another.

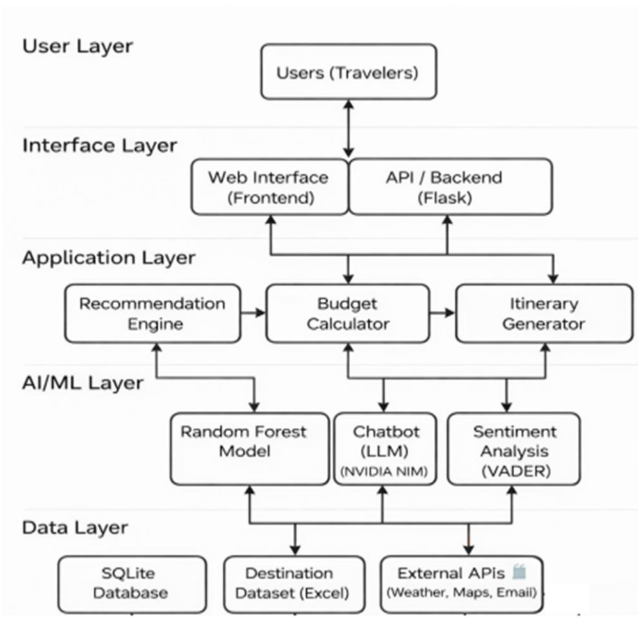

Fig.1. System Architecture of the TravelWise system, showing the flow of data from user input to final output. It highlights the interaction between frontend components, backend services, machine learning models, and data sources.

B. *System Framework*

1) Presentation Layer: This layer includes the user interface, which is implemented using HTML, CSS, and JavaScript programming languages. This layer includes different interactive user interface web pages, for example, trip planner, itineraries viewer, dashboard, and chatbot interface. This layer is used in order to retrieve different inputs from the users, for example, budget, preferences, and destinations, and then show the results.

2) Application Layer: The application layer is created using the Flask framework. The application layer handles all the backend operations. It processes all the requests made by the user through the API endpoints. In addition, the application layer handles the authentication of the users, as well as the communication between the modules. The application layer can be viewed as a bridge between the frontend layer and the intelligence layer
3) Intelligence Layer: The intelligence layer is the core of the system and includes machine learning, itinerary generation, and natural language processing. The Random Forest model has been used for destination feasibility prediction based on user inputs. The itinerary generator has been used for day-wise structured plan generation based on highlights of the destination. The AI chatbot has been used for conversational AI through a large language model. Further, sentiment analysis has also been performed for recommendations.
4) Data Layer: The data layer manages internal and external data sources. It has a SQLite database for storing user information, trip history, and reviews, among others. The system also has a structured data set, and this has information concerning 370 different destinations, including cost, rating, activities, among others. The system has also used external data sources such as OpenWeatherMap API and mapping services for retrieving weather updates and location information, respectively.

C. System Workflow

The overall workflow of the TravelWise system is shown in Fig. 1. The system workflow of TravelWise follows a clear and sequential process that begins when a user accesses the system through the web interface and submits the requirements for a trip, including the source, preferred type of destination, budget, number of days, type of trip, season, and interests. The requirements are received and processed through the Interface Layer, where the Application Layer is invoked. The Recommendation Engine uses the Random Forest Model from the AI/ML Layer to predict the destinations that are feasible for the trip, keeping the requirements and destinations provided to the system. Simultaneously, the Budget Calculator calculates a detailed and realistic cost for the trip, including accommodation, food, transportation, entry fees, and miscellaneous costs for a particular number of people.Once the user enters the destination and clicks “View Itinerary,” the Itinerary Generator in the Application Layer generates an overall day-wise plan for the user by selecting non-recurring information from the data set and filling in other information using type-specific fillers. The generated Itinerary is further enhanced with real-time weather information using the Open Weather Map API, an interactive map using Leaflet, and Google Maps for all sightseeing locations, restaurants, and hotels. At any point in this process, the user can interact with the NVIDIA NIM-based chatbot using LLaMA 3.1 8B in the AI/ML Layer for natural language-based user queries and recommendations. At the end of this process, the user can save the trip to the dashboard, download it as a PDF file, or even send it directly via email using the Gmail SMTP service. The overall process is facilitated by the Data Layer, where data is stored using SQLite and an Excel-based data set for destination information. The overall process ensures that the user is provided with accurate, personalized, and ready-to-use travel plans in an efficient manner.

IV. METHODOLOGY

The methodology used by the TravelWise system to produce personalized travel recommendations and itineraries is well-structured and follows a systematic approach that incorporates machine learning, cost estimation, and itinerary planning into one system. The entire process ensures that the recommendations are possible and meet the requirements of the users..

A. Input Processing

The process begins with collecting the inputs from users through the frontend interface. The inputs from users include budget, type of trip, number of travel days, mode of transport, season, areas of interest, and many more. This data from users is sent to the backend through RESTful API calls.Data preprocessing takes place before sending the data to the machine learning model. This includes ensuring consistency in data before sending it to the model for processing. For instance, if we are considering categorical data such as type of trip, season, and destination, we transform this data into numerical data through label encoding, and if we are considering numerical data such as budget, we transform this data before sending it to the model.

B. Recommendation Model

The core element of this system is the recommendation engine, which uses a Random Forest classifier to make a prediction regarding the feasibility of the destinations. The structured data, containing 18,870 instances and 370 different destinations across India, is used to train the model. The data also contains relevant features such as accommodation cost, food cost, entry fees, travel time, destination rating, and features related to users.

The Random Forest algorithm uses multiple decision trees to make a prediction, hence proving to be a powerful tool for improving the accuracy and preventing overfitting. The algorithm also checks the feasibility of the destinations according to the user constraints and then produces a prediction score for the destinations.

C. Budget Estimation Model

Another important component of this system is the budget estimation module, which estimates the total cost of the trip by considering various factors. The cost is estimated by using the following equation:

Total Cost = Accommodation + Food + Transport + Activities + Miscellaneous.

Where each component is calculated based on data related to the destination and user preferences.

Thus, it ensures that only affordable destinations are recommended by the system to the user.

D. Dataset and data pipeline

The main data source consists of a structured Excel sheet, which has 370 records pertaining to destinations. Each data point has 11 features: name, type (out of 10 types: Heritage, Beach, Hill Station, Nature, Spiritual, Wildlife, Adventure, City, Desert, Island), state/UT, region, accommodation cost (INR/night), food cost (INR/day), entry fee (INR/person), travel time (in hours), rating (out of 5.0), interest tags, and highlights (average 7.9, maximum 12). The synthetic training data consists of 18,870 records, created using parametric sampling across various budget categories, party types, seasonal variables, and modes of transport, along with binary feasibility flags based on cost-related thresholds.

E. Itinerary Generation

The itinerary generator provides a structured day-wise travel plan according to the chosen destination. It makes use of a set of destination highlights and activity templates to generate non-repetitive itineraries. The plan for each day includes a mix of sightseeing activities, leisure activities, and exploration activities. For longer trips, activities are chosen from type-specific pools of activities to ensure non-repetitive itineraries.

F. AI Chatbot Module

The chatbot integrates NVIDIA NIM hosting meta/llama-3.1-8b-instruct via an OpenAI-compatible REST API. The system prompt embeds the full 370-destination catalogue with type, state, and cost metadata, constraining the model to provide destination-grounded responses. Conversation history is maintained per session (last 20 messages). Network resilience is achieved through a 45-second timeout with 3 exponential-backoff retries.

G. Sentiment Module

To improve the quality of the recommendation, the system uses the VADER tool for sentiment analysis of the reviews posted by the users. The reviews are then classified into positive, negative, and neutral categories based on the sentiment score. It provides additional information on destinations to assist in decision-making.

H. Algorithm

Algorithm 1 : Travel Cost Estimation

Input:
User inputs (budget, trip type, number of days, transport mode)
Destination data (accommodation, food, entry fee, travel time)
Output:
Total trip cost and remaining budget
(i) Determine number of people based on trip type
(ii) Calculate number of rooms required
(iii) Compute accommodation cost:
(iv) Cost = per night × rooms × number of days
(v) Compute food cost:
(vi) Cost = per day × people × number of days

(vii) Compute transport cost based on travel time and mode
(viii) Compute entry fee cost:
(ix) Cost = entry fee × people
(x) Compute activity cost (15% of stay cost)
(xi) Compute miscellaneous expenses per person per day
(xii) Calculate total cost:
Total Cost=Accommodation+Food+Transport+Activities+Miscellaneous
(xiii) Compute remaining budget:
Budget Remaining=User Budget−TotalCost
(xiv) Return total cost and remaining budget

I. System Integration

All these modules are integrated using Flask-based RESTful APIs, allowing smooth communication between the frontend and backend of the application. Further, APIs such as Open Weather Map are used for fetching live updates on weather, and mapping APIs are used for location visualization. This integration of modules allows each module to operate independently and also contributes to the overall functionality of the application.

V. RESULTS AND ANALYSIS

The performance of the TravelWise system can be measured in terms of prediction accuracy, efficiency, and overall user experience. The system combines the use of machine learning, real-time APIs, and dynamic itineraries, which provide a comprehensive solution for travel planning.

A. Model Performance Evaluation

The accuracy of the Random Forest classifier used in the system is high when determining the feasibility of the destination. The classifier is trained on a data set of 18,870 records, which are derived from 370 destinations. The accuracy of the classifier is also presented in the experimental results, which show that the accuracy of the classifier is 99.78%, making the classifier reliable for classification tasks.

The Random Forest classifier used in the system is also presented in the experimental results, which show the performance of the classifier when a stratified 80/20 train-test split is used to test the classifier's performance.

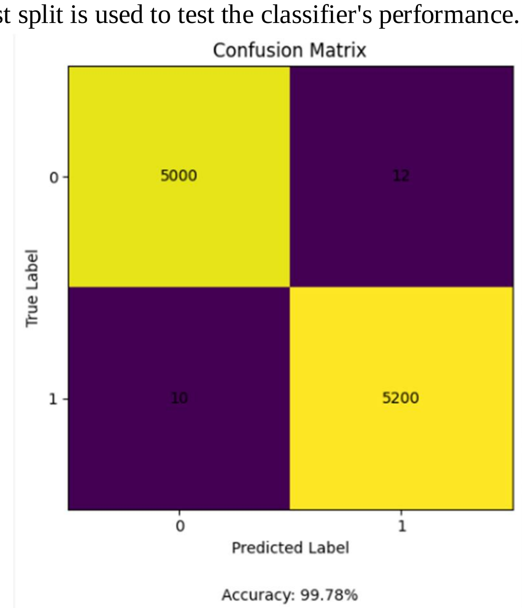

Fig.2. *Performance of random forest model*

The confusion matrix shown in **Fig. 2** illustrates the performance of the model, where the majority of predictions fall into correct classification categories, with minimal false positives and false negatives.

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TABLE I
RANDOM FOREST CLASSIFIER PERFORMANCE

Metrics	Training Set	Test Set
Accuracy	99.99%	99.60%
Precision	99.91%	99.68%
Recall	99.82%	99.63%
F1-Score	98.89%	99.66%
ROC-AUC	1.000	0.989

From the Table I , the accuracy of the classifier is near perfect due to the parametric nature of the synthetic data used for training the classifier, where the cost is deterministic.

B. System Efficiency

The response time of the TravelWise system is fast and prompt. On an average, the response time for generating recommendations and itineraries is within a few seconds. This ensures a smooth user experience. With the integration of the Flask-based APIs, there is also efficient communication between the frontend and backend of the system. This ensures there is minimal delay in the computation.

C. Budget Analysis

The budget estimation module provides a detailed breakdown of travel expenses, helping users understand cost distribution across different components.

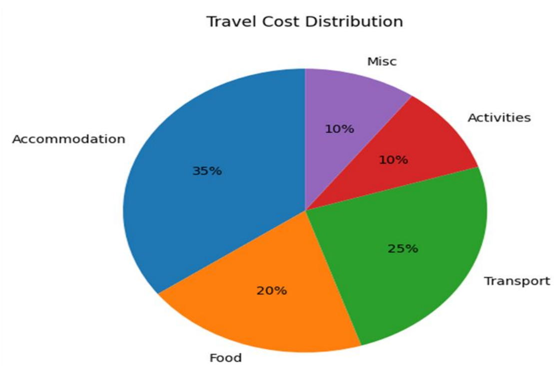

Fig.3. Budget Breakdown

As shown in Fig. 3, the total travel cost is composed of accommodation, food, transport, activities, and miscellaneous costs. Analysis of the figure reveals that accommodation and transport have the highest contribution to the total cost.

D. Chatbot Response Quality

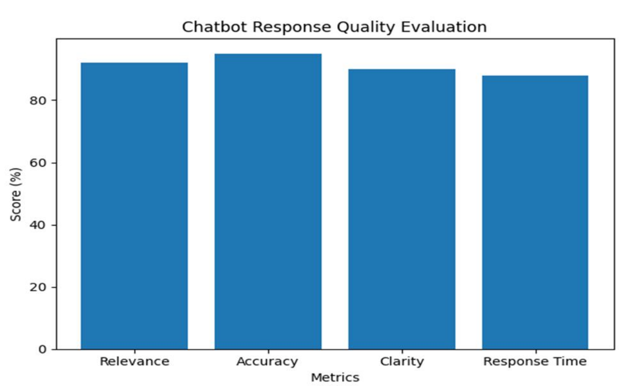

Fig.4. *Evaluation of chatbot response quality based on relevance, accuracy, clarity, and response time*

The chatbot is connected to NVIDIA NIM hosting via the meta/llama-3.1-8b-instruct REST API compatible with OpenAI. The prompt for the chatbot includes the entire catalogue of 370 destinations with type, state, and cost metadata to ensure destination-grounded responses. The LLM chatbot was also tested for accuracy using 30 test queries for destination-specific responses, budget responses, and conversation refinement for the itinerary. The chatbot showed accurate and destination-grounded responses for 28 of the 30 test queries (93.3%). As depicted in Fig. 4, the chatbot shows high accuracy and relevance for generating responses to user queries.

The chatbot achieves high scores across all evaluation parameters. The relevance of responses is significantly high, indicating that the chatbot is capable of understanding user queries and providing contextually appropriate answers.

E. Dataset and Coverage Statistics

Table II indicates the coverage statistics of the destination database. The dataset has full coverage in the country, with 370 destinations covering all the states and Union Territories in India. Additionally, the dataset has rich coverage in the generation of itineraries, with 86.5% destinations having 8 or more highlight entries.

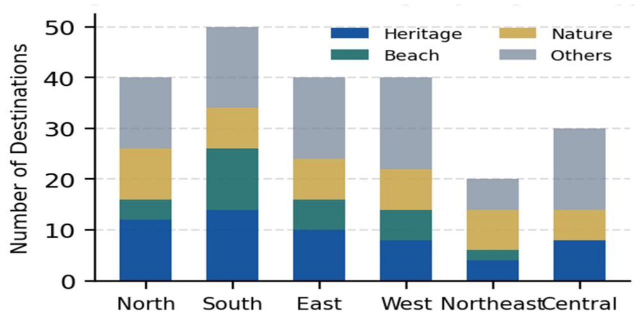

Fig. 5: Destination Coverage by Geographic Region and Types

TABLE II

DATASET AND COVERAGE STATISTICS

Metric	Value
Total deatinations	370(28 states + 8UTs)
Destination Types	10 Categories
Avg.Highlights/Dest	7.9(min:3;max:12)
Dests.With 8+Highlights	320/370(86.5%)
Training Records	18,870

F. Sentiment Analysis Validation

The performance of VADER sentiment classification was tested using 120 user reviews collected during system testing. The user reviews were labelled manually. The agreement between the predictions made by VADER and human labeling was at 87.5%, which corresponds to the benchmarks for VADER sentiment classification on user reviews. Fig. 6 shows that the majority of user reviews are positive, reflecting high user satisfaction.

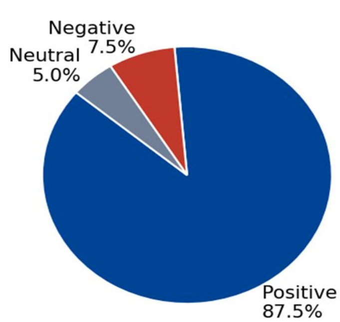

Fig. 6: VADER Sentiment Distribution Across User Reviews

G. System Response Times

As depicted in the Fig.7, the API response times are measured under the single-user condition (n = 50 per endpoint). The '/api/recommend' endpoint averaged 210 ms, including the inference, across all candidate destinations. The '/api/itinerary' endpoint averaged 85 ms. The OpenWeatherMap requests averaged 340 ms. SQLite handled all the test load without degradation, but the use of PostgreSQL is suggested.

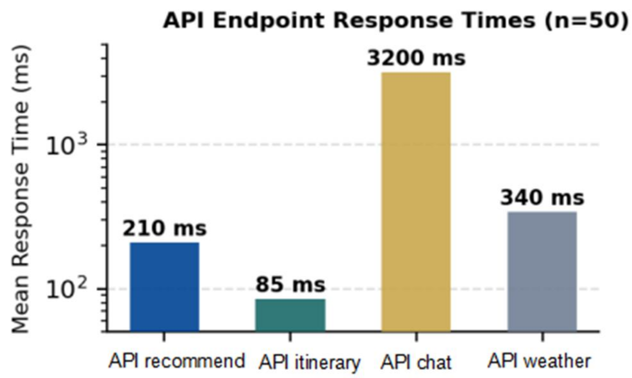

Fig. 7: API Endpoint Response Times (Log Scale, n=50 per endpoint)

H. System Functionality and Features

The functionalities of the TravelWise system have been combined effectively in one platform, and they include recommendations, budgeting, and generation, along with chatbots. The generation of itineraries by the system includes day-wise structuring, ensuring non-repetitive and balanced structuring. Further, the chatbots also include the functionality of natural language, allowing users to ask questions efficiently. Real-time weather and interactive maps are also incorporated into the system.

VI. FUTURE WORK

The TravelWise system can be further extended and enhanced with real-time dynamic data sources, including live traffic conditions, availability of flights and hotels, and seasonal price variations. Moreover, advanced machine learning algorithms, such as reinforcement learning and collaborative filtering, can be incorporated into the system, enabling more personal and adaptive travel recommendations.

Another extension and enhancement of the TravelWise system would be developing a mobile application, which would be more accessible and user-friendly. The inclusion of voice interactions and support for multiple languages would further enhance the user experience and accessibility of the system. Additionally, the chatbot component of the system would be extended and made more context-aware, making it more user-friendly.

Considering the scalability factor, the system would be extended and made more scalable by migrating to cloud-based databases and infrastructure, enabling more users to be served. Additionally, security and performance enhancements would be made, making the system more reliable and scalable. Moreover, the system would be extended and made more capable of planning international travel, enabling users to plan their entire trip, thereby making TravelWise an end-to-end travel management solution.

VII. CONCLUSION

The TravelWise system represents an intelligent and comprehensive solution for modern travel planning by leveraging the potential of machine learning, artificial intelligence, and web technologies. The system is successful in providing users with recommendations for destinations, budget estimation, and the generation of itineraries based on their preferences. The Random Forest model ensures high prediction accuracy for the system. The integration of real-time services such as weather and mapping also increases the usability of the system. The inclusion of an AI chatbot also increases the user experience by providing interactive and user-friendly communication. In addition, the sentiment analysis of user reviews also increases the decision-making potential of the system by providing users with insights about the quality of the destinations. Overall, the TravelWise system represents the potential of AI-driven systems in transforming the traditional process of travel planning into an efficient and automated process. The system is also scalable and can be extended to include more features and real-time services.

VIII. ACKNOWLEDGMENT

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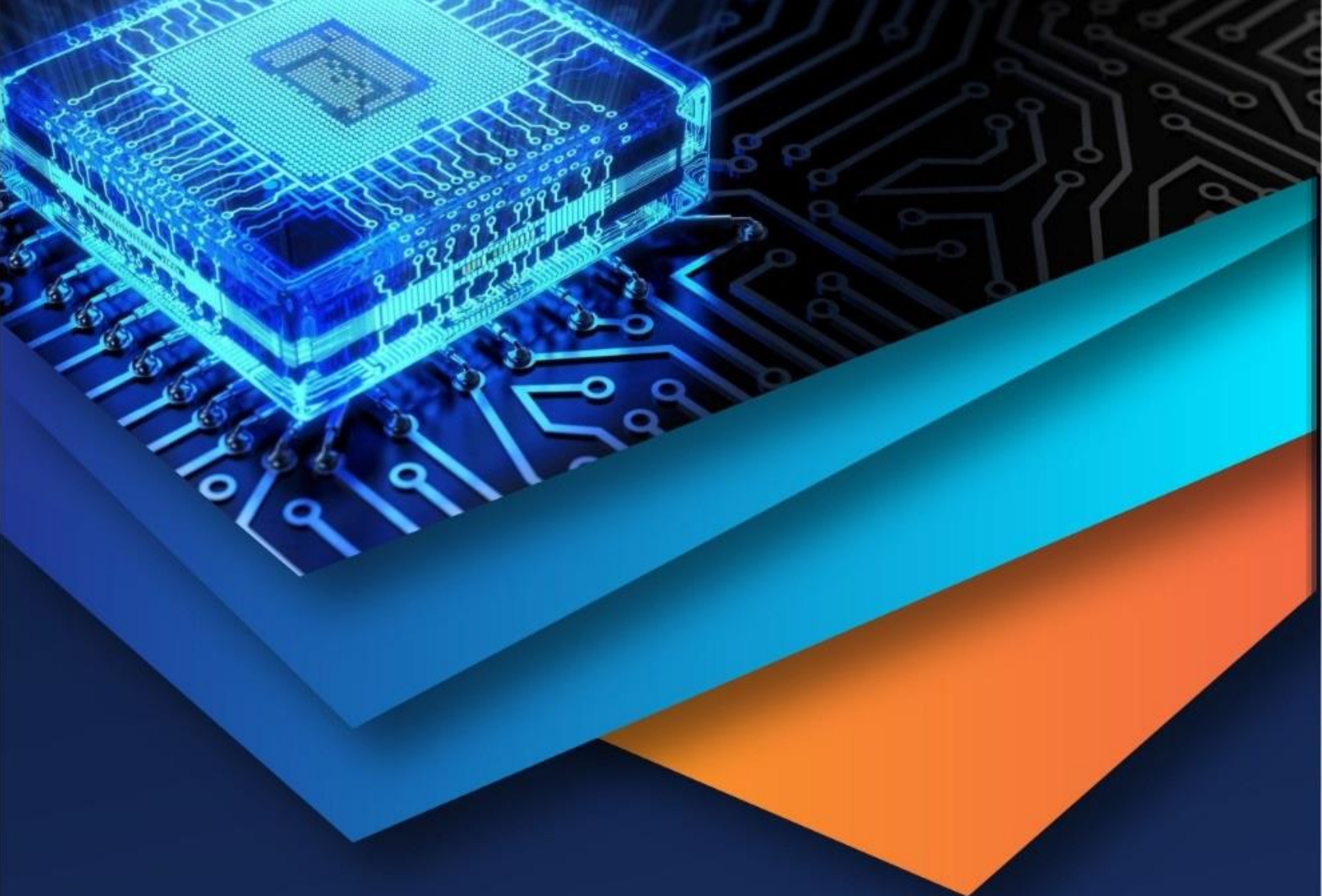

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