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Context-Aware Conversational AI for Intelligent Travel Planning and Smart Tourism

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Abstract: The increasing use of digital technologies in tourism has created a demand for intelligent travel assistance systems that provide personalised recommendations, contextual information, and convenient trip planning. This paper presents an AI-powered multilingual travel guide designed to support tourism across Karnataka, India. The proposed system integrates natural language processing, machine-learning-based intent recognition, tourism information retrieval, destination recommendation, and budget-aware itinerary generation within a web-based platform. Developed using Python Flask, the application supports information about 62 tourist destinations and enables users to interact in English, Kannada, and Hindi. Its conversational engine combines Term Frequency–Inverse Document Frequency (TF-IDF)-based intent classification, keyword rules, context-aware dialogue processing, and hybrid information retrieval to generate relevant travel responses. A content-based recommendation component considers traveller interests, destination characteristics, ratings, popularity, geographical proximity, seasonality, and saved places. The itinerary planner generates day-wise travel schedules, estimates expenses, organises destinations geographically, and supports planning according to budget constraints. Voice interaction, destination exploration, user accounts, saved destinations, and itinerary export further extend the platform's functionality. The system uses SQLite by default and supports optional integration with a large language model for response generation. This paper presents the system architecture, implementation methodology, major functional modules, and approach to functional evaluation. The work demonstrates an integrated software architecture for multilingual, AI-assisted regional tourism and identifies opportunities for further evaluation and real-time tourism information integration.

Keywords: Artificial Intelligence, Smart Tourism, Conversational AI, Multilingual Chatbot, Information Retrieval, Recommendation Systems, Intelligent Trip Planning.

I. INTRODUCTION

Tourism is an important contributor to regional economic development, cultural exchange, and employment. Karnataka, a state in India, offers diverse tourist attractions, including historical monuments, religious destinations, hill stations, waterfalls, wildlife sanctuaries, beaches, and cultural heritage sites. However, travellers may need to consult multiple sources to obtain destination information, compare attractions, organise travel schedules, estimate expenses, and understand local travel requirements. These activities can make trip planning time-consuming, particularly for travellers unfamiliar with the region.

Traditional tourism websites primarily provide predefined destination descriptions, static recommendations, and general travel information. Although these platforms help users discover tourist attractions, they may not adequately support conversational queries, personalised recommendations, multilingual interaction, or itinerary generation based on individual requirements. Travellers increasingly need systems that can interpret natural-language questions and provide relevant guidance according to their interests, travel duration, budget, and destination preferences.

Advances in Artificial Intelligence (AI), Natural Language Processing (NLP), machine learning, and information retrieval provide opportunities to address these limitations. Conversational AI enables users to communicate with travel applications using natural language, while machine-learning techniques can identify query intents and improve the relevance of responses. Information retrieval techniques help locate relevant content from tourism knowledge sources, and recommendation algorithms can rank destinations according to user preferences and destination characteristics. Integrating these capabilities into a unified platform can simplify travel-related decision-making.

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This paper presents the design and implementation of an AI-powered multilingual travel guide and intelligent trip planning system focused on Karnataka tourism. The application is developed using Python Flask and integrates conversational assistance, destination exploration, recommendation mechanisms, and itinerary generation. It provides information about 62 tourist destinations and supports interaction in English, Kannada, and Hindi. The conversational component combines TF-IDF-based intent classification, keyword-based rules, contextual dialogue processing, and hybrid tourism information retrieval. An optional large language model integration extends the system's response-generation capabilities.

The system also includes a recommendation component that considers traveller interests, destination characteristics, ratings, popularity, geographical proximity, seasonal suitability, and saved destinations. Its itinerary planner generates day-wise schedules, estimates travel expenses, orders destinations geographically, and supports budget-aware planning. Voice interaction provides an additional means of accessing travel assistance, while user accounts and saved itineraries support continued use of the platform.

The principal contributions of this work are as follows:

1. The design of an integrated web-based architecture combining conversational AI, tourism information retrieval, destination recommendation, and itinerary generation.
2. The implementation of multilingual travel assistance supporting English, Kannada, and Hindi.
3. The integration of intent classification and hybrid information retrieval to identify user requirements and retrieve relevant tourism information.
4. The development of a recommendation mechanism that considers multiple destination characteristics and traveller preferences.
5. The implementation of a budget-aware itinerary planner that generates day-wise travel schedules and estimates expenses.
6. The integration of voice interaction, destination management, user accounts, saved places, and itinerary export within a regional tourism application.

II. RELATED WORK

Artificial Intelligence has increasingly influenced tourism applications through personalised recommendations, conversational interfaces, intelligent itinerary generation, and context-aware decision support. Traditional tourism platforms primarily rely on predefined destination information and manually configured recommendations, whereas AI-enabled systems aim to understand traveller requirements and provide more adaptive assistance. Recent research has explored machine learning, Natural Language Processing (NLP), Large Language Models (LLMs), and Retrieval-Augmented Generation (RAG) to improve the relevance and accessibility of travel-related information.

A. Conversational AI for Tourism

Conversational AI enables travellers to interact with tourism applications using natural-language questions rather than navigating through multiple predefined menus. NLP techniques support the identification of user intent and the extraction of relevant information from queries. Recent developments in LLMs have expanded the ability of conversational systems to interpret complex requests, maintain dialogue context, and generate human-like responses.

The previously published study, *Context-Aware Conversational AI for Intelligent Travel Planning and Smart Tourism*, examines conversational AI, contextual personalisation, information retrieval, and intelligent travel planning. It identifies challenges associated with maintaining conversational context, integrating diverse tourism information sources, supporting multilingual interaction, and ensuring the reliability of generated recommendations. These findings provide a research foundation for developing integrated tourism applications that combine conversational interaction with structured tourism knowledge.

The system presented in this paper adopts a practical conversational approach by combining machine-learning-based intent classification, keyword rules, contextual dialogue processing, and tourism information retrieval. This design supports travel-related queries while providing a structured mechanism for locating relevant destination information.

B. Tourism Information Retrieval

Information retrieval plays an important role in helping travellers obtain relevant information from large collections of destination descriptions and tourism-related content. Keyword-based retrieval is straightforward to implement but may not adequately identify relevant information when users express similar requirements using different words. Vector-space approaches, including TF-IDF, represent text according to the importance of its terms and enable similarity-based document retrieval.

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Hybrid retrieval approaches can combine lexical similarity with additional matching techniques to improve the identification of relevant content. Word-level features help identify shared terms and expressions, while character-level n-grams can assist with partial-word matches and variations in spelling.

The proposed system incorporates hybrid TF-IDF-based retrieval using word and character n-grams. This mechanism helps identify tourism information relevant to user queries. Combining retrieval with intent classification and conversational context provides a structured approach to processing travel questions. However, retrieval relevance must be evaluated experimentally before improvements in accuracy or response quality can be claimed.

C. Personalised Destination Recommendation

Recommendation systems help travellers discover destinations according to their preferences and travel objectives. Content-based recommendation methods compare user interests with the characteristics of available destinations. Additional factors, including ratings, popularity, geographical proximity, seasonal suitability, and previously saved destinations, can further influence recommendation ranking.

In tourism applications, these factors are important because destination suitability depends on more than general popularity. A traveller interested in historical monuments may require different recommendations from someone seeking wildlife experiences or hill stations. Similarly, distance, travel duration, and seasonal conditions can influence the practical suitability of a destination.

The system described in this paper incorporates multiple destination-related factors into its recommendation process. By combining traveller interests with destination characteristics and other available signals, the system aims to provide more relevant suggestions than a list based solely on popularity. The effectiveness of the recommendation mechanism requires evaluation using suitable test cases and, where available, user feedback.

D. Intelligent Itinerary Planning

Travel itinerary generation involves selecting destinations, allocating visits across travel days, organising the order of attractions, and estimating the overall cost. Manual planning can become complicated when travellers have limited time, restricted budgets, or several destinations to visit. Intelligent planning mechanisms can simplify this process by considering multiple travel constraints.

Existing research has investigated optimisation algorithms, recommendation-based planning, and language-model-driven agents for travel planning. These approaches differ in their handling of destination selection, geographical constraints, temporal requirements, and user preferences. Although generative AI can support flexible planning conversations, reliable itinerary generation also requires structured destination information and explicit planning rules.

The proposed system incorporates day-wise itinerary generation, geographical ordering of destinations, expense estimation, and budget-aware planning. These functions connect destination discovery with practical trip organisation. The system's itinerary quality should be assessed through functional testing of travel duration, destination ordering, budget constraints, and the validity of generated schedules.

E. Research Gap and Motivation

The reviewed research indicates that conversational assistance, tourism information retrieval, recommendation systems, and itinerary planning address complementary aspects of intelligent tourism. However, implementing these functions as separate services can require travellers to switch between different applications and repeatedly enter their preferences.

A regional tourism platform can address this fragmentation by integrating destination discovery, conversational assistance, multilingual interaction, personalised recommendations, and itinerary generation within a common web application. Regional language support is particularly relevant when serving travellers with different language preferences.

Motivated by these requirements, this work presents an integrated AI-assisted tourism system focused on Karnataka. Its main emphasis is the implementation of multiple travel-support functions within a single application using a Flask-based backend, hybrid information retrieval, machine-learning-based intent recognition, recommendation logic, and itinerary planning. Unlike a literature review or conceptual framework, this paper focuses on the system design and implementation. Its practical contribution is the integration of these components into a regional tourism application, while empirical evaluation remains necessary to quantify their effectiveness.

III. PROPOSED SYSTEM

The proposed system presents an AI-powered multilingual travel guide designed to simplify tourism information discovery and travel planning for Karnataka. It integrates natural language processing, tourism information retrieval, destination recommendation, and itinerary generation within a web-based application. The system allows users to explore tourist destinations, obtain relevant travel information, and prepare personalised itineraries through an interactive interface.

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The application is developed using Python and the Flask web framework. SQLite is used as the default database configuration, while the database connection can be configured through the application's database settings. The system supports English, Kannada, and Hindi to improve accessibility for users with different language preferences.

A. System Architecture

The system follows a modular architecture consisting of a user interface, Flask application layer, natural language processing module, tourism information retrieval module, recommendation engine, itinerary planning module, and database layer.

The user interface accepts text-based queries and user selections. The Flask application processes incoming requests and directs them to the appropriate module. For conversational queries, the language-processing component identifies the likely intent using TF-IDF-based text features, a Logistic Regression classifier, and keyword-based rules. The information retrieval component then identifies relevant tourism information using word-level and character-level TF-IDF features.

The recommendation module ranks destinations using factors such as content similarity, ratings, popularity, distance, season, and saved places. The itinerary planning module organises selected destinations into a day-wise travel plan and supports route ordering and cost estimation. The database stores relevant application information, including user accounts, destinations, saved places, and itinerary-related records.

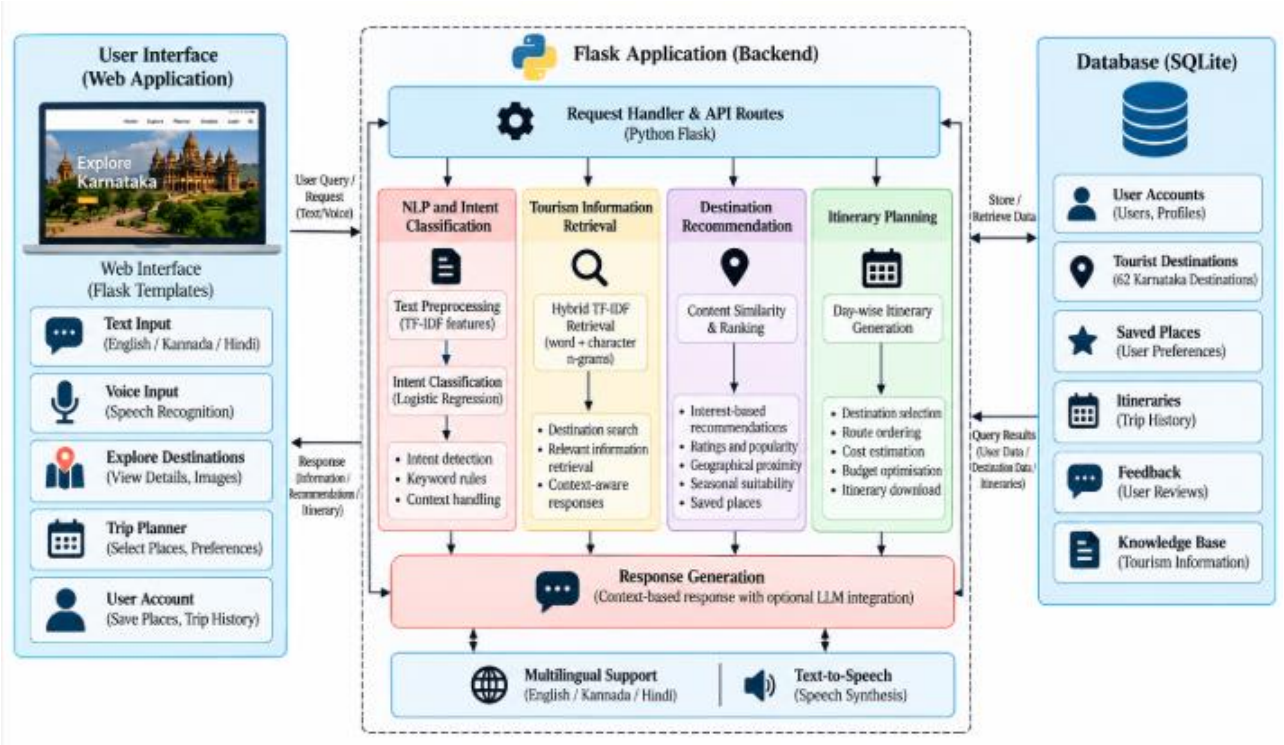


Fig. 1. System Architecture of the Proposed AI-Powered Multilingual Travel Guide

B. Multilingual Conversational Interface

The conversational interface enables users to ask questions about travel and tourism in natural language. Instead of requiring users to navigate multiple pages or search using predefined keywords, the system is designed to interpret queries and provide relevant information through a conversational interaction.

The system supports English, Kannada, and Hindi. It also includes browser-based speech recognition and speech synthesis to support voice interaction in compatible browsers. An optional text-generation integration can be configured to enhance conversational responses when the required API configuration is available.

The conversational component is intended to help users obtain destination information and travel guidance in a more accessible manner. The relevance of a response depends on the information available to the application and the capabilities enabled in its configuration.

C. Tourism Information Retrieval

The tourism information retrieval module provides access to information about tourist destinations in Karnataka. The project includes a collection of 62 destinations that users can explore through the application.

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The retrieval process uses TF-IDF representations with word-level and character-level features to identify tourism information relevant to a user's query. Word-level features help match meaningful terms, while character-level features can support matching when words contain spelling variations or partial similarities.

The retrieved information is used to support destination exploration and conversational responses. This approach provides a structured mechanism for finding relevant information without relying entirely on external generative AI services.

D. Destination Recommendation Module

The recommendation module assists users in identifying destinations that may suit their interests and travel requirements. It considers multiple factors, including content similarity, destination ratings, popularity, distance, seasonal suitability, and previously saved places.

These factors help the application organise destination suggestions according to available information and user preferences. By combining multiple recommendation signals, the system aims to provide more useful suggestions than a simple unranked destination list.

The recommendations depend on the availability and quality of destination information. The module should therefore be understood as a decision-support feature rather than a guarantee that a destination is suitable for every traveller.

E. Intelligent Itinerary Planning

The itinerary planning module helps users organise a trip by arranging selected destinations into a day-wise plan. It supports route ordering and cost estimation to assist users in preparing a practical travel schedule.

The planning process considers the destinations selected by the user and organises them into an itinerary. Route ordering helps establish a travel sequence, while cost estimation provides an approximate view of expected expenses. Budget optimisation functionality supports planning around the user's available budget.

The generated itinerary provides a starting point for travel preparation. Actual travel times, transportation costs, opening hours, weather conditions, and other real-world constraints may need to be verified separately when planning a trip.

F. User and Administrative Management

The system provides user management features that allow users to save destinations, access trip history, and download itineraries. The administrative module supports the management of destination information, users, itineraries, feedback, and the tourism knowledge base. The database layer stores and retrieves the information required by these features. SQLite is used as the default database configuration for local development and testing, while the configurable database connection supports adaptation to other supported database systems.

G. Overall Workflow

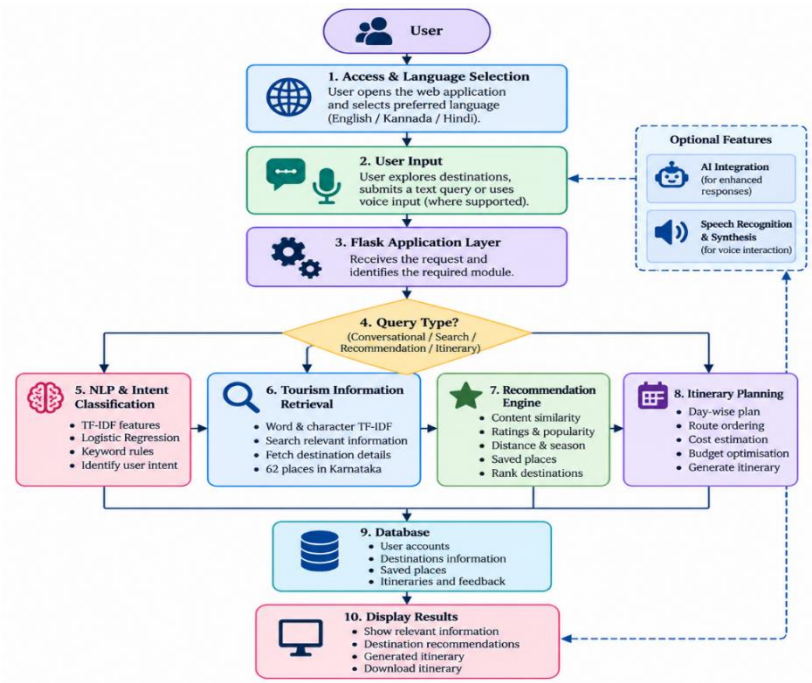


Fig. 2. Workflow of the Proposed Travel Guide and Trip Planning System

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IV. IMPLEMENTATION AND METHODOLOGY

The proposed system integrates natural language processing (NLP), machine-learning-based intent classification, TF-IDF-based information retrieval, content-based recommendation, and constraint-aware itinerary generation. The application is implemented using Python and Flask, with SQLite for persistent data storage and Scikit-learn for machine-learning operations. The tourism dataset contains information about 62 destinations in Karnataka, including descriptive content and destination-related attributes. The processing pipeline converts user queries into structured travel requirements, retrieves relevant tourism information, and generates responses or itineraries according to the identified intent and available travel constraints.

A. Natural Language Processing and Query Understanding

The query-understanding module extracts travel-related entities, including destination, starting city, number of days, traveller count, budget, interests, travel style, and month. It uses text preprocessing, language detection, destination matching, and rule-based extraction to convert natural-language queries into structured information.

For example, the query "Plan a three-day trip to Coorg from Bangalore for four people within ₹15,000" is analysed to identify the destination, starting location, duration, number of travellers, and budget. The extracted entities are passed to the intent classifier and itinerary planner. The implementation also includes handling for common destination-name variations and budget expressions such as "8k" and "10 thousand".

B. Machine-Learning-Based Intent Classification

The intent-classification module combines a Logistic Regression classifier with keyword-based rules. The machine-learning pipeline uses two TF-IDF feature representations: word-level n-grams and character-level n-grams. The word-level vectorizer uses unigram and bigram features, while the character-level vectorizer uses character sequences of lengths two to four. Sublinear term-frequency scaling is enabled in both vectorizers.

Let x represent the input query and C the set of supported intents. The classifier predicts the intent with the highest estimated probability.

Equation (1): Intent Classification

$$\hat{c} = arg\ max\ \{P(c \mid x) : c \in C\}$$

Here, ĉ represents the predicted intent, P(c | x) represents the estimated probability of intent c given the input query x, and C represents the set of supported intents.

The implementation uses Logistic Regression with a regularisation parameter C = 8.0, a maximum of 3,000 iterations, and balanced class weights. Rule-based patterns provide additional handling for specific query types. The final intent-selection logic also considers extracted entities, allowing travel-planning requests to be distinguished from general destination recommendations. This hybrid design combines statistical text classification with explicit domain-specific rules.

C. TF-IDF-Based Tourism Information Retrieval

The tourism information retrieval module identifies relevant passages from the destination database and tourism knowledge base. It uses a hybrid representation comprising word-level and character-level TF-IDF features. The word-level vectorizer uses unigram and bigram features, while the character-level vectorizer uses character n-grams of lengths three to five, with a maximum of 60,000 character features.

The TF-IDF weight of a term t in document d can be expressed as follows.

Equation (2): TF-IDF Weighting

$$TF\text{-}IDF(t, d) = TF(t, d) \times IDF(t)$$

Here, TF(t, d) denotes the term frequency and IDF(t) represents inverse document frequency. The exact weighting and normalisation follow the configured Scikit-learn vectorizers.

For a query q, the similarity between its vector representation and a document vector d can be measured using cosine similarity.

Equation (3): Cosine Similarity

$$Similarity(q, d) = (q \cdot d) / (||q|| \times ||d||)$$

Here, q and d represent the query and document vectors, respectively, and ||q|| and ||d|| represent their magnitudes.

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The retrieval module ranks candidate passages and returns the most relevant results. It can also use destination identifiers and predicted intent to narrow retrieval. This retrieval-augmented generation (RAG) approach supplies tourism-related context to the response-generation module. When an OpenAI API key is configured, the optional language model generates responses using retrieved passages; otherwise, the application uses its built-in response generator.

D. Content-Based Destination Recommendation

The recommendation module represents destinations using textual attributes, including category, tags, and descriptive information. A TF-IDF vectorizer transforms these attributes into numerical feature vectors. Cosine similarity is then used to compare destinations with user interests and identify similar places.

Personalisation also considers saved destinations. The implementation compares a user profile derived from saved places with destination representations to estimate relevance. Additional ranking signals include ratings, popularity, distance, and season. These signals help produce recommendations that reflect both destination characteristics and user preferences. Budget filtering and trip-cost estimation are handled by the itinerary-planning module.

E. Intelligent Itinerary Generation and Budget Optimisation

The itinerary planner generates day-wise travel plans using the selected destination, starting city, duration, traveller count, interests, travel style, transport preference, and optional budget. It selects suitable attractions, groups nearby locations into daily plans, and orders selected stops using a greedy nearest-neighbour procedure based on geographic distance.

For two locations with latitude-longitude coordinates (φ_1, λ_1) and (φ_2, λ_2), the great-circle distance can be estimated using the Haversine formula.

Equation (4): Haversine Intermediate Value

$$a = \sin^2(\Delta\varphi / 2) + \cos(\varphi_1) \times \cos(\varphi_2) \times \sin^2(\Delta\lambda / 2)$$

Equation (5): Great-Circle Distance

$$d = 2R \times \arcsin(\sqrt{a})$$

Here, $\Delta\varphi$ and $\Delta\lambda$ represent the differences in latitude and longitude, respectively, and R represents the assumed Earth radius. The implementation uses geographic distance to identify and order nearby stops.

The cost model estimates transport, local transport, accommodation, food, entry fees, and miscellaneous expenses. The total estimated cost is calculated as follows.

Equation (6): Total Trip Cost

$$C_total = C_transport + C_local + C_accommodation + C_food + C_entry + C_misc$$

Here, C_total represents the total estimated trip cost, while the remaining terms represent the corresponding expense categories.

When the initial plan exceeds the specified budget, the planner explores less expensive travel styles and transport combinations and may remove optional paid stops. If a feasible combination is found, the itinerary is adjusted to fit the budget. Otherwise, the system reports that the budget cannot be satisfied by the selected plan. The resulting itinerary includes a day-wise schedule and an estimated cost breakdown.

F. Multilingual Conversational Interface

The application supports English, Kannada, and Hindi. Language detection and multilingual text patterns enable the query-understanding and intent-classification modules to process queries in these languages. The conversational engine maintains context across follow-up messages, allowing users to modify previously stated travel requirements without repeating the entire query.

The web interface supports voice input and speech output through browser speech capabilities. An optional gTTS-based server endpoint provides an additional speech-generation path for supported languages when required. The conversational module combines the predicted intent, extracted entities, prior dialogue context, retrieved tourism passages, and relevant itinerary or recommendation results to construct the response.

G. Data Storage and Application Integration

The system uses Flask to connect the user interface with the NLP, retrieval, recommendation, and itinerary-planning modules. SQLite, accessed through Flask-SQLAlchemy, stores application information, including user accounts, destinations, saved places, trips, chat sessions, feedback, and knowledge documents. Destination data is initially loaded

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from JSON files, and the data-preparation process uses pandas to remove duplicates, fill missing values, normalise text, and validate selected attributes.

The integrated application supports destination exploration, conversational assistance, personalised recommendations, itinerary generation, trip saving, and administrative management. The modular design separates query understanding, intent classification, information retrieval, recommendation, and planning, making the components easier to test and maintain.

V. RESULTS AND DISCUSSION

The proposed AI-powered multilingual travel guide and intelligent trip-planning system was implemented and functionally tested to evaluate the operation of its major components. The application integrates destination exploration, natural language processing, machine-learning-based intent classification, tourism information retrieval, personalised recommendations, itinerary generation, multilingual interaction, and data management. The evaluation focused on verifying the functionality of these modules and their integration within a unified web application for Karnataka tourism.

A. Functional Testing

Functional testing was conducted to verify that the implemented features performed their intended operations. The test cases covered destination exploration, intent classification, information retrieval, destination recommendation, itinerary generation, budget management, multilingual interaction, voice functionality, conversational context, user authentication, data management, and application integration.

TABLE I. FUNCTIONAL TESTING RESULTS

Test ID	Module	Test Description	Result
T1	Destination Exploration	Verify access to Karnataka tourist destination information	Pass
T2	Intent Classification	Verify identification of travel-related user queries	Pass
T3	Information Retrieval	Verify retrieval of relevant tourism information	Pass
T4	Destination Recommendation	Verify generation of destination suggestions	Pass
T5	Itinerary Generation	Verify generation of day-wise travel plans	Pass
T6	Budget Management	Verify itinerary adjustment based on budget constraints	Pass
T7	Multilingual Support	Test interactions in English, Kannada, and Hindi	Pass
T8	Voice Interaction	Verify supported speech input and output functionality	Pass
T9	Conversational Context	Verify handling of follow-up travel queries	Pass
T10	Data Management	Verify storage and retrieval of supported application data	Pass
T11	User Authentication	Verify implemented registration, login, and logout workflows	Pass
T12	Application Integration	Verify interaction between the major application modules	Pass

The tested functionalities operated successfully during the reported testing process. These results indicate that the tested application workflows functioned as intended. The table reports functional outcomes and does not represent a quantitative evaluation of the underlying machine-learning model.

B. Destination Exploration and Information Retrieval

The application provides tourism information for 62 destinations across Karnataka. The destination exploration module allows users to discover places and access destination-related information. This functionality forms the foundation of the tourism assistance system.

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The information retrieval module uses word-level and character-level Term Frequency–Inverse Document Frequency (TF-IDF) representations to identify relevant tourism content. Cosine similarity is used to compare query and document representations. The hybrid text representation supports retrieval based on both word patterns and character sequences.
The retrieved information supplies contextual content to the conversational response-generation module. When the optional OpenAI API integration is configured, the application can use a language model to generate responses based on retrieved information. Otherwise, the built-in response generator provides the configured response functionality.

C. Intent Classification and Conversational Assistance

The intent-classification module combines Logistic Regression with keyword-based rules to identify the purpose of user queries. Word-level and character-level TF-IDF features are used to represent the input text. Entity extraction provides additional information, including destination, starting city, trip duration, traveller count, and budget.
Testing covered the handling of supported travel-query categories and the integration of intent recognition with the conversational workflow. The hybrid approach combines statistical text classification with domain-specific rules to support the interpretation of travel requests.
Although functional testing verifies the operation of the intent-classification workflow, additional experiments using a labelled test dataset would be required to establish classification accuracy, precision, recall, and F1-score.

D. Personalised Destination Recommendation

The recommendation module represents destinations using textual attributes, including categories, tags, and descriptive information. TF-IDF vectorisation and cosine similarity support the identification of destinations relevant to user interests.
The system also considers saved destinations and additional ranking signals, such as ratings, popularity, distance, and season, where the corresponding information is available. Functional testing verified the recommendation workflow and its integration with the tourism information available in the application.
This approach supports content-based destination discovery and personalisation. A separate user study would be required to determine how closely the recommendations match travellers' preferences.

E. Intelligent Itinerary Generation and Budget Management

The itinerary planner generates day-wise travel plans using user-specified requirements, including destination, starting city, trip duration, traveller count, interests, travel style, transport preference, and budget.
The planner selects suitable attractions and orders selected stops using a greedy nearest-neighbour procedure based on geographic distance. This method provides a practical way to arrange locations according to proximity but does not guarantee a globally optimal route.
The system estimates expenses across categories such as transportation, local transport, accommodation, food, entry fees, and miscellaneous costs. When the estimated expenditure exceeds the specified budget, the planner attempts to explore less expensive options and adjust optional activities.
Functional testing covered itinerary generation and budget-handling workflows. The system provides a structured travel schedule and estimated cost breakdown. Actual route efficiency and cost-estimation accuracy would require comparison with suitable reference data.

F. Multilingual Interaction and Data Management

The application supports English, Kannada, and Hindi to accommodate users with different language preferences. The multilingual conversational interface was tested as part of the overall application evaluation. Voice input and speech output are supported through the available browser speech capabilities, with an optional server-side text-to-speech mechanism.
The application uses Flask to integrate the user interface with the conversational, retrieval, recommendation, and itinerary-planning components. SQLite, accessed through Flask-SQLAlchemy, stores supported application information, including user accounts, destinations, saved places, trips, chat sessions, and feedback.
Testing covered the relevant data-management and integration workflows. The modular architecture separates the major components, supporting maintainability and further development.

G. Overall Discussion

The functional evaluation covered the major modules of the proposed system and their integration into a unified travel assistance platform. The application combines destination exploration, conversational assistance, information retrieval, personalised recommendations, multilingual interaction, and itinerary generation within a single system focused on Karnataka tourism.

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The main contribution of the proposed approach is the integration of these capabilities into a common travel-planning workflow. Users can explore destinations, submit natural-language queries, obtain relevant tourism information, and generate itineraries based on their stated requirements.

The evaluation is limited to the functional testing performed on the application. Quantitative experiments are still necessary to establish the classification performance of the machine-learning model, retrieval relevance, recommendation quality, route efficiency, and user satisfaction. The use of geographic distance as a routing measure also means that generated routes may differ from actual road routes and travel times.

VI. LIMITATIONS

Although the proposed system provides multilingual tourism assistance and intelligent trip planning, certain limitations remain.

1. **Limited Destination Coverage:** The current system covers 62 tourist destinations in Karnataka. It does not yet provide comprehensive information about every tourist attraction in the state.
2. **Dependence on Available Data:** The accuracy and relevance of tourism information and recommendations depend on the completeness and quality of the available destination data.
3. **Intent Classification Limitations:** The Logistic Regression-based intent classifier and keyword rules may not correctly interpret every complex, ambiguous, or unfamiliar travel query.
4. **Retrieval and Response Limitations:** TF-IDF-based retrieval primarily relies on textual similarity and may not always identify the most contextually relevant information. Responses generated by the optional language model may also contain inaccurate information.
5. **Route Optimisation Constraints:** The itinerary planner uses a greedy nearest-neighbour approach based on geographic distance. It does not guarantee the shortest overall route and may not account for real-time traffic, road conditions, or actual travel duration.
6. **Estimated Travel Costs:** Budget calculations are estimates and may differ from actual expenses because transportation fares, accommodation prices, food costs, and attraction entry fees can change.
7. **Multilingual Processing:** Although English, Kannada, and Hindi are supported, the accuracy of responses may vary depending on the language, query complexity, and availability of suitable language-processing resources.
8. **Limited Quantitative Evaluation:** Functional testing verified the operation of the implemented features; however, further experiments are required to measure classification accuracy, retrieval performance, recommendation effectiveness, itinerary quality, and user satisfaction.

Addressing these limitations through improved datasets, advanced language-processing techniques, real-time information integration, and systematic performance evaluation could enhance the reliability and practical usefulness of the proposed system.

VII. CONCLUSION AND FUTURE SCOPE

A. Conclusion

This paper presented an AI-powered multilingual travel guide and intelligent trip-planning system designed to support tourism across Karnataka, India. Developed using Python Flask, the system provides information about 62 tourist destinations and supports interactions in English, Kannada, and Hindi. It integrates natural language processing, machine-learning-based intent classification, tourism information retrieval, personalised destination recommendations, and budget-aware itinerary generation within a unified web application.

The system combines Logistic Regression, keyword-based rules, TF-IDF-based information retrieval, and cosine similarity to interpret supported travel queries and retrieve relevant tourism information. Its recommendation module helps users discover destinations based on their interests, while the itinerary planner generates day-wise travel schedules and estimates expenses according to user preferences and budget constraints. Additional features, including voice interaction, user accounts, saved destinations, and itinerary management, contribute to a convenient travel-planning experience.

Functional testing indicated that the tested application features operated as intended. However, limitations remain in destination coverage, data availability, contextual understanding, route optimisation, and travel cost estimation. Further quantitative evaluation is necessary to measure the performance and effectiveness of the AI components.

Overall, the proposed system demonstrates the potential of integrating artificial intelligence and multilingual technologies to improve access to regional tourism information and simplify travel planning in Karnataka.

B. Future Scope

The proposed system can be enhanced in several ways to improve its functionality, accuracy, and practical usefulness.

1. **Real-Time Route Optimisation:** Integrate mapping services and live traffic information to improve route planning and travel-time estimation.

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2. **Advanced Conversational AI:** Improve contextual understanding and enable the chatbot to handle complex queries, follow-up questions, and personalised travel requests more effectively.
3. **Expanded Language Support:** Add more Indian languages and improve the accuracy of Kannada and Hindi responses.
4. **Real-Time Tourism Information:** Integrate reliable data sources for weather conditions, attraction opening hours, ticket availability, transportation schedules, and local events.
5. **Mobile Application Development:** Develop Android and iOS applications to provide convenient access to travel assistance while users are exploring destinations.
6. **Enhanced Personalisation:** Improve destination recommendations using traveller feedback, preferences, and interaction history.
7. **Performance Evaluation:** Conduct quantitative experiments to measure intent-classification accuracy, information retrieval relevance, recommendation quality, itinerary efficiency, and user satisfaction.

These enhancements could improve the reliability, adaptability, and usability of the system while contributing to the development of intelligent and accessible tourism services in Karnataka.

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