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TOURISM RECOMMENDATION SYSTEM

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Abstract: One of the most troublesome parts of coordinating an excursion is choosing where to go in view of the data that is all open on the web and through different sources. It's an issue that past the travel industry Proposal Framework have endeavored to address. The functional and convenience parts of the undertaking, as well as a portion of the more specialized ones, like exactness of the framework, have both had been disregarded. To take care of this issue, a total comprehension of travelers' navigation and new plans empowering their data search is required. A creative human focused the travel industry Suggestion Framework is proposed in this exploration to help voyagers in another city in picking what to see and do. A certifiable informational index is utilized for both expert and functional contemplations. To restrict the quantity of contributions to the framework, the framework is developed using two-steps include choice procedure, and ideas are given utilizing Count Vectorizer and Tfidf Vectorizer Trial proof shows that the monetary the travel industry Proposal Framework can offer vacationer puts that are custom-made to the inclinations of the clients.

***Index Terms* -** Personalized recommendations, Machine learning algorithms, Travel Planning and User feedback services.

I. INTRODUCTION

Welcome to India, where every corner tells a story, and every experience is a journey into the heart of diversity. India's tourism landscape is a kaleidoscope of cultures, landscapes, and traditions, inviting travelers to embark on an unforgettable adventure like no other. From the majestic Himalayas to the tranquil backwaters of Kerala, from the bustling streets of Delhi to the serene beaches of Goa, India offers a tapestry of experiences that cater to every traveler's whim and fancy. In recent years, India has emerged as one of the world's fastest-growing tourism destinations, captivating visitors with its rich heritage, vibrant festivals, and warm hospitality.

With a renewed focus on sustainable tourism practices and infrastructure development, India is poised to welcome even more travelers seeking authentic experiences that leave a lasting impression. Whether you're drawn to the timeless beauty of the Taj Mahal, eager to explore the ancient temples of Hampi, or craving the spicy flavors of street food in Mumbai, India promises to enchant and delight at every turn. Join us as we embark on a journey of discovery through the captivating wonders of India's tourism landscape, where every moment is an adventure waiting to unfold. Welcome to India, where the journey is as unforgettable as the destination.

As of my last update in January 2022, I don't have access to real-time data on the latest numbers of tourists recommended to visit India for tourism. However, the Indian government and tourism boards regularly release statistics and projections regarding tourist arrivals and recommendations. For the most current and accurate information on recommended tourism numbers to India, I suggest checking official sources such as the Ministry of Tourism of the Government of India or tourism promotion boards. These organizations typically provide updates on tourist arrivals, trends, and recommendations to visit India. Additionally, international organizations like the World Tourism Organization (UNWTO) may also offer insights into global tourism trends and recommendations for visiting specific destinations, including India.

So, by comparing the algorithms that are used first to recommended best places so there are many algorithms used to get best accuracy from the data. So, we have referred a paper that they have used many machines learning algorithm to get their best accuracy and probability of the model and by using that they have got their best accuracy in Random Forest Algorithm.

After that they have compared each column with other column to give the best recommendation to the user. So basically, the data they have taken was in numerical format that they can have the best accuracy to compare with each other and the data we have taken using web scrapping so the data we have is fully in text format and so if we try to convert it into numeric format the whole data could not be converted into it. And so, we have used the Count vectorizer and Tfidf vectorizer algorithm so by seeing these we have used these two algorithms to give the best recommendation to the user. And also, for web scrapping we have use beautiful soap algorithm to recommend the best places to the user.

Our tourism recommendation system harnesses the advanced capabilities of Count Vectorizer and TF-IDF Vectorizer algorithms to revolutionize the way travelers explore destinations. Count Vectorizer processes textual data by converting words into numerical representations, enabling us to quantify their significance within travel-related content. Similarly, TF-IDF Vectorizer calculates the importance of words by considering their frequency in a document relative to the entire corpus. By analyzing vast amounts of travel-related data, including destination descriptions, hotel reviews, and user preferences, our system generates personalized recommendations tailored to each traveler's unique interests, whether they're seeking cultural landmarks, adventure activities, or culinary experiences. By leveraging these vectorization techniques, we deliver bespoke travel experiences that align with travelers' preferences, providing them with unforgettable journeys tailored to their individual tastes and expectations. Count Vectorizer and TF-IDF Vectorizer are sophisticated algorithms that analyze textual data to extract meaningful features, enabling us to understand the preferences and interests of travelers more effectively. By converting text into numerical representations, these techniques allow us to quantify the significance of words and phrases within travel related content, such as reviews, descriptions, and user feedback.

II. RELATED WORK

1.Emerging concerns from bad online reviews of tourists from e-tourism to f-tourism:

One of the foremost troublesome perspectives of sorting out a trip is choosing on a put based on the data available online and through other sources. Typically, an issue that previous travel proposal frameworks have attempted to address. In this inquire about, we offer an interesting Travel Suggestion Framework that suggests settings to visitors based on the voyager's dataset. A real-world information set is utilized for both proficient and operational contemplations. Experiments have appeared that the proposed Travel Proposal Framework is able of making proposals on the foremost prevalent visitor attractions. Our tourism recommendation system utilizes Count Vectorizer and TF-IDF Vectorizer algorithms to provide personalized travel recommendations based on travelers' unique interests and preferences.

2.Semantics of Online Tourism and Travel Information Search:

This paper looks at Web convenience for travel looking for data utilizing semantic arrange examination. Web ease of use is the level of coordinate between data producers' and consumers' mental representations of Web structure and substance. Jumbled mental models between tourism marketers and voyagers hampered the Internet's utility as a travel asset. Semantic organize examination can appear contrasts between these two mental models and give exhortation for ideal Web data giving. The creators investigate travel data providers' mental models through semantics organize hypothesis when promoting their goals online and show a preparatory semantic organize results.

3.E-Tourism: Internet and ICT in Tourism: Peripheral Hotel Units:

E-tourism, incorporating internet and ICT into tourism, offers substantial benefits for peripheral hotel units in India. By leveraging online platforms like websites and social media, these hotels can broaden their visibility and reach a wider audience. Implementing ICT solutions such as property management systems and mobile applications streamlines operations and enhances guest experiences, while collaborative destination marketing efforts boost the appeal of peripheral regions. Embracing e-tourism enables peripheral hotel units to overcome geographical constraints, enhance competitiveness, and contribute to the growth of India's tourism industry.

Conclusions: Even in small towns, Greek tourist firms use ICT. Most units use the internet reservation system, and it's predicted to double in five years. E-marketing utilization is satisfactory, and most respondents believe it's essential for an enterprise's success. Most tourism units seem unfamiliar with eCRM systems (E-CRM). Digital travel agencies and social networking sites let tourist units communicate with potential customers. Online reservations have helped increase customer arrivals, giving the tourism industry guarded hope despite the financial crisis.

III. RESEARCH METHODOLOGY

TF-IDF Vectorization and Count Vectorization are two common techniques used in natural language processing (NLP) and recommendation systems for transforming text data, such as product descriptions, reviews, or user profiles, into numerical representations that can be used for various machine learning tasks, including recommendation.

1.Count Vectorization (Count Vectorizer):

- Count Vectorization, often implemented using the Count Vectorizer in libraries like scikit-learn, is a simple and widely used method for text representation.
- It works by creating a fixed-length vector for each document (text snippet) in your dataset.
- For each document, it counts the occurrences of each word (or n-gram) in a predefined vocabulary. The result is a matrix where each row represents a document, and each column represents a word from the vocabulary.
- The values in the matrix represent the count of each word's occurrence in the respective document.
- Count Vectorization does not consider the importance of words and treats all words equally. It's primarily used to create a bag-of-words (BoW) representation.

2.TF-IDF Vectorization (Term Frequency-Inverse Document Frequency):

- TF-IDF Vectorization, implemented using the Tfidf Vectorizer in libraries like scikit-learn, is a more advanced technique that takes into account both term frequency and the importance of terms in a document collection.
- TF-IDF assigns a weight to each term in a document based on its frequency (term frequency, TF) and its rarity across the entire document collection (inverse document frequency, IDF).
- TF-IDF aims to highlight words that are frequent in a specific document but relatively rare in the entire corpus. These are often more meaningful and representative of the document's content.
- The TF-IDF score for a term in a document is calculated as the product of its term frequency (TF) and inverse document frequency (IDF).
- TF-IDF representations are usually sparse, as many terms in a vocabulary will have low IDF scores and result in zero values in the vectors.

IV. MODELING AND ANALYSIS

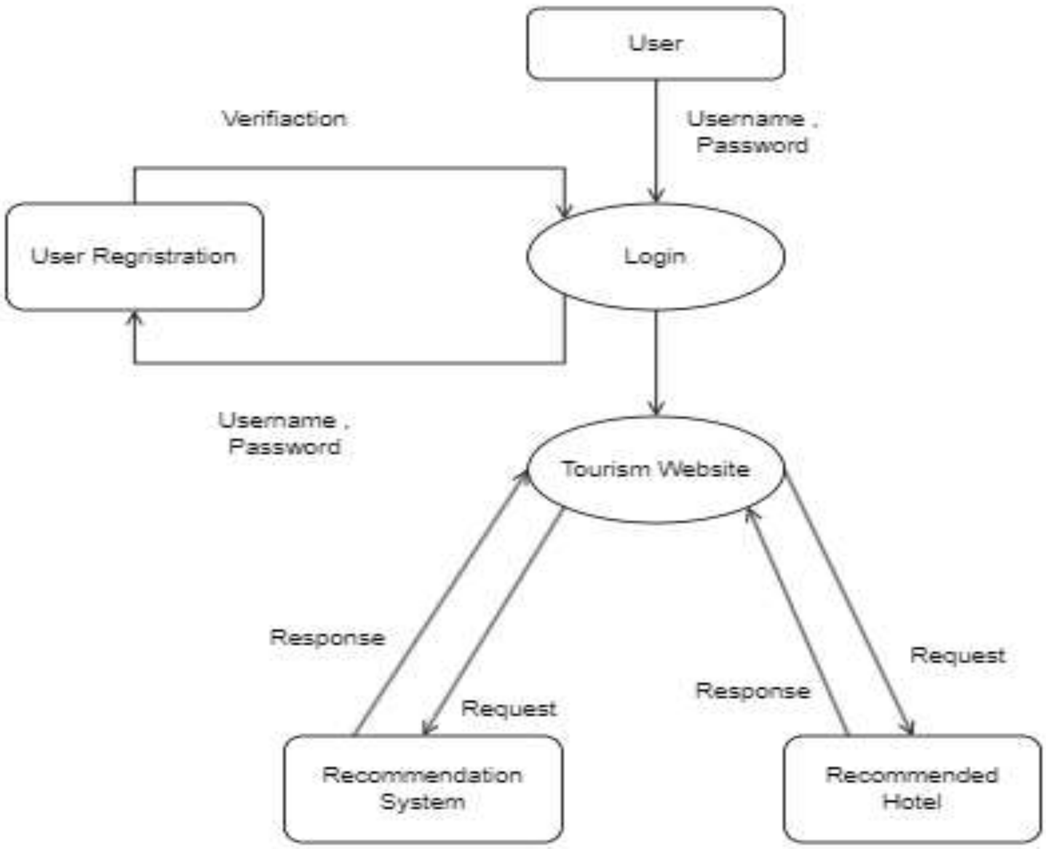

Fig 4.2.1 Flowchart

This flowchart illustrates the key steps in a tourism recommendation system:

- User provide input and preferences.
- The system collects and analyses user data.
- A recommended algorithm is used to generate recommendations.
- The systems filters recommendations based on your preferences.
- A list of recommendations is generated.

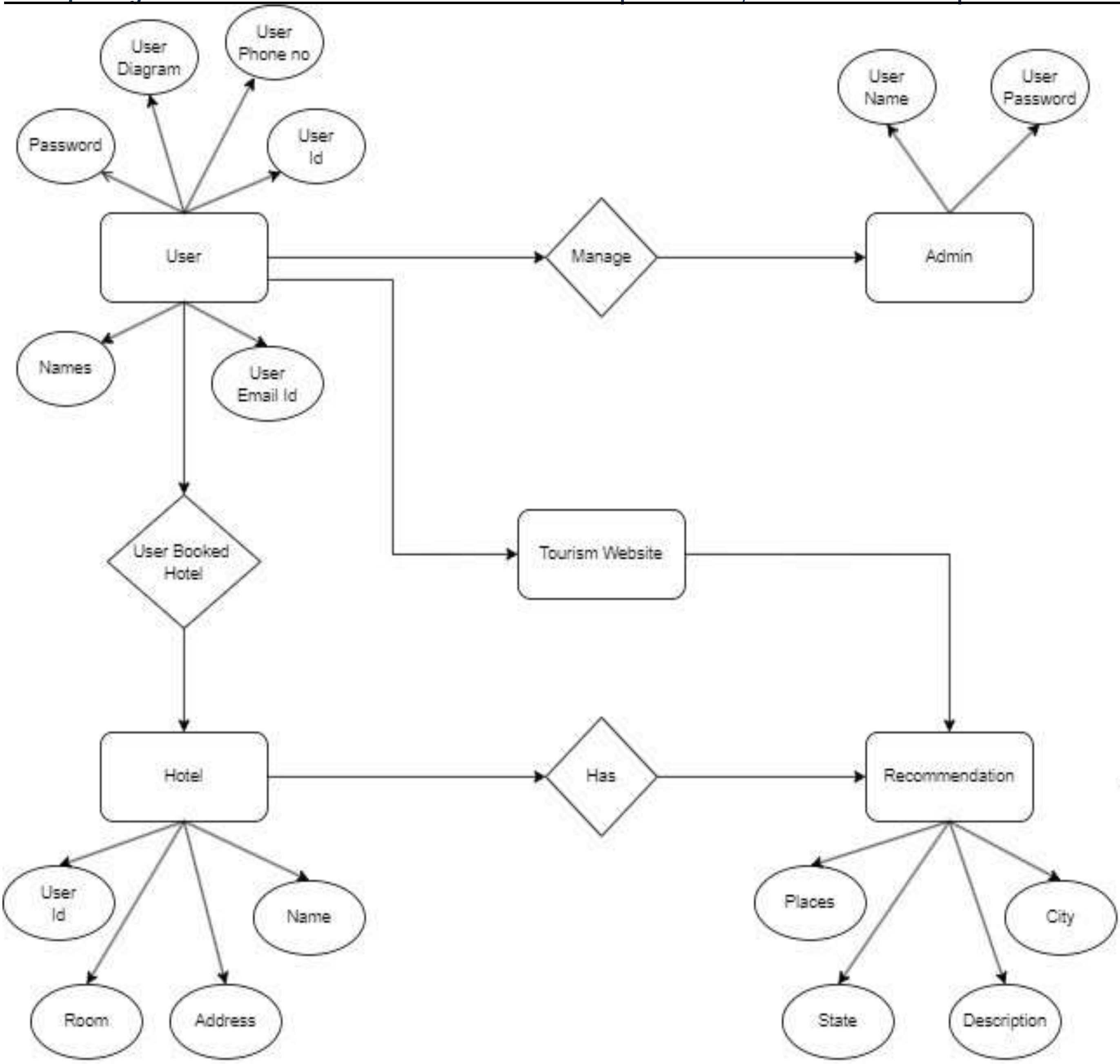

Fig 4.2.2 ER Diagram

Creating a comprehensive Entity-Relationship (ER) diagram for a tourism recommendation system would require careful consideration of the specific requirements, but here's a simplified representation to give you an idea:

Entities:

- User
- Location
- Activity
- Review
- Recommendation

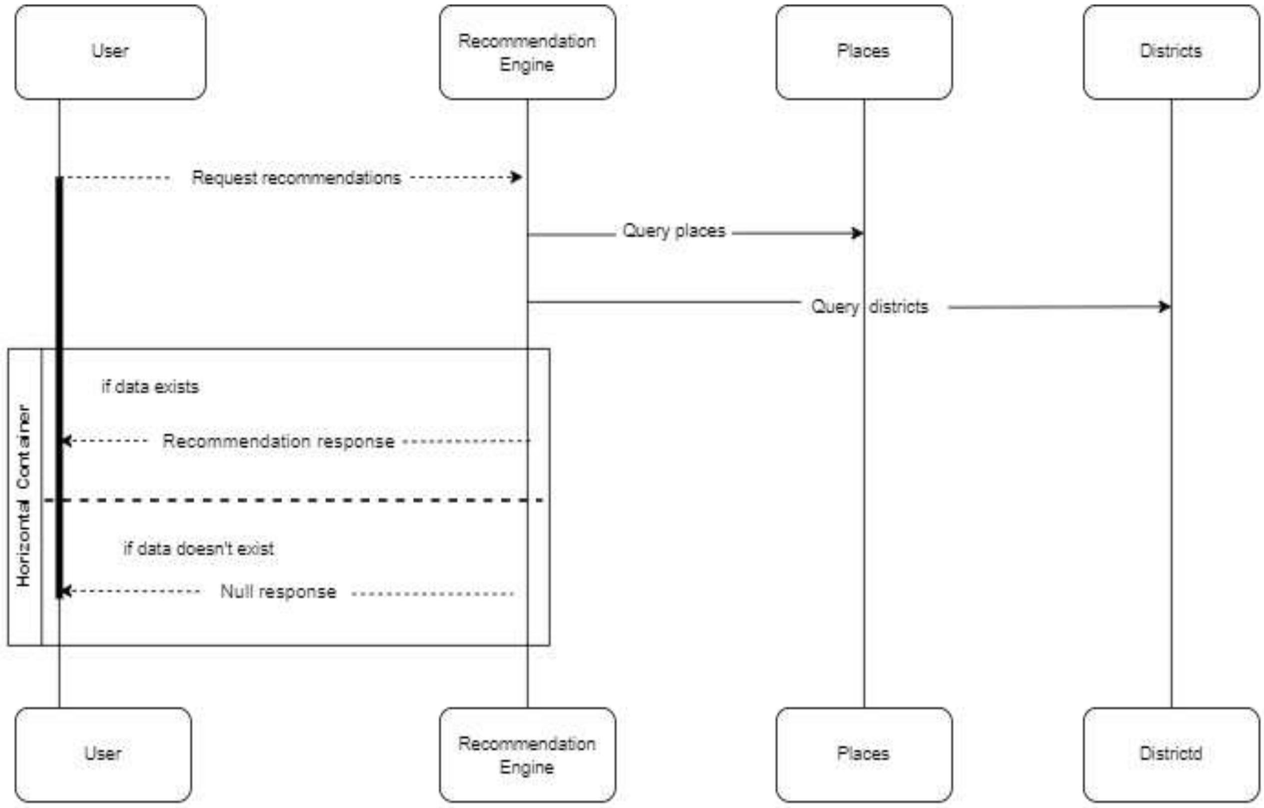

Fig 4.2.3 Sequence Diagram

A sequence diagram for a Tourism Recommendation System visually represents the interactions and flow of activities among various components or actors within the system. Here's a brief description of the key elements and their interactions in a sequence diagram for such a system:

- **User:**

  The user initiates the interaction by accessing the recommendation system through a web or mobile interface.

- **User Profile:**

  The system checks the user's profile, which includes preferences, travel history, and personal information, to understand their specific needs and interests.

- **Data Collection:**

  The system collects data from various sources, including user profiles, historical travel data, reviews, and real-time information.

- **Recommendation Engine:**

  The recommendation engine processes the collected data and user profile to generate personalized recommendations, including travel destinations, accommodations, activities, and dining options.

- **User Interface:**

  The recommendations are presented to the user via the user interface, enabling them to explore and interact with the suggestions

V. RESULTS AND DISCUSSION

1. **Import library:** We have imported libraries and we have read the csv file and then checked first five records.

In [1]:
```
import pandas as pd
import numpy as np
import warnings
warnings.filterwarnings('ignore')
import ast
import re
from nltk.corpus import stopwords
from nltk.tokenize import word_tokenize
```

In [2]:
```
df = pd.read_csv('final_data_tourism.csv')
```

In [3]:
```
df.head()
```

Out[3]:

	Unnamed: 0	state	district	place	description	img_url
0	0	Andhra Pradesh	Guntur	Amaravati Stupa	Amarāvati Stupa is a ruined Buddhist stūpa at ...	//upload.wikimedia.org/wikipedia/commons/thumb...
1	1	Andhra Pradesh	Guntur	Bhattiprolu	Bhattiprolu is a village in Bapatla district o...	//upload.wikimedia.org/wikipedia/commons/thumb...
2	2	Andhra Pradesh	Guntur	Ethipothala Falls	Ethipothala Falls is a 70 feet (21 m) high riv...	//upload.wikimedia.org/wikipedia/commons/thumb...
3	3	Andhra Pradesh	Guntur	Kondaveedu Fort	Kondaveedu Fort is a historically significant ...	//upload.wikimedia.org/wikipedia/commons/thumb...
4	4	Andhra Pradesh	Guntur	Nagarjuna Sagar Dam	Nagarjuna Sagar Dam is a masonry dam across th...	//upload.wikimedia.org/wikipedia/commons/thumb...

In [4]:
```
df.head()
```

Out[4]:

	Unnamed: 0	state	district	place	description	img_url
0	0	Andhra Pradesh	Guntur	Amaravati Stupa	Amarāvati Stupa is a ruined Buddhist stūpa at ...	//upload.wikimedia.org/wikipedia/commons/thumb...
1	1	Andhra Pradesh	Guntur	Bhattiprolu	Bhattiprolu is a village in Bapatla district o...	//upload.wikimedia.org/wikipedia/commons/thumb...
2	2	Andhra Pradesh	Guntur	Ethipothala Falls	Ethipothala Falls is a 70 feet (21 m) high riv...	//upload.wikimedia.org/wikipedia/commons/thumb...
3	3	Andhra Pradesh	Guntur	Kondaveedu Fort	Kondaveedu Fort is a historically significant ...	//upload.wikimedia.org/wikipedia/commons/thumb...
4	4	Andhra Pradesh	Guntur	Nagarjuna Sagar Dam	Nagarjuna Sagar Dam is a masonry dam across th...	//upload.wikimedia.org/wikipedia/commons/thumb...

fig 5.1 import library

2. **Data Pre-processing:** Data Pre-processing in machine learning involves cleaning, transforming and organizing data to improve its quality and suitability for model training.

Data Preprocessing

```
In [8]:  df['description'][0]

Out[8]:  'Amarâvati Stupa is a ruined Buddhist stūpa at the village of Amaravathi, Palnadu district, Andhra Pradesh, India, probably bui
lt in phases between the third century BCE and about 250 CE. It was enlarged and new sculptures replaced the earlier ones, begi
nning in about 50 CE.  The site is under the protection of the Archaeological Survey of India, and includes the stûpa itself  a
nd the Archaeological Museum.The surviving important sculptures from the site are now in a number of museums in India and abroa
d; many are considerably damaged. The great majority of sculptures are in relief, and the surviving sculptures do not include v
ery large iconic Buddha figures, although it is clear these once existed. The largest collections are the group in the Governme
nt Museum, Chennai (along with the friezes excavated from Goli), that in the Amaravati Archaeological Museum, and the group in
the British Museum in London. Others are given below.Art historians regard the art of Amaravati as one of the three major style
s or schools of ancient Indian art, the other two being the Mathura style, and the Gandharan style. Largely because of the mari
time trading links of the East Indian coast, the Amaravati school or Andhra style of sculpture, seen in a number of sites in th
e region, had great influence on art in South India, Sri Lanka and South-East Asia.Like other major early Indian stupas, but to
an unusual extent, the Amaravarti sculptures include several representations of the stupa itself, which although they differ, p
artly reflecting the different stages of building, give a good idea of its original appearance, when it was for some time "the
greatest monument in Buddhist Asia", and "the jewel in the crown of early Indian art".'
```

```
In [9]:
import re
from nltk.tokenize import word_tokenize
from nltk.corpus import stopwords

def clean_text(text):
    if isinstance(text, str):
        # Remove special characters and digits
        text = re.sub(r'[^a-zA-Z\s]', '', text)

        # Convert text to lowercase
        text = text.lower()

        # Tokenize the text
        words = word_tokenize(text)

        # Remove stop words
        stop_words = set(stopwords.words('english'))
        words = [word for word in words if word not in stop_words]

        # Join the words back into a clean sentence
        cleaned_text = ' '.join(words)

        return cleaned_text
    else:
        # Handle non-string values (e.g., None or NaN) by returning an empty string
        return ''
```

fig 5.2.1 data pre-processing

```
In [10]:
# Apply the clean_text function to the 'description' column
df['description'] = df['description'].apply(clean_text)

In [11]:  df['description'][0]

Out[11]:  'amarvati stupa ruined buddhist stpa village amaravathi palnadu district andhra pradesh india probably built phases third centu
ry bce ce enlarged new sculptures replaced earlier ones beginning ce site protection archaeological survey india includes stpa
archaeological museumthe surviving important sculptures site number museums india abroad many considerably damaged great majori
ty sculptures relief surviving sculptures include large iconic buddha figures although clear existed largest collections group
government museum chennai along friezes excavated goli amaravati archaeological museum group british museum london others given
belowart historians regard art amaravati one three major styles schools ancient indian art two mathura style gandharan style la
rgely maritime trading links east indian coast amaravati school andhra style sculpture seen number sites region great influence
art south india sri lanka southeast asialike major early indian stupas unusual extent amaravarti sculptures include several rep
resentations stupa although differ partly reflecting different stages building give good idea original appearance time greatest
monument buddhist asia jewel crown early indian art'

In [12]:
def convert(x):
    x = x.replace(' ','')
    return x

In [13]:
df['new state'] = df['state'].apply(convert)
df['new district'] = df['district'].apply(convert)
df['new place'] = df['place'].apply(convert)

In [14]:
df['des'] = df['new state']+" "+df['new district']+" "+df['new place']+" "+df['description']
df['des'][0]

Out[14]:  'AndhraPradesh Guntur AmaravatiStupa amarvati stupa ruined buddhist stpa village amaravathi palnadu district andhra pradesh ind
ia probably built phases third century bce ce enlarged new sculptures replaced earlier ones beginning ce site protection archae
ological survey india includes stpa archaeological museumthe surviving important sculptures site number museums india abroad ma
ny considerably damaged great majority sculptures relief surviving sculptures include large iconic buddha figures although clea
r existed largest collections group government museum chennai along friezes excavated goli amaravati archaeological museum grou
p british museum london others given belowart historians regard art amaravati one three major styles schools ancient indian art
two mathura style gandharan style largely maritime trading links east indian coast amaravati school andhra style sculpture seen
number sites region great influence art south india sri lanka southeast asialike major early indian stupas unusual extent amara
varti sculptures include several representations stupa although differ partly reflecting different stages building give good id
ea original appearance time greatest monument buddhist asia jewel crown early indian art'

In [15]:  new_df = df[['state','district','place','description','img_url','des']]
```

fig 5.2.2 data pre-processing

3. **Count Vector:** Count vector in machine learning is a technique that converts text data into a numerical format by counting the frequency of each word in a document.

```
In [21]: from sklearn.feature_extraction.text import CountVectorizer,TfidfVectorizer
         from sklearn.metrics.pairwise import linear_kernel,cosine_similarity

In [22]: cv = CountVectorizer(max_features=2000,stop_words='english')
         vector = cv.fit_transform(new_df['des']).toarray()

In [23]: similarity_des = cosine_similarity(vector)

In [24]: def recommded(place,model,df):
             if place in list(df['district']):
                 for p in df[df['district'] == place]['place']:
                     print(p)
             else:
                 place_index = df[df['place'] == place].index[0]
                 distances = sorted(enumerate(model[place_index]),reverse=True,key=lambda x: x[1])[1:25]
                 for i in distances:
                     print(df.iloc[i[0]]['place'])


         recommded('Marleshwar',similarity_des,new_df)

Vasa, Rajasthan
Jirawala Tirth
Jhari Falls
Rajsamand Lake
Sundha Mata Temple
Kemmangundi
Arimbra Hills, Malappuram
Kusuma
Kodikuthimala
Mirpur Jain Temple
Ponmudi
Mungathala
Varman, Rajasthan
Paithalmala
Sahasrakund Waterfall
Kudremukha
Shree Pavapuri Tirth Dham
Harshnath Temple
Antpur
Kamshet
Shri Raghunath Ji Temple
Ambika Mata Temple
Kumbhalgarh Wildlife Sanctuary
Bhadra Wildlife Sanctuary
```

Fig 5.3 count vector algorithm

4. **Tfidf Vector:** A "tfidf vector" in machine learning is a numerical representation of a document that combines the term frequency (tf) and inverse document frequency (idf) to measure the importance of terms in a corpus.

```
In [25]: tf = TfidfVectorizer(max_features=2000,stop_words='english')
         vector2 = tf.fit_transform(new_df['des']).toarray()

In [26]: tf_similarity_des = cosine_similarity(vector2)

In [27]: tf_similarity_des

Out[27]: array([[1.        , 0.00927859, 0.04001786, ..., 0.01286866, 0.02676745,
                 0.02653135],
                [0.00927859, 1.        , 0.03026255, ..., 0.01302531, 0.00863121,
                 0.03093879],
                [0.04001786, 0.03026255, 1.        , ..., 0.11545003, 0.04462203,
                 0.04055442],
                ...,
                [0.01286866, 0.01302531, 0.11545003, ..., 1.        , 0.23777692,
                 0.2613346 ],
                [0.02676745, 0.00863121, 0.04462203, ..., 0.23777692, 1.        ,
                 0.31634375],
                [0.02653135, 0.03093879, 0.04055442, ..., 0.2613346 , 0.31634375,
                 1.        ]])

In [28]: recommded('Marleshwar',tf_similarity_des,new_df)

Vasa, Rajasthan
Jirawala Tirth
Mirpur Jain Temple
Mungathala
Arimbra Hills, Malappuram
Shree Pavapuri Tirth Dham
Chandravati
Kusuma
Sundha Mata Temple
Kudremukha
Kemmangundi
Jhari Falls
Varman, Rajasthan
Paithalmala
Fort Vasai
Rajsamand Lake
Ambika Mata Temple
Pookode Lake
Kodikuthimala
Nilgiri Mountains
Antpur
Joychandi Pahar
Ramakkalmedu
Ponmudi
```

fig 5.4 tfidf vector algorithm

5. **Pickle:** In machine learning, "pickle" refers to a Python module used for serializing and deserializing Python objects, commonly employed for saving and loading machine learning models.

```
In [29]:
import pickle
with open('tourism.pkl','wb') as f:
    pickle.dump(similarity_des,f)
```

fig 5.5 Created model using pickle

6. **Home Page:** A tourism recommendation system homepage provides curated destination options, hotel suggestions, popular attractions, user experiences, information about the platform, login and registration options, and contact details for assistance.

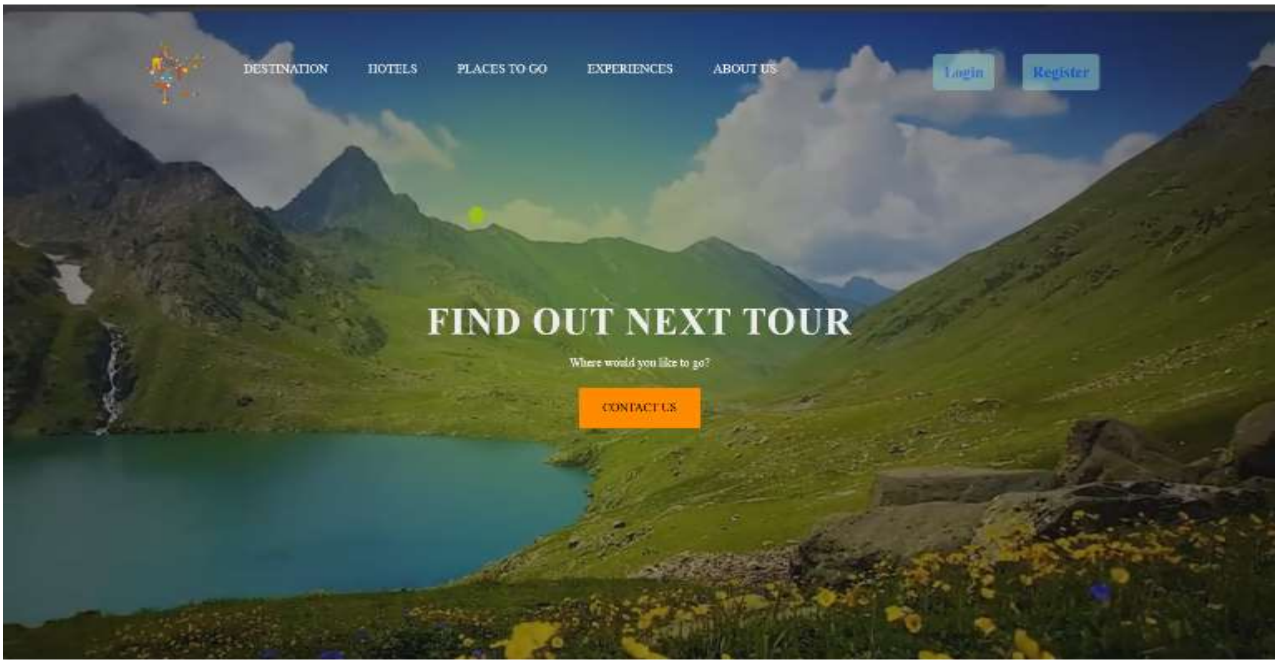

fig 5.6 home page

7. **Sign Up Page:** A tourism recommendation system sign-up page allows users to create personalized accounts for accessing tailored travel recommendations and exclusive offers.

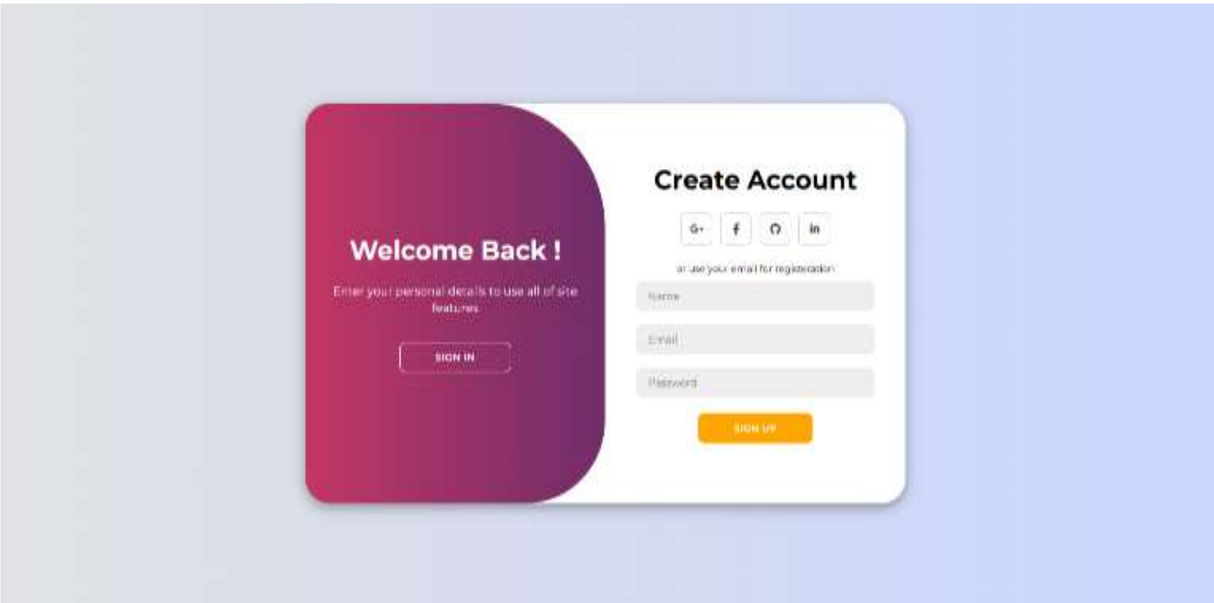

fig 5.7 sign-up page

8. **Login Page:** A tourism recommendation system login page allows users to access personalized travel recommendations and bookings.

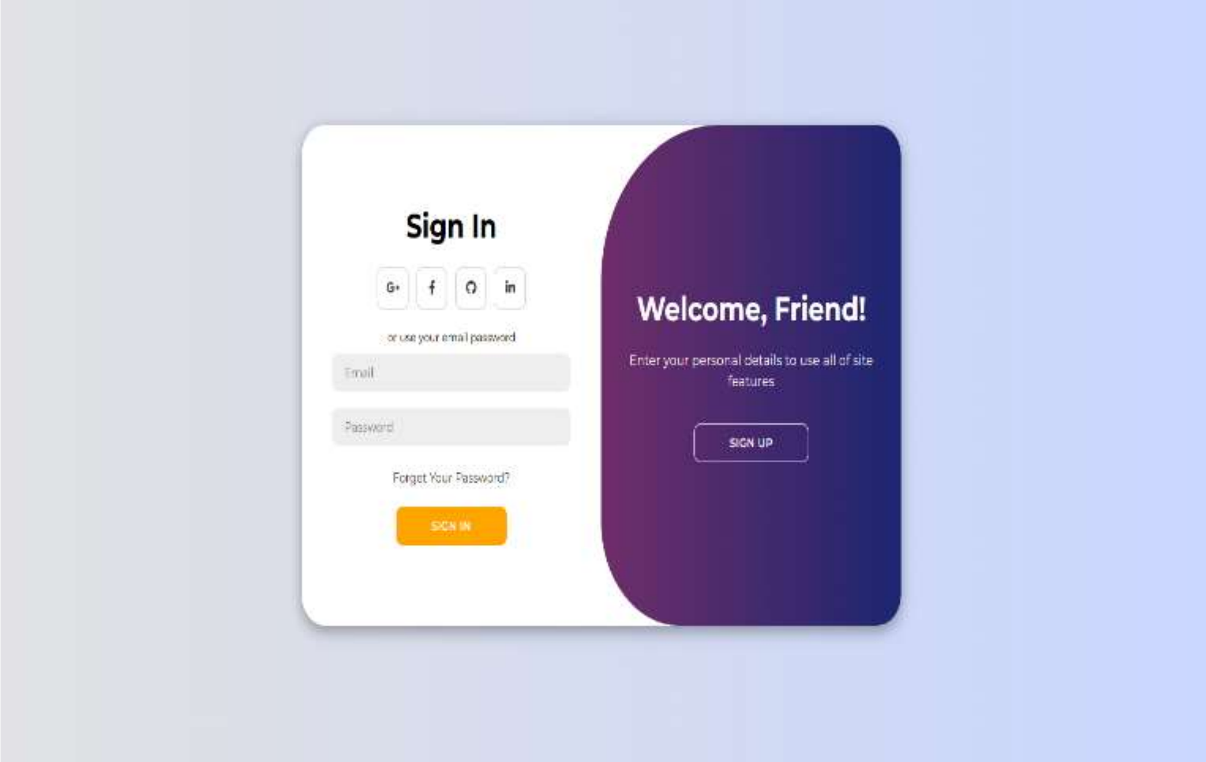

fig 5.8 login page

9. **About Us Page:** The "About Us" page of a tourism recommendation system provides an overview of the platform's mission, team, and commitment to delivering personalized and reliable travel recommendations.

fig 5.9 about us page

10. Destination Page: A tourism recommendation system destination page presents curated information, user reviews, and personalized suggestions for a specific travel location.

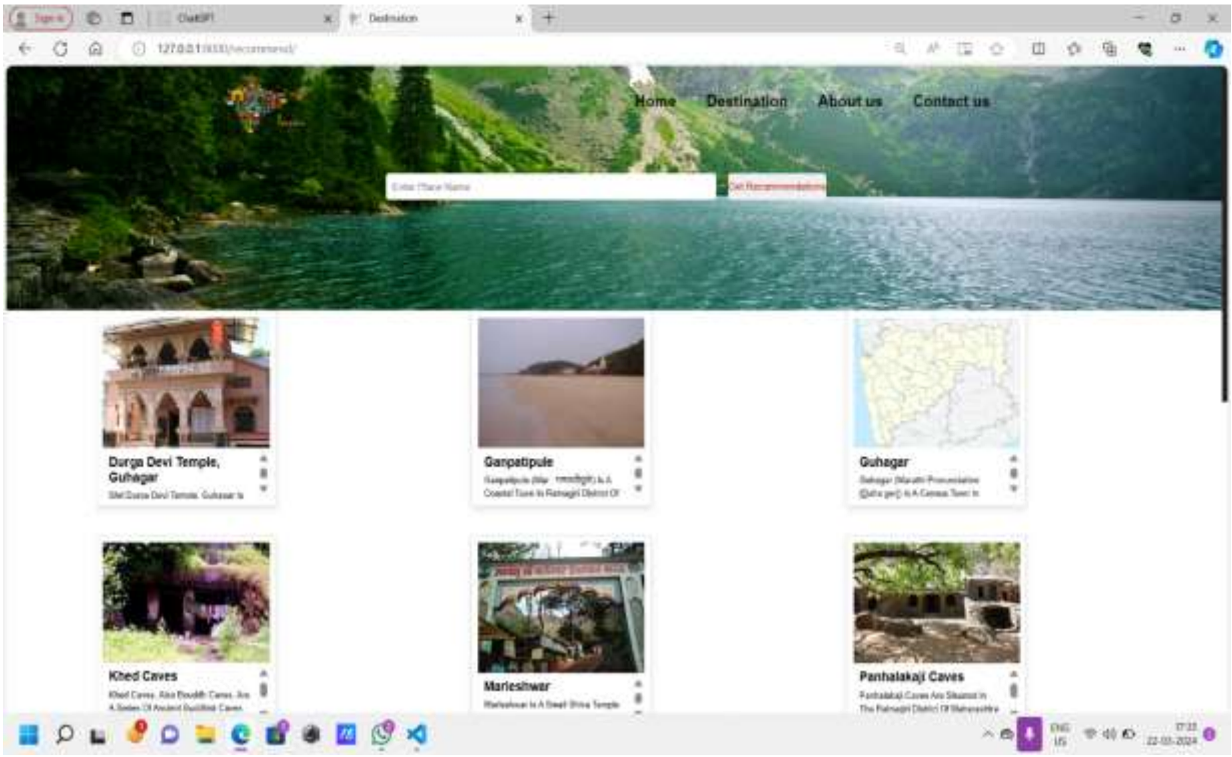

fig 5.10 destination page

11. Hotel Page: In these we aslo recommended the hotels nearby the destination which user have booked for their trip so it will be easy to book their hotels.

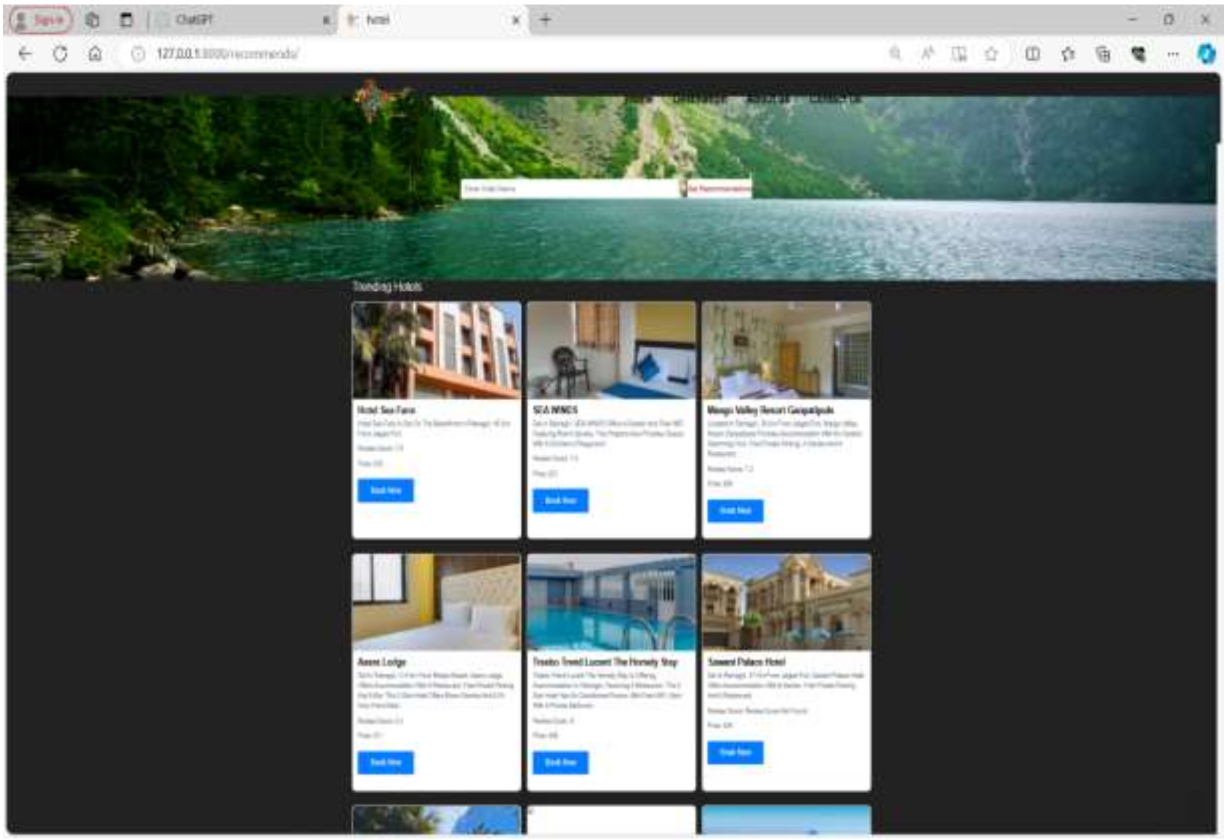

fig 5.11 hotel page

12. **Travel Dashboard:** "A tourism recommendation system's 'Travel Dashboard' page offers destination checking, hotel checking, and place checking, along with quick links, extra links, and contact and follow options."

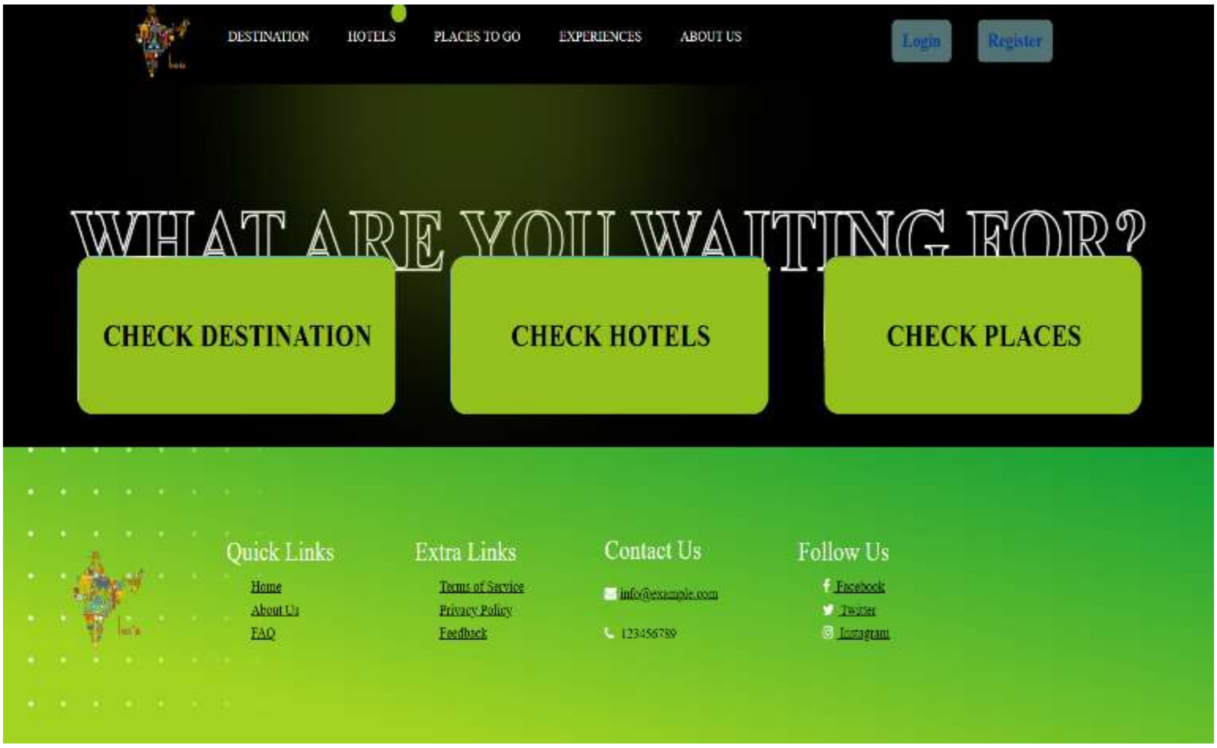

fig 5.12 travel dashboard page

13. **Contact Us:** The contact us page of a tourism recommendation system provides a platform for users to reach out for inquiries, support, or feedback regarding their travel experiences or the platform's services.

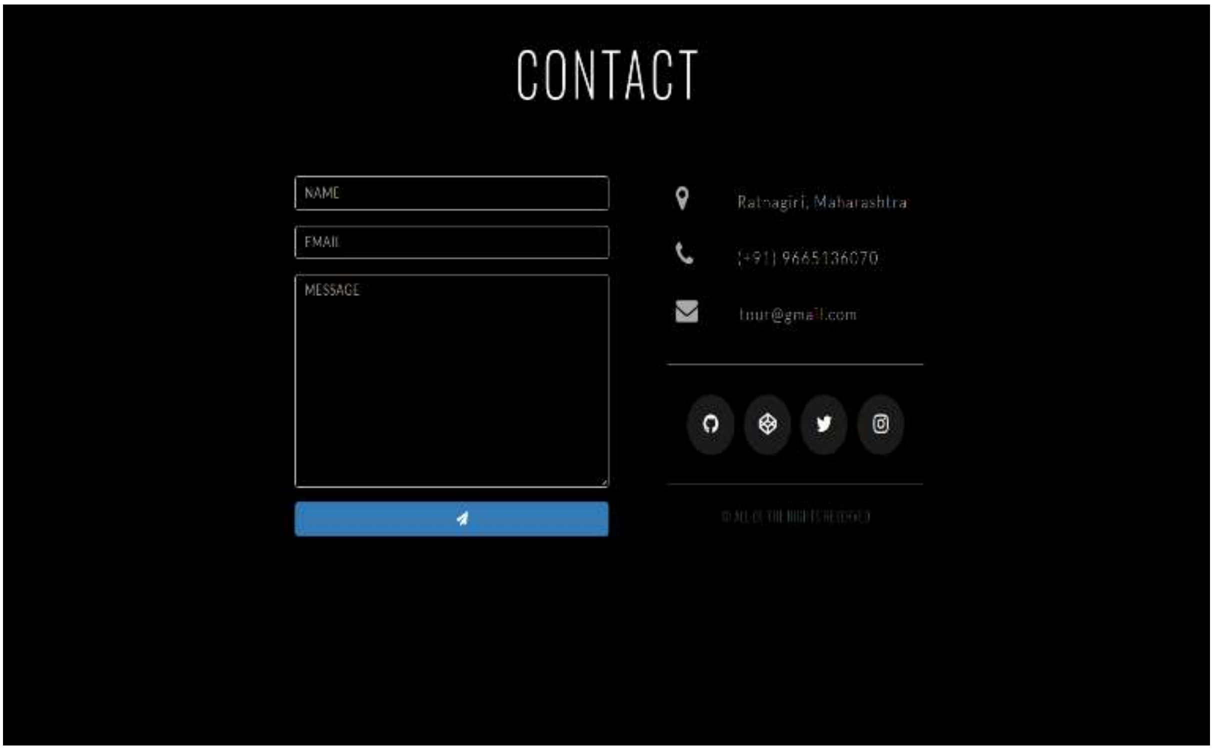

fig 5.13 contact us page

VI. CONCLUSION AND FUTURE SCOPE

In conclusion, tourism recommendation systems have become integral tools in the travel and tourism industry. These systems enhance the travel experience by providing personalized suggestions, saving time and effort, and helping travelers' make informed decisions.

The utilization of TF-IDF (Term Frequency-Inverse Document Frequency) and Count Vectorizer techniques within tourism recommendation systems presents a promising avenue for enhancing the travel experience. By leveraging these advanced text analysis methods, such systems can efficiently process and analyze vast amounts of textual data to provide personalized recommendations tailored to individual traveler preferences.

The incorporation of TF-IDF enables the system to identify and prioritize relevant terms within the corpus, thereby improving the accuracy and relevance of recommendations. Additionally, Count Vectorizer facilitates the conversion of textual data into numerical representations, allowing for efficient mathematical operations and modeling.

Through the synergy of TF-IDF and Count Vectorizer, tourism recommendation systems can offer travelers comprehensive and insightful suggestions for accommodations, attractions, dining options, and activities. These recommendations are not only based on the frequency of terms but also consider the significance of terms across the entire corpus, leading to more informed and contextually relevant suggestions.

Furthermore, the iterative refinement and optimization of these techniques enable tourism recommendation systems to continuously adapt and improve, ensuring that recommendations remain up-to-date and reflective of evolving traveler preferences and trends.

In essence, the integration of TF-IDF and Count Vectorizer techniques empowers tourism recommendation systems to deliver personalized, accurate, and valuable suggestions, thereby enhancing the overall travel experience for users.

Future Scope: -

The future scope for tourism recommendation systems lies in advanced personalization, incorporating AI-driven predictive analytics, real-time data integration, immersive technologies like VR/AR, and seamless integration with social media platforms for enhanced user experiences. These systems will continue to evolve to provide tailored recommendations based on user preferences, behaviors, and contextual data, ultimately revolutionizing how people discover, plan, and enjoy travel experiences.

- Personalization and Context-Aware Recommendations
- Predictive Analytics
- Sustainability and Responsible Tourism
- Accessibility and Inclusivity

VII. REFERENCES

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