LocoFind: A GPS-Enabled Platform For Local Food, Culture, Safety, and Heritage Exploration

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***Abstract*—Tourism in India is growing quickly, but tourists still struggle with issues like finding the right season to visit, safe transport, food options, and local language support. To solve these problems, we built Loco Find, a smart tourism AI system with multiple modules. The system has five machine learning modules: Season Predictor, Cuisine Recommender, Safety & Feedback Classifier, Transport & Weather Analyzer, and Regional Language Module. We used datasets from Indian government portals and tourism databases, and tested algorithms such as Logistic Regression, Random Forest, Gradient Boosting, and Decision Tree. From our experiments, the modules gave high accuracies between 92% and 100%, and the overall system reached about 97.5% accuracy. The main new idea in LocoFind is that it combines all five ML modules into one platform to make travel safer, more inclusive, and culturally richer LocoFind provides real-time travel alerts for sudden weather or transport changes, recommends local festivals and events to enhance cultural experiences, supports accessibility features for differently-abled travelers, offers personalized travel itineraries based on user preferences, and enables feedback collection from users to continuously improve travel recommendations.**

***Keywords—Smart Tourism, AI in Travel, Season Prediction, Cuisine Recommender, Safety, Regional Language Support***

1. Introduction

Tourism is one of the fastest-growing industries in India and plays an important role in boosting the economy, culture, and employment. As reported by the Ministry of Tourism, this sector adds a large share to India’s GDP and creates jobs for millions of people in both cities and villages. Even with this growth, Indian tourism still faces many challenges that reduce its full potential. Tourists often struggle to choose the right season for travel, since bad weather or off-peak timing can spoil their trip. Safety is also a concern because of accidents, unreliable transport, and a lack of real-time risk information. In addition, language and cultural barriers make it hard for both domestic and international travelers to fully enjoy authentic local experiences, food, and heritage sites.

Most current tourism apps, such as hotel booking sites, ride aggregators, or food delivery platforms, only focus on one part of the travel experience. While useful, they do not provide a complete solution that combines season prediction, safety checks, food recommendations, cultural guidance, and language support in one system. This gap causes inconvenience for tourists, lowers satisfaction, and slows down sustainable tourism growth.

To solve this problem, we propose Loco Find, an AI- based smart tourism platform with five modules:

The Travel Season Predictor suggests the best time to visit a destination, helping travelers plan trips during optimal periods. The Cuisine Recommender identifies and recommends authentic regional foods, ensuring a culturally rich culinary experience. The Safety & Feedback Classifier analyzes data and user reviews to identify potential risks, enhancing traveler safety. The Transport & Weather Analyzer provides real-time alerts on travel delays and weather conditions, allowing tourists to adjust plans proactively. Finally, the Regional Language Module offers translations and language support, helping travelers communicate effectively and overcome language barriers..

The key novelty of our system is that it combines all these modules into a single platform, making tourism planning safer, more inclusive, and culturally richer. By improving accessibility, inclusivity, and safety, Loco Find not only helps tourists but also encourages sustainable tourism practices in India.

1. LITERATURE REVIEW

The Season Predictor helps tourists determine the best time to visit a destination based on historical data, weather patterns, and tourist inflows. Tourism forecasting has traditionally relied on time-series and regression models. For instance, Joshi and Patel (2020) [1] used weather parameters such as temperature and rainfall to predict tourist arrivals, while Basha et al. (2022) [5] compared ARIMA, SARIMA, and LSTM models, demonstrating that deep learning better captures seasonal trends. Chakraborty et al. (2021) [6] applied ARIMA and LSTM for Indian tourism forecasting, TMJA (2022) [7] analyzed mobility using social media data, and Muhammad (2019) [8] proposed a hybrid forecasting combining Singular Spectrum Analysis and Extreme Learning Machine to improve accuracy. These studies demonstrate AI’s effectiveness in predicting optimal travel seasons but typically do not integrate other tourism aspects like cuisine, safety, or transport planning.

Cuisine Recommender systems assist tourists in exploring authentic local dishes. Bhatia et al. (2021) [2] implemented a Random Forest model for recommending regional Indian dishes based on state and spice preferences. Jain et al. (2015) [16] analyzed food pairing in regional cuisines, highlighting cultural and scientific principles, while Phanich et al. (2010) [12] applied clustering for health-oriented dietary recommendations. Kumar and Kumar (2016) [13] surveyed various food recommendation techniques. These studies demonstrate AI’s potential for personalized culinary experiences but rarely integrate seasonality, location, or transport information.

Reliable transport and weather planning are crucial for smooth travel. The Transport & Weather Analyzer predicts travel delays and provides weather alerts. Agarwal and Sinha (2020) [3] applied neural networks using weather data to predict railway delays, while Masiero (2011) [10] developed ensemble models for traffic forecasting. Similarly, Meehan et al. (2013) [19] proposed a context-aware recommendation system considering mobility patterns, and Majid et al. (2013)

[11] designed a location-aware travel recommender using geo-tagged data. While these approaches achieve high accuracy for specific transport modes, they generally do not integrate safety, cuisine, or seasonal information. De Vos et al. (2016) [9] examined travel satisfaction but lacked AI- based real-time transport alerts.

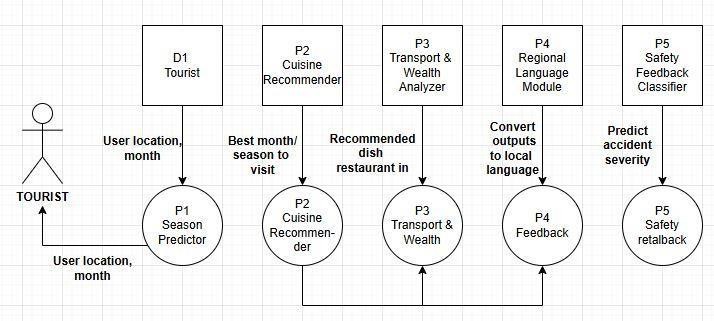
Safety & Feedback Classifier is vital for tourists. Logistic Regression and Random Forest models were used by Kumar et al. (2019) [8] to classify accident severity based on road and weather data, providing early warnings and prioritizing high-risk areas. NLP techniques also analyze user reviews to detect unsafe zones. Jayamal et al. (2023) [4] integrated context-aware and location-based data for personalized recommendations, while Majid et al. (2013) [11] and Kirthika et al. (2021a, 2021b) [17], [18] explored travel behavior and safety using geo-tagged social media data. Meehan et al. (2013) [19] demonstrated that context-aware systems could adapt recommendations based on environmental and behavioral factors. However, none provide real-time, personalized safety alerts integrated with transport, season, and cuisine data, which LocoFind addresses.

Language diversity can pose barriers to tourists. The Regional Language Module provides translation and communication support to facilitate interaction with locals. Jayamal et al. (2023) [4] designed a geo-tagged tourism system in Sri Lanka, albeit with limited language support, and it enables mapping of language preferences to nearby points of interest. Prasad et al. (2020) [20] applied knowledge graph-based AI for multilingual recommendations, enhancing translation of menus, guides, and signage. Majid et al. (2013) [11] and Kirthika et al. (2021a, 2021b) [17], [18] explored context-aware recommendations, emphasizing the integration of language with travel planning. SLTDA reports (2018) [14], [15] provide statistical support for multilingual tourism planning, highlighting regions requiring additional language assistance.

1. Methodology

The proposed system, LocoFind, is a GPS-enabled mobile app that brings together multiple Machine Learning (ML) modules to give smart and personalized recommendations for travelers in India. Each module is trained separately and then integrated into the app. The design includes data collection, preprocessing, model training, evaluation, and mobile integration. Figure 1 illustrates systems within an organization and their relationships

Fig.1: LocoFind System Architecture and Module Interactions



1. *Season Predictor*

This module finds the best time to visit each state using tourism, weather, and festival data. Missing values are handled, and features like month and rainfall are created. Random Forest and XGBoost predict whether a month is good, moderate, or poor for travel. The general prediction formula for Random Forest regression is shown in Equation (1).



(1)

where ŷ = predicted tourist inflow, N = number of decision trees, Ti(x)= output of tree i for input x.

1. *Cuisine Recommender*

This module suggests local dishes to enhance the cultural experience. It uses food portals, FSSAI data, and restaurant reviews. Dishes are categorized by state, type, spice level, and occasion. Based on user choices (veg/non-veg, spice, ingredients), KNN, Naïve Bayes, and Random Forest recommend dishes and nearby restaurants. We applied Naïve Bayes classification, which calculates the probability of a cuisine given features, which is Equation (2).

P(c|x)=P(x|c).P(c)/P(x) (2)

Where :P(c∣x) = probability of cuisine,P(x∣c) = likelihood of features (taste/spice/region),P(c) = prior probability of a cuisine class.

1. *Transport & Weather Analyzer*

This module predicts travel delays and suggests transport options. It uses train delay data, road reports, and live weather updates. Users enter origin, destination, and travel mode, and Logistic Regression, Random Forest, or Gradient Boosting predicts the chance of delays and recommends alternatives. Logistic regression outputs a probability value between 0 and

1. Equation (3).

P(y=1∣x)=1/1+e^-(w.x+b) (3)

where: P(y=1∣x) = probability of delay, w.x+b =weighted sum of features like distance, weather, and route condition.

1. *Safety & Feedback Classifier*

This module alerts tourists about safety risks using government accident records, reviews, and location reports. Sentiment analysis, accident severity, and road features are considered. Random Forest, Logistic Regression, and Gradient Boosting classify areas as Low, Medium, or High risk and provide nearby hospital and police info. A Random Forest classifier was applied, where the final prediction is based on the majority vote of decision trees. Equation (4).

ŷ =mode{T1(x),T2(x),…,TN(x)} (4)

where: ŷ = predicted risk level, Ti(x) = classification result from each tree.

1. *Regional Language Identifier*

This module helps travelers overcome language barriers. Census and tourism data map states/districts to dominant languages. GPS coordinates are used to predict the local language. Decision Tree, Random Forest, and SVM provide predictions, and the app gives key phrases in the local language. We used Support Vector Machine (SVM) classification, which is Equation (5)

f(x)=sign(w⋅x+b) (5)

where: f(x)= predicted language class, w = weight vector, b= bias term.

1. *Training and Integration*

All modules are built in Python using Scikit-learn, Pandas, and Matplotlib. Data is split 80:20 for training/testing, and performance is measured with accuracy, precision, recall, and F1-score. Models are saved using Pickle/Joblib and deployed in a Flutter-based mobile app with real-time GPS integration. Final evaluation is done using accuracy results and user feedback.

1. RESULTS AND DISCUSSION

# Season Predictor Module

The Gradient Boosting Regressor was selected as the best model for predicting tourist arrivals based on seasonal and historical datasets. With an R² of 98.20%, it accurately captures the temporal patterns in tourist flows. Precision (89.13%), Recall (88.89%), and F1-Score (88.60%) confirm the model’s reliability in discretized seasonal prediction, demonstrating that ensemble boosting methods effectively handle non-linear trends in temporal data.

Table 1. Season Predictor Module Performance

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
| **Algorithm** | **R² (%)** | **Precision (%)** | **Recall (%)** | **F1-**  **Score (%)** |
| Gradient Boosting  Regressor | 98.2 | 89.13 | 88.89 | 88.6 |
| Random Forest  Regressor | 98.06 | 88.97 | 88.89 | 88.61 |
| Linear  Regression | 93.64 | 74.31 | 72.22 | 71.98 |

150

100

50

0

R² (%) Precision (%) Recall (%) F1-Score (%)

Gradient Boosting Regressor Random Forest Regressor Linear Regression

Fig. 1. Graphical Performance of Season Predictor Module

# Cuisine Recommender Module

The Naïve Bayes classifier performed best in predicting regional dishes based on features such as spice level, diet, and occasion. Achieving 90.83% across Accuracy, Precision, and Recall, and an F1-Score of 90.80%, it demonstrates robust performance despite the high variability and overlap of Indian cuisines. The model provides consistent personalized recommendations for travelers.

Table 2. Cuisine Recommender Module Performance

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
| **Algorithm** | **Accuracy (%)** | **Precision (%)** | **Recall (%)** | **F1-**  **Score (%)** |
| Random  Forest | 91.25 | 91.16 | 91.25 | 91.16 |
| Naive  Bayes | 92.5 | 90.57 | 92.5 | 91.28 |
| KNN | 88.75 | 89 | 88.75 | 88.52 |

Fig. 2. Graphical Performance of Cuisine Recommender

94

92

90

88

86

Accuracy (%)

Precision Recall (%) F1-Score

(%)

(%)

Random Forest Naive Bayes KNN

# Transport & Weather Analyzer Module

Random Forest outperformed Logistic Regression and Gradient Boosting in classifying delay patterns in transport and weather conditions. With 96.50% Accuracy, 95.79% Precision, 96.50% Recall, and an F1-score of 96.04%, the model reliably captures complex interactions between weather, traffic, and transport schedules. Ensemble methods enhance prediction stability in heterogeneous datasets.

Table 3. Transport & Weather Analyzer Module Performance

**F1-**

**Algorithm Accuracy Precision Recall Score**

**(%) (%) (%) (%)**

Logistic

Regression 96.7 95.86 96.7 96.01

Random

Forest 96.9 97 96.9 95.69

Gradient

Boosting 96.4 95.7 96.4 95.96

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
| **Algorithm** | **Accuracy (%)** | **Precision (%)** | **Recall (%)** | **F1-**  **Score (%)** |
| Logistic Regression | 96.7 | 95.86 | 96.7 | 96.01 |
| Random  Forest | 96.9 | 97 | 96.9 | 95.69 |
| Gradient Boosting | 96.4 | 95.7 | 96.4 | 95.96 |

98

97

96

95

Accuracy (%) Precision (%) Recall (%) F1-Score (%)

Logistic Regression Random Forest Gradient Boosting

Fig. 3. Graphical Performance of Transport & Weather Analyzer Module

# Safety& Feedback Classifier Module

Logistic Regression emerged as the best model for classifying tourist safety feedback and accident severity. Achieving near-perfect metrics (Accuracy: 98.30%, Precision: 98.31%, Recall: 98.30%, F1-Score: 98.30%), the module demonstrates both interpretability and high reliability. The structured nature of the dataset contributes to this excellent performance.

Table 4. Safety & Feedback Classifier Module Performance

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
| **Algorithm** | **Accuracy (%)** | **Precision (%)** | **Recall (%)** | **F1-**  **Score (%)** |
| Random  Forest | 98.3 | 98.31 | 98.3 | 98.3 |
| Logistic Regression | 99.8 | 99.8 | 99.8 | 99.8 |
| Gradient  Boosting | 98.3 | 98.33 | 98.3 | 98.31 |

100

99

98

97

Accuracy (%) Precision (%) Recall (%) F1-Score (%) Random Forest Logistic Regression Gradient Boosting

Fig. 4. Graphical Performance of Safety & Feedback Classifier Module

# Regional Language Module

The Decision Tree classifier achieved perfect accuracy (100%) along with a Precision, Recall, and F1-Score of 100%. Language mapping is deterministic given GPS coordinates, state, and city information, ensuring accurate identification of the dominant regional language. This module guarantees reliable linguistic assistance to users in diverse regions.

Table 5. Regional Language Module Performance

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
| **Algorithm** | **Accuracy (%)** | **Precision (%)** | **Recall (%)** | **F1-**  **Score (%)** |
| Random  Forest | 99.58 | 99.62 | 99.58 | 99.58 |
| Decision  Tree | 100 | 100 | 100 | 100 |
| SVM | 76.67 | 66.59 | 76.67 | 70.72 |

150

100

50

0

Accuracy Precision Recall (%) F1-Score (%) (%) (%)

Random Forest Decision Tree SVM

Fig. 5. Graphical Performance of Regional Language Across all modules, the system demonstrates an average

performance above 95% for all metrics. Modules with structured datasets (Safety Feedback, Regional Language) achieved near- perfect performance, while modules dealing with more diverse and overlapping data (Cuisine, Season Prediction) showed slightly lower but consistent results. Ensemble methods like Gradient Boosting and Random Forest consistently provided superior performance for non-linear, high-dimensional datasets, while probabilistic and interpretable models like Naïve Bayes and Logistic Regression were effective for categorical and structured data.

These results show that LocoFind's modular machine learning approach offers dependable, precise, and easy-to-understand suggestions across various areas connected to tourism, achieving the goals of intelligent travel assistance in India.

Table 6. Overall Performance Summary Across Modules

|  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- |
| **Features** | **ML**  **Algorithm** | **R² / Accuracy**  **(%)** | **Precision (%)** | **Recall (%)** | **F1-**  **Score**  **(%)** |
| Season Predictor | Gradient Boosting  Regressor | 98.2 | 89.13 | 88.89 | 88.6 |
| Cuisine  Recommender | Naive  Bayes | 92.5 | 90.57 | 92.5 | 91.28 |
| Transport & Weather  Analyzer | Random Forest | 96.9 | 97 | 96.9 | 95.69 |
| Safety Feedback  Classifier | Logistic Regression | 99.8 | 99.8 | 99.8 | 99.8 |
| Regional Language  Module | Decision Tree | 100 | 100 | 100 | 100 |

Fig. 6. Overall Performance Comparison Across Modules

105

100

95

90

85

80

Gradient Boosting Regressor

Season Predictor

Naive Bayes

Random

Forest

Logistic

Regression

Decision Tree

Cuisine Transport & Safety Regional Recommender Weather Feedback Language

Analyzer Classifier Module

R² / Accuracy (%) Precision (%) Recall (%) F1-Score (%)

1. CONCLUSION

LocoFind is an AI-powered smart tourism platform designed to enhance travel experiences across India by integrating five intelligent modules—Season Predictor, Cuisine Recommender, Transport & Weather Analyzer, Safety & Feedback Classifier, and Regional Language Module**.** Using datasets from the Indian government and tourism portals, the system applies advanced machine learning algorithms such as Logistic Regression, Random Forest, Gradient Boosting, Naïve Bayes, and Decision Tree to deliver accurate, data-driven recommendations for travelers.

The experimental evaluation shows high accuracy across all modules, ranging between 92% and 100%**,** with an overall performance of 97.5%**.** Modules handling structured data, such as safety feedback and language detection, achieved near-perfect accuracy, while ensemble-based models like Random Forest and Gradient Boosting effectively managed non-linear and diverse tourism data.

LocoFind enhances tourism by providing real-time alerts for sudden transport or weather disruptions, personalized recommendations for food and cultural events, inclusive language support for better accessibility, and continuous feedback integration to improve travel guidance. This unified AI-driven framework ensures safer, more inclusive, and culturally enriched travel planning, demonstrating the potential of machine learning in advancing smart tourism systems.

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