Tourism Itinerary Generation Based on Image Similarity

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Abstract: This paper presents a new method for the generation of personalized tourism itineraries using visual similarity. Using advanced computer vision and optimization, our approach allows users to upload an image of the aesthetic they are looking for and receive recommendations for tourist attractions that look like the input. Homographic warping is used for precise image pre-processing, the CLIP model for embedding generation and FAISS for rapid similarity search. Google Maps API and Google OR-tools are used for geocoding and solving a Vehicle Routing Problem with Time Windows (VRPTW) in order to generate the optimal daily itineraries. The proposed solution can be placed between visual cues and travel planning, and it provides a user-friendly interface for the generation of itineraries that can be tailored to the individual's preferences.

Keywords: Computer Vision, Semantic Search, CLIP, Vector Similarity Search, Geospatial Data, Google Maps API, Itinerary Optimization, Google OR-Tools, Real-Time Travel Data, Personalized Recommendations, AI-Powered Travel Planning.

1. Introduction

The present system of tourism planning depends on textual data combined with quantifiable metrics including reviews and ratings and social media popularity. Current traditional travel recommendation systems depend on these data points to recommend destinations although they fail to consider the abundant visual signs which powerfully sway travel choices. People are increasingly turning to visually-focused platforms such as Instagram and Pinterest and travel blogs to find inspiration through images that represent destinations. The evolution demonstrates a major weakness in traditional tourism planning because it fails to effectively utilize emotional and sensory visual content. In response to this gap, our research introduces an innovative method that suggests tourist attractions based on the visual similarity of an input image. Our system designed to find visual features that attract travelers uses state-of-the-art image processing methods to make recommendations based on similar attractions. The fundamental algorithm includes homographic warping to select and enhance the essential image regions while the CLIP model analyzes them to produce high-dimensional embeddings that define the aesthetic value of the input. The efficiency of searching through this precomputed database with FAISS enables rapid similarity searches.

Our system does not stop at image processing, and it uses the Google Maps API to both validate and geocode the suggested attractions through geospatial data analysis. This guarantees that in addition to matching the traveler's visual expectations the recommendations are also realistic from a geographical perspective. To boost travel planning quality, we add route optimization through Google OR-tools which enables us to produce practical daily schedules by implementing restrictions about travel periods and pauses for eating and staying overnight. When modelling itineraries as Vehicle Routing Problems with Time Windows (VRPTW), our approach provides guaranteed realistic and user-preference based solutions for each day's route.

Our method represents a significant departure from the norm, by incorporating visual similarity as a key factor in destination recommendation. It not only captures the changing characteristics of consumer behavior in the digital age and advances the state of art in recommender systems, but also posits a framework for future research where sensory and aesthetic dimensions play a central role in personalized travel planning.

2. Research Background

The evolution of tourism recommendation systems has been enhanced by artificial intelligence as well as machine learning techniques and geospatial analytics to improve user experience. The research focuses on important topics such as image-based recommendation systems, semantic search in tourism, itinerary optimization, and hybrid recommendation models in order to review their strengths and limitations.

2.1 Image-Based Tourism Systems

By applying computer vision capabilities, travel recommendation systems identify landmarks as well as travel destinations and attractions. He et al. (2016) proposed a landmark recognition system based on CNN which enhanced the accuracy of image classification but did not offer personalized suggestions. In extending this work, Liu et al. (2021) included deep feature embeddings to recognize tourist attractions but missing was real-time contextualization.

Google Lens functions as an image recognition tool which finds widespread use yet fails to deliver personalized itinerary planning. Wang et al. (2022) investigated image-based travel suggestions which depended on static datasets resulting in limited adaptability to actual travel situations. Tanaka Lee (2023) created an AI model which recommends domestic choices instead of international travel options but the approach failed to incorporate real-time travel restrictions.

2.2 Semantic Search in Tourism

Tourism recommendation systems provide more accurate answers to natural language queries because of semantic search's ability to understand the context of user requests. Sentence-BERT was presented by Reimers and Gurevych in 2019 and brought a significant enhancement to text embeddings specifically for semantic similarity. The majority of applications for tourism that use Sentence-BERT continue to rely on structured text inputs and do not feature image-based query support. A knowledge graph-enhanced tourism search engine was introduced by Zhao et al. (2020), which enhanced discovery of tourist destinations. The research did not build upon multimodal data or real-time contextual elements because their work exclusively focused on textual connections. Travel blogs served as the text data source which a context-aware recommendation system was developed to analyze for sentiment by Chen et al. in 2021.

2.3 Itinerary Optimization

For several years, research into optimizing travel itineraries has remained a significant tourism research problem. Chen et al. (2018) applied genetic algorithms to route optimization which led to efficient path selection yet did not incorporate dynamic user preferences. Itinerary generation using reinforcement learning by Wang et al. in 2021 used historical travel data for route adaptations yet had no real-time response to environmental changes.

2.4 Itinerary Optimization

In order to improve the personalization, recommendation systems based on hybrid approach combine collaborative filtering and content-based filtering. The paper by Luo et al. (2018) enhanced the ranking accuracy through the combination of user generated reviews and destination metadata but it does not include other types of multimodal input sources like images. The two systems that make use of hybrid models are TripAdvisor and Sygic Travel; however, both of them rely on the user ratings and the predefined templates which make them less adaptable for the dynamic itinerary planning. Xiao et al. (2022) investigated the possibility of integrating deep learning techniques with knowledge graphs to build recommendations that reflect user behavior.

Table 1. Literature Survey and Review

Paper Title	Author(s)	Publication	Year	Strengths	Weaknesses
Image-Based Travel Recommender [4]	Fujita, Nakayama	Springer	2021	Personalized recommendations for niche locations.	Limited scalability to larger or diverse areas.
Picture-Based Tourism System [5]	Wang, Li	Francis Press	2022	Uses images for implicit preference elicitation.	May struggle with ambiguous or low-quality images.
Vision-Based Domestic Travel [6]	Tanaka, Lee	ResearchGate	2023	Suggests local alternatives to foreign destinations.	Lacks cultural and experiential differentiation.
Geo-Tagged Photo Tourism [7]	Zhou, Chen	arXiv	2021	Uses multi-level similarity for better recommendations.	Requires extensive labeled datasets; computationally intensive.
Travel Info Retrieval via Photos [8]	Gomez, Tran	arXiv	2022	Allows interactive discovery using personal images.	Accuracy depends on image diversity and quality.
Hybrid Travel Recommendation [9]	Singh, Patel	AIP	2023	Combines user ratings and image preferences.	LDA and SVD may not fully capture nuanced visual data.
Tourism Image Classification [10]	Zhang, Wei	PMC	2023	High classification accuracy; useful for automated tagging.	Requires extensive labeled datasets for training.
Global Tourism via Geo-Photos [11]	Gomez, Liu	ResearchGate	2020	Uses large-scale geotagged data for recommendations.	Depends on web photo availability; lacks real-time adaptation.
AI-Enhanced Travel Planning [12]	Ahmed, Rao	ResearchGate	2024	Uses AI-inspired image enhancement for better recognition.	Experimental stage; lacks real-world testing.
Multimodal Route Optimization [13]	Park, Choi	Frontiers	2024	Combines AI models for high accuracy and personalization.	High computational cost; requires significant processing power.

3. Proposed System

Our proposed system is several such modules are interconnected to address critical aspects of the itinerary generation process:

3.1 Image Recognition and Feature Extraction

First, the system performs image pre-processing where homographic warping is applied if necessary to focus on the most important segments of the input image. This step ensures only significant visual elements are analyzed in the subsequent process.

3.2 Embedding Generation

Following pre-processing, the refined input is then passed through the CLIP model. The CLIP model, a vision language model, is able to extract high dimensional embeddings that capture the visual characteristics of the input image. These embeddings act as a compact representation of the visual content of the image.
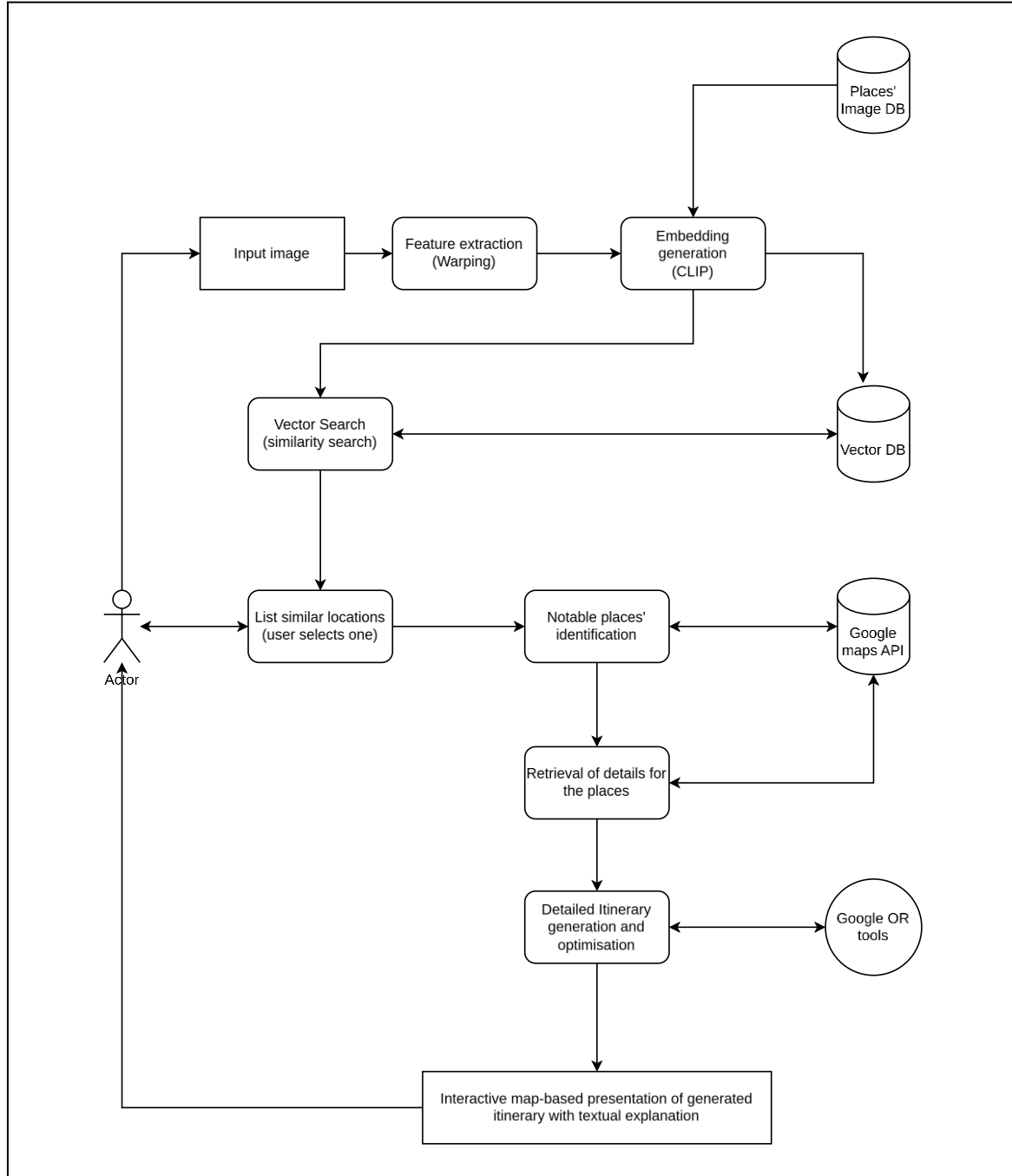
Fig. 1: Prosposed Workflow

3.3 Vector Search and Similarity Matching

The produced embeddings are contrasted with a precomputed vector database to rapidly locate visually equivalent attractions. The vector database is populated by aggregating multiple images of each location and then applying the centroid method. FAISS is utilized to carry out efficient similarity searches, speedily retrieving the top matching locations based on cosine similarity.

3.4 Noteworthy Places Identification

After getting the similar embeddings, the corresponding tourist places are further processed by getting the Google Maps API. Place names are turned into geographic coordinates through geocoding while extra details like ratings and opening hours alongside user reviews are obtained to give a full picture of each location.

3.5 Itinerary Creation and Optimization

The system allows users to define where they are planning to travel as well as what parameters such as start and end dates, search radius and what type of attractions they are interested in. The itinerary generation is represented as a VRPTW. To solve the routing problem, we apply Google OR-tools, and take into consideration constraints such as the daily travel time, meal breaks, and lodging. The optimization will guarantee that it is possible to follow each day's route and that it is feasible and reasonable for the user

3.6 User Interface and Interaction

With Streamlit we develop a user-friendly interface to support interactive image uploads search result visualization and itinerary customization. The integration of Folium provides the capability to display the final itinerary on an interactive map to improve user experience.

3.7 Real-time Data Integration

The system is able to integrate in real time with external data sources. For instance, the Google Maps API gives real time geocoding and place details and, in addition, concurrent requests can provide the latest details on places of interest and business hours nearby.

3.8 System Workflow

Here is how the system works in full extent:

1) Input Processing: A homographic warp is applied to the image which is then uploaded by users.

2) Embedding Generation: The processed image is passed through the CLIP model to produce normalized embeddings.

3) Similarity Search: FAISS is employed to compare the input embeddings with those in the database in order to retrieve the top visually similar places.

4) Place Selection: Users choose a search result to select a place.

5) Geocoding and Nearby Place Identification: The Google Maps API is used to geocode the selected place and then identify additional nearby attractions based on user-defined criteria.

6) Itinerary Optimization: Using Google OR-tools, a VRPTW is solved which also includes constraints such as meal breaks, opening hours and lodging.

7) Output Presentation: The final itinerary is presented to the user along with an interactive map for visualization.

The mathematical background to our approach is discussed in detail in the next section.

4. Mathematical Formulation

4.1 Homographic Warping

We apply a homographic transformation to extract the relevant portion of the image. For an input point in homogeneous co-ordinates,

$$\begin{bmatrix} x \\ y \\ 1 \end{bmatrix} \tag{1}$$

the warped point is given by:

$$\begin{bmatrix} x' \\ y' \\ w' \end{bmatrix} = H \cdot \begin{bmatrix} x \\ y \\ 1 \end{bmatrix} \tag{2}$$

where H is the homography matrix and the corresponding normalized co-ordinates are calculated as:

$$(x'', y'') = \left(\frac{x'}{w'}, \frac{y'}{w'} \right) \tag{3}$$

4.2 CLIP Embedding Generation and Normalization

The CLIP model maps an input image I to a high-dimensional embedding:

$$e = f(I) \tag{4}$$

where f denotes the CLIP encoding function. We then normalize the embedding:

$$e_{\text{nr}} = \frac{e}{|e|_2} \tag{5}$$

4.3 Aggregation via Centroid Computation

For a given tourist location with multiple image embeddings $e_1, e_2, \ldots, e_n$, the aggregated embedding is computed as:

$$e_c = \frac{1}{n} \sum_{i=1}^{n} e_i \tag{6}$$

4.4 Cosine Similarity for Vector Search

Given a query embedding q and a stored embedding e_i, the cosine similarity is computed as:

$$\text{sim}(q, e_i) = q \cdot e_i \tag{7}$$

(we assume both vectors to be already normalized)

4.5 Haversine Distance for Geospatial Calculations

To compute the distance between two geographic points (ϕ_i, λ_i) and (ϕ_j, λ_j) we use the haversine formula

$$d_{ij} = 2R \arctan 2 \left(\sqrt{a}, \sqrt{1-a} \right) \qquad (8)$$

where

$$a = \sin^2 \left(\frac{\Delta\phi}{2} \right) + \cos(\phi_i) \cos(\phi_j) \sin^2 \left(\frac{\Delta\lambda}{2} \right) \qquad (9)$$

and

$$\Delta\phi = \phi_j - \phi_i, \quad \Delta\lambda = \lambda_j - \lambda_i \qquad (10)$$

and R is the Earth's radius.

4.6 Travel Time Calculation

Assuming a constant travel speed v, the travel time between two points is given by:

$$t_{ij} = \frac{d_{ij}}{v} \qquad (11)$$

4.7 VRPTW Time Window Constraint and Objective Function

For the itinerary optimization, we model the problem as a Vehicle Routing Problem with Time Windows (VRPTW). For two consecutive stops i and j, the service start time must satisfy:

$$s_i + \tau + t_{ij} \leq s_j \qquad (12)$$

where s_i is the service start time at node i, t_{ij} is the travel time between node i and j, τ is the service duration at node j, s_j is the service start time at node j.

The overall objective is to minimize the total travel cost combined with penalties for skipped stops:

$$\min \sum_{(i,j) \in E} c_{ij} \, x_{ij} + \sum_{i \in V \setminus \{0\}} p_i \, (1 - y_i) \qquad (13)$$

where c_{ij} is the travel cost from node i to node j, x_{ij} is the binary variable indicating whether the edge *(i, j)* is in the route, p_i is the penalty for not visiting node i, y_i indicates whether node i is visited, V represents the set of all nodes, E denotes the set of all edges, *V\{0}* denotes set of all nodes except the depot (starting and ending point).

5. Data Collection and Preprocessing

5.1 Data Collection

From Kaggle, we obtained a dataset of 50 unique tourist locations with multiple images of each to represent different views of the location. The collected data provides sufficient scope for the system to learn the visual characteristics of each location while ensuring that the representations learned from one location are not misleading due to outliers or limited views.

5.2 Data Preprocessing

With CLIP, each image in the dataset is transformed into embeddings. The centroid method aggregates embeddings from every image belonging to the same location, which leads to a strong and representative image for each place. This technique helps in reducing the effects of outliers and results in a more general and accurate visual representation for every tourist destination. The aggregated embeddings are then normalized and stored in a vector database which is indexed by FAISS to enable fast similarity matching.

6. Implementation

6.1 Embedding Extraction with a Pre-trained Vision Model

The system uses the pre-trained 'openai/clip-vit-base-patch32' model from Hugging Face to extract image embeddings. The model is loaded with memory efficient settings and images are processed in batches to get the best out of CPU/GPU performance.
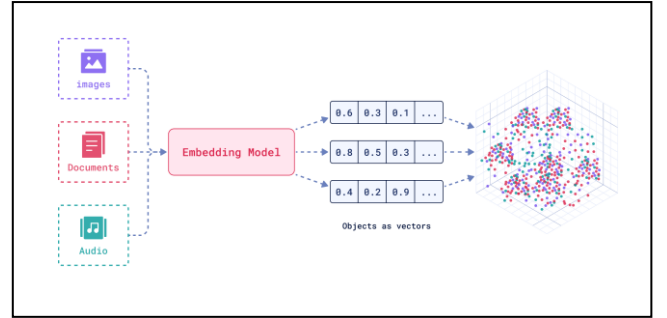

Fig. 2: Vector Embeddings

6.2 Aggregation and Centroid Computation

For every tourist location, multiple image embeddings are computed and then aggregated. The centroid (average embedding) is computed which ensures that the final representation does not only reflect the overall appearance of a location but also the common visual elements. This aggregated embedding is then used as the key identifier in the similarity search process.

6.3 Efficient Similarity Search using FAISS

FAISS is used to create an index of the aggregated embeddings. With the normalization of the embeddings and the use of inner product as a proxy for cosine similarity, the system is able to carry out rapid similarity searches. This allows real time retrieval of visually similar places when given a query image.

6.4 Optimization Strategies

Itinerary planning is represented as a VRPTW problem with inclusion of factors such as travel time, opening hours of businesses and meal breaks. This problem is solved using Google OR tools with a greedy initial solution and guided local search to enhance the solution. The optimization process helps to ensure that the itinerary is as practical as well as consistent with user preferences.

7. Results

7.1 Image-Based Input Location Identification

The outcome of our experimental research indicates that image-based search effectively returns tourist attractions with visual resemblance to the image which the user supplies. A results table (Table II) indicates high precision in images to attractions relationship.

Table 2. Image Similarity Results

Input Image	Match 1	Match 2	Match 3
	Select Machu Picchu	Select Chichen Itza Mexico	Select The Pyramids of Giza
	Select Eiffel Tower	Select Arc de Triomphe	Select Tower Bridge
	Select Angkor Wat	Select Machu Picchu	Select Tian Tan Buddha
	Select The Great Sphinx	Select The Pyramids of Giza	Select Chichen Itza Mexico

7.2 User Selection and Customization Parameters

The system's interactive interface enables users to make precise adjustments to their search criteria. Users can choose different place categories and define the search area as well as define the travel period. The software customization and intuitive design are depicted through screenshot in Fig 3.

Fig. 3: Itinerary Customization Options

7.3 Itinerary Generation and Interactive Map

After the input image and extra parameters are entered the system produces a precise daily schedule. The final output is displayed as an interactive map which displays the planned route with clear markers for each stop, all rendered using Folium. Real-time map data with itinerary details works together to create a better travel planning experience.
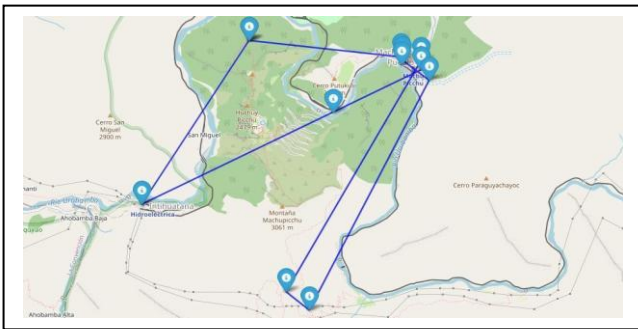

Fig. 4: Sample Interactive Map of Generated Itinerary

8.   Future Scope and Limitations

The proposed approach for creating personalized tourism itineraries based on visual similarity holds a promising potential. However, several avenues exist for further enhancement and refinement:

8.1 Scalability and dataset diversity

The current implementation is based on 50 locations of tourists dataset from Kaggle. The system's robustness and generalizability would increase if the dataset is expanded to include more diverse range of attractions from different geographic regions. More data can also reduce bias and can help in capturing regional aesthetics.

8.2 Real-Time Adaptation

The ability to dynamically change planned routes through additional real time information like weather and traffic and current crowd behavior would allow for more effective response to changing circumstances. This enhancement would increase the practicality of the itineraries as well as their actual feasibility in real world conditions that are changing.

8.3 Enhanced Feature Extraction

This paper explores the capabilities of the CLIP model for image encoding and recommends directions for improvement through alternative or combination with textual cues. Research into the fusion of multiple data modalities could produce more precise user modelling outcomes for future work.

8.4 User Feedback Integration

The integration of a process to gather user feedback on recommendations can help to gradually enhance the system. An adaptive learning loop that responds to user interactions combined with satisfaction metrics provides a more personalized and context-aware itinerary generation system that improves over time.

8.5 Computational efficiency

Further optimization of the processing pipeline to reduce latency – for example, by improving batch processing strategies or using distributed computing techniques – could help. Improving computational efficiency is important for guaranteeing a seamless user experience and this becomes especially important when handling large datasets.

8.6 Dependency on External APIs

The system's use of external services especially the Google Maps API for geocoding, place details, and routing information has the potential to be slow because of API rate limits and network latency. Investigating other methods to reduce these delays could improve real time performance and system resilience.

8.7 General Limitations

The effectiveness of the current system depends on the quality and representativeness of the dataset used. Pre-trained models have limitations when it comes to tracking seasonal and local trends, which affects the model's ability to perform well in all scenarios. Resolving these challenges is crucial for successful deployment in diverse, real-world contexts.

9. Conclusion

This paper develops a new approach for tourism itinerary planning using visual similarity. The methodology helps the practical travel planning process by integrating advanced image processing techniques such as homographic warping and CLIP-based embedding generation with efficient similarity search via FAISS and itinerary optimization modeled as a VRPTW using Google OR tools. Using the Google Maps API, geospatial data is incorporated to guarantee that the recommendations are visually appealing and also geographically viable. The approach has significant potential for transforming travel recommendation systems even though there are limitations such as reliance on external APIs and a limited initial dataset. The future work will include the addressing of these limitations and a further development of the system's capabilities to work in real time, in order to create more user focused travel planning solutions.

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