TRAVEL BUDDY

A PROJECT WORK
Submitted in partial fulfillment of
Requirements for the award of the degree of

Bachelor of Technology
in

COMPUTER SCIENCE & INFORMATION TECHNOLOGY

by

V.Shahith Kumar(22331A0761)
K.Keerthi (22331A0722)
M.Stitha Prazna(22331A0765)

Under the esteemed guidance of

Mrs. M. Swarna, M.Tech,(Ph.d)
Associate Professor

MAHARAJ VIJAYARAM GAJAPATHI RAJ COLLEGE OF ENGINEERING (A)

(Affiliated to Jawaharlal Nehru Technological University, Kakinada)

VIZIANAGARAM

2024 - 25

MAHARAJ VIJAYARAM GAJAPATHI RAJ COLLEGE OF ENGINEERING (A)

VIZIANAGARAM

BONAFIDE CERTIFICATE

Certified that this is a bonafide record of project work entitled “TRAVEL BUDDY“, done by V.Shahith Kumar Regd. No. 22331A0761, K.Keerthi Regd. No. 22331A0722, M.Stitha Prazna Regd. No. 22331A0765 in partial fulfillment for the award of the degree of “**Bachelor of Technology** “ in Computer Science & Information Technology, M.V.G.R. College of Engineering, Vizianagaram , year 2024 – 25.

.M. Swarna, M.Tech ,(Ph.D) Associate Professor	Head of the Department Information Technology

ACKNOWLEDGEMENT

As a note of acknowledgement, with great solemnity and sincerity, we offer our profuse thanks to Mrs.M.Swarna Madam, Associate Professor, Dept. of IT, for guiding us all through our project work, giving a right direction and shape to our learning by extending her expertise and experience in the field of education. Really, we are indebted to her for her excellent and enlightened guidance. Let us lay it on the line we should thank Mrs.M.Swarna Madam and Dr.B.Anjana Devi Madam who remained all through our project work as a great source of inspiration for their resourceful counsel and for inducing in us their empirical knowledge that pivoted the goal and destination of our project.

We consider it our privilege to express our deepest gratitude to Dr. P Srinivasa Rao, Professor and Head of the Department for his valuable suggestions and constant motivation that greatly helped the project work to complete successfully.We also thank Dr. R Ramesh, Principal, for extending his utmost support and cooperation in providing all the provisions for the successful completion of the project.We sincerely thank all the members of the staff in the Department of Information Technology for their sustained help in our pursuits. We thank all those who contributed directly or indirectly in successfully carrying out this work.

V.Shahith Kumar(22331A0761)
K.Keerthi(22331A0722)
M.Stitha Prazna(22331A0765)

TABLE OF CONTENTS

ABSTRACT

A dynamic platform designed to transform the way people plan and experience travel. The goal of this project is to offer tailored travel recommendations based on user preferences and seamlessly connect like-minded individuals to share memorable adventures. Through advanced algorithms, we recommend travel destinations that align with individual interests, whether it's adventure, relaxation, culture, or nature. In addition, our user matching feature ensures that solo travelers can easily find companions who share similar travel styles, making it easier to embark on exciting journeys with new friends or travel buddies. It also plans our trip based on the destinations we are going to specify what to do each day and cost for each section of the trip part.

The importance of personalized recommendations extends beyond user satisfaction. It also influences travel patterns, promotes destination diversity, and can even drive local economies by encouraging travelers to explore lesser-known locations. This research focuses on exploring effective methods for destination recommendation and user matching, with the aim of developing a dynamic, scalable framework that can enhance the travel experience for users across different contexts and industries. By aligning travel recommendations with the users' personal preferences and motivations, this approach promises to transform the way people plan their trips, ensuring that their journeys are not only enjoyable but deeply meaningful.

Our platform goes beyond traditional travel recommendations by not only suggesting the best destinations tailored to your interests, budget, and travel style but also matching you with fellow travelers who share similar passions . Our user matching feature allows you to connect with travel buddies, share experiences, and create memories that will last a lifetime.

INTRODUCTION

Travel planning has evolved significantly with the rise of digital platforms, yet many existing solutions fail to provide truly personalized experiences. Traditional travel recommendation systems often focus on popular destinations, overlooking the unique preferences and social aspects that make a journey memorable. Our platform aims to revolutionize travel by offering tailored destination suggestions based on individual interests while also facilitating meaningful connections between like-minded travelers.

Through advanced algorithms, we provide intelligent travel recommendations that align with users' preferences, whether they seek adventure, relaxation, culture, or nature. Additionally, our innovative user-matching feature helps solo travelers find compatible companions, fostering shared experiences and enhancing the overall travel journey. Beyond recommendations, our platform assists in detailed itinerary planning, ensuring travelers know what to do at each destination, along with cost breakdowns for better financial planning.

By integrating personalized recommendations with social connectivity, our system not only enhances user satisfaction but also promotes diverse travel patterns, supports lesser known destinations, and drives local economic growth. This research focuses on developing a scalable, dynamic framework that redefines the way people plan and experience travel, making trips more immersive, efficient and socially engaging.

PROBLEM STATEMENT

Travel planning is a complex and time-consuming process that often lacks personalization, making it difficult for travelers to find destinations, companions, and itineraries that align with their unique preferences and budgets. Traditional travel recommendation systems provide generic suggestions without considering individual interests, travel styles, or real-time factors, leading to suboptimal travel experiences. Moreover, solo travelers frequently struggle to find compatible companions, which can result in missed opportunities for shared experiences and increased travel costs.

Another challenge in travel planning is itinerary creation. Many travelers rely on multiple platforms to research destinations, estimate costs, and organize their schedules, leading to fragmented and inefficient planning. Without a dynamic system that seamlessly integrates these components, travelers may end up with uncoordinated plans, unexpected expenses, and less fulfilling journeys.

Furthermore, mainstream travel platforms tend to focus on popular destinations, neglecting lesser-known locations that could provide unique and enriching experiences. This lack of diversity in recommendations limits travelers' exposure to new cultures and places while also concentrating tourism in overcrowded areas, which can negatively impact both the traveler experience and local economies.

To address these challenges, there is a need for an intelligent and dynamic travel platform that leverages advanced algorithms to provide highly personalized destination recommendations, facilitate user matching for compatible travel companionship, and generate optimized itineraries with cost estimations. By integrating these features into a seamless and scalable framework, this system aims to enhance the overall travel experience, promote destination diversity, and make trip planning more efficient and enjoyable for all users.

USER REQUIREMENTS

1.Functional Requirements:

User Management: User registration and authentication (email, social login).
User profile management (preferences, travel history, interests)

Travel Recommendation Engine: Personalized travel recommendations based on user preferences.Dynamic ranking of destinations based on user inputs
.Machine learning-based destination prediction

Travel Companion Matching: Algorithm-based user matching based on preferencesChat or messaging feature for connected users

Itinerary Planning: Customizable daily travel itinerary.Cost estimation and budget tracking.

2. Non-Functional Requirements:

Performance: Fast response time for recommendations (< 2 seconds)

Scalability: Cloud-based deployment for high availability.Auto-scaling for peak travel seasons

TECHNOLOGIES USED:

1.Frontend: HTML, CSS, JavaScript.

2.Backend:Flask,MLFlas

3.Machine Learning: Scikit-learn for destination recommendation algorithms,Clustering for user profile matching.

4.Database: MYSQL for storing user profiles and expenses.

SYSTEM REQUIREMENTS

HARDWARE REQUIREMENTS:

1. Processor: Intel i5 / Ryzen 5 or better

2. RAM: Minimum 8GB (16GB recommended)

3. Storage: 512GB SSD (1TB recommended for large data storage)

4. Operating System: Windows 10 / Linux (Ubuntu 20+)

5. Internet Speed: Minimum 100 Mbps for smooth API access

SOFTWARE REQUIREMENTS:

1.Operating System: Windows 10/11 or Linux (Ubuntu 18.04/20.04/22.04) or macOS Monterey/Ventura

2.Backend Requirements:

Python 3.8+ Core language for backend development

Flask-CORS To handle frontend-backend communication

HTML5, CSS3 For structuring and styling the user interface

LITERATURE SURVEY

The travel industry has seen a significant shift towards personalization in recent years, fueled by advancements in data science and machine learning. Personalized travel recommendation systems aim to enhance user experiences by suggesting destinations, accommodations, and activities based on individual preferences and historical data. Moreover, with the increasing trend of social travel, user matching systems have emerged to connect like-minded travelers, fostering collaborative travel experiences. This literature survey explores the application of machine learning techniques such as Random Forest for destination recommendation and Cosine Similarity for user matching in dynamic travel platforms.

- **Random Forest for Travel Recommendation**: Random Forest (RF) has been widely adopted in recommendation systems due to its robustness, scalability, and ability to handle large and complex datasets. RF's ensemble learning approach, combining multiple decision trees, enables the algorithm to provide personalized travel recommendations based on diverse features such as user preferences, historical data, demographics, and contextual factors.

    - **Zhang et al. (2016)** utilized Random Forest for predicting tourist destination preferences by integrating data on past travel behavior and user ratings. Their study demonstrated the effectiveness of RF in providing personalized recommendations by processing heterogeneous input features such as past travel data, user demographics, and even environmental factors (e.g., weather).
    - **Liu et al. (2018)** used Random Forest to classify users based on their travel patterns and preferences. This segmentation allowed for more accurate destination recommendations, improving user satisfaction by tailoring suggestions to the unique needs of each travel group.
    - **Wang et al. (2017)** investigated how RF could prioritize features like budget, preferred activities, and previous trips in making travel recommendations. Their study showed that RF can rank the significance of different features, enabling more precise and relevant travel suggestions.

The scalability of Random Forest, combined with its ability to handle diverse data types (e.g., structured and unstructured data), makes it an ideal algorithm for large-scale travel recommendation platforms.

2.Hybrid Approaches in Recommendation Systems: A significant challenge faced by recommendation systems, especially in new user scenarios (cold-start problem), is the lack of sufficient data. Several studies have proposed hybrid approaches combining RF with collaborative filtering or content-based methods.

- **Chen et al. (2019)** proposed a hybrid recommendation system combining Random Forest and collaborative filtering to address the cold-start problem. By integrating the strengths of both methods, their model successfully provided personalized recommendations even for users with limited historical data.
- **Fernández-Delgado et al. (2014)** demonstrated how combining decision trees (like RF) with other machine learning algorithms can improve recommendation accuracy by leveraging complementary strengths and providing better feature interpretation.

User Matching Systems with Cosine Similarity:

- **Cosine Similarity in Social and Travel Platforms**: Cosine similarity is a popular metric used in collaborative filtering and user matching systems. This technique compares user preferences based on vector representations, where the cosine of the angle between two vectors indicates the degree of similarity. It is particularly useful for matching users with similar interests or behaviors.

- **Koren et al. (2009)** applied cosine similarity in collaborative filtering, demonstrating its usefulness in recommending items (such as destinations or activities) based on the similarity between users' preferences. This concept has been extended to social travel platforms where it helps match users with similar travel interests.
  - **Jannach et al. (2010)** explored the use of cosine similarity in social media systems, matching users based on shared interests or content. This approach has been adapted in travel platforms to connect travelers with similar preferences for activities, destinations, or cultural experiences.

- **Cosine Similarity for User Matching in Travel Platforms**: Cosine similarity has proven effective in travel recommendation systems, especially in the context of matching travelers based on shared interests or preferences.

    - **Chen et al. (2017)** developed a travel matching system that used cosine similarity to connect users with similar travel preferences. Their system converted user profiles into vectors based on activities such as hiking, sightseeing, or cultural exploration. The cosine similarity score helped identify users with similar travel goals, facilitating the formation of travel buddy connections.
    - **Bhardwaj et al. (2019)** applied cosine similarity to match travelers based on their preferred destinations and activities. By calculating the similarity between user profiles, their system helped travelers find companions with compatible interests.

5.Integration of Random Forest and Cosine Similarity:

1.Enhancing User Experience: The combination of Random Forest and Cosine Similarity presents a powerful framework for personalized travel platforms. While RF excels in providing tailored destination recommendations based on diverse user features, Cosine Similarity enhances social connectivity by matching users with similar interests. Integrating these two techniques can create a holistic system that not only offers personalized travel suggestions but also fosters social interaction among like-minded travelers.

- **Zhang et al. (2017)** integrated Random Forest and collaborative filtering for travel recommendations and matching users based on their preferences. By combining the strengths of both methods, they were able to enhance both the recommendation accuracy and the social aspect of the travel experience.

- **Burke (2002)** discussed hybrid recommender systems that combine various recommendation techniques to improve both accuracy and user engagement. The integration of Random Forest and Cosine Similarity aligns with this concept, enabling dynamic recommendations and meaningful user connections.

2.Scalability and Real-Time Processing: The scalability of both Random Forest and Cosine Similarity makes this integration particularly useful for large-scale travel platforms. RF's parallelizable structure allows for efficient processing of large datasets, while Cosine Similarity ensures that real-time user matching can be performed without significant computational overhead.

- **Huang et al. (2017)** demonstrated the scalability of Random Forest in travel recommendation systems, handling millions of users and destinations without significant performance loss. Similarly, Cosine Similarity has been shown to be efficient in matching users even with large databases, making it suitable for dynamic platforms that require real-time recommendations and social matching.

The combination of Random Forest and Cosine Similarity offers a powerful approach to enhancing user experiences in dynamic travel platforms. By leveraging machine learning techniques to provide personalized recommendations and facilitate social matching, travel platforms can create a more engaging and tailored experience for users. These methods not only improve the quality of recommendations but also promote social connectivity, enabling travelers to find companions with shared interests and embark on memorable journeys together. This literature survey highlights the growing importance of personalized and social travel experiences and suggests that the integration of advanced machine learning techniques can transform the way people plan and experience travel.

EXISTING SYSTEM

1.Online Travel Agencies (OTAs) like Expedia and Booking.com recommend destinations based on user searches and preferences, but don’t focus on user matching. They offer filters like budget and activities, but personalized suggestions are limited.

2.Social Travel Platforms like Couchsurfing and Meetup allow users to connect based on similar travel interests or meetups, but don’t provide personalized destination recommendations.

3.Travel Social Networks like Travello and TripIt provide destination recommendations based on social connections and user behavior but focus more on sharing travel experiences rather than user matching for group travel.

4.AI-Powered Platforms like Kayak and Hopper use predictive analytics to suggest destinations based on trends and user data, but don’t focus on matching users with other travelers.

5.Niche Travel Platforms like Lonely Planet focus on curated destination guides, with recommendations based on specific interests but lack social matching features.

PROPOSED SYSTEM

1.User Profile Creation: Travelers create personalized profiles by sharing preferences, travel history, interests, and trip details (e.g., budget, activities, trip companions).

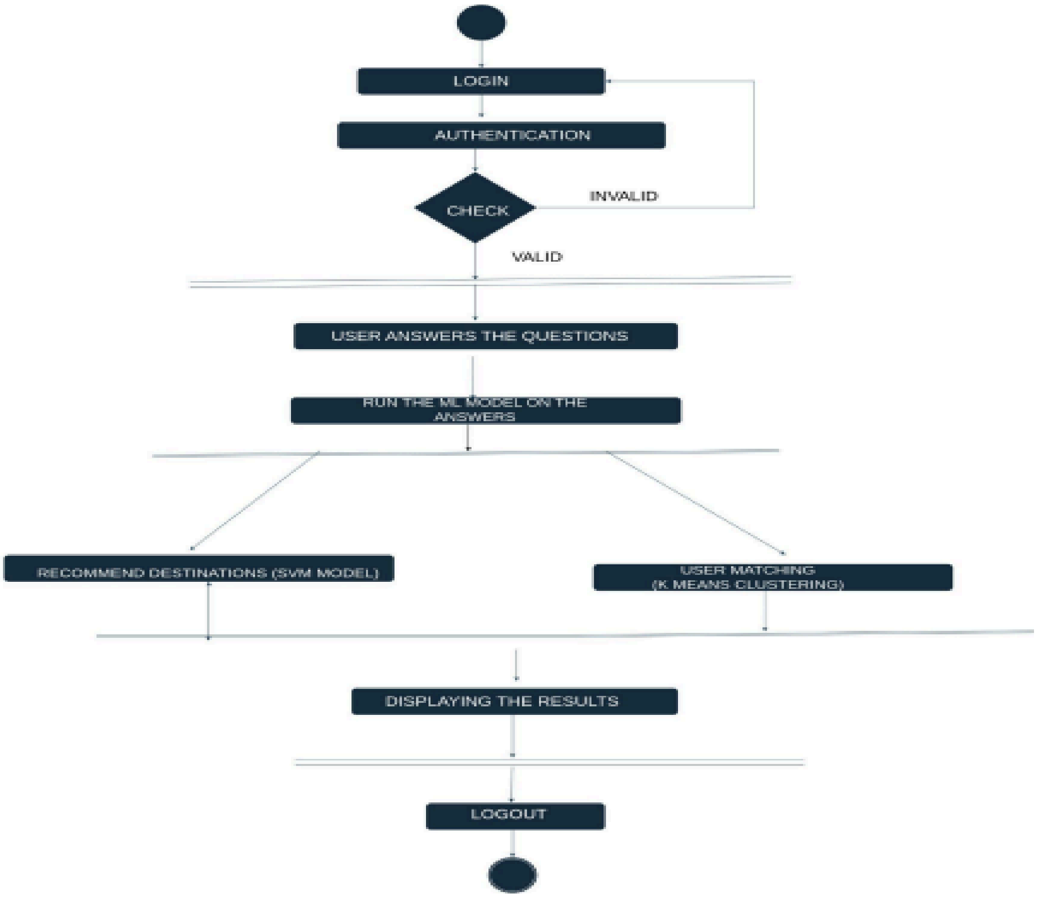
2.Destination Recommendation: Using machine learning algorithm Random Forest Classifier the system suggests destinations tailored to individual preferences, considering factors like activities, weather, seasonality.

3.User Matching: The platform can match travelers with similar interests or those looking to join solo trips, providing a social aspect where users can connect and travel together.

4.Travel Planning: Based on the destination recommended to the user, we plan the entire trip for the user along with a budget for each day and each task.

5. **Tracking Expenses:** Track costs by day by day,set daily/total trip budgets,track spending expenses during the trip.

SYSTEM DESIGN



METHODOLOGY

1.Data Collection & User Profiling: Collect user data through preference surveys, travel history, and behavioral analysis.Implement machine learning models to categorize users based on travel interests (adventure, relaxation, culture, nature, etc.).Use real-time data integration from sources like travel APIs, weather updates, and cost databases to enhance recommendations.

2.Personalized Destination Recommendation: SystemUtilize collaborative filtering (based on similar user preferences) and content-based filtering (matching destinations with user interests).

3. User Matching Algorithm for Travel Companionship: Develop a similarity-based matching algorithm (e.g., cosine similarity, Jaccard index) to connect users with shared travel styles.Integrate profile verification and chat features to ensure secure and meaningful interactions between matched users.

4. Automated Itinerary Planning & Cost Estimation: Optimize travel routes and schedules.Implement a cost estimation module that considers transportation, accommodation, activities, and meal expenses.Provide an interactive itinerary builder, allowing users to customize their daily plans while staying within their budget.

5. System Architecture & Scalability: Develop a cloud-based microservices architecture to support dynamic scaling and real-time updates**.**Design a mobile-friendly web and app interface with an intuitive user experience (UX/UI).

ALGORITHM

Using Random Forest in the Travel Platform :

The Random Forest algorithm is a machine learning technique that can be used to improve multiple aspects of the travel platform, such as destination recommendations, user matching, trip cost estimation, and sentiment analysis. It works by creating multiple decision trees and combining their results to make more accurate predictions.

1. Personalized Travel Recommendations

How It Works

The model is trained on historical travel data, including user preferences (adventure, relaxation, culture, nature), budget, and travel history.When a user inputs their travel preferences, the Random Forest algorithm predicts the best destinations that match their interests.

Example Process:

User selects preferences: Budget, preferred climate, activities (hiking, museums, beaches).The system analyzes past data from similar users.Random Forest predicts and ranks the best travel destinations.

COSINE SIMILARITY:

Cosine Similarity is a mathematical technique used to measure the similarity between two users or items. It is useful in user matching (travel buddies) and destination recommendations based on preferences.

1. User Matching for Travel Companions:

How It Works:

Each user’s travel preferences (e.g., adventure, budget, food, culture) are converted into a numerical vector.Cosine Similarity calculates how close two users' preferences are (values range from 0 to 1, where 1 means perfect match).Travelers with higher similarity scores are recommended as potential travel buddies.

Example Process:

User A Preferences: [Adventure=1, Culture=0, Beach=1, Budget Travel=1]

User B Preferences: [Adventure=1, Culture=1, Beach=0, Budget Travel=1]

Cosine Similarity Score = 0.77 (high similarity → good match).

Users with the highest scores are recommended to each other.

SAMPLE CODE

```
from flask import Flask, request, render_template, redirect, session, jsonify
import pandas as pd
from sklearn.ensemble import RandomForestClassifier
from sklearn.metrics.pairwise import cosine_similarity
from sklearn.preprocessing import OneHotEncoder, StandardScaler
import numpy as np
import jwt
from functools import wraps
from flask_sqlalchemy import SQLAlchemy
from werkzeug.security import generate_password_hash, check_password_hash
import os
import secrets
from datetime import datetime
import re

app = Flask(__name__)
app.secret_key = secrets.token_hex(16)
app.config['SQLALCHEMY_DATABASE_URI'] = 'sqlite:///database.db'
app.config['SQLALCHEMY_TRACK_MODIFICATIONS'] = False
db = SQLAlchemy(app)

# Database Models (unchanged)
class User(db.Model):
    id = db.Column(db.Integer, primary_key=True)
    username = db.Column(db.String(80), unique=True, nullable=False)
    password = db.Column(db.String(200), nullable=False)
```

```
class Expense(db.Model):
    id = db.Column(db.Integer, primary_key=True)
    user_id = db.Column(db.Integer, db.ForeignKey('user.id'), nullable=False)
    amount = db.Column(db.Float, nullable=False)
    category = db.Column(db.String(50), nullable=False)
    description = db.Column(db.String(200), nullable=True)
    date = db.Column(db.DateTime, nullable=False, default=datetime.utcnow)

class Message(db.Model):
    id = db.Column(db.Integer, primary_key=True)
    sender_id = db.Column(db.Integer, db.ForeignKey('user.id'), nullable=False)
    recipient_name = db.Column(db.String(80), nullable=False)
    content = db.Column(db.String(500), nullable=False)
    timestamp = db.Column(db.DateTime, nullable=False, default=datetime.utcnow)
    read = db.Column(db.Boolean, default=False)

# Load datasets
data = pd.read_csv(r"C:\Users\shahi\OneDrive\Desktop\New folder\myenv\my_flask_project\merged_travel_and_peopleE.csv")
data.columns = data.columns.str.strip()
data['Budget (₹)'] = pd.to_numeric(data['Budget (₹)'].str.replace(',', ''), errors='coerce').fillna(5000).astype(int)

itinerary_data = pd.read_csv(r"C:\Users\shahi\OneDrive\Desktop\New folder\myenv\my_flask_project\repeated_travel_destinations.csv")
itinerary_data.columns = itinerary_data.columns.str.strip()

city_coords = pd.read_csv(r"C:\Users\shahi\OneDrive\Desktop\New folder\myenv\my_flask_project\city_coordinates.csv")
city_coords.set_index('City', inplace=True)
```

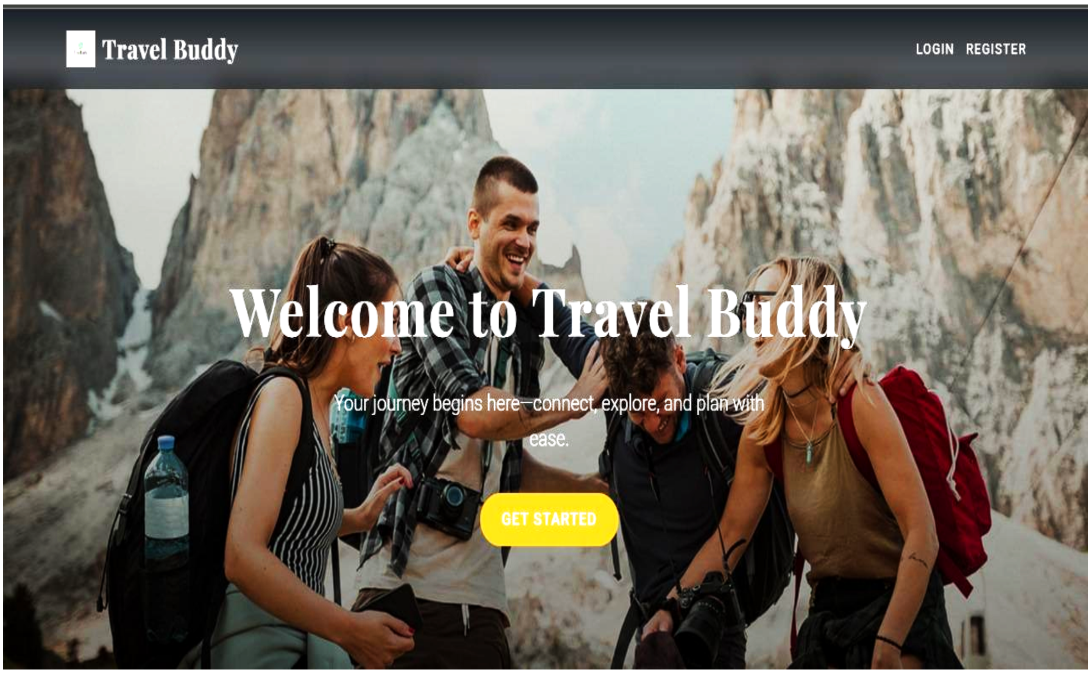
```python
# Recommendation setup (unchanged)
features = ["Type", "Weather", "Budget (₹)", "Vibe", "Travel Goal"]
encoder = OneHotEncoder(handle_unknown='ignore', sparse_output=False)
encoded_features = encoder.fit_transform(data[features])
scaler = StandardScaler()
scaled_features = scaler.fit_transform(encoded_features)
rf_model = RandomForestClassifier(n_estimators=100, random_state=42)
rf_model.fit(scaled_features, data["Destination"])

destination_images = {
            "Agra": "Agra.jpeg", "Andaman": "ANDAMAN.jpg", "Cherrapunji": "Cherrapunjii.jpeg", "Coorg": "Coorg.jpeg",
            "Darjeeling": "Darjeeling.webp", "Goa": "GOA.jpg", "Gokarna": "Gokarna.jpeg", "Gulmarg": "GULMARG.jpeg",
         "Haridwar": "Haridwarr.jpeg", "Jaipur": "Jaipur.jpeg", "Jaisalmer": "Jaisalmer.jpeg", "Kedarnath": "kedarnathh.jpeg",
          "Kovalam": "kovalam.jpeg", "Ladakh": "Ladakh.jpeg", "Lakshadweep": "lakshadweep.jpeg", "Mahabaleshwar": "Mahabaleshwar.jpg",
         "Manali": "Manali.jpeg", "Mount Abu": "Mount Abuu.jpg", "Munnar": "munnar.jpeg", "Ooty": "OOTY.jpeg",
       "Pondicherry": "pondi.jpeg", "Rameswaram": "rameswaram.jpg", "Ranikhet": "Ranikhett.jpg", "Rishikesh": "rishikesh.webp",
     "Shimla": "SHIMLA.jpeg", "Spiti Valley": "Spiti Valleyy.jpg", "Sundarbans": "Sundarbanss.jpeg", "Udaipur": "Udaipurr.jpeg",
    "Varanasi": "Varanasii.jpeg", "Vizag": "Vizag.jpg"
}

# Helper Functions (unchanged except get_dynamic_itinerary)
def haversine_distance(lat1, lon1, lat2, lon2):
    R = 6371
    lat1, lon1, lat2, lon2 = map(np.radians, [lat1, lon1, lat2, lon2])
```

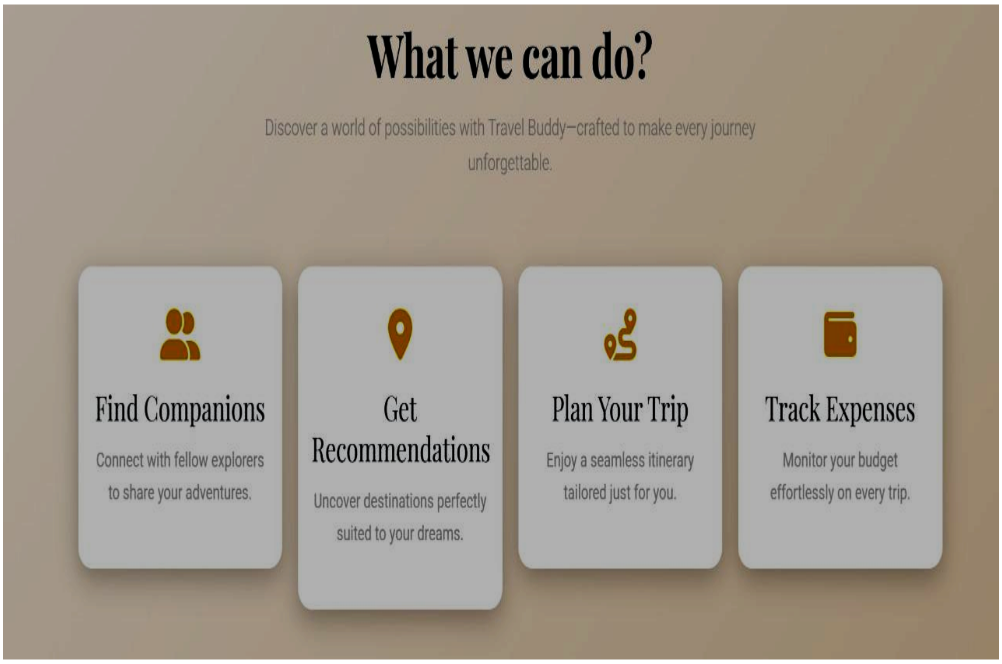
```python
    dlat = lat2 - lat1

    dlon = lon2 - lon1

    a = np.sin(dlat/2)**2 + np.cos(lat1) * np.cos(lat2) * np.sin(dlon/2)**2

    c = 2 * np.arcsin(np.sqrt(a))

    return R * c


def parse_cost(cost_str):

    if isinstance(cost_str, (int, float)):

        return int(cost_str)

    if not isinstance(cost_str, str):

        return 0

    return int(re.sub(r'[₹,]', '', cost_str))


def extract_activity_costs(activity_str):

    if not isinstance(activity_str, str):

        return 0

    cost_pattern = r'₹([\d,]+)|Free'

    costs = re.findall(cost_pattern, activity_str)

    total = 0

    for cost in costs:

        if cost and cost != 'Free':

            total += int(cost.replace(',', ''))

    return total


def get_dynamic_itinerary(destination, days, preferences):

                                                     dest_itinerary             =
itinerary_data[itinerary_data["Destination"].str.strip().str.lower()          ==
destination.strip().lower()]

    max_days = int(dest_itinerary['Day'].max()) if not dest_itinerary.empty else
6  # Default to 6 if no data
```

```
    days = min(days, max_days) if max_days > 0 else days

    if not dest_itinerary.empty:
        itinerary = dest_itinerary.head(days).to_dict(orient='records')
        if len(itinerary) < days:
            repeated = dest_itinerary.to_dict(orient='records')
            while len(itinerary) < days:
                for entry in repeated:
                                                        if   len(itinerary)   <   days:
itinerary.append(entry)
    else:
        itinerary = [
            {
                'Day': i + 1,
                'Morning Activity (Cost)': f"Explore {destination} (₹500)",
                     'Afternoon Activity (Cost)': f"Sightseeing in {destination}
(₹700)",
                'Evening Activity (Cost)': f"Relax in {destination} (₹600)",
                'Daily Cost (₹)': 1800
            } for i in range(days)
        ]

    vibe = preferences.get('Vibe', 'Relaxing').lower()
    goal = preferences.get('Travel Goal', 'Adventure').lower()
    adjusted_itinerary = []
    for day in itinerary:
        adjusted_day = day.copy()
        if 'adventure' in goal:
               for time_slot in ['Morning Activity (Cost)', 'Afternoon Activity
```

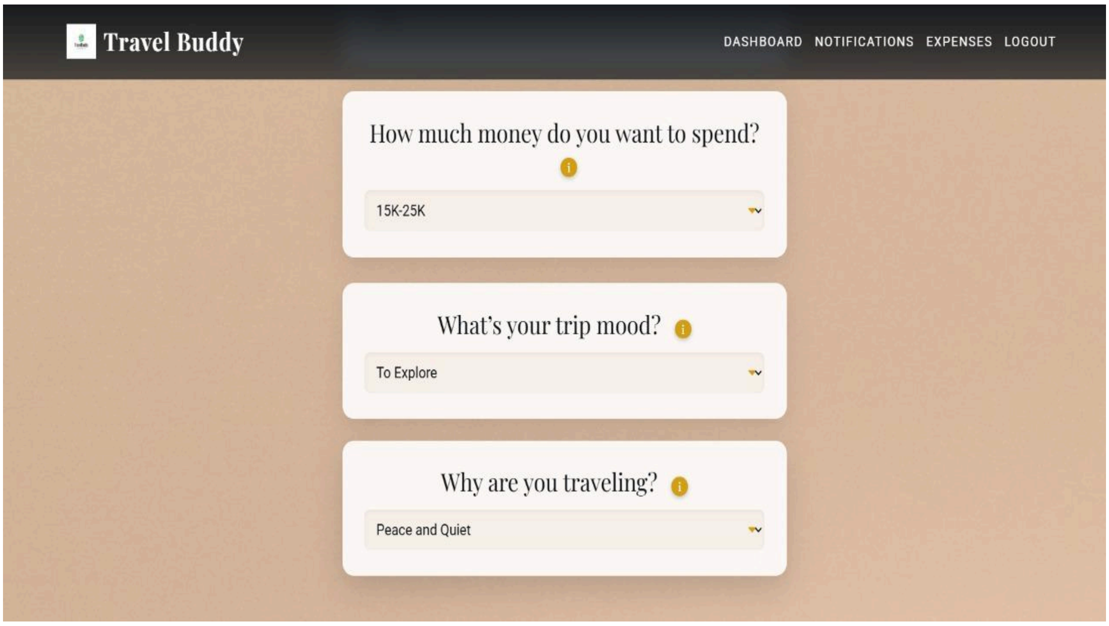
```
(Cost)', 'Evening Activity (Cost)']:
                if time_slot in adjusted_day and adjusted_day[time_slot]:v
    form_data = session.get('form_data')
    option = session.get('option')
    matched_users = session.get('matched_users', [])
    current_index = session.get('current_match_index', 0)
      matched_user = matched_users[current_index] if matched_users and
current_index < len(matched_users) else None
    destination = session.get('trip_destination')
        itinerary = itinerary_data[itinerary_data["Destination"] ==
destination].to_dict(orient='records') if destination else []
        return render_template('dashboard.html', expenses=user_expenses,
recommended_dest=recommended_dest,
                                             form_data=form_data, option=option,
matched_user=matched_user,
                          itinerary=itinerary, destination=destination)


@app.route('/logout')
def logout():
    session.clear()
    return redirect('/login')


if __name__ == '__main__':
    with app.app_context():
        db.create_all()
    app.run(debug=True)
```

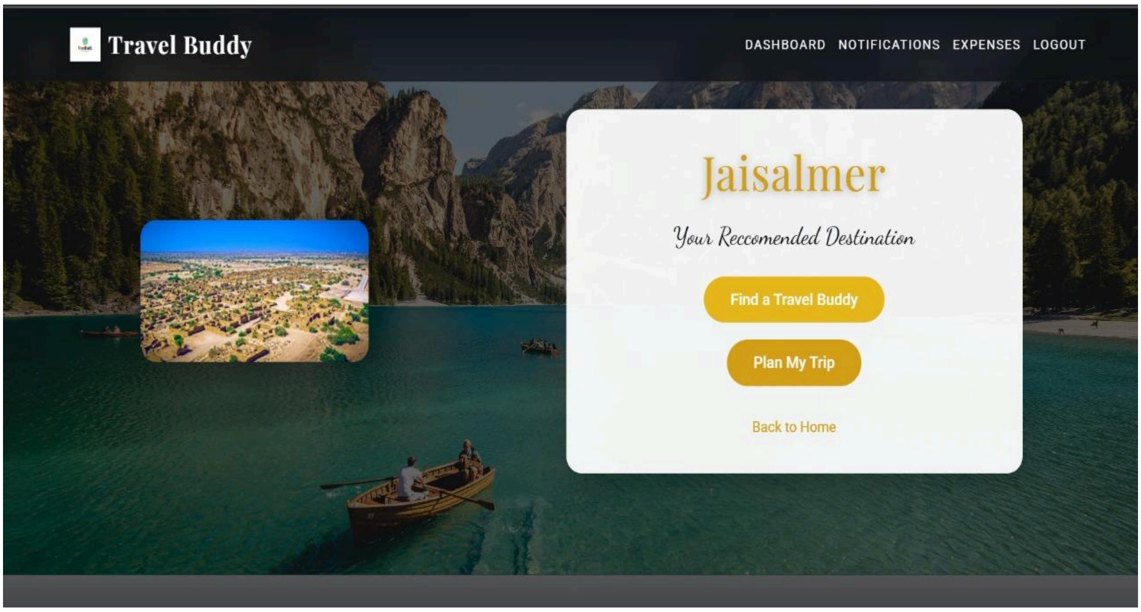
OUTPUT SCREENSHOTS

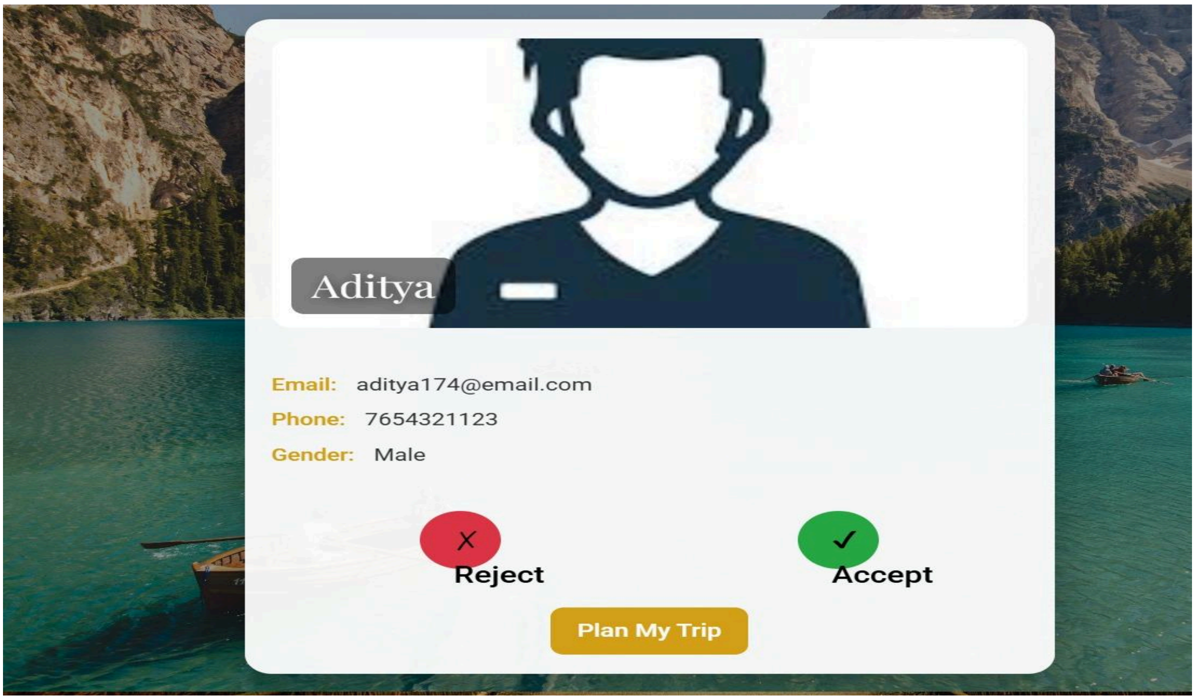


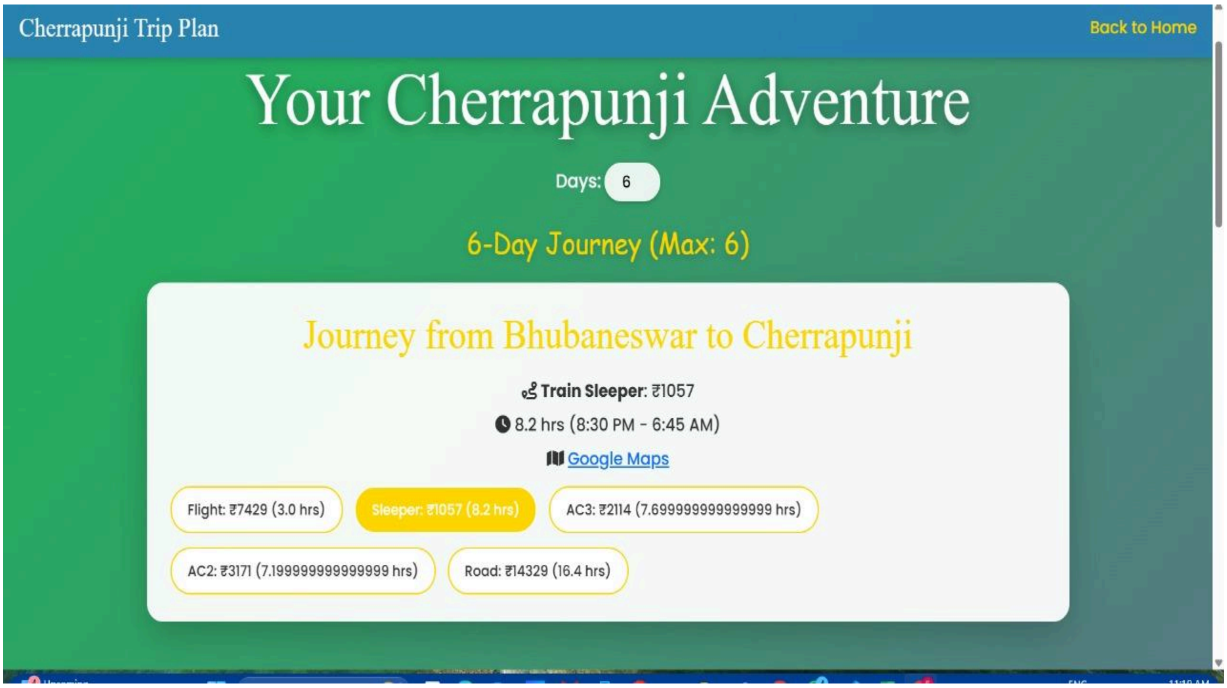



Choose Your Journey
DESTINATIONS
TRAVEL COMPANIONS
BOTH

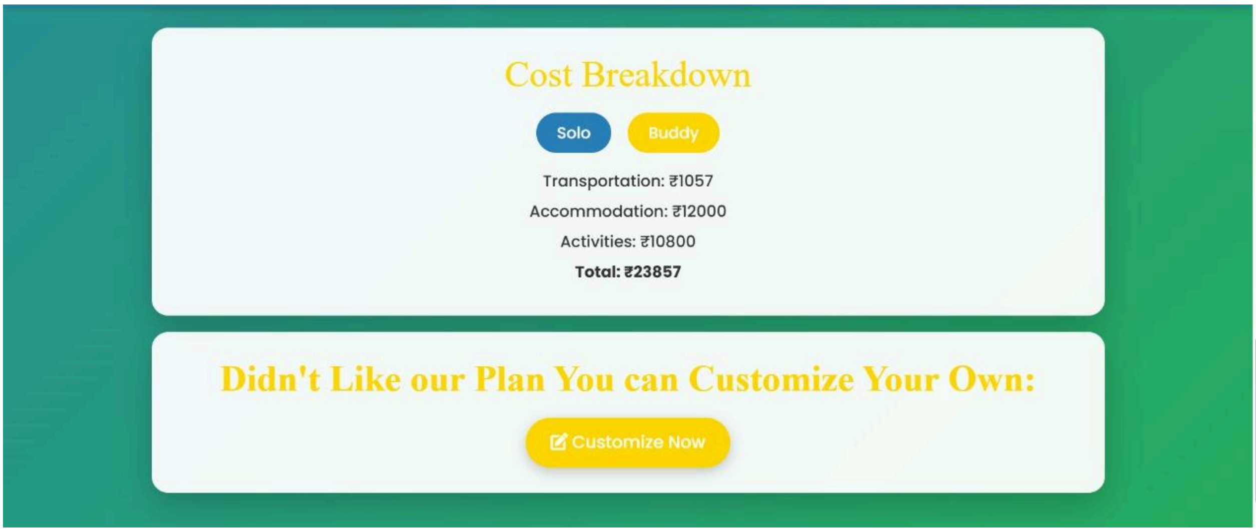

Travel Buddy
DASHBOARD
NOTIFICATIONS
EXPENSES
LOGOUT
How much money do you want to spend?
15K-25K
What's your trip mood?
To Explore
Why are you traveling?
Peace and Quiet

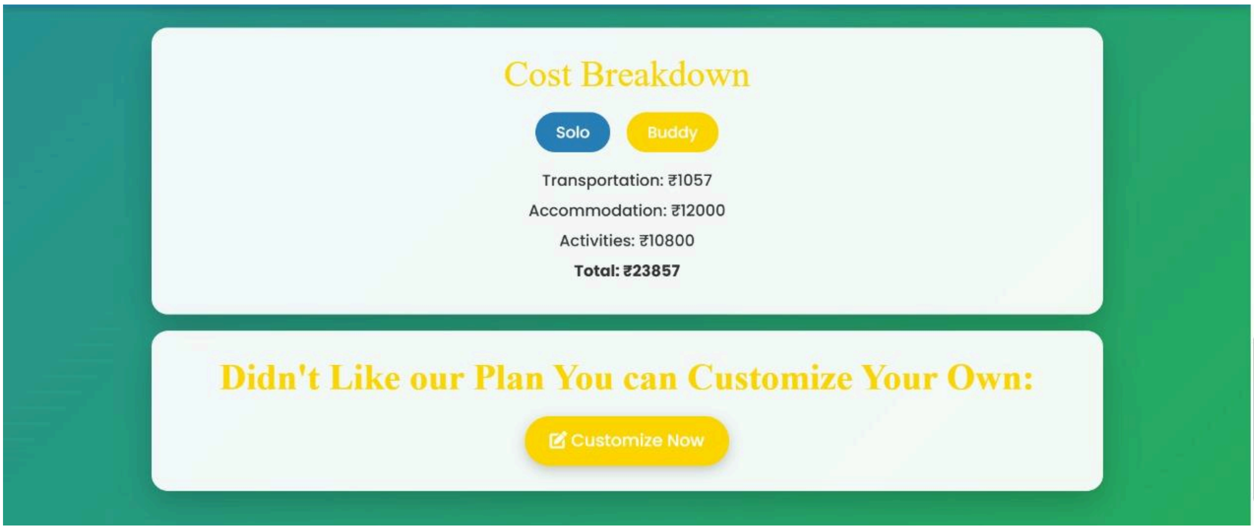

Travel Buddy
DASHBOARD
NOTIFICATIONS
EXPENSES
LOGOUT
Jaisalmer
Your Reccomended Destination
Find a Travel Buddy
Plan My Trip
Back to Home


Aditya
Email: aditya174@email.com
Phone: 7654321123
Gender: Male
Reject
Accept
Plan My Trip


Cherrapunji Trip Plan
Back to Home
Your Cherrapunji Adventure
Days: 6
6-Day Journey (Max: 6)
Journey from Bhubaneswar to Cherrapunji
Train Sleeper: ₹1057
8.2 hrs (8:30 PM - 6:45 AM)
Google Maps
Flight: ₹7429 (3.0 hrs)
Sleeper: ₹1057 (8.2 hrs)
AC3: ₹2114 (7.699999999999999 hrs)
AC2: ₹3171 (7.199999999999999 hrs)
Road: ₹14329 (16.4 hrs)


Day 1
₹1800
Morning
Explore Cherrapunji (₹500)
Afternoon
Sightseeing in Cherrapunji (₹700)
Evening
Relax in Cherrapunji (₹600)
Day 2
₹1800
Morning
Explore Cherrapunji (₹500)
Afternoon
Sightseeing in Cherrapunji (₹700)
Evening
Relax in Cherrapunji (₹600)
Day 3
₹1800
Morning
Explore Cherrapunji (₹500)
Afternoon
Sightseeing in Cherrapunji (₹700)
Evening
Relax in Cherrapunji (₹600)
Day 4
₹1800
Morning
Explore Cherrapunji (₹500)
Day 5
₹1800
Morning
Explore Cherrapunji (₹500)
Day 6
₹1800
Morning
Explore Cherrapunji (₹500)


Cost Breakdown
Solo
Buddy
Transportation: ₹1057
Accommodation: ₹12000
Activities: ₹10800
Total: ₹23857
Didn't Like our Plan You can Customize Your Own:
Customize Now


Cost Breakdown
Solo
Buddy
Transportation: ₹1057
Accommodation: ₹12000
Activities: ₹10800
Total: ₹23857
Didn't Like our Plan You can Customize Your Own:
Customize Now

ADVANTAGES

1.Personalized Travel Experience: Uses advanced algorithms to suggest destinations that match individual interests (e.g., adventure, relaxation, culture, or nature).Ensures that each trip is tailored to personal preferences, making travel more meaningful and enjoyable.

2. Enhanced Social Connectivity: Connects like-minded travelers, making it easier for solo travelers to find compatible travel buddies.Encourages shared experiences, fostering friendships and cultural exchange.

3. Smart Itinerary Planning: Automatically generates detailed travel plans, including daily activities and cost breakdowns.Saves users time and effort by organizing trips efficiently.

4. Promotes Destination Diversity: Encourages travelers to explore lesser-known locations, reducing over-tourism in popular destinations.Supports local economies by directing tourists to unique, off-the-beaten-path spots.

5. Cost-Effective Travel Planning: Helps users budget their trips effectively by providing estimated costs for each part of the journey.Allows travelers to plan within their financial limits while maximizing experiences

6. Scalability & Adaptability: Can be used by different types of travelers, from solo adventurers to groups and families.Adaptable across industries, including travel agencies, tourism boards, and hospitality businesses.

LIMITATIONS

1.Data Accuracy and Availability – The platform's recommendations depend on user data, travel trends, and third-party sources. Inaccurate or incomplete data may result in suboptimal suggestions.

2.Privacy and Security Risks – Collecting user preferences and facilitating traveler matching raise privacy concerns. Ensuring data security and preventing misuse of personal information is a challenge.

3.Scalability Challenges – As user demand grows, maintaining real-time recommendations and seamless user interactions may require significant computational resources and infrastructure.

4.Subjective Travel Preferences – Travel experiences are personal and may not always align with algorithmic suggestions, leading to potential dissatisfaction among users.

5.User Engagement Dependency – The effectiveness of recommendations and usermatching relies on active user participation. Low engagement can limit the platform’s success.

6.Fluctuating Travel Costs and Availability – Estimated trip costs may not always reflect real-time fluctuations in transportation, accommodation, and activity prices, affecting budget planning.

.**7.Cultural and Regional Differences –** Travel preferences vary based on cultural backgrounds, local customs, and legal restrictions, which may not be fully accounted for in recommendations.

8.Potential Travel Companion Mismatches – Despite advanced matching algorithms, differences in personality, expectations, and unforeseen circumstances can result in travel companion mismatches.

CONCLUSION

This dynamic travel platform revolutionizes the way people plan, experience, and share their journeys. By providing personalized travel recommendations based on individual preferences and connecting like-minded travelers, it ensures that every trip is tailored to the user's unique interests, whether they seek adventure, relaxation, culture, or nature. The platform's advanced algorithms not only suggest destinations that align with personal motivations but also facilitate the formation of meaningful connections between solo travelers and potential companions. This approach fosters a more diverse exploration of destinations, promotes local economies, and enhances the overall travel experience. Ultimately, this platform empowers travelers to embark on memorable and enriching adventures, transforming the way we travel and connect with others.

Our platform represents a groundbreaking shift in travel planning, offering a truly personalized experience that goes beyond traditional recommendation systems. By combining tailored destination suggestions with the ability to connect like-minded travelers, we empower users to plan more meaningful, enriching journeys. Our advanced algorithms ensure that each recommendation aligns with individual interests, while our user-matching feature fosters valuable connections, making travel not only about the destinations but also about the shared experiences along the way. With detailed itinerary planning and cost breakdowns, we enable travelers to make informed decisions, enhancing both the enjoyment and efficiency of their trips. Ultimately, our platform not only redefines how people approach travel but also contributes to the promotion of diverse destinations and local economies, creating a more immersive, sustainable, and socially connected travel experience for all.

FUTURE SCOPE

1. AI-Driven Hyper-Personalization: AI will refine recommendations by analyzing user behavior, past travel experiences, and feedback to create highly personalized itineraries. Real-time data (weather, local events, crowd density) will be integrated to optimize travel recommendations dynamically. The platform will continuously evolve, adapting to user travel patterns and offering smarter suggestions over time.

2. Enhanced User Matching & Social Travel: Advanced algorithms will match travelers based on personality traits, travel preferences, and even behavioral data.Tools for managing group trips, shared expenses, and collaborative itinerary planning.

3. Smart Itinerary Planning & Cost Optimization:AI-powered cost estimations with real-time expense tracking and budget-friendly alternatives. Dynamic itinerary updates based on last-minute changes, transportation delays, or local conditions.Patnering with local providers for exclusive discounts, deals, and authentic travel experiences.

4. Sustainable & Ethical Travel Recommendations: Eco-Friendly Travel Suggestions: AI will recommend sustainable accommodations, transport, and experiences.Carbon Footprint Tracking: Users can monitor and offset their travel impact through eco-conscious initiatives.Support for Local Communities: Encouraging visits to lesser-known destinations to distribute tourism benefits evenly.

6. Blockchain & Secure Transactions: Smart Contracts for Bookings: Secure and automated payment processing for hotels, flights, and experiences.Decentralized Reviews & Ratings: A transparent, tamper-proof review system ensuring authentic user feedback.

REFERENCES

- Breiman, L. (2001). Random forests. *Machine Learning, 45*(1), 5-32.
- Burke, R. (2002). Hybrid recommender systems: Survey and experiments. *User Modeling and User-Adapted Interaction, 12*(4), 331-370.
- Fernández-Delgado, M., Cernadas, E., Barro, S., & Amorim, D. (2014). Do we need hundreds of classifiers to solve real world classification problems? *Journal of Machine Learning Research, 15*, 3133-3181.
- Guo, G., Zhang, J., Yorke-Smith, N. (2016). TrustSVD: Collaborative filtering with both the explicit and implicit influence of user trust and of item ratings. *Proceedings of the AAAI Conference on Artificial Intelligence*.
- Koren, Y., Bell, R., & Volinsky, C. (2009). Matrix factorization techniques for recommender systems. *IEEE Computer, 42*(8), 30-37.
- Lops, P., Gemmis, M. D., & Semeraro, G. (2011). Content-based recommender systems: State of the art and trends. *Recommender Systems Handbook*, 73-105.
- Pazzani, M. J., & Billsus, D. (2007). Content-based recommendation systems. *The Adaptive Web*, 325-341.
- Singhal, A. (2001). Modern information retrieval: A brief overview. *IEEE Data Engineering Bulletin, 24*(4), 35-43.
- Zhang, S., Xu, C., Chen, G., & Zhang, L. (2017). A random forest-based approach to tourism recommendation systems. *Proceedings of the International Conference on Web Intelligence.*