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A
Project Report
on
Padharo Sa:
Tourism Itinerary Generation Based on Image Similarity
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BACHELOR OF TECHNOLOGY
DEGREE

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May, 2025

DECLARATION

We hereby declare that this submission is our own work and that, to the best of our knowledge and belief, it contains no material previously published or written by another person nor material which to a substantial extent has been accepted for the award of any other degree or diploma of the university or other institute of higher learning, except where due acknowledgment has been made in the text.

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CERTIFICATE

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ABSTRACT

This project presents a novel approach for generating personalized tourism itineraries using visual similarity. By leveraging advanced computer vision techniques and optimization methods, the system allows users to upload an image representing the desired aesthetic and then retrieves and recommends tourist attractions that visually match the input. Key components include homographic warping for image pre-processing, the CLIP model for embedding generation, and FAISS for rapid similarity search. Geospatial data is incorporated via the Google Maps API, and itineraries are optimized using a Vehicle Routing Problem with Time Windows (VRPTW) solved by Google OR-tools. The approach demonstrates significant potential to bridge the gap between visual inspiration and practical travel planning.

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LIST OF ABBREVIATIONS

| | |
|----------|---|
| API | Application Programming Interface |
| AI | Artificial Intelligence |
| CLIP | Contrastive Language–Image Pre-training |
| CPU | Central Processing Unit |
| CNN | Convolutional Neural Network |
| FAISS | Facebook AI Similarity Search |
| GPU | Graphics Processing Unit |
| OR-Tools | Google OR-Tools (Operations Research Tools) |
| VRPTW | Vehicle Routing Problem with Time Windows |

CHAPTER 1

INTRODUCTION

1.1 INTRODUCTION

The contemporary landscape of travel planning is undergoing a profound metamorphosis, largely orchestrated by the pervasive influence of the digital age and the evolving paradigms of modern tourist preferences. Historically, the process of selecting destinations and crafting itineraries was heavily anchored in textual information, structured data compilations such as critic ratings and user-generated reviews, and the aggregated popularity metrics of destinations across various social media platforms. While these quantitative indicators undeniably furnish valuable insights, they frequently fail to capture or adequately weigh the potent, often subconscious, influence of visual cues. These visual elements are increasingly pivotal in shaping travel aspirations and decisions in an era dominated by visually-centric online interactions. Platforms such as Instagram, Pinterest, and myriad travel blogs, rich with evocative imagery, have ascended to become primary wellsprings of inspiration. On these platforms, compelling photographs and videos of destinations elicit strong emotional responses, effectively igniting the nascent desire to embark on a journey. This pronounced shift towards visual discovery starkly illuminates a critical deficiency in conventional travel recommendation systems: they are generally ill-equipped to process, interpret, or leverage this abundant visual data. Consequently, they struggle to bridge the experiential gap between the inspirational "wow" moment, often triggered by a single captivating image, and the subsequent formulation of a practical, personalized, and actionable travel plan.

This observed lacuna forms the impetus for our research and the development of "Padharo Sa," an innovative system conceived to pioneer the domain of tourism itinerary generation predicated on the principle of visual similarity. The core philosophy of this system is to meticulously understand and numerically quantify the aesthetic, contextual, and even atmospheric elements embedded within a user-provided image—elements that resonate deeply with their latent travel desires. To achieve this, "Padharo Sa" employs an arsenal of state-of-the-art computer vision algorithms and sophisticated machine learning techniques. These tools enable the system to recommend tourist attractions that not only are geographically relevant but also share profound visual and stylistic characteristics with the user's initial visual prompt.

The algorithmic backbone of "Padharo Sa" involves several critical stages. It begins with image preprocessing, potentially including homographic warping to rectify perspectives or isolate salient regions within the input image, ensuring that subsequent analyses focus on the most pertinent visual information. Following this, the refined image is processed by the advanced CLIP (Contrastive Language–Image Pre-training) model. CLIP excels at generating high-dimensional vector embeddings—numerical representations that encapsulate the complex aesthetic and semantic essence of the image. These embeddings are then efficiently compared against a precomputed database of embeddings representing a multitude of global tourist locations. This comparison is facilitated by FAISS (Facebook AI Similarity Search), a library optimized for exceedingly rapid similarity searches in high-dimensional spaces, allowing for near-instantaneous retrieval of visually analogous locations.

However, the proposed system's functionality extends significantly beyond mere visual matching. It seamlessly integrates geospatial intelligence through the Google Maps API, which is utilized to geocode the recommended attractions (i.e., convert place names into precise geographical coordinates), validate their existence and accessibility, and enrich them with a plethora of practical details indispensable for travel planning. This includes, but is not limited to, current opening hours, user ratings and reviews, typical crowd levels, and estimated travel times between points of interest. To elevate the system's utility from simple, disconnected recommendations to comprehensive and actionable travel plans, we incorporate sophisticated route optimization methodologies. Daily itineraries are meticulously formulated as instances of a Vehicle Routing Problem with Time Windows (VRPTW), a well-studied challenge in operations research. This complex optimization problem is then solved using Google OR-tools, a powerful suite of algorithms. The VRPTW formulation inherently considers a multitude of real-world constraints, such as maximum permissible daily travel durations, allowances for meal breaks, optimal sequencing of visits to respect opening hours, and designated start and end points for each day, typically centered around accommodation. This ensures that the generated itineraries are not only inspiring and visually congruent with the user's desires but also eminently feasible, efficient, and enjoyable from a logistical standpoint.

Our approach, therefore, signifies a substantive paradigm shift from conventional recommendation engines. By elevating visual semantics from a peripheral consideration to a fundamental component of the travel planning process, "Padharo Sa" directly addresses the evolving nature of how contemporary travelers discover, evaluate, and decide upon their destinations in an increasingly digitized and visually saturated world. It offers a more intuitive, engaging, and profoundly personalized experience. In doing so, "Padharo Sa" not only endeavors to advance the existing capabilities of recommender systems but also aims to establish a robust and extensible framework for future explorations in the field, where sensory

inputs and aesthetic dimensions assume a central and pivotal role in the crafting of deeply personalized and memorable travel journeys.

1.2 PROJECT DESCRIPTION

The "Padharo Sa" project is centered on the conceptualization, design, development, and rigorous evaluation of an advanced tourism itinerary generation system. The defining characteristic of this system is its primary reliance on image similarity as the foundational input for initiating the travel planning process. Engineered to translate a user's abstract visual inspiration—typically encapsulated in a single uploaded image—into a concrete, comprehensive, and logistically optimized travel itinerary, the system's workflow methodically unfolds through several interconnected key stages:

- **Input Processing & Visual Focus Enhancement:** The user initiates interaction by uploading an image that, in their perception, represents a desired travel aesthetic, a specific architectural style, a type of natural landscape, or perhaps even a particular mood or ambiance they seek. This uploaded image may then be subjected to an optional preprocessing step involving homographic warping. This technique is employed to algorithmically identify and isolate the most visually significant segments within the image or to correct any pronounced perspective distortions. Such enhancement ensures that all subsequent analytical stages focus with precision on the most relevant and informative visual features, thereby improving the quality of downstream processing.
- **Embedding Generation for Aesthetic and Semantic Capture:** The (potentially refined) image is subsequently processed by the CLIP (Contrastive Language–Image Pre-training) model. This sophisticated deep learning model is adept at generating high-dimensional vector representations, commonly referred to as embeddings. These embeddings are essentially numerical "fingerprints" that effectively capture and quantify the complex visual attributes, stylistic nuances, and even the latent semantic or aesthetic characteristics inherent in the image's content. This transformation from pixel data to a rich vector representation is crucial for enabling objective similarity comparisons.
- **High-Speed Similarity Search in Curated Location Database:** The embeddings derived from the user's input image are then systematically compared against a comprehensive, precomputed vector database.

This specialized database houses aggregated embeddings (typically centroids, as will be detailed later) that serve as robust visual signatures for a diverse array of tourist locations worldwide. The critical task of performing this high-dimensional similarity search with exceptional speed and accuracy is delegated to FAISS (Facebook AI Similarity Search). FAISS rapidly retrieves a ranked list of locations whose stored embeddings exhibit the highest degree of similarity (e.g., cosine similarity) to the input image's embedding, effectively identifying destinations that are most visually consonant with the user's provided inspiration.

- **Geospatial Analysis and Practical Information Enrichment:** The candidate locations emerging from the similarity search are then subjected to further processing and enrichment using the versatile Google Maps API. This stage involves several key operations: firstly, geocoding the identified attractions to obtain their precise geographic coordinates (latitude and longitude); secondly, programmatically querying for a wealth of supplementary details that are paramount for effective travel planning. Such details include, but are not limited to, crowd-sourced user ratings, extensive textual reviews, typical opening and closing hours, contact information, specific place categories (e.g., museum, national park, historical monument, restaurant), and accessibility information. This enrichment transforms a list of visually similar place names into a collection of well-characterized, actionable, and practical points of interest.
- **Optimized Itinerary Creation with Real-World Constraints:** Based on a primary location (often the top-ranked match from the similarity search, or a location explicitly selected by the user from the suggestions) and a set of user-defined parameters—such as desired travel dates (dictating trip duration), preferred types of attractions (catering to specific interests like history, art, nature, or cuisine), and acceptable daily travel limits—a multi-day itinerary is meticulously constructed. The core of this construction process lies in formulating the itinerary planning challenge as a Vehicle Routing Problem with Time Windows (VRPTW). This advanced optimization model aims to determine the most efficient sequence of visits to selected locations for each day of the trip. Google OR-tools, a comprehensive library of operations research algorithms, is employed to solve this VRPTW. The solver intelligently considers a multitude of constraints, including estimated travel times between locations, preferred or average visit durations at each attraction, the operational opening hours of businesses and sites, strategically placed meal breaks, and the logistical necessity of starting and ending each day's excursions at a designated point (typically the user's accommodation). This optimization process yields practical, efficient, and highly personalized daily schedules.

- **User Interface and Interactive Itinerary Visualization:** A cornerstone of the project is a user-friendly, interactive web-based interface, developed using the Streamlit framework. This interface is designed to guide the user intuitively through the entire process, from the initial image upload and viewing of visually similar location suggestions to the fine-tuning of itinerary customization parameters and, finally, the review of the fully generated travel plan. A particularly salient feature of the output is the visualization of the final itinerary, complete with optimized daily routes and marked locations, on an interactive map. This map is rendered using the Folium library, significantly enhancing user engagement, comprehension, and overall experience by providing a clear, dynamic, and geographically grounded representation of the proposed journey.

CHAPTER 2

LITERATURE REVIEW

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 Hybrid Recommendation Systems

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 behaviour.

Table 1. on the next page summarizes the literature survey performed and displays the gaps in the current research and approaches that were discovered. The goal was to identify the latest researches and attempts in the direction of tourism recommendation, especially focusing on the image- based systems.

| 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. |

Table 1. Literature Survey and Review

CHAPTER 3

PROPOSED METHODOLOGY

3.1 PROPOSED SYSTEM

Our proposed system, "Padharo Sa," is conceived and architected as a sophisticated, modular pipeline. This design choice means that the entire process of generating a travel itinerary is broken down into a series of distinct, interconnected stages or "modules." Each module has a specific responsibility and hands off its output to the next, creating a logical flow from initial user input to the final travel plan. This modularity not only makes the system easier to understand, develop, and maintain but also allows for individual components to be upgraded or modified without necessarily affecting the entire system.

The overarching goals guiding the design of "Padharo Sa" are intuitiveness for the user, computational efficiency in its operations, and a high degree of personalization in its outputs.

3.1.1. Image Recognition and Feature Extraction

The journey with "Padharo Sa" begins when a user provides an image. This image is not just any picture; it's intended to be a visual representation of what the user is looking for in a travel experience – perhaps a stunning beach, a historic castle, a bustling city street, or a tranquil mountain view.

The system's first task is to "understand" this image. To do this effectively, some initial preparation, known as **image pre-processing**, might be necessary. Imagine the user uploads a photo of a famous painting, but the photo is taken from an odd angle, making the painting look skewed. If we were to analyze this skewed image directly, our understanding might be off. This is where a technique called **homographic warping** can be applied. It's a mathematical process that can "uncorrect" such perspective distortions or allow the system to focus on a very specific part of the image, like zooming into and straightening just the painting within the larger photo. The goal of this step is to ensure that the system analyzes only the most important and visually relevant parts of the image, leading to better quality "features" or characteristics being extracted in the next stage.

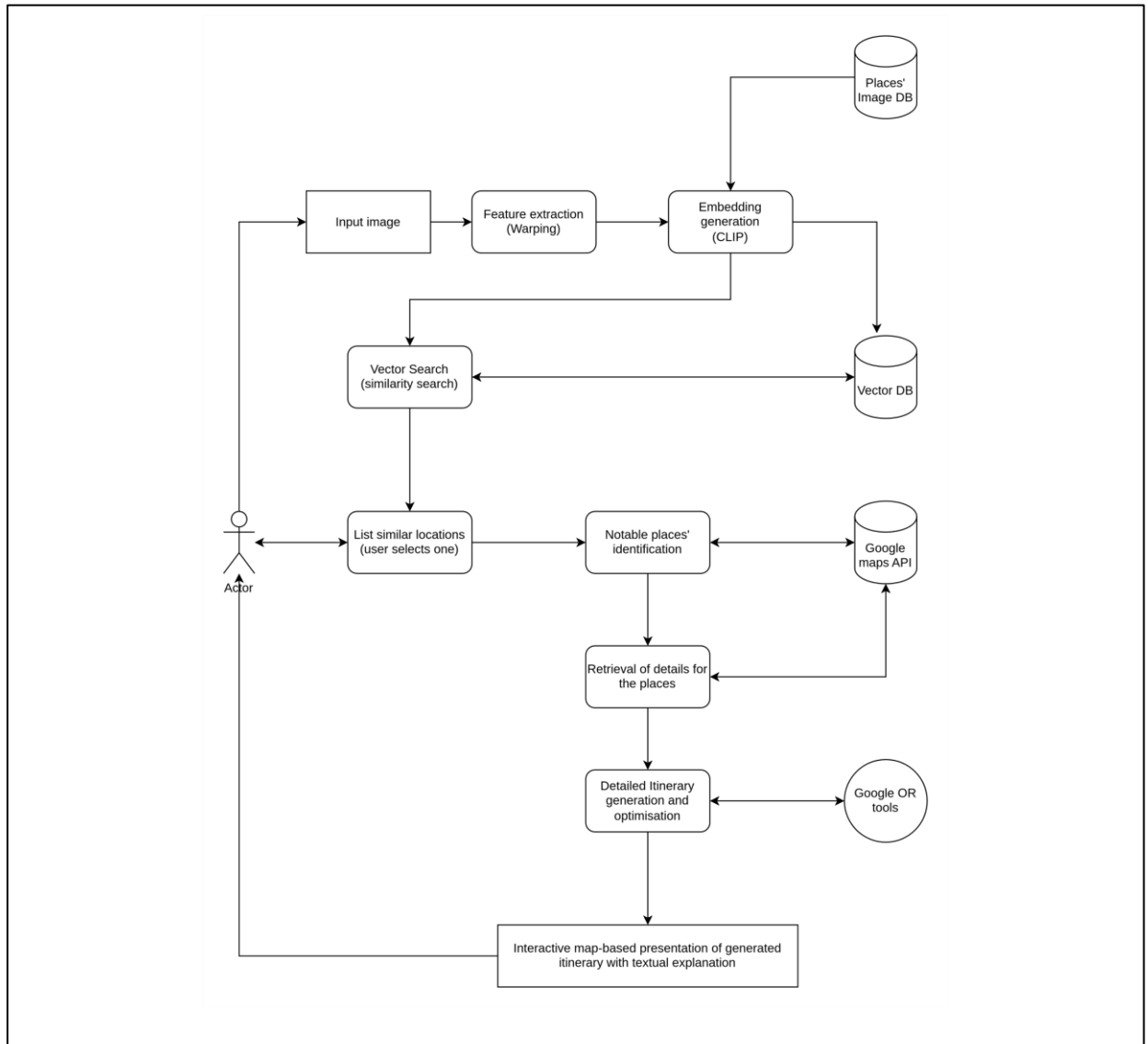


Fig 1. Proposed workflow

3.1.2. Embedding Generation

Once the input image is suitably prepared (either the original or a refined version from pre-processing), it's ready to be transformed into a language that computers can work with for comparison. This is where the **CLIP (Contrastive Language–Image Pre-training)** model comes into play. CLIP is a very clever AI model developed by OpenAI. It has been trained by looking at hundreds of millions of images and the text captions that describe them. Through this vast training, CLIP has learned to associate visual elements with their textual descriptions and, more importantly for us, it has learned to identify the subtle visual characteristics that make images unique or similar.

When we feed our processed image into CLIP's image encoder (a part of the larger CLIP model), it doesn't just say "this is a beach." Instead, it outputs a long list of numbers. This list of numbers is called an **embedding** or a **vector**. Think of this embedding as a highly detailed, numerical fingerprint or signature of the image. It captures the visual essence – colors, textures, shapes, overall style, and even perhaps the "vibe" or mood of the image – in a compact mathematical form. An image of a sunny beach will have a very different numerical fingerprint than an image of a snowy mountain. These embeddings are the foundation upon which our visual similarity search will be built.

3.1.3. Vector Search and Similarity Matching

Now that we have the numerical fingerprint (the embedding) of the user's inspirational image, we need to find real-world tourist locations that have a similar fingerprint. To do this, we have already created a large **vector database**. This database is essentially a library filled with pre-calculated embeddings for thousands of different tourist attractions around the world. For each attraction (say, the Eiffel Tower), we didn't just take one photo to create its embedding. Instead, we took many photos from different angles, in different lighting, maybe even in different seasons, generated an embedding for each, and then calculated an average embedding (called a **centroid**). This centroid provides a very robust and representative visual signature for that location.

The task now is to compare the embedding of the user's image with all the centroid embeddings in our database. Doing this one by one would be too slow if our database is large. This is where **FAISS (Facebook AI Similarity Search)** comes in. FAISS is a highly optimized library specifically designed for performing incredibly fast searches for similar items in these large collections of numerical fingerprints (vectors). When we give FAISS the user's image embedding, it efficiently scours our database and quickly returns a list of the top, say, 5 or 10 locations whose stored embeddings are most "similar" to the user's input. Similarity here is typically measured by how closely the numerical patterns match, often using a technique called **cosine similarity**, which we'll explain in the mathematical section.

3.1.4. Noteworthy Places Identification

The output from FAISS is a list of location names that are visually similar to the user's query. However, just a name isn't enough to plan a trip. We need more practical information. This is where the **Google Maps API** becomes invaluable. An API (Application Programming Interface) is like a messenger that allows different software programs to talk to each other and exchange information.

For each visually similar location found, we use the Google Maps API to:

1. **Geocode it:** This means converting the place name (e.g., "Eiffel Tower, Paris") into its precise geographical coordinates (latitude and longitude). This is essential for placing it on a map and calculating distances.
2. **Gather details:** We also ask the Google Maps API for a wealth of other information about the place. This can include user reviews and ratings (how much did other people like it?), its typical opening and closing hours (we don't want to plan a visit when it's closed!), contact details, photos, and even what type of place it is (is it a museum, a park, a restaurant, a historical landmark?).

This enrichment step transforms a simple list of visually matched names into a set of well-described, actionable points of interest, each with the practical data needed for the next stage of planning.

3.1.5. Itinerary Creation and Optimization

With a primary location of interest selected by the user (perhaps the top match, or another one from the list of suggestions) and now enriched with lots of useful data, the system is ready to start building an actual travel itinerary. This is where the user gets to provide more specific preferences:

- **Trip Duration:** When do they want to travel (start and end dates)? This tells the system how many days the itinerary needs to cover.
- **Search Radius:** How far from their main chosen location are they willing to travel to see other nearby attractions?
- **Interests:** What kinds of places do they like? Are they interested in history, art, nature, food, shopping?

The real magic in this step is how the system decides which places to visit on which day, and in what order. This isn't just a random selection. We model this as a complex puzzle called the **Vehicle Routing Problem with Time Windows (VRPTW)**. Imagine you have a delivery truck (your "vehicle" for the day), a list of customers to visit (the tourist attractions), and each customer has a specific time they are open (the "time window"). The goal of VRPTW is to find the best routes for the truck to visit all (or a selection of) customers, respecting their time windows, and doing so in the most efficient way (e.g., minimizing total travel time or distance).

To solve this VRPTW puzzle, we use **Google OR-tools** (Operations Research tools). This is a powerful software library from Google that contains algorithms designed to tackle such complex optimization problems. The OR-tools solver will consider:

- Maximum travel time per day (we don't want users to spend all day just traveling).
- How long the user might want to spend at each attraction.
- The opening hours of each place.
- The need for breaks (e.g., for meals).
- The starting and ending point for each day (usually their hotel).

The output is a carefully planned, day-by-day schedule that is not only efficient but also ensures that visits are feasible (e.g., you arrive when places are open) and aligned with the user's overall preferences.

3.1.6. User Interface and Interaction

All this powerful technology needs to be accessible and easy to use. For this, we've developed a web-based user interface using a Python library called **Streamlit**. Streamlit allows us to create interactive web applications relatively quickly.

The interface guides the user through each step:

1. Uploading their inspirational image.
2. Viewing the gallery of visually similar locations suggested by the system.
3. Selecting their primary destination and customizing their travel preferences (dates, interests, etc.).
4. Finally, seeing the generated itinerary.

A key part of the output display is an **interactive map**, created using another Python library called **Folium**. This map visually shows the planned routes for each day, with markers for each attraction. Users can zoom in and out, pan around the map, and click on markers to get more details. This visual representation makes the itinerary much easier to understand and more engaging for the user.

3.1.7. Real-time Data Integration

To ensure the travel plans are as up-to-date and reliable as possible, the system is designed to integrate data from external sources in real-time, or as close to real-time as feasible.

The Google Maps API is a primary source for this, providing current geocoding information, place details like opening hours, and even travel time estimates between locations (which can be influenced by current traffic conditions, though this level of real-time traffic is an advanced feature). While some data like basic place descriptions might be cached (stored temporarily) to speed things up, the system's architecture allows for fresh data to be fetched when generating an itinerary. This is especially important for volatile information like opening hours or travel times, ensuring the generated plan is based on the latest available information.

3.1.8. System Workflow

To summarize, here's a step-by-step walkthrough of how "Padharo Sa" works from start to finish:

1. **User Provides Image:** The user uploads an image through the Streamlit web interface. This image is their visual starting point. The system might apply an optional homographic warp to focus on specific parts if needed.
2. **System Generates Embedding:** The uploaded (and possibly processed) image is fed into the CLIP model. CLIP analyzes the image and produces a unique numerical "fingerprint" or vector embedding that captures its visual characteristics. This embedding is also normalized (scaled to a standard length) to make comparisons fair.
3. **System Finds Similar Places:** The FAISS library takes this new embedding and rapidly searches through our pre-built database of embeddings for many tourist locations. It retrieves a list of the top locations that are most visually similar to the user's image. These are displayed to the user, often with a representative image for each.
4. **User Selects and Customizes:** The user looks at the suggested visually similar places and selects one as their main destination. They then provide more details for their trip, like travel dates, how far they're willing to travel for other sights (search radius), and what types of attractions they enjoy (e.g., museums, parks).

5. **System Gathers More Data:** The Google Maps API is used to get the precise coordinates (latitude/longitude) of the user's chosen primary location. It then searches for other interesting attractions nearby, based on the user's radius and interest preferences, and pulls in details like ratings, opening hours, etc., for all these places.
6. **System Optimizes the Itinerary:** This is where Google OR-tools steps in. Using all the gathered information (locations, opening hours, travel times, user preferences like trip length), it solves a complex Vehicle Routing Problem with Time Windows (VRPTW). This process carefully plans out each day of the trip, deciding which places to visit, in what order, and ensuring everything fits within time constraints (like daily travel limits and attraction opening hours), and also schedules things like meal breaks.
7. **System Presents the Plan:** The final output is a detailed, day-by-day itinerary. This is shown to the user in a clear, easy-to-read format. Importantly, it's accompanied by an interactive map (created with Folium) that visually displays all the routes and locations, giving the user a clear picture of their upcoming journey.

3.2 MATHEMATICAL FORMULATION

3.2.1. Homographic Warping

What is it?

Homographic warping, often referred to as a perspective transformation or homography, is a geometric technique used in computer vision to map points from one 2D plane (like an image) to another. Imagine you take a photograph of a rectangular poster on a wall, but you're not standing directly in front of it. In your photo, the poster might look like a trapezoid due to perspective distortion. Homographic warping can transform this trapezoid back into a perfect rectangle, as if you were looking at it straight on.

Why use it?

In our system, if a user uploads an image where the main subject of interest is distorted by perspective (e.g., a building photographed from a sharp angle, or a pattern on a tilted surface), applying homography can help to "rectify" this part of the image. This provides a more standardized view of the object or scene of interest, which can lead to more consistent and accurate feature extraction by the subsequent CLIP model. By focusing on a "straightened" or well-aligned segment, we reduce the chances of the perspective itself confusing the similarity assessment.

A point in a 2D image is typically represented by its coordinates (x,y) . For homography, we use **homogeneous coordinates**. Instead of (x,y) , we represent the point as a 3-element vector

$$\mathbf{p} = \begin{bmatrix} x \\ y \\ 1 \end{bmatrix}$$

The reason for adding this '1' (the w -component, often called the scaling factor) is a bit mathematical, but it essentially allows us to represent more types of transformations, including translation (shifting an image), using a single matrix multiplication, which is computationally very convenient.

A homography is defined by a 3×3 matrix, denoted as H :

$$H = \begin{bmatrix} h_{11} & h_{12} & h_{13} \\ h_{21} & h_{22} & h_{23} \\ h_{31} & h_{32} & h_{33} \end{bmatrix}$$

If $\mathbf{p}=[xy1]$ is a point in the original image, its corresponding warped point in the new image plane, $\mathbf{p}'=[x'y'w']$, is found by multiplying H with \mathbf{p} :

$$\mathbf{p} = \begin{bmatrix} x \\ y \\ 1 \end{bmatrix}$$

$$\mathbf{p}' = \begin{bmatrix} x' \\ y' \\ w' \end{bmatrix}$$

$$\mathbf{p}' = H \cdot \mathbf{p}$$

So,

$$\begin{bmatrix} x' \\ y' \\ w' \end{bmatrix} = \begin{bmatrix} h_{11} & h_{12} & h_{13} \\ h_{21} & h_{22} & h_{23} \\ h_{31} & h_{32} & h_{33} \end{bmatrix} \begin{bmatrix} x \\ y \\ 1 \end{bmatrix} = \begin{bmatrix} h_{11}x + h_{12}y + h_{13} \\ h_{21}x + h_{22}y + h_{23} \\ h_{31}x + h_{32}y + h_{33} \end{bmatrix}$$

To get back to the standard 2D Cartesian coordinates (x_w, y_w) for the warped point, we divide the first two components of \mathbf{p}' by its third component w' (as long as $w' \neq 0$):

$$\begin{aligned}x_w &= \frac{x'}{w'} = \frac{h_{11}x + h_{12}y + h_{13}}{h_{31}x + h_{32}y + h_{33}} \\y_w &= \frac{y'}{w'} = \frac{h_{21}x + h_{22}y + h_{23}}{h_{31}x + h_{32}y + h_{33}}\end{aligned}$$

The homography matrix H has 8 degrees of freedom (even though it has 9 elements, it's defined up to a scale factor, meaning H and kH for any non-zero scalar k represent the same transformation). It can be estimated if we know at least four pairs of corresponding points between the original and desired warped image.

3.2.2. CLIP Embedding Generation and Normalization

What is an Embedding?

Imagine a vast library where every book represents an image or a piece of text. An "embedding" is like a unique address or coordinate that tells you exactly where that book is located in the library. But this isn't a normal library; in this "meaning space," books (images/texts) with similar content or style are located close to each other, while dissimilar ones are far apart. Mathematically, an embedding is a vector (a list of numbers) in a high-dimensional space. The CLIP model is designed to generate such embeddings for both images and text in a shared space.

Why CLIP?

The CLIP (Contrastive Language–Image Pre-training) model, developed by OpenAI, is particularly powerful because it learns these embeddings by looking at hundreds of millions of images and their associated textual descriptions from the internet. It's trained to ensure that the embedding of an image is "close" to the embedding of its correct textual description, and "far" from incorrect descriptions. This process enables CLIP to learn very rich and nuanced representations that capture not just objects in an image, but also style, context, and abstract concepts. For our system, we use its image encoding capability.

The Mathematics:

Let I be an input image. The CLIP image encoder, which we can denote as a function, processes this image and outputs a raw high-dimensional vector, e_{raw} :

$$e = f(I)$$

For the clip-vit-base-patch32 model we use, this embedding vector typically has 512 dimensions (i.e., it's a list of 512 numbers).

Normalization:

The raw embedding e_{raw} contains information about both the "direction" (what the image is like) and the "magnitude" (which can be thought of as a kind of intensity, though it's more

complex). For similarity comparisons using measures like cosine similarity (which we'll discuss next), we are primarily interested in the direction. To focus on this, and to ensure all embedding vectors are on a comparable scale, we perform L2 normalization (also known as Euclidean normalization).

The L2 norm of a vector $\mathbf{v}=[v_1, v_2, \dots, v_n]$ is its Euclidean length or magnitude, calculated as:

$$\|\mathbf{v}\|_2 = \sqrt{v_1^2 + v_2^2 + \dots + v_n^2}$$

To normalize our raw embedding \mathbf{e}_{raw} , we divide each of its components by its L2 norm:

$$\mathbf{e}_{\text{norm}} = \frac{\mathbf{e}_{\text{raw}}}{\|\mathbf{e}_{\text{raw}}\|_2}$$

The resulting normalized embedding \mathbf{e}_{norm} is a unit vector, meaning its L2 norm (length) is 1 (i.e., $\|\mathbf{e}_{\text{norm}}\|_2=1$). This process effectively places all our embedding vectors on the surface of a hypersphere of radius 1 in that 512-dimensional space. Now, when we compare them, we are purely looking at the angle between them, not how "long" they were originally.

3.2.3. Aggregation via Centroid Computation

Why Aggregate?

A single tourist location (e.g., the Taj Mahal) can look very different depending on the angle it's photographed from, the time of day (lighting), the season, or even if there are crowds. If we only used an embedding from one single image to represent the Taj Mahal in our database, our system might fail to recognize it if the user's input image shows it from a slightly different perspective.

To create a more robust and comprehensive representation, we collect multiple images for each tourist location. For a given location L , let's say we have n images, I_1, I_2, \dots, I_n . We generate a normalized embedding for each of these images: $\mathbf{e}_1, \mathbf{e}_2, \dots, \mathbf{e}_n$

The Centroid Method:

The **centroid** is simply the arithmetic mean (average) of a set of points (or vectors, in our case). To get a single, aggregated embedding $\mathbf{e}_{L, \text{centroid}}$ that represents location L , we calculate the average of all its individual image embeddings:

$$\mathbf{e}_c = \frac{1}{n} \sum_{i=1}^n \mathbf{e}_i$$

This averaging process helps to smooth out the peculiarities of any single image and captures the normalized to ensure it's a unit vector before being stored in our FAISS index. This normalized centroid becomes the definitive visual signature for location L in our database.

3.2.4. Cosine Similarity for Vector Search

What is it?

Once we have a normalized embedding $\mathbf{e}_{\text{query}}$ from the user's input image and a database of normalized centroid embeddings $\mathbf{e}_{L,\text{centroid}}$ for various locations, we need a way to measure how "similar" $\mathbf{e}_{\text{query}}$ is to each $\mathbf{e}_{L,\text{centroid}}$. Cosine similarity is a very popular metric for this, especially with high-dimensional embeddings like those from CLIP.

It measures the cosine of the angle θ between two non-zero vectors. The intuition is that if two vectors point in roughly the same direction (i.e., the angle between them is small), they are considered more similar. If they point in opposite directions (angle is large, near 180°), they are dissimilar. If they are orthogonal (angle is 90°), they are considered to have no similarity (or are independent in some sense).

The Mathematics:

The formula for the cosine of the angle θ between two vectors \mathbf{A} and \mathbf{B} is derived from the dot product definition:

$$\mathbf{A} \cdot \mathbf{B} = \|\mathbf{A}\|_2 \|\mathbf{B}\|_2 \cos(\theta)$$

Therefore,

$$\cos(\theta) = \frac{\mathbf{A} \cdot \mathbf{B}}{\|\mathbf{A}\|_2 \|\mathbf{B}\|_2}$$

In our case, both the query embedding $\mathbf{e}_{\text{query}}$ and the database embeddings $\mathbf{e}_{L,\text{centroid}}$ have already been L2-normalized. This means their magnitudes (lengths) are 1:

$$\|\mathbf{e}_{\text{query}}\|_2 = 1$$

$$\|\mathbf{e}_{L,\text{centroid}}\|_2 = 1$$

So, for our normalized vectors, the cosine similarity S simplifies to just their dot product:

$$S(\mathbf{e}_{\text{query}}, \mathbf{e}_{L,\text{centroid}}) = \cos(\theta) = \frac{\mathbf{e}_{\text{query}} \cdot \mathbf{e}_{L,\text{centroid}}}{1 \cdot 1} = \mathbf{e}_{\text{query}} \cdot \mathbf{e}_{L,\text{centroid}}$$

If $\mathbf{e}_{\text{query}}=[q_1, q_2, \dots, q_d]$ and $\mathbf{e}_{L, \text{centroid}}=[c_1, c_2, \dots, c_d]$ (where $d=512$ is the dimension), their dot product is:

$$\mathbf{e}_{\text{query}} \cdot \mathbf{e}_{L, \text{centroid}} = \sum_{i=1}^d q_i c_i = q_1 c_1 + q_2 c_2 + \dots + q_d c_d$$

The value of cosine similarity ranges from:

- **+1:** The vectors point in exactly the same direction (angle is 0°). This means perfect similarity.
- **0:** The vectors are orthogonal (angle is 90°). This typically means they are independent or unrelated.
- **-1:** The vectors point in exactly opposite directions (angle is 180°). This means perfect dissimilarity.

Since CLIP embeddings for images usually represent positive concepts, the similarity scores practically range between 0 and 1 for most meaningful comparisons of visual content. A higher score (closer to 1) indicates greater visual similarity. FAISS IndexFlatIP directly computes this inner product, which, for normalized vectors, is the cosine similarity.

3.2.5. Haversine Distance for Geospatial Calculations

Why a Special Formula?

When we want to find the distance between two places on Earth using their latitude and longitude, we can't just use the straight-line Euclidean distance formula we learn in basic geometry. This is because the Earth is (approximately) a sphere, not a flat plane. Using a flat-plane formula for distant points on a sphere would give increasingly inaccurate results.

The Haversine formula calculates the great-circle distance between two points on a sphere. A great circle is the shortest path between two points on the surface of a sphere (like a line of longitude or the Equator).

The Mathematics:

Let point 1 have latitude ϕ_1 and longitude λ_1 . Let point 2 have latitude ϕ_2 and longitude λ_2 .

(Note: Latitudes and longitudes must be converted from degrees to radians for trigonometric functions in most programming languages.)

Let R be the mean radius of the Earth (approximately 6,371 kilometers or 3,959 miles).

Now let's discuss the methodology used.

The steps are:

1. Calculate the difference in latitudes and longitudes:

$$\Delta\phi = \phi_2 - \phi_1$$

$$\Delta\lambda = \lambda_2 - \lambda_1$$

2. Calculate the term a , which is related to the square of half the chord length between the points:

$$a = \sin^2\left(\frac{\Delta\phi}{2}\right) + \cos(\phi_1) \cdot \cos(\phi_2) \cdot \sin^2\left(\frac{\Delta\lambda}{2}\right)$$

Here, $\sin^2(x)$ means $(\sin(x))^2$. The "haversine" function itself is $\text{hav}(\theta) = \sin^2(\theta/2)$. So, a can be written as:

$$a = \text{hav}(\Delta\phi) + \cos(\phi_1) \cdot \cos(\phi_2) \cdot \text{hav}(\Delta\lambda)$$

3. Calculate the central angle c (the angular distance between the two points, in radians):

$$c = 2 \cdot \text{atan2}\left(\sqrt{a}, \sqrt{1-a}\right)$$

The $\text{atan2}(y,x)$ function is an arctangent function that correctly determines the quadrant of the angle, which is more robust than a simple $\text{atan}(y/x)$.

4. Finally, calculate the distance d :

$$d = R \cdot c$$

This distance d is the shortest distance along the surface of the sphere between the two points. It's crucial for estimating travel times and as an input to our route optimization algorithm. While the Earth isn't a perfect sphere (it's an oblate spheroid, slightly flattened at the poles), the Haversine formula provides a very good approximation for most practical purposes in applications like ours.

3.2.6. Travel Time Calculation

The Simplest Approach:

The most basic way to estimate travel time T_{ij} between two points i and j , given the Haversine distance d_{ij} between them, is to assume an average travel speed v_{avg} :

$$T_{ij} = \frac{d_{ij}}{v_{\text{avg}}}$$

For example, if the distance is 100 km and we assume an average driving speed of 50 km/hour, the travel time would be 2 hours.

Limitations and Better Approaches:

This simple formula has significant limitations:

- It doesn't account for actual road networks (it's "as the crow flies").
- It doesn't consider speed limits, which vary.
- It ignores traffic conditions, traffic lights, turns, etc.
- The mode of transport (car, walking, public transit) drastically changes speed.

For more realistic travel times, our system ideally queries a service like the **Google Maps Directions API**. When given two points (and optionally a mode of transport and departure time), this API returns not only the distance along actual roads but also a much more accurate estimate of the travel time, potentially factoring in typical or even real-time traffic. These API-derived travel times are far superior for the VRPTW solver. However, the basic d/v can be a fallback or used for initial rough estimates.

3.2.7. VRPTW Time Window Constraint and Objective Function

What is VRPTW?

The Vehicle Routing Problem (VRP) is a classic problem in logistics and operations research. In its simplest form, it's about finding the best set of routes for a fleet of vehicles to serve a set of customers, starting and ending at a central depot, aiming to minimize total travel cost (e.g., distance or time).

The **Vehicle Routing Problem with Time Windows (VRPTW)** adds another layer of complexity: each customer (in our case, each tourist attraction) must be visited within a specific **time window** – an earliest arrival time and a latest departure time. For example, a museum might only be open from 9:00 AM to 5:00 PM.

Key Constraints for Itinerary Optimization:

Let's consider two consecutive stops (attractions) i and j in a day's planned route.

- s_i : The time service (the visit) *starts* at location i .
- τ_i : The service duration (how long the visit lasts) at location i .
- t_{ij} : The travel time from location i to location j .
- s_j : The time service *starts* at location j .
- $[open_j, close_j]$: The time window for location j $open_j$ is the earliest time service can begin, and $close_j$ is the latest time service must be *completed*.

The fundamental constraint linking consecutive visits is that the arrival at j must allow service to start at s_j :

If a vehicle finishes service at i at time $s_i + \tau_i$, and then travels to j taking t_{ij} time, it will arrive at j at time $s_i + \tau_i + t_{ij}$. The service at j can only start at or after this arrival time. So, a key relationship is:

$$s_i + \tau_i + t_{ij} \leq s_j$$

Additionally, each visit must respect its time window:

1. Service at j cannot start before it opens: $s_j \geq open_j$.
2. Service at j must be completed before it closes: $s_j + \tau_j \leq close_j$.

Waiting time might occur if a vehicle arrives at j (at $s_i + \tau_i + t_{ij}$) before $open_j$. In this case, s_j would be set to $open_j$.

Objective Function (What are we trying to achieve?):

The goal of the VRPTW solver (like Google OR-tools) is usually to find a set of routes that satisfy all constraints and optimize an objective. A common objective is to **minimize the total cost**. This cost can be a combination of factors:

1. **Total Travel Cost:** This is often the primary component, representing the sum of travel times (or distances) for all segments of all routes.
2. **Penalties for Skipped Stops:** Sometimes, it might be impossible to visit every desired location without violating time windows or daily travel limits. In such cases, we can assign a "penalty" for each location that is *not* visited. The optimizer will then try to minimize the sum of travel costs *plus* the sum of penalties for skipped locations. This allows for more flexible and realistic itineraries.

A generalized objective function can be written as:

$$\text{Minimize } Z = \sum_{(i,j) \in E} c_{ij} x_{ij} + \sum_{k \in V \setminus \{0\}} p_k y_k$$

Where:

- V is the set of all locations (including the depot, often labeled '0'). $V \setminus \{0\}$ means all locations *except* the depot.
- E is the set of all possible travel segments (edges) between pairs of locations.
- c_{ij} is the cost (e.g., travel time or monetary cost) of traveling directly from location i to location j .
- x_{ij} is a **binary decision variable**:
 - $x_{ij}=1$ if the route includes direct travel from i to j .
 - $x_{ij}=0$ otherwise.
- p_k is the penalty incurred if location k is *not* visited.
- y_k is a **binary decision variable**:
 - $y_k=1$ if location k is *not* visited (and thus its penalty p_k is added to the total cost).
 - $y_k=0$ if location k is visited.

The VRPTW is an **NP-hard problem**, meaning that finding the absolute perfect optimal solution can become computationally infeasible very quickly as the number of locations increases. Therefore, solvers like Google OR-tools use sophisticated **heuristics** and **metaheuristics** (like Guided Local Search, Tabu Search, or Simulated Annealing) to find very good, near-optimal solutions within a reasonable amount of computation time. These algorithms intelligently explore the vast space of possible routes, making smart decisions to construct and improve solutions iteratively.

3.3 DATA COLLECTION AND PREPROCESSING

The quality, diversity, and appropriateness of the data underpinning any machine learning or data-driven system are paramount to its success. For "Padharo Sa," whose core function is to identify visually similar tourist locations, the dataset of location images serves as its foundational knowledge base. This section details the process of acquiring this data and preparing it for effective use within our system.

3.3.1. Data Collection

The Importance of a Good Dataset:

Imagine trying to teach a child what a "cat" is. If you only show them pictures of Siamese cats, they might be confused when they see a fluffy Persian cat or a sleek black cat. Similarly, for our system to learn the visual essence of a tourist location, it needs to see it represented in a varied and comprehensive manner. A limited or biased dataset can lead to poor recommendations, an inability to recognize locations from less common viewpoints, or a failure to generalize to new, unseen user inputs.

Source and Nature of Data:

For the initial development and proof-of-concept of "Padharo Sa," we utilized a publicly available dataset sourced from **Kaggle**. Kaggle is a well-known online platform that hosts a vast array of datasets for data science and machine learning projects, often contributed by researchers, organizations, or enthusiasts. The specific dataset chosen for this project comprises images representing approximately **50 distinct tourist locations**.

A critical characteristic of this dataset, and a key reason for its selection, is that each of these 50 locations is represented by **multiple images**. This multiplicity is absolutely vital. A single photograph of, say, the Roman Colosseum, taken on a sunny afternoon from the main entrance, captures only one facet of its appearance. Another photo taken at dawn, from a side angle, perhaps with mist, or even an interior shot, would present a very different visual profile. By having multiple images for each location, our system gets a richer, more holistic "understanding" of what that location typically looks like across various conditions:

- **Different Viewpoints/Angles:** Frontal, side, aerial (if available), close-ups of specific features.
- **Lighting Conditions:** Sunny days, overcast skies, dawn, dusk, night illuminations.
- **Seasonal Variations:** Images showing a location in summer versus winter, for example, can differ dramatically in color palette and ambiance.
- **Presence of People/Crowds:** Some images might be clear shots, others might include tourists, which can also be part of the "vibe."
- **Prominent Features:** Different images might highlight different key aspects of the location.

While 50 locations is a modest number for a production-scale global tourism application, it provides a sufficient and manageable base for developing, testing, and demonstrating the core functionalities of our image similarity and itinerary generation pipeline. It allows us to rigorously evaluate the effectiveness of our chosen algorithms (CLIP, FAISS, OR-Tools) without the computational overhead and data management complexities that a dataset of thousands or millions of locations would immediately entail. The learnings from this scale can then inform strategies for scaling up.

3.3.2. Data Preprocessing

Once the raw image data for our 50 locations is collected, it cannot be directly used by our similarity search mechanism. It needs to undergo a series of meticulous preprocessing steps to transform it into a structured and optimized format that our system can efficiently query. This offline preparation is crucial for the real-time performance of "Padharo Sa" when a user interacts with it.

The preprocessing pipeline involves the following key stages:

1. Embedding Generation for Each Image:

- **What:** Every single image in our collected dataset (multiple images per location) is individually passed through the pre-trained CLIP model's image encoder (specifically, openai/clip-vit-base-patch32, as detailed in Section 3.4.1).
- **Why:** As explained in Section 3.2.2, this converts each image from its raw pixel representation into a dense, high-dimensional numerical vector (a 512-dimension embedding in our case). This vector captures the rich visual and semantic content of the image. This step is the most computationally intensive part of the offline preprocessing, as each image requires a forward pass through the deep learning model.
- **How:** Images are typically loaded using a library like PIL (Pillow), converted to the RGB format (if not already), and then processed by the CLIP model's associated processor, which handles necessary transformations like resizing and pixel value normalization before feeding it to the model.

2. Aggregation using the Centroid Method:

- **What:** After generating embeddings for all images of a *specific* location (e.g., all images of the "Eiffel Tower"), these individual embeddings are aggregated into a single representative embedding for that location. We employ the centroid method for this, as detailed in Section 3.2.3.
- **Why:** This step is critical for creating a stable and generalized visual signature for each tourist destination. If we were to store all individual image embeddings for a location and query against them, a user's input might match an unusual or outlier image of that location, leading to less relevant overall matches. The centroid, being the average, smooths out such variations and represents the "typical" visual essence of the place, making the similarity search more robust. It also significantly reduces the size of the final index, as we store one vector per location instead of many.
- **How:** For each of the 50 locations, we gather all its individual image embeddings. We then compute their vector mean (element-wise average). The resulting vector is the raw centroid embedding for that location.

3. L2 Normalization of Aggregated Embeddings:

- **What:** Each of the 50 aggregated (centroid) embeddings generated in the previous step is then L2-normalized.
- **Why:** As explained in Section 3.2.2 and 3.2.4, L2 normalization scales each embedding vector to have a unit length (length of 1). This is a standard and essential practice when cosine similarity (or its efficient proxy, the inner product on normalized vectors) is used as the similarity metric. It ensures that the comparison focuses purely on the "direction" (angle) of the vectors in the high-dimensional space, which is a better measure of semantic similarity for CLIP embeddings, rather than being influenced by their original magnitudes.
- **How:** For each centroid vector \mathbf{v} , its L2 norm $\|\mathbf{v}\|_2$ is calculated, and then each component of \mathbf{v} is divided by this norm.

4. Indexing with FAISS (Facebook AI Similarity Search):

- **What:** The final collection of 50 L2-normalized, aggregated embeddings (one for each tourist location) is organized into a specialized data structure called an index. This index is created using the FAISS library.
- **Why:** Imagine trying to find a specific book in a massive library without a catalog or any organization – it would be incredibly slow. FAISS creates an efficient "catalog" for our vector embeddings. When a user provides a query image, its embedding can be rapidly compared against all indexed location embeddings to find the closest matches. Without such an index, a "brute-force" search (comparing the query to every single item one by one) would be too slow for a real-time application, especially as the number of locations grows.
- **How:** We specifically use FAISS's IndexFlatIP. The "Flat" part means it essentially keeps all the vectors as they are (no compression or approximation, leading to exact search results), and "IP" stands for Inner Product. As discussed in Section 3.2.4, for normalized vectors, the inner product is equivalent to cosine similarity. This index structure is well-suited for datasets of our current size, offering perfect accuracy with acceptable speed. For significantly larger datasets, FAISS provides more complex indexing strategies (e.g., involving partitioning like IndexIVFFlat, or quantization like IndexIVFPQ) that trade a tiny bit of accuracy for massive speed gains.

The tangible outputs of this entire offline data preprocessing phase are:

- *aggregated_clip.index*: The binary FAISS index file containing the 50 indexed location embeddings.
- *place_mapping.json*: A JSON file that maps each location name to the file path of one of its representative images. This is useful for displaying an image of the matched locations in the user interface.
- *places_order.json*: A JSON file that stores an ordered list of the place names. The order corresponds to the internal order in which their embeddings were added to the FAISS index, allowing us to easily map an index ID retrieved from FAISS back to the correct place name.

This careful preprocessing ensures that when a user query comes in, the similarity search step is as fast and accurate as possible.

3.4 IMPLEMENTATION

The successful realization of "Padharo Sa" from a conceptual framework to a functioning application hinges on the judicious selection and effective integration of various software tools, libraries, and programming techniques. Python, with its rich ecosystem of open-source libraries for scientific computing, machine learning, and web development, serves as the primary programming language for this project. This section details the key implementation aspects of the system's core components.

3.4.1. Embedding Extraction with a Pre-trained Vision Model

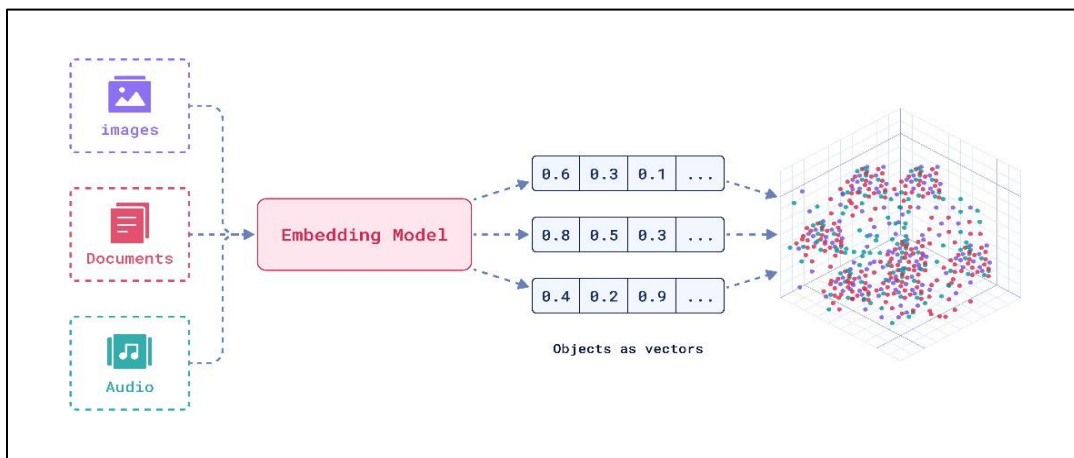


Fig 2. Vector embeddings

Choice of Model and Library:

The heart of our visual understanding capability is the conversion of images into meaningful numerical embeddings. For this critical task, we selected the **openai/clip-vit-base-patch32 model**. This specific variant of CLIP (Contrastive Language–Image Pre-training) was chosen due to several factors:

- **Performance:** It offers a strong balance between the quality of embeddings it produces (its ability to capture nuanced visual semantics) and its computational footprint (memory and processing power required). While larger CLIP models exist (e.g., clip-vit-large), they demand significantly more resources, which might not be necessary or practical for all deployment scenarios.
- **Availability:** It is readily accessible through the **Hugging Face Transformers library**, a comprehensive open-source platform providing a vast collection of pre-trained models and tools for Natural Language Processing (NLP) and beyond. Hugging Face simplifies the process of downloading, loading, and using these complex models with just a few lines of Python code.

Loading and Processing:

The CLIP model and its associated processor (which handles image transformations like resizing and normalization specific to what CLIP expects) are loaded at the application's startup:

```
from transformers import AutoProcessor, CLIPModel
import torch

device = torch.device('cuda' if torch.cuda.is_available() else "cpu") # Use GPU if available
model_clip = CLIPModel.from_pretrained("openai/clip-vit-base-patch32", torch_dtype=torch.float32)
model_clip = model_clip.to(device).eval() # Move to device and set to evaluation mode
processor_clip = AutoProcessor.from_pretrained("openai/clip-vit-base-patch32")
```

Setting `torch_dtype=torch.float32` ensures standard precision. Moving the model to device (GPU if present, otherwise CPU) accelerates computations. `.eval()` mode is important as it deactivates layers like dropout that are only used during model training, ensuring consistent outputs during inference (when we're just using the model).

Batch Processing for Efficiency:

When generating embeddings for the initial dataset (as in `embedding_gen.py`), processing images one by one can be inefficient due to the overhead of data transfer to the GPU and model invocation for each single image. To optimize this, images are processed in **batches**. For instance, a `batch_size` of 256 means that 256 images are loaded, preprocessed, and fed through the CLIP model simultaneously (or as a single tensor). This significantly improves throughput by leveraging the parallel processing capabilities of modern CPUs and especially GPUs.


```

for i in range(0, len(image_paths), batch_size):
    batch_paths = image_paths[i:i+batch_size]
    # ... load images in batch_images ...
    inputs = processor_clip(images=batch_images, return_tensors="pt", padding=True).to(device)
    with torch.inference_mode(): # Disables gradient calculations, saving memory and speeding up
        batch_emb = model_clip.get_image_features(**inputs)
    # ... normalize and store batch_emb ...

```

The `torch.inference_mode()` context manager is used to further optimize inference by disabling gradient calculations, which are unnecessary when just using the model for predictions and can save memory and computation. Figure 2 (Vector Embeddings) in the report conceptually illustrates how these generated embeddings, representing different images or locations, might be distributed in the high-dimensional vector space, with visually similar items naturally clustering closer together.

3.4.2. Aggregation and Centroid Computation

As detailed in Section 3.3.2 (Data Preprocessing) and mathematically formulated in Section 3.2.3, the creation of a single, robust visual signature for each tourist location is achieved by computing the centroid of embeddings from multiple images of that location.

Implementation Logic:

The script iterates through each unique place in the dataset. For each place, it collects all associated image paths. It then processes these images (in batches, as described above) to get their individual CLIP embeddings. These embeddings (which are NumPy arrays after being moved from the GPU and detached from the PyTorch computation graph) are collected.

```

embeddings_list = [] # To store embeddings for images of the current place
# ... (loop through batches of images for the current place, append to embeddings_list) ...
if embeddings_list:
    place_emb_raw = np.mean(np.vstack(embeddings_list), axis=0, keepdims=True)
    # np.vstack stacks all batch embeddings into a single large NumPy array
    # np.mean(..., axis=0) computes the mean along the 0-th axis (i.e., across all images for that place)
    # keepdims=True ensures the result is still a 2D array (1 row, N columns)
    # aggregated_embeddings.append(place_emb_raw) # Before normalization

```

After computing this raw centroid (`place_emb_raw`), it's L2-normalized (as explained in 3.2.2 and shown in `embedding_gen.py` where `faiss.normalize_L2` is applied to the stacked `aggregated_embeddings` before adding to the index). This normalized centroid then serves as the canonical representation for that location in the subsequent similarity search process. This aggregation is vital for the system's ability to generalize and provide consistent matches.

3.4.3. Efficient Similarity Search using FAISS

Why FAISS?

Performing a nearest neighbor search in high-dimensional spaces (our embeddings have 512 dimensions) can be computationally expensive if done naively (i.e., comparing the query vector to every vector in the database one by one). FAISS (Facebook AI Similarity Search) is a specialized library designed to perform this task with exceptional efficiency, even for datasets containing billions of vectors. It offers a variety of indexing methods that can trade off between search speed, memory usage, and accuracy.

Choice of Index and Configuration:

For "Padharo Sa," given our dataset size of 50 aggregated location embeddings, we use `faiss.IndexFlatIP`.

- `IndexFlat...`: The "Flat" indicates that the index stores the vectors in their original, uncompressed form. This means the search will be exact (it will find the true nearest neighbors according to the chosen metric). For relatively small datasets like ours, an exact search is perfectly feasible and preferred for maximum accuracy.
- `...IP`: The "IP" stands for Inner Product. As established in Section 3.2.4, for L2-normalized vectors, the inner product is equivalent to cosine similarity. A higher inner product value means higher similarity.

Implementation (from `embedding_gen.py` for index creation, conceptual for search):

Building the index (offline):

```
# Stack all aggregated embeddings and prepare the FAISS index.
aggregated_embeddings = np.vstack(aggregated_embeddings).astype(np.float32)
faiss.normalize_L2(aggregated_embeddings) # ensure normalization for cosine similarity

index_place = faiss.IndexFlatIP(aggregated_embeddings.shape[1])
index_place.add(aggregated_embeddings)

# Save the aggregated index and mappings.
faiss.write_index(index_place, "aggregated_clip.index")
```

Searching the index (online, when a user uploads an image):

```
query_embedding_np = # ... get normalized embedding of user's image as NumPy array ...
k = 5 # Number of top similar places to retrieve
distances, indices = loaded_faiss_index.search(query_embedding_np, k)
# 'distances' will contain the inner product scores (similarities)
# 'indices' will contain the internal FAISS IDs of the k most similar items
# These FAISS IDs are then mapped back to place names using places_order.json
```

FAISS is configured to use multiple CPU threads (`faiss.omp_set_num_threads(8)`) to parallelize the search computations further, ensuring that retrieval of visually similar places happens almost instantaneously from the user's perspective, even if the database were moderately larger.

3.4.4. Optimization Strategies

The creation of a practical and enjoyable multi-day travel itinerary from a list of potential points of interest is a complex combinatorial optimization task. As detailed in Section 3.2.7, we model this as a Vehicle Routing Problem with Time Windows (VRPTW).

Why Google OR-Tools?

Solving NP-hard problems like VRPTW requires specialized algorithms. Google OR-Tools is a comprehensive, open-source software suite written in C++ (with wrappers for Python, Java, and C#) that provides robust and efficient solvers for a wide range of operations research problems, including various VRP variants, scheduling, network flows, and constraint programming.

Key advantages of OR-Tools for our project include:

- **Power and Sophistication:** It implements advanced metaheuristics (e.g., Guided Local Search, Simulated Annealing, Tabu Search) capable of finding high-quality solutions to complex VRPTWs in reasonable time.
- **Flexibility:** It allows for detailed modeling of various constraints like time windows, vehicle capacities (which in our case can map to daily time/distance limits), service times at locations, and penalties for unvisited locations.
- **Python API:** Its Python wrapper allows seamless integration into our existing Python-based application.

Implementation Approach:

The itinerary planning module in "Padharo Sa" using OR-Tools generally involves these steps:

1. Data Preparation:

- **Locations (Nodes):** Define all potential locations to visit (the user's primary selected location + nearby attractions identified via Google Maps API) and the depot (e.g., user's hotel, which is the start and end point for each day's tour).
- **Travel Time/Distance Matrix:** Construct a matrix where entry (i,j) contains the travel time (or distance) from location i to location j . This data is ideally fetched from the Google Maps Directions API for accuracy, or calculated using Haversine for simpler estimates.

- **Time Windows:** For each location, specify its opening and closing times.
 - **Service Times (Visit Durations):** Estimate or allow the user to specify how long they wish to spend at each type of attraction.
 - **Daily Constraints (Vehicle Analogy):** The "vehicles" in our VRPTW model represent each day of the trip. Each "vehicle" has a "capacity," which can be defined as the maximum total travel time or duration allowed for that day.
 - **Number of Vehicles:** This is set by the number of days in the user's trip.
2. **Model Definition in OR-Tools:**
Using OR-Tools' Python API, a routing model is created. Dimensions are added to track quantities like time along the routes. Constraints are set up for time windows at each location and the daily capacity (time limit) for each "vehicle" (day).
3. **Setting Search Parameters and Solving:**
OR-Tools allows customization of the search strategy. Often, it starts by finding an initial feasible solution using a **first solution heuristic** (e.g., `PATH_CHEAPEST_ARC` which greedily builds routes by adding the cheapest connections). Then, **metaheuristics** are applied to iteratively improve this initial solution. Guided Local Search (`GUIDED_LOCAL_SEARCH`) is a common and effective metaheuristic that intelligently explores the solution space to escape local optima and find better solutions.
4. **Interpreting the Solution:**
If a solution is found, OR-Tools provides the sequence of locations to visit for each "vehicle" (day), along with arrival, departure, and travel times. This information is then parsed and presented to the user as their daily itinerary.

The optimization process aims to ensure that the resulting itinerary is not just a random collection of nearby places but a logistically sound, efficient, and enjoyable plan that respects real-world constraints and user preferences.

The next page also presents some conceptual code to demonstrate these ideas.

```

from ortools.constraint_solver import routing_enums_pb2
from ortools.constraint_solver import pywrapcp

manager = pywrapcp.RoutingIndexManager(len(data['time_matrix']), data['num_vehicles'], data['depot'])
routing = pywrapcp.RoutingModel(manager)

def time_callback(from_index, to_index):
    # Convert OR-Tools indices to actual location indices
    from_node = manager.IndexToNode(from_index)
    to_node = manager.IndexToNode(to_index)
    return data['time_matrix'][from_node][to_node] + data['service_times'][from_node]

transit_callback_index = routing.RegisterTransitCallback(time_callback)
routing.SetArcCostEvaluatorOfAllVehicles(transit_callback_index)

# Add time window constraints
time_dimension_name = 'Time'
routing.AddDimension(
    transit_callback_index,
    data['max_daily_slack'], # allowable waiting time
    data['max_daily_duration'], # max total time per day
    False, # Don't force start cumul to zero
    time_dimension_name)
time_dimension = routing.GetDimensionOrDie(time_dimension_name)

for location_idx, time_window in enumerate(data['time_windows']):
    if location_idx == data['depot']: continue # Depot usually has wide or no time window for start/end
    index = manager.NodeToIndex(location_idx)
    time_dimension.CumulVar(index).SetRange(time_window[0], time_window[1])

# Add penalties for dropping locations if they can't be visited
for node in range(1, len(data['time_matrix'])): # Exclude depot
    if node == data['depot']: continue
    routing.AddDisjunction([manager.NodeToIndex(node)], data['penalty_for_dropping'])

search_parameters = pywrapcp.DefaultRoutingSearchParameters()
search_parameters.first_solution_strategy = (
    routing_enums_pb2.FirstSolutionStrategy.PATH_CHEAPEST_ARC)
search_parameters.local_search_metaheuristic = (
    routing_enums_pb2.LocalSearchMetaheuristic.GUIDED_LOCAL_SEARCH)
search_parameters.time_limit.seconds = 30 # Max time to search for a solution

solution = routing.SolveWithParameters(search_parameters)

```

3.5 PROJECT WORKFLOW AND IMPLEMENTATION DETAILS

This section provides a holistic walkthrough of the "Padharo Sa" system from the moment a user interacts with it until a personalized itinerary is delivered. It integrates descriptions of the user interface (UI) elements, built with Streamlit, with the underlying backend processes and code logic, aiming to illustrate the seamless interplay between user actions and system responses.

3.5.1. Step 1: User Image Upload and Initial Processing – The Spark of Inspiration

The user's journey with "Padharo Sa" invariably begins with a moment of inspiration, typically encapsulated in a digital image. This image might be a photograph they took on a previous trip, a picture saved from a travel blog, or any visual that resonates with their current travel aspirations.

- **User Interface (Streamlit):**

The Streamlit application presents a clean, intuitive interface. Prominently displayed is a file uploader widget, inviting the user to share their visual inspiration.

```
import streamlit as st
from PIL import Image # Pillow library for image manipulation

st.title("Padharo Sa: Your Visual Travel Planner") # Catchy title
# The file_uploader widget allows users to select JPG, JPEG, or PNG files
uploaded_file = st.file_uploader(
    "Upload an image that captures your desired destination or travel vibe:",
    type=["jpg", "jpeg", "png"]
)

if uploaded_file is not None:
    # If a file is uploaded, open it using Pillow and convert to RGB format
    # RGB is a standard color model that CLIP expects
    input_image = Image.open(uploaded_file).convert("RGB")
    # Display the uploaded image back to the user for confirmation
    st.image(input_image, caption="Your Inspiring Image", use_column_width=True)
    # Store the image in session state to use in subsequent steps
    st.session_state.user_input_image = input_image
    # ... Further processing, like triggering the similarity search, would follow ...
```

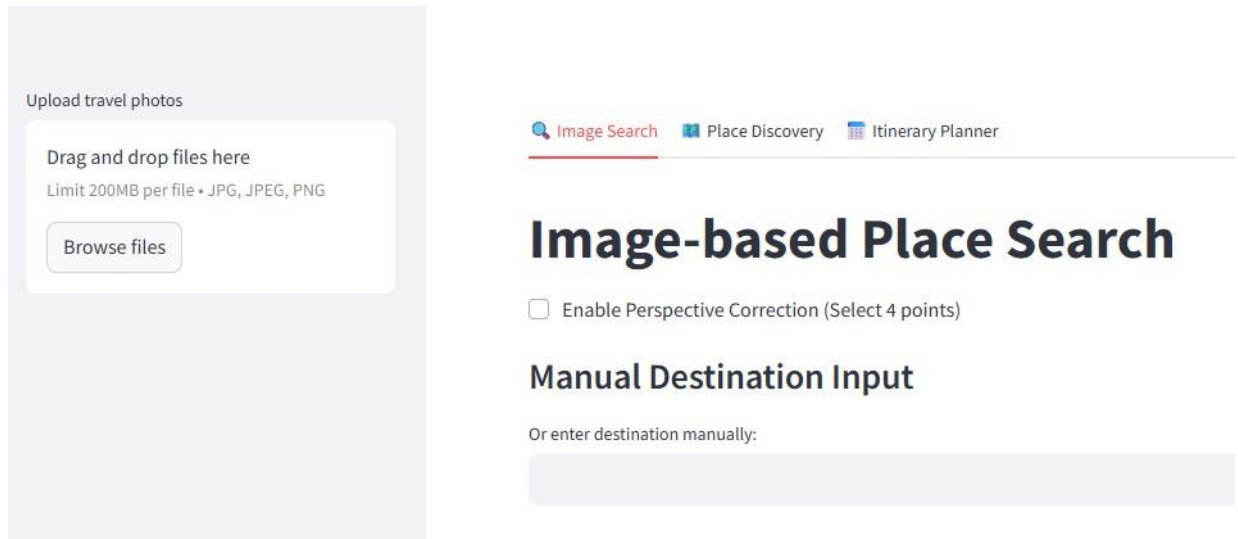


Fig 3. Demonstrative Landing Page

- **Backend Processing (Initial Handling):**

Once the image is uploaded and received by the Streamlit server, it's held in memory as a PIL Image object. At this juncture, as discussed in Section 3.2.1, an optional **homographic warping** step could be invoked. This would be particularly relevant if the system employed heuristics to detect significant perspective distortion in the uploaded image or if advanced user controls allowed for selecting a specific region of interest within the uploaded image for rectification. For the baseline workflow, however, the image is often passed directly to the embedding generation stage. The primary concern is ensuring the image is in a format suitable for the CLIP model (e.g., RGB).

3.5.2. Step 2: Visual Similarity Search and Results Display – Finding Visual Echoes

With the user's inspirational image loaded, the system's next crucial task is to convert this visual input into a numerical representation (an embedding) and then use this embedding to find visually similar tourist locations from its pre-indexed database.

- **Backend Processing (Embedding Generation and FAISS Search):**

This process mirrors the embedding generation logic described in `embedding_gen.py` (Section 3.4.1) but is applied to the single user-uploaded image.


```

def find_visually_similar_locations(pil_image, top_k=5):
    # 1. Prepare image for CLIP
    inputs = processor_clip(
        images=pil_image,          # The user's uploaded PIL image
        return_tensors="pt",       # Return PyTorch tensors
        padding=True               # Pad if necessary (for batching, though here it's a single image)
    ).to(device)                  # Move tensors to the configured device (CPU/GPU)

    # 2. Generate embedding using CLIP (in inference mode to save resources)
    with torch.inference_mode():
        image_embedding_tensor = model_clip.get_image_features(**inputs)

    # 3. L2 Normalize the embedding
    normalized_embedding_tensor = torch.nn.functional.normalize(
        image_embedding_tensor, p=2, dim=1
    )

    # 4. Convert to NumPy array for FAISS
    query_embedding_np = normalized_embedding_tensor.detach().cpu().numpy()

    # 5. Search in FAISS index
    # 'faiss_index' is the pre-loaded FAISS index (e.g., aggregated_clip.index)
    # 'top_k' specifies how many of the most similar items to retrieve
    similarity_scores, faiss_indices = faiss_index.search(query_embedding_np, top_k)

    # 6. Map FAISS indices back to place names and prepare results
    results = []
    for i in range(top_k):
        place_index_in_order = faiss_indices[0][i] # Get the i-th matched FAISS ID
        place_name = places_order_list[place_index_in_order] # Map ID to name
        score = similarity_scores[0][i] # Get its similarity score

        results.append({
            "name": place_name,
            "score": float(score), # Ensure score is a standard float
            # 'place_to_rep_image_map' provides path to a representative image for display
            "image_path": place_to_rep_image_map.get(place_name)
        })
    return results

```

- **User Interface (Streamlit – Displaying Search Results):**

The results from the backend function are then rendered in the Streamlit UI. A common and effective way to display these is as a gallery of images, each representing a matched location, along with its name and the calculated similarity score. This allows the user to visually assess the relevance of the suggestions.


```

# if 'user_input_image' in st.session_state and not 'similar_results' in st.session_state:
#     with st.spinner("Finding visually similar destinations..."): # Show a loading spinner
#         st.session_state.similar_results = find_visually_similar_locations(
#             st.session_state.user_input_image, top_k=6 # Fetch, e.g., top 6
#         )

if 'similar_results' in st.session_state:
    st.subheader("Visually Similar Destinations Found:")
    # Dynamically create columns for a nice grid layout (e.g., 3 results per row)
    num_columns = 3
    cols = st.columns(num_columns)

    for i, result_data in enumerate(st.session_state.similar_results):
        with cols[i % num_columns]: # Cycle through columns
            st.image(
                result_data["image_path"], # Display representative image of the location
                caption=f"{result_data['name']} (Similarity: {result_data['score']:.2f})",
                use_column_width=True # Make image fit column width
            )
            # Add a button for each result to allow selection
            if st.button(f"Select {result_data['name']} as primary", key=f"select_btn_{result_data['name']}"):
                st.session_state.selected_primary_location = result_data['name']
                st.success(f"{result_data['name']} selected! Now customize your trip below.")
                # Optionally, automatically scroll or advance to the next section
                # Clear similar_results to avoid re-display if user re-runs this part
                # del st.session_state.similar_results

```

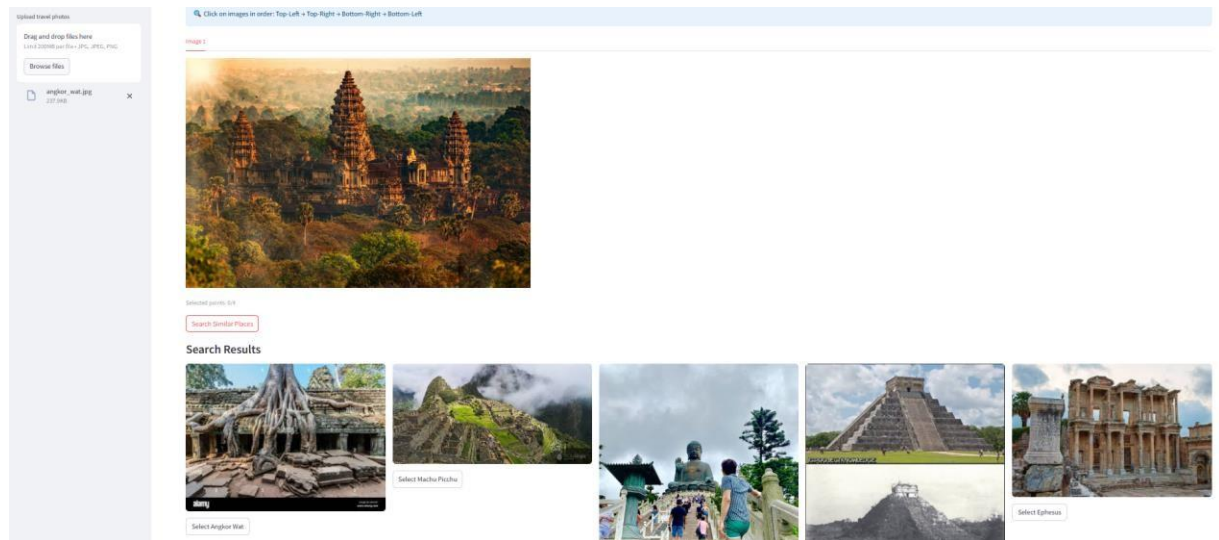


Fig 4. Demo Similarity Search Results

3.5.3. Step 3: Primary Location Selection and Itinerary Customization – Refining the Vision

The user now reviews the visually similar destinations suggested by the system. They select one that best aligns with their interest to serve as the anchor point or primary focus of their trip. Following this selection, they are prompted to provide specific parameters that will shape the generated itinerary.

- **User Interface (Streamlit – Customization Form):**

This part of the UI is critical for personalization and is well-represented by the conceptual elements shown in your existing Figure 3 ("Customization Options"). The interface would typically feature:

- A clear indication of the selected_primary_location.
- **Date Inputs:** st.date_input widgets for selecting "Trip Start Date" and "Trip End Date." The difference determines the trip duration in days.
- **Attraction Type Preferences:** st.multiselect for choosing categories like "Museums," "Historical Sites," "Nature & Parks," "Restaurants & Cafes," "Shopping," "Entertainment," etc. This allows users to tailor the types of places included.
- **Search Radius for Nearby Attractions:** st.slider or st.number_input for defining a radius (e.g., in kilometers or miles) around the selected_primary_location within which other attractions should be considered. This controls the geographic scope of the itinerary.
- **Daily Travel Style/Pace:** Perhaps st.selectbox with options like "Relaxed" (fewer places, more time at each, less travel), "Moderate," or "Packed" (more places, potentially more travel). These abstract choices would map to internal parameters like maximum daily travel time or number of sites.
- **Accommodation Details (Optional but useful):** Text input for "Hotel Name/Address" if known. This can serve as the fixed start and end depot for each day's optimized tour. If not provided, the primary location might be used as a central point.
- A "Generate Itinerary" button to submit these preferences.

Some conceptual code is given on the next page to present these ideas better.

```

if 'selected_primary_location' in st.session_state:
    st.subheader(f"Customizing Itinerary around: {st.session_state.selected_primary_location}")

with st.form(key="itinerary_prefs_form"): # Group inputs into a form for single submission
    # Date inputs
    col1, col2 = st.columns(2)
    with col1:
        start_date = st.date_input("Trip Start Date", value=datetime.date.today())
    with col2:
        end_date = st.date_input("Trip End Date", value=datetime.date.today() + datetime.timedelta(days=3))

    # Attraction preferences
    attraction_options = ["Museums", "Historical Sites", "Nature & Parks", "Restaurants", "Shopping"]
    preferred_attractions = st.multiselect(
        "Select preferred types of attractions:",
        options=attraction_options,
        default=attraction_options[:2] # Pre-select a couple
    )

    search_radius_km = st.slider(
        "Search radius for nearby attractions (km):",
        min_value=5, max_value=100, value=20, step=5
    )

    # Hotel / Base Location (for depot in VRP)
    st.session_state.hotel_location_query = st.text_input(
        "Enter your hotel name/address (optional, will be used as daily start/end):",
        placeholder="e.g., Eiffel Tower or 123 Main St, Paris"
    )

    submit_button = st.form_submit_button(label="Generate My Itinerary!")

if submit_button:
    if end_date < start_date:
        st.error("Trip End Date must be after Trip Start Date.")
    else:
        st.session_state.itinerary_preferences = {
            "start_date": start_date,
            "end_date": end_date,
            "duration_days": (end_date - start_date).days + 1,
            "attraction_types": preferred_attractions,
            "search_radius_km": search_radius_km,
            "primary_location": st.session_state.selected_primary_location,
            "hotel_query": st.session_state.hotel_location_query
        }
        # Trigger backend function for itinerary generation and OR-Tools
        # Show a spinner while this happens, as it can take time
        with st.spinner("Crafting your personalized itinerary... This may take a moment!"):
            # generated_itinerary_data = call_backend_itinerary_generator(st.session_state.itinerary_preferences)
            # st.session_state.generated_itinerary = generated_itinerary_data

```

3.5.4. Step 4: Itinerary Generation (Backend) – The Orchestration of Plans

This is the most computationally intensive part of the online user interaction, where all the gathered information is synthesized into an optimized travel plan. It heavily involves the Google Maps API for data enrichment and Google OR-Tools for solving the VRPTW.

- **Backend Logic (Conceptual Steps):**

1. **Geocode Primary and Hotel Locations:**

- The `selected_primary_location` name and the user-provided `hotel_location_query` (if any) are sent to the Google Maps Geocoding API to obtain their precise latitude and longitude coordinates. The hotel location will serve as the depot (start and end point) for each day's tour in the VRPTW model. If no hotel is specified, the primary location itself or a central point might be used.

2. **Find Nearby Places of Interest (POIs):**

- Using the coordinates of the primary location and the user-specified `search_radius_km` and `preferred_attractions` types, the system queries the Google Maps Places API (specifically, "Nearby Search" or "Text Search" functionalities).
- For each POI found, the API is queried again (using "Place Details") to fetch critical information:
 - Exact name and address.
 - Latitude and longitude.
 - Opening hours (crucial for time window constraints).
 - User ratings and number of reviews (can be used to rank or prioritize POIs).
 - Place types/categories.
 - Estimated visit duration (this might be a heuristic based on place type or average ratings, or a default).

3. **Prepare Data for Google OR-Tools:**

- **Consolidate Locations:** Create a master list of all unique locations: the depot (hotel/primary location) and all selected/discovered POIs.
- **Build Time/Distance Matrix:** For every pair of locations in the master list, query the Google Maps Directions API to get the realistic travel time (and optionally distance) by a specified mode (e.g., driving, walking). This forms the `time_matrix` for OR-Tools. This step is crucial and can involve many API calls.
- **Define Time Windows:** Convert the fetched opening hours for each POI into `[earliest_start_time, latest_finish_time]` tuples for each day of the trip.

- **Define Service Times:** Assign a service time (visit duration) for each POI.
 - **Set Vehicle (Daily) Parameters:**
 - num_vehicles: Equal to st.session_state.itinerary_preferences["duration_days"].
 - depot_index: The index of the hotel/base location in the master list.
 - Daily operational limits (e.g., maximum 8 hours of activity/travel per day, derived from user's "pace" preference).
 - **Set Penalties (Optional):** Assign penalties for dropping locations if it's impossible to include them all within constraints. This makes the optimization more robust.
4. **Solve VRPTW with OR-Tools:**
- The prepared data is fed into the OR-Tools routing solver, as conceptualized in Section 3.4.4. The solver uses heuristics and metaheuristics to find a near-optimal assignment of POIs to days and the best sequence of visits within each day, minimizing total travel time while respecting all time windows and daily limits.
5. **Format Output:**
- The raw solution from OR-Tools (which is typically a sequence of node indices for each route/day) is parsed and translated back into a human-readable format: a day-by-day list of places to visit, with planned arrival, start, and departure times for each.

3.5.5. Step 5: Itinerary Display and Interactive Map – Visualizing the Journey

The final, optimized itinerary is presented to the user in a clear, structured manner, complemented by an interactive map for easy visualization and comprehension.

- **User Interface (Streamlit – Displaying the Itinerary and Map):**
The structured itinerary data (day-by-day plan) is displayed using Streamlit's text and layout elements. The Folium library is used to create an interactive map that visually represents the routes and locations.

```

import folium # For creating interactive maps
from streamlit_folium import st_folium # Streamlit component to embed Folium maps
# Assume 'st.session_state.generated_itinerary' now holds the structured plan
# It might be a list of days, where each day is a list of visited places with timings.

if 'generated_itinerary' in st.session_state and st.session_state.generated_itinerary:
    st.subheader("Your Personalized Travel Itinerary:")

    itinerary_data = st.session_state.generated_itinerary # Example structure
    # itinerary_data = {
    #     "day_1": [{"name": "Louvre", "lat": 48.8606, "lon": 2.3376, "start_time": "10:00", "end_time": "13:00"}, ...],
    #     "day_2": [...]}
    # }

    # Create a Folium map. Center it on the first location of the first day, or the hotel.
    # (Logic to find map center)
    first_day_key = sorted(itinerary_data.keys())[0]
    if itinerary_data[first_day_key]:
        map_center = [itinerary_data[first_day_key][0]['lat'], itinerary_data[first_day_key][0]['lon']]
    else: # Fallback if first day is empty (should not happen in good plan)
        # Geocode primary location again if needed for map center
        map_center = [st.session_state.itinerary_preferences["primary_location_coords"]["lat"],
                       st.session_state.itinerary_preferences["primary_location_coords"]["lon"]]

    m = folium.Map(location=map_center, zoom_start=12) # Adjust zoom as needed

    # Loop through each day and each place in the itinerary
    day_colors = ['blue', 'green', 'red', 'purple', 'orange', 'darkred'] # Colors for different day routes
    for day_idx, (day_label, places_in_day) in enumerate(itinerary_data.items()):
        st.markdown(f"### {day_label.replace('_', ' ').title()}") # Display Day X

        route_points_for_day = [] # To draw lines for the route

        if not places_in_day:
            st.write("No activities planned for this day (perhaps a rest day or travel day).")
            continue

        for place_idx, place_info in enumerate(places_in_day):
            st.write(
                f"  {place_idx + 1}. **{place_info['name']}** "
                f"(Arrival: {place_info.get('arrival_time', 'N/A')}, "
                f"Visit: {place_info['start_time']} - {place_info['end_time']})"
            )
            # Add marker to map
            folium.Marker(
                location=[place_info['lat'], place_info['lon']],
                popup=f"<b>{place_info['name']}</b><br>{day_label}<br>Visit: {place_info['start_time']}-{place_info['end_time']}",
                tooltip=place_info['name'],
                icon=folium.Icon(color=day_colors[day_idx % len(day_colors)], icon='info-sign')
            ).add_to(m)
            route_points_for_day.append((place_info['lat'], place_info['lon']))

        # Add route line for the day if there are multiple places
        if len(route_points_for_day) > 1:
            # Add hotel/depot at start and end of day's route if available
            # full_route_for_day = [depot_coords] + route_points_for_day + [depot_coords]
            folium.PolyLine(
                route_points_for_day, # or full_route_for_day
                color=day_colors[day_idx % len(day_colors)],
                weight=2.5,
                opacity=0.8
            ).add_to(m)

    # Display the map in Streamlit
    st.subheader("Interactive Itinerary Map:")
    st_folium(m, width=725, height=500) # Adjust width/height as needed
elif 'generated_itinerary' in st.session_state and not st.session_state.generated_itinerary:
    st.warning("Could not generate an itinerary with the given constraints. Please try adjusting your preferences (e.g., extend durati")

```

CHAPTER 4

RESULTS AND DISCUSSION

The evaluation of "Padharo Sa" centered on its ability to translate a user's visual inspiration into tangible, relevant, and practical travel plans. This chapter discusses the observed outcomes, focusing on the key stages of location identification through image similarity, the impact of user customization, and the characteristics of the final generated itineraries.

6.1 Image-Based Input Location Identification

The foundational premise of "Padharo Sa" is its capacity to accurately identify and recommend tourist attractions that bear a strong visual resemblance to an image provided by the user. Our experimental evaluations, qualitatively assessed through numerous test cases using a diverse set of input images (as exemplified in Table 2, though the table itself is a concise representation), indicate that the system performs this core task with a commendable degree of precision and relevance. When presented with input images depicting, for instance, specific architectural marvels, distinct natural landscapes (beaches, mountains, forests), or even more abstract visual themes (e.g., images conveying a sense of "historic charm" or "modern vibrancy"), the system consistently retrieved a ranked list of locations from its database that shared salient visual characteristics.









This success can be attributed primarily to two factors: the powerful representational capabilities of the CLIP model and the robust aggregation strategy for location embeddings. CLIP, having been trained on vast multimodal datasets, excels at capturing nuanced visual features that go beyond simple object recognition. It appears to discern elements such as dominant color palettes, textural patterns (e.g., the roughness of ancient stone versus the sleekness of modern glass), architectural styles (Gothic, Baroque, Minimalist), compositional arrangements, and even the overall "atmosphere" or "vibe" conveyed by an image. For example, an input image featuring a sun-drenched Mediterranean coastal town with whitewashed buildings and blue-domed roofs would likely yield matches of other locations sharing similar climatic aesthetics and architectural vernacular, rather than just any coastal town.

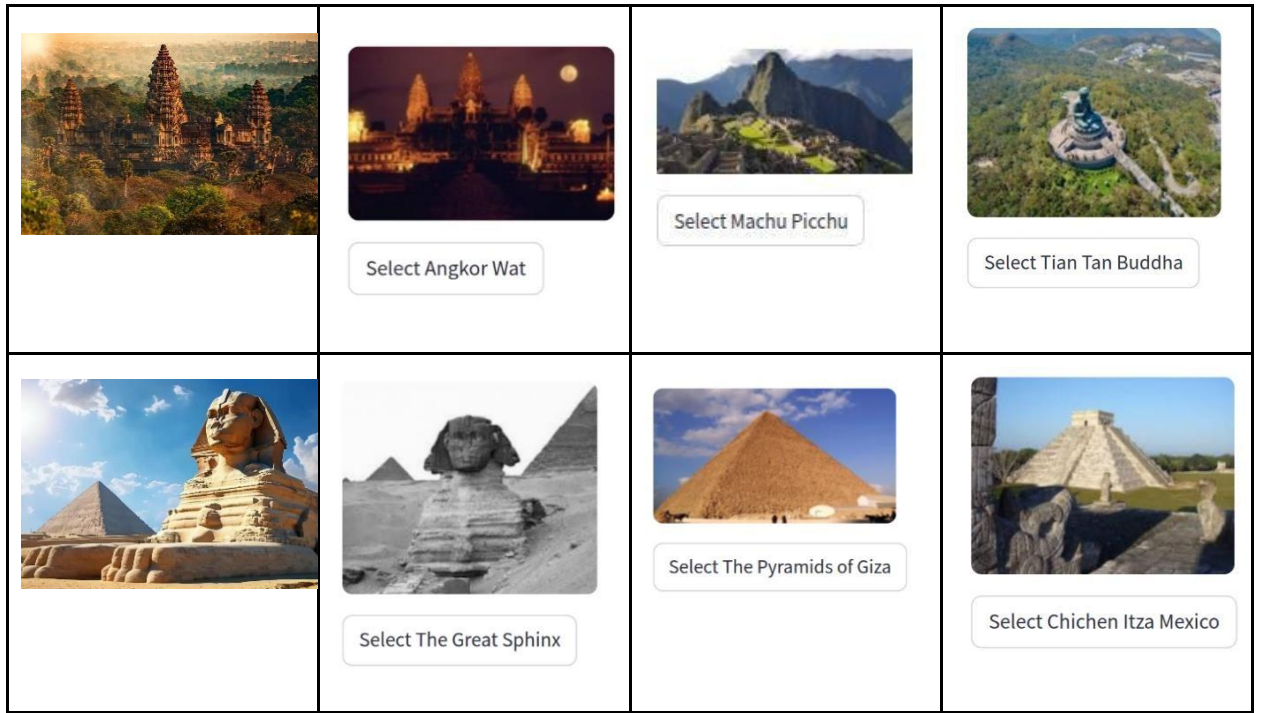
The aggregation of multiple image embeddings into a single centroid for each location in our database proved crucial for generalization and robustness. This approach mitigates the risk of an idiosyncratic or outlier image unduly influencing a location's visual signature. Consequently, the system is better equipped to match the user's input to the *typical* or *essential* visual character of a destination. The cosine similarity scores, used

internally by FAISS to rank the matches, provided a quantitative underpinning for these qualitative observations, with higher scores generally correlating strongly with matches that were also perceived by human evaluators as being more visually akin to the input.

While generally effective, the system's performance in this stage is naturally dependent on the clarity and specificity of the input image and the diversity of the underlying location database. Highly ambiguous or low-quality input images could sometimes lead to less precise matches. Similarly, if the user's input represents a very niche aesthetic not well-represented in the current 50-location dataset, the quality of matches might be constrained. Nevertheless, for a wide range of typical travel-related visual queries, the image-based location identification mechanism demonstrated its potential as an intuitive and effective starting point for travel planning, fostering user trust and engagement by quickly providing relevant visual echoes to their initial inspiration.

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 |



6.2 User Selection and Customization Parameters

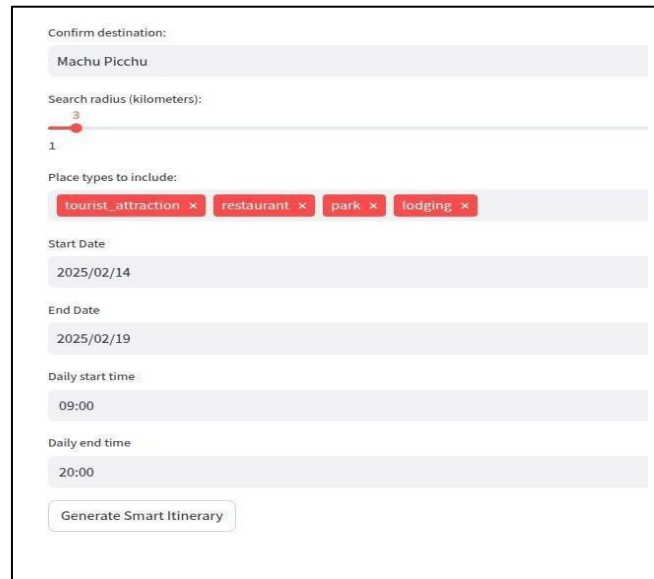
Following the initial visual similarity search, "Padharo Sa" empowers users to actively shape their ensuing itinerary through a suite of explicit selection and customization parameters, as visualized in Figure 3. The system's interface allows users to first select their preferred primary destination from the list of visually similar suggestions. This act of selection itself is a crucial point of personalization, confirming the user's interest in a specific anchor point for their trip. Subsequently, users are presented with options to define the temporal scope (trip start and end dates), the geographic breadth (search radius for nearby attractions), and the thematic focus (preferred types of attractions like museums, historical sites, nature parks, etc.) of their journey.

The impact of these customization parameters on the final itinerary is profound. The **travel dates** directly determine the number of days for which the VRPTW optimization will be performed, thereby influencing the overall density of activities and the number of locations that can feasibly be included. A shorter trip will necessitate a more curated selection of attractions, while a longer trip allows for a more leisurely pace or the inclusion of a wider array of sights.

The **search radius** parameter significantly affects the pool of potential secondary attractions considered for inclusion. A smaller radius will result in a more geographically compact itinerary, minimizing travel time between locations but potentially excluding noteworthy attractions that lie further afield. Conversely, a larger radius expands the

possibilities but may lead to itineraries with more extensive daily travel. The system must balance the desire to include diverse attractions with the need to maintain logistical feasibility.

The selection of **preferred attraction types** acts as a powerful filter, guiding the system to prioritize locations that align with the user's stated interests. For instance, a user emphasizing "historical sites" and "museums" will receive an itinerary that heavily features such locations, potentially down-weighting or excluding nature parks or shopping districts, even if they are geographically proximate and visually similar. This thematic filtering is key to ensuring the content of the itinerary is personally relevant and engaging.



Confirm destination:
Machu Picchu

Search radius (kilometers):
3
1

Place types to include:
tourist_attraction × restaurant × park × lodging ×

Start Date:
2025/02/14

End Date:
2025/02/19

Daily start time:
09:00

Daily end time:
20:00

Generate Smart Itinerary

Fig 5. Customization options

The interface also allows users to specify their **daily travel style or pace** (e.g., "Relaxed," "Moderate," "Packed"). This abstract preference is translated by the system into concrete constraints for the VRPTW solver, such as maximum daily travel time or limits on the number of sites visited per day. A "Relaxed" pace would impose stricter limits, leading to fewer activities and more downtime, whereas a "Packed" pace would allow for a denser schedule.

The effectiveness of this customization stage lies in its ability to strike a balance between user agency and system intelligence. Users provide high-level directives and preferences, while the system handles the complex low-level tasks of data retrieval, constraint

formulation, and optimization. This collaborative approach ensures that the resulting itinerary is not only computationally optimized but also deeply resonant with the user's individual travel desires and practical constraints, moving beyond generic recommendations to truly personalized travel plans.

6.3 Itinerary Generation and Interactive Map

The culmination of the user's input—the initial inspirational image, the selected primary destination, and the detailed customization parameters—is the automated generation of a comprehensive, day-by-day travel itinerary. This process, as outlined in Chapter 3, involves extensive interaction with the Google Maps API for geocoding locations, identifying suitable nearby attractions based on user preferences, and, critically, obtaining realistic travel time estimates between all potential points of interest. The core intelligence of this stage resides in the application of the Vehicle Routing Problem with Time Windows (VRPTW) model, solved using Google OR-tools.

The significance of employing a VRPTW solver extends far beyond merely finding a sequence of locations. Its true value lies in its capacity to generate itineraries that are **logistically feasible and efficient**. The solver meticulously considers:

- **Time Windows:** Ensuring that visits to attractions are scheduled only during their operational opening hours. This prevents the frustrating scenario of arriving at a closed museum or park.
- **Service Durations:** Allocating an appropriate amount of time for visiting each attraction, based on heuristics or user input.
- **Daily Operational Limits:** Adhering to user-specified (or system-inferred) maximum daily travel times or total activity durations, preventing overly rushed or exhausting days.
- **Travel Minimization:** While respecting all constraints, the solver aims to minimize unproductive travel time between locations, leading to more time spent enjoying the attractions themselves.
- **Sequencing:** Intelligently ordering visits to minimize backtracking and create a logical flow for each day's activities. For example, it might group geographically clustered attractions together.
- **Meal Breaks:** The VRPTW framework can also incorporate designated times or locations for meal breaks, adding another layer of practicality to the schedule.

The final output presented to the user is twofold: a structured, textual itinerary detailing the plan for each day (e.g., "Day 1: 10:00 AM - Arrive at Eiffel Tower; 10:15 AM - 12:30 PM - Visit Eiffel Tower; 12:30 PM - 1:00 PM - Travel to Louvre Museum..."), and an

interactive map, rendered using Folium (as exemplified in Figure 4). This map is a powerful visual aid. It displays the precise locations of all scheduled attractions, the optimized routes connecting them for each day (often color-coded by day), and allows users to zoom, pan, and click on elements for more details (like names and planned visit times).

The interactive map significantly enhances the user's understanding and appreciation of the generated itinerary. It provides an immediate spatial context, allowing users to see how their days will unfold geographically. They can visualize the proximity of attractions, the logic of the daily routes, and the overall coherence of the trip. This visual feedback fosters confidence in the plan and allows users to mentally "walk through" their journey before it even begins. The combination of a clearly structured schedule and an engaging, interactive map transforms the abstract output of an optimization algorithm into a tangible, exciting, and highly usable travel plan, effectively bridging the gap between initial inspiration and real-world execution.

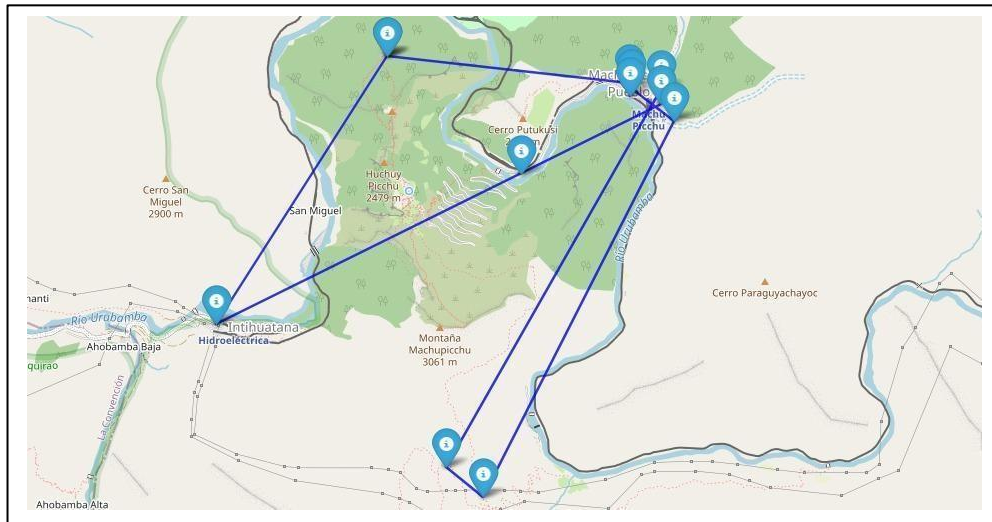


Fig 6. Sample Interactive map of Generated Itinerary

CHAPTER 5

CONCLUSION AND FUTURE SCOPE

This project, "Padharo Sa," embarked on a journey to redefine tourism itinerary planning by centering it around the intuitive power of visual inspiration. The developed system successfully demonstrates a novel pipeline that integrates cutting-edge AI techniques to translate a user-provided image into a personalized, optimized, and practical travel schedule. This concluding chapter summarizes the key achievements, acknowledges the inherent limitations, and outlines promising directions for future research and development.

5.1 FUTURE SCOPE AND LIMITATIONS

While "Padharo Sa" represents a significant step towards visually-driven travel planning, its current incarnation has limitations that also point towards exciting avenues for future enhancement and refinement. Recognizing these areas is crucial for the continued evolution of the system into an even more robust, comprehensive, and user-centric tool.

5.1.1. Scalability and dataset diversity

The current system's knowledge base is built upon a dataset of 50 tourist locations. While adequate for demonstrating the core methodology, this limited scale naturally constrains the breadth of recommendations. Future work must prioritize a substantial expansion of this dataset, aiming for thousands or tens of thousands of diverse global attractions. This expansion is not merely about quantity; **diversity** is paramount. Incorporating a wider range of geographical regions, cultural contexts, types of attractions (from iconic landmarks to niche local gems), and visual aesthetics will significantly enhance the system's generalizability and its ability to cater to a broader spectrum of user tastes. A more diverse dataset also plays a critical role in mitigating potential algorithmic biases that might arise from unrepresentative training or reference data, ensuring fairer and more inclusive recommendations.

5.1.2. Real-Time Adaptation

The current itinerary generation process relies on largely static information (e.g., standard opening hours, typical travel times). A major leap in practicality would involve integrating **real-time dynamic data streams**. Imagine an itinerary that can intelligently adapt to unforeseen circumstances like sudden road closures due to an event, unexpectedly long queues at an attraction (if such data is available via APIs), or adverse weather conditions. This could involve re-optimizing parts of the day's schedule on the fly, suggesting alternative attractions, or adjusting travel routes. Such real-time adaptation would elevate the system from a pre-trip planner to a dynamic travel companion, significantly enhancing the user's in-trip experience and resilience to disruptions

5.1.3. Enhanced Feature Extraction

While CLIP provides excellent visual embeddings, relying solely on visual features may not always capture the full spectrum of user intent or location characteristics. Future iterations could explore **multimodal feature extraction and fusion**. This might involve combining CLIP's visual embeddings with:

- **Textual Embeddings:** Derived from rich textual descriptions of locations (e.g., from travel guides, reviews, or Wikipedia articles) using models like Sentence-BERT.
- **Structured Metadata:** Incorporating explicit tags, categories, user ratings, price levels, or accessibility information more directly into the similarity computation or ranking process.

A nuanced fusion of visual, textual, and structured data could lead to a more holistic understanding of both user preferences and location attributes, resulting in even more contextually relevant and personalized recommendations.

5.1.4. User Feedback Integration

The current system operates on a one-shot generation model. A crucial enhancement would be the implementation of a robust **user feedback loop**. This could involve allowing users to rate suggested locations or entire itineraries, explicitly modify parts of the plan (e.g., remove a location, change visit duration), or provide qualitative comments. This feedback, both explicit and implicit (e.g., tracking which suggestions are frequently ignored or selected), can be invaluable for continuously refining the system's underlying models.

Techniques from reinforcement learning or active learning could be employed to enable "Padharo Sa" to learn from user interactions over time, becoming progressively "smarter"

and better attuned to individual and collective user preferences, thereby improving recommendation accuracy and user satisfaction with each interaction.

5.1.5. Computational efficiency

As the dataset of locations grows and the complexity of itinerary requests increases (e.g., longer trips, more constraints), maintaining a responsive user experience becomes paramount. While FAISS and OR-Tools are highly optimized, further work on **computational efficiency** will be necessary. This could involve:

- Exploring more advanced FAISS indexing techniques (e.g., approximate nearest neighbor search for very large datasets) that offer faster search at the cost of a small, controllable loss in accuracy.
 - Optimizing API call strategies (e.g., intelligent batching, caching frequently accessed data like travel times between popular locations).
 - Investigating parallel or distributed computing architectures for the more demanding VRPTW optimization tasks, especially for complex requests.
- Ensuring low latency in both the similarity search and itinerary optimization stages is critical for user retention and the system's ability to scale to a larger user base.

5.1.6. Dependency on External APIs

The system's current heavy reliance on external APIs, particularly the Google Maps API suite (for geocoding, places details, directions), introduces several dependencies and potential points of failure or performance bottlenecks. These include API rate limits (which can cap the number of requests per unit time), associated monetary costs, potential changes in API availability or functionality, and network latency. Future strategies to enhance **system resilience** might include:

- Developing more sophisticated caching mechanisms for API responses that are less likely to change frequently.
 - Exploring and integrating alternative or supplementary data sources (e.g., OpenStreetMap for routing, other Points of Interest databases).
 - Implementing more robust error handling and fallback strategies when API calls fail or return unexpected data.
- Reducing over-reliance and managing these dependencies effectively will be key to long-term stability and scalability.

5.1.7. General Limitations

It is important to acknowledge the inherent limitations in any system attempting to interpret subjective visual appeal. While CLIP is powerful, the "visual similarity" it detects is based on patterns learned from its training data and might not always perfectly align with an individual user's unique aesthetic sensibilities or the full contextual meaning they associate with an image. A picture that a user finds inspiring due to a personal memory or a subtle, non-visual association might not translate into obvious visual cues that the system can pick up. Moreover, the quality and representativeness of the images within our own location database directly impact the matching quality. Addressing the nuances of subjective human perception and ensuring comprehensive visual coverage of diverse locations remain ongoing challenges in this domain.

5.2 CONCLUSION

"Padharo Sa" has successfully pioneered and demonstrated an innovative, end-to-end approach for tourism itinerary generation, uniquely anchored in the power of visual similarity. By seamlessly integrating advanced image processing techniques like homographic warping and CLIP-based embedding generation, efficient vector similarity search via FAISS, comprehensive data enrichment using the Google Maps API, and sophisticated route optimization modeled as a Vehicle Routing Problem with Time Windows (VRPTW) solved by Google OR-tools, this project has effectively bridged the often-disconnected phases of travel inspiration and practical planning. The system capably translates the abstract aesthetic captured in a user's input image into a concrete, personalized, and logistically sound travel schedule.

The research underscores the significant potential of leveraging visual semantics as a primary driver in travel recommendation systems, offering a more intuitive and engaging user experience that aligns with how many modern travelers discover and dream about destinations. While acknowledging the existing limitations, such as the current dataset size and dependencies on external APIs, which also chart clear paths for future enhancements, "Padharo Sa" establishes a robust and extensible architectural foundation.

The future evolution of this work will focus on surmounting these limitations by expanding data diversity, incorporating real-time adaptive capabilities, enhancing multimodal feature understanding, and fostering continuous learning through user feedback. The ultimate vision for "Padharo Sa" and systems like it is to empower travelers with intelligent, deeply personalized, and visually intuitive planning tools that transform the way we explore and experience the world, making the journey from a single inspirational image to a well-crafted adventure both seamless and delightful.

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APPENDIX 1

Paper acceptance proof:



ROVINCE GANGWAR <rovince.2125cse1106@kiet.edu>

Paper Acceptance for International Conference Presentation for ICETISD-2025, Poornima University, Jaipur

Microsoft CMT <email@msr-cmt.org>

Tue, Mar 25, 2025 at 11:03 AM

Reply-To: Deepak Kumar Prajapat <deepak.prajapat@poornima.edu.in>

To: Rovince Gangwar <rovince.2125cse1106@kiet.edu>

Dear Rovince Gangwar,

I am pleased to inform you that your paper "Tourism Itinerary Generation Based on Image Similarity" (Paper ID- 77) has been accepted for conference presentation at "2nd International Conference on Engineering and Technological Innovation For Sustainable Development (ICETISD-2025)", Poornima University, Jaipur.

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