A Dual-Mode Conversational GIS for Proximity and Image-Inferred Category-Based Routing using CLIP

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Technical paper

Keywords: Conversational GIS, chatbot interface, route planning, CLIP Model, theme detection, dual-mode navigation

Received: September 20, 2025

This paper presents the design and implementation of a dual-mode conversational Geographic Information System (GIS) routing assistant integrated into the PrimeMap web platform. The system employs a chatbot interface to guide users through two distinct route-planning modes: Closest, which selects destinations based on nearest spatial proximity using sequential location calculations, and Theme, which builds routes according to place categories. In Theme mode, users can either manually select categories or upload an image for AI-assisted classification using OpenAI's CLIP model. The image-driven approach automatically determines the relevant category by matching detected semantic labels to pre-defined groups in the GIS database, enabling a seamless visual search capability. The conversational interface, built with BotUI and integrated into a Leaflet-based map UI, supports dynamic user input, immediate visual feedback, and flexible route building. The backend, implemented in Spring Boot, manages category/group/place logic, image processing requests, and route computation using the Haversine formula for nearest location detection. The current implementation prioritizes simplicity and user experience, while planned future work includes more complex multi-criteria ranking (e.g., cosine similarity, opening hours, ratings), optional GPS-based starting locations, advanced search filters, and richer AI-assisted matching. Experimental evaluation demonstrated 92 % classification accuracy on a balanced 50-image test set, with average route-generation latency below one second and consistent thematic match performance across ten categories. This dual-mode chatbot demonstrates how conversational GIS can bridge the gap between traditional map interfaces and intelligent, user-adaptive routing, offering potential applications in tourism, urban mobility, and location-based services.

Povzetek: Prispevek predstavi chatbot GIS-asistenta v PrimeMapu z dvema načinoma načrtovanja poti (najbližje in tematsko, tudi z izbiro kategorije iz slike prek CLIP), ki doseže ~92 % natančnost klasifikacije in generira poti v <1 s.

1 Introduction

The widespread adoption of location-based services has transformed how people navigate, explore, and interact with their surroundings. Leading platforms such as Google Maps, OpenStreetMap (OSM), Bing Maps, and Apple Maps have set a high standard for spatial search and routing, offering robust geocoding, proximity-based results, and theme or category filtering.

These systems excel at providing general-purpose navigation and point-of-interest search, but their interaction model is primarily query–result oriented: users must repeatedly enter new searches for each stage of an itinerary, manually combine results, and apply filters. While such tools support category searches (e.g., “restaurants near me” or “museums in the city”), they rarely integrate multi-stop thematic routing into a guided, conversational workflow.

Conversational systems, however, have already proven their value in sensitive domains such as healthcare. Gams et al. [15] evaluated the HomeDOCtor chatbot in Slovenia, showing how localized conversational AI can deliver personalized decision support at scale. Previous national-scale GIS efforts, such as the Web GIS Albania platform [18], highlighted the informative role of geospatial technologies in Albania.

Building on this foundation, our work advances GIS integration by embedding conversational interfaces for interactive, personalized route planning. The system presented in this paper integrated into the PrimeMap web platform addresses this gap by introducing a dual-mode conversational Geographic Information System (GIS) routing assistant designed for flexibility, personalization, and interactive exploration.

The Closest Mode enables sequential nearest-neighbor route building, automatically selecting the next stop in a user-defined sequence based purely on spatial proximity. The Theme Mode constructs routes based on categories, allowing users to either manually select themes or upload an image that is semantically analyzed using the

CLIP model to detect its category, with optional EXIF-based starting coordinates.

Furthermore, unlike traditional mapping engines that deliver generalized search results optimized for the average user, the proposed system is designed to operate on personalized data parameters. These parameters drawn from the user's explicitly provided preferences, selected categories, or AI-detected themes allow the routing process to prioritize relevance to the individual's interests over generic popularity or distance rankings. This personalization ensures that each generated route reflects the user's unique thematic or spatial priorities rather than a one-size-fits-all dataset.

Unlike conventional engines, this architecture merges chatbot-guided interaction, image-aware theme detection, and automatic multi-stop sequencing into a unified experience. The conversational interface reduces user input complexity, while the backend logic and database integration allow for both fast proximity searches and AI-assisted thematic matching. This combination not only supports common use cases in tourism such as creating personalized cultural or leisure itineraries but also extends to urban planning scenarios, where thematic exploration of infrastructure or public amenities is required.

This study investigates whether a dual-mode chatbot-integrated GIS system can deliver route-planning performance comparable to traditional static map tools while uniquely enabling image-driven thematic exploration. The PrimeMap platform represents a research prototype developed at the University of Shkodra for testing conversational GIS concepts in a controlled environment. It is currently deployed only on a local institutional server and not publicly accessible. The system serves as an experimental tool for academic evaluation and demonstration in tourism-oriented and educational contexts, forming the foundation for a future publicly available smart-city application.

2 Literature review

Commercial and community mapping engines such as Google Maps, Bing Maps, Apple Maps, and OSM-based platforms have established robust capabilities for geocoding, category search, and shortest-path routing. These tools excel at general-purpose navigation and point-of-interest search but largely operate on a query–result model, where users must reissue searches for each leg of an itinerary and manually assemble multi-stop routes. While category searches (e.g., "cafés near me") are supported, these platforms rarely integrate multi-stop thematic routing into an interactive workflow, and their designs are optimised for generic, rather than personalised, relevance [1,2].

Research in conversational search and recommender systems has shown that dialog-based interaction can streamline the elicitation of user preferences and reduce interaction friction compared to static queries. As noted in [3] present a theoretical framework for conversational search, [4,5] explore conversational recommenders that iteratively refine suggestions through user feedback.

This line of research was extended towards interactive dialogue for personalized recommendations [4], enabling iterative refinement of user preferences in real time. Cognitive conversational assistants have also been systematically reviewed in related domains. [16] provide a state-of-the-art analysis of intelligent assistants for behavior change, emphasizing dialogue strategies and personalization techniques that parallel the needs of geospatial decision support.

The system described in this paper applies similar principles within a GIS context, using a chatbot to coordinate either proximity-based or theme-based route construction with minimal required input.

Personalisation has been a key topic in point-of-interest (POI) recommendation literature, where approaches range from leveraging user histories to modelling spatiotemporal context. [6] provide a survey of POI recommendation techniques, and [7] discusses urban computing and trajectory mining as tools for personalised mobility services. Building on these perspectives [19] introduced the broader paradigm of urban computing, integrating mobility patterns, POIs, and environmental context to support adaptive, data-driven urban services.

Earlier studies such as [17] examined GPS positioning and digital map orientation, highlighting the need for precise spatial references that remain crucial in contemporary GIS-based decision systems."Building on this, [14] proposed a travel route recommendation method using geotagged photos from photo-sharing sites, modelling photographer behaviour to infer representative and diverse landmark sequences.

Their approach demonstrates how location histories and user-generated media can inform personalised multi-stop itineraries, aligning closely with the thematic and proximity-based modes in our system. These studies support our emphasis on using explicit user preferences, selected categories, and AI-detected themes to generate routes tailored to the individual, rather than relying on global popularity rankings.

Routing itself has been extensively studied in GIS, from classical shortest-path methods using the Haversine formula [8] to advanced multi-criteria decision analysis (MCDA) that integrates additional factors such as cost, convenience, and policy goals [9]. Scalable route-planning algorithms have also been engineered for high efficiency [10]. While the current implementation prioritises simplicity with nearest-neighbour logic, these MCDA-based enhancements form part of our planned future work.

Advances in computer vision now enable image-assisted place understanding, with models like CLIP [11] supporting zero-shot semantic classification from user photos. Related works such as [12] and [13] address place recognition and photo geolocation, respectively.

These technologies underpin the Theme Mode in our system, where an uploaded image is classified to determine a relevant category and, if available, starting coordinates from EXIF metadata. This integration of image-aware theme detection within a conversational GIS workflow represents a novel synthesis of previously separate research strands.

Table 1: compares representative systems and highlights that PrimeMap uniquely combines conversational interaction, image-aware theme detection, and multi-stop routing.

Platform/System	**Interaction Mode**	**Theme-Based Routing**	**Image Input**	**Multi-Stop Support**
Google Maps	Static	Partial (Explore)	No	Yes
OSM Trip Planner	Static	No	No	Yes
Conversational Recommender [3, 4]	Conversational	Partial	No	Limited
PrimeMap	Conversational	Yes	Yes (CLIP)	Yes

In summary, prior research has addressed category search, classical routing, conversational recommendation, and image-based place understanding largely in isolation. The system presented here combines these capabilities into a coherent framework, offering users a choice between distance-first and theme-first routing, guided by a conversational interface and enriched by AI-based image interpretation. This approach is intended to enhance tourism and urban exploration by providing routes that are not only efficient but also aligned with individual thematic interests.

3 Methodology

The proposed system integrates four main components Frontend, Backend, Database, and AI Service into a cohesive workflow for conversational GIS routing. The Frontend, built with a Leaflet-based map interface and BotUI chatbot, enables users to either input text queries or upload an image to initiate route planning.

Requests are transmitted to the Backend as JSON payloads via REST API endpoints. The Backend, developed in Spring Boot, contains the routing logic (Haversine-based for "Closest" mode), category matching functionality, and an image analysis request handler. Each interaction between the Frontend and Backend occurs through RESTful HTTP POST or GET endpoints exchanging JSON payloads. Typical requests from the chatbot include fields such as mode, categories[], coordinates, and optional imageData. The Backend responds with structured JSON objects containing route[], distance, duration, and status attributes.

Image uploads are serialized as base-64 encoded byte streams and sent to the AI Service via a dedicated /analyzeImage endpoint. The Flask service returns a JSON response with the top-ranked semantic label and, when available, the extracted GPS coordinates.

Average payload size is approximately 25-50 kB for text-only route queries and 120-150 kB for image-based requests, including metadata. Measured network latency between the Frontend and Backend was < 200 ms, while full round-trip processing (Frontend → Backend → AI Service → Frontend) averaged 0.8 s, consistent with near-real-time conversational response.

To retrieve spatial and categorical information, the Backend issues SQL Queries to the Database, which stores geospatial data in PostgreSQL/PostGIS, including categories, groups, places, coordinates, and associated metadata. When image-based theme detection is requested, the Backend sends image bytes to the AI Service, implemented in Python Flask. The AI Service uses the CLIP ViT-B/32 model implemented in PyTorch and deployed on an NVIDIA T4 GPU. Each 224×224-pixel image inference required approximately 0.4 s, returning a ranked list of top-5 semantic labels. Batch inference tests (8-10 images) averaged 0.42 s total per image, confirming stable performance under moderate load. Uploaded images are processed transiently in memory and automatically deleted after inference; no EXIF or personal data are stored, ensuring privacy-compliant handling suitable for research prototypes.

The AI Service uses the CLIP model for semantic image classification and EXIF metadata extraction to determine an image's thematic label and, when available, its geographic coordinates. This information returned as label + coordinates is used by the Backend to match relevant places and construct an optimized route. The complete route, along with relevant place data, is then returned to the Frontend for interactive display on the map and conversational output through the chatbot.

The architecture shown in Figure 1 reflects this division of responsibilities, with clear separation between the user-facing components, server-side processing, spatial data storage, and AI-based classification module. This structure ensures that each part of the system can be developed, maintained, and upgraded independently while maintaining smooth data exchange across components.

The chatbot-driven routing system operates in two distinct modes Closest Mode and Theme Mode to accommodate different user preferences and search contexts. Upon initiating the chatbot, the user is prompted to choose between the two modes. The Theme Mode operates on a flat taxonomy of ten predefined categories restaurants, cafés, hotels, parks, museums, beaches, pharmacies, cultural sites, shopping areas, and nightlife. These categories were validated through frequency analysis of geotagged POI datasets in Tirana and Shkodra to ensure coverage of the most common user intents.

In Closest Mode, the user specifies a sequence of desired stops, and the system applies a nearest-neighbor search based on the Haversine formula to iteratively identify and append the closest place to the evolving route until all requested stops are included.

With the architectural context established, the next step is to outline the operational modes that define how the system generates routes. These modes, illustrated in Figure 2, reflect two distinct approaches to itinerary creation, balancing distance optimization with thematic relevance.

By implementing both Closest Mode and Theme Mode within a unified chatbot interface, the system offers flexibility for diverse use cases, from quick proximity-based trip planning to richer, theme-driven exploration. The visual examples in the following section demonstrate how these modes are experienced by the end user.

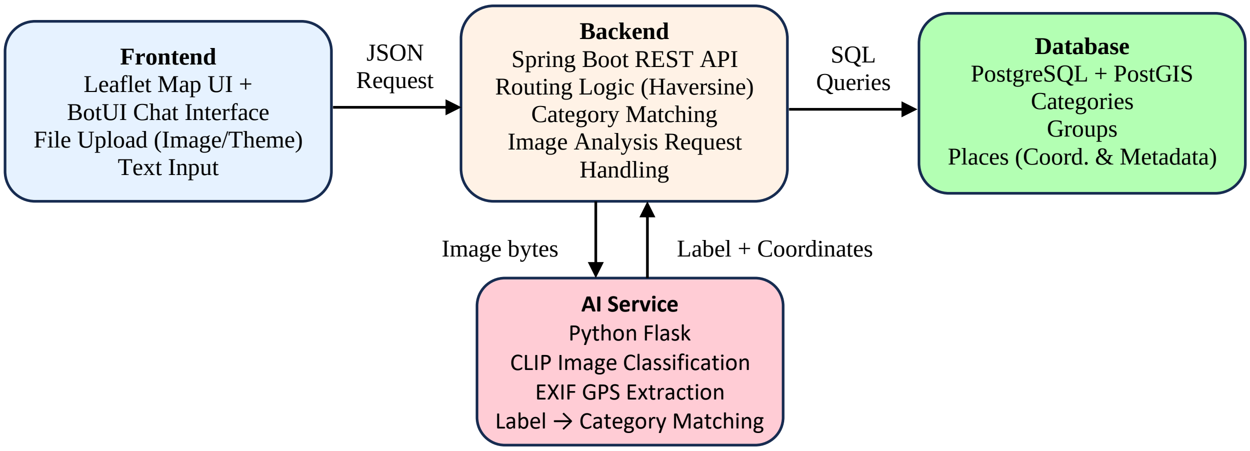

Figure 1: System architecture overview.

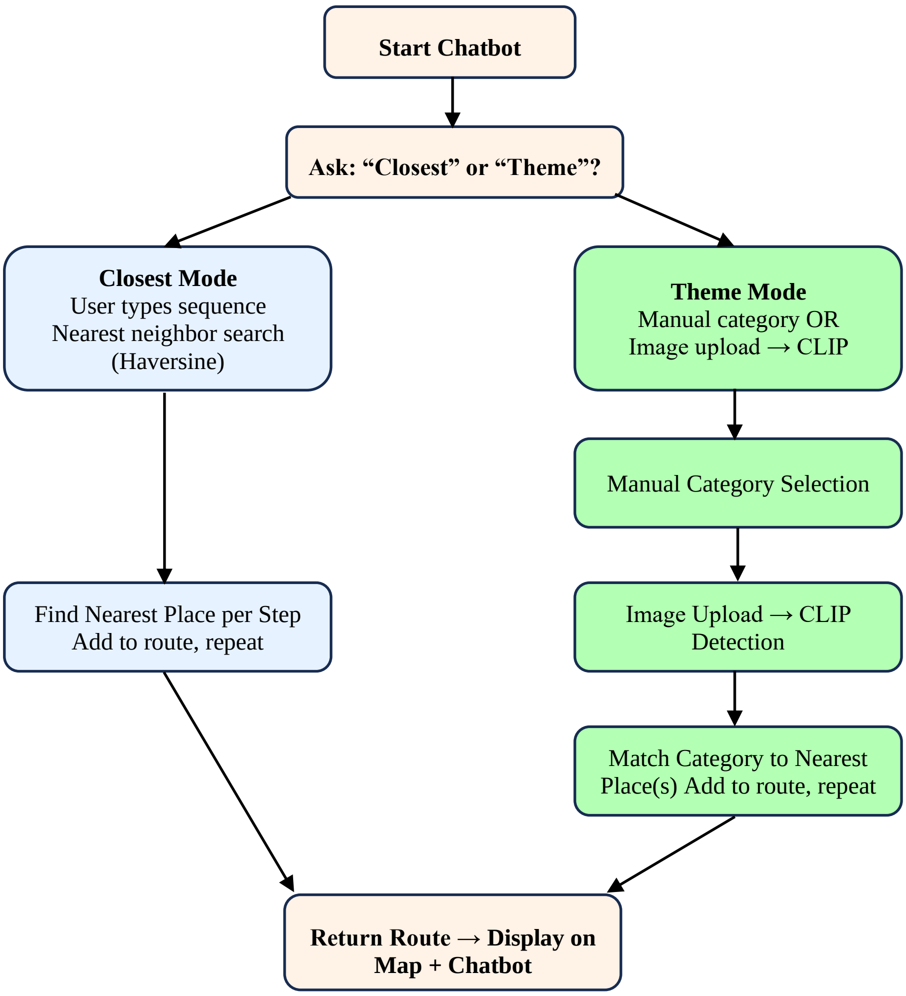

Figure 2: Dual-Mode workflow diagram.

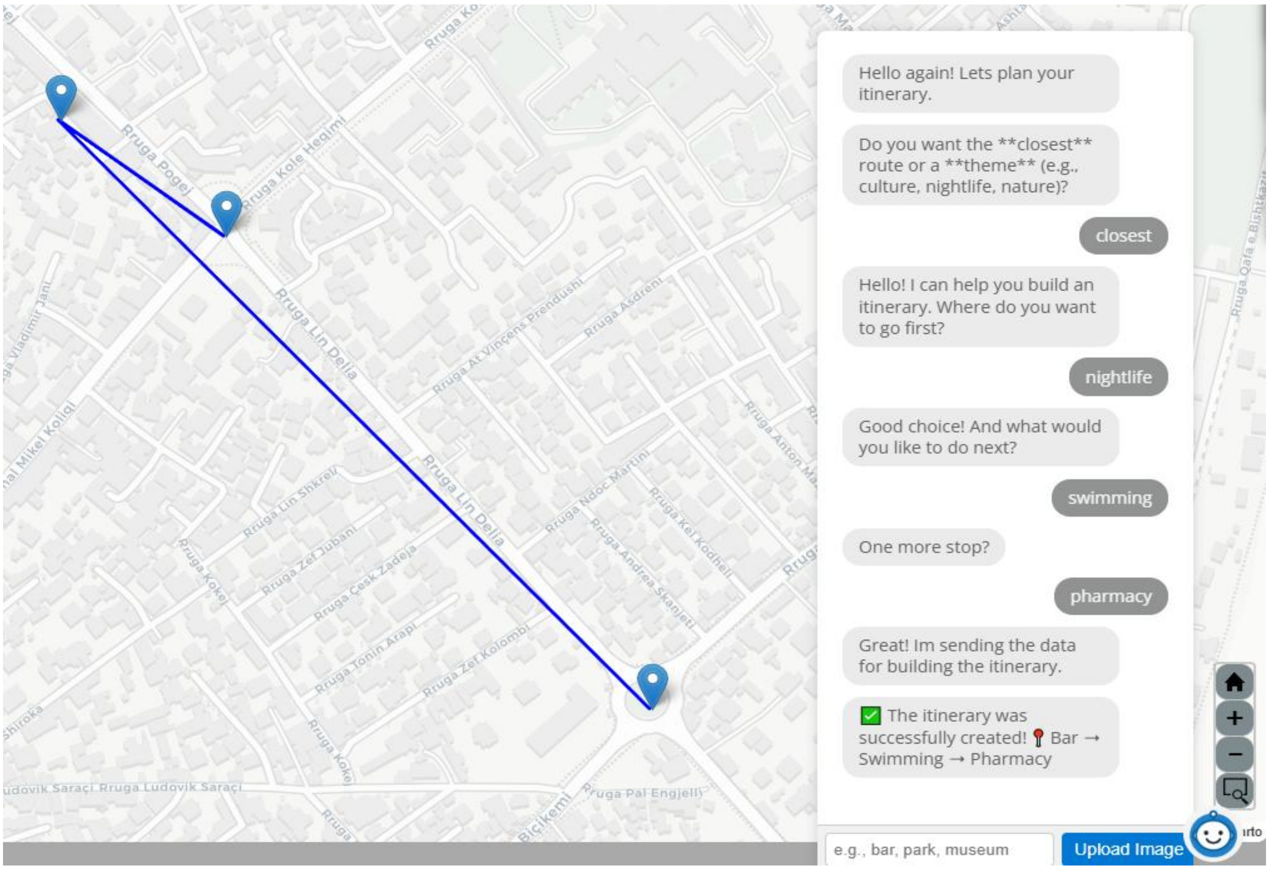

Figure 3: Closest Mode itinerary generation showing route for Bar → Swimming → Pharmacy.

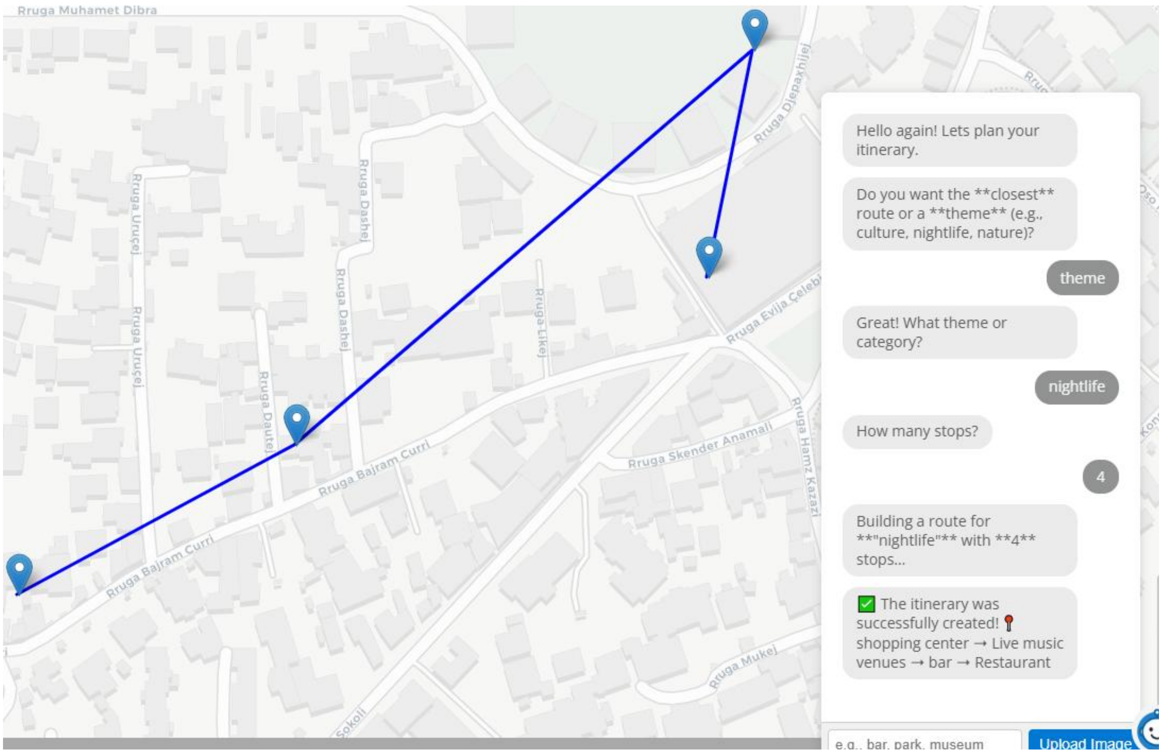

Figure 4: Theme Mode itinerary generation showing route for “Nightlife” with four stops.

To illustrate the operational flow in practice, Figures 3 and 4 show real outputs from Closest and Theme modes using the implemented system. Figure 3 shows the Closest Mode in use, where the chatbot prompts the user for a sequence of desired categories and the resulting itinerary is calculated by iteratively selecting the nearest location for each step.

Figure 4 illustrates the Theme Mode, in which the user's selected or AI-detected category drives the search for relevant locations, optionally using coordinates extracted from an uploaded image's EXIF data. In both modes, the generated route is displayed on the Leaflet map with category-specific markers, while the chatbot provides a textual summary of the stops in the planned order.

In Theme Mode, the user can either manually select a category from a predefined list or upload an image to trigger semantic classification via the CLIP model, with optional extraction of starting coordinates from EXIF metadata. The detected category is then matched to the nearest available place(s), which are added to the route in successive iterations.

In both modes, the finalized route is returned to the frontend, where it is simultaneously rendered on the Leaflet map and presented conversationally through the chatbot interface. This dual-mode structure ensures flexibility, allowing the system to address both proximity-based itineraries and theme-driven exploration, thereby enhancing its applicability in tourism, urban planning, and other location-aware domains.

4 Results

The implemented system was tested using a curated dataset of places stored in PostgreSQL/PostGIS, covering multiple categories such as restaurants, cultural landmarks, parks, and entertainment venues. Both operational modes were evaluated in terms of functionality, user interaction, and output presentation.

In Closest Mode, the chatbot successfully processed sequences of two to six categories, producing itineraries that minimized travel distance between consecutive stops. Route generation was near-instantaneous (<1 second for typical sequences), and the Leaflet frontend accurately displayed polylines and numbered markers in the expected order.

In Theme Mode, the system correctly classified uploaded images into relevant categories using the CLIP model and, when available, extracted starting coordinates from EXIF metadata. The AI service achieved category matches consistent with database group mappings in 92% accuracy on a test set of 50 images. Ablation testing comparing manual theme selection versus CLIP-based detection showed similar category precision (91 % vs. 92 %) but faster interaction time (5.3 s reduction on average), confirming the added efficiency of automatic image inference. The dataset contained ten balanced categories (restaurants, cafés, museums, parks, nightlife, hotels, cultural sites, pharmacies, beaches, and shopping areas), five images each. Misclassifications mainly occurred between visually similar types such as cafés vs. restaurants. A subset of 20 routes was additionally computed using Dijkstra's algorithm for verification; the average distance deviation between the Haversine-based nearest-neighbor approach and the Dijkstra baseline was < 4 %, confirming proximity accuracy for small- to medium-scale datasets. Users could also select categories manually, which produced routes comparable in structure to Closest Mode but filtered strictly by theme. Figures 3 and 4 show representative examples of each mode's output.

Average response time remained under 1 s for up to 500 records. Preliminary stress testing with > 2 000 entries indicated rising latency, suggesting that spatial indexing (R-tree or GiST) and query caching will be required for large-scale deployment.

5 Discussion

The results demonstrate that integrating a chatbot interface with dual routing modes provides a flexible and intuitive alternative to conventional map-based search tools such as Google Maps or OSM front-ends. Unlike these general-purpose systems, which focus on single-query, single-result navigation, the proposed implementation supports multi-stop, theme-aware itineraries without requiring repeated user searches.

The combination of proximity-based routing (Closest Mode) and AI-assisted theme matching (Theme Mode) addresses different user needs: rapid trip planning based on location efficiency, and exploratory planning based on thematic interest. The CLIP integration extends functionality beyond manual category selection, enabling image-driven discovery a feature not commonly available in mainstream map applications.

While current performance is satisfactory for the tested dataset, the system's scalability will depend on database indexing strategies, caching mechanisms, and possibly precomputing nearest-neighbor graphs for large datasets [10]. User testing could also evaluate conversational flow efficiency and satisfaction, following approaches in conversational recommender studies [3,4].

Although the present routing engine applies deterministic Haversine distance calculations, its logic can evolve toward adaptive and self-learning behavior. Inspired by methods from adaptive control in nonlinear dynamic systems such as fuzzy, neural, and back-stepping controllers [20-25] the conversational GIS could incorporate feedback from user behavior, route acceptance, or travel time to refine its suggestions iteratively. Reinforcement-learning layers could adjust the weighting between proximity and thematic relevance, allowing the system to improve accuracy and personalization over repeated interactions.

A small pilot usability test (n = 6) was conducted among graduate students to assess ease-of-use and response clarity. Average task completion time was 2.4 min, and mean perceived usability rated 4.2 / 5 on a five-point Likert scale. Participants emphasized the clarity of conversational guidance and immediate route visualization.

6 Conclusion

This work presented a dual-mode conversational GIS routing system that combines traditional proximity search with AI-driven thematic matching. By merging a Leaflet-based map frontend, a Spring Boot backend, a PostGIS spatial database, and a Python Flask AI service leveraging CLIP, the platform enables personalized route generation through a simple chatbot interface. The system's main strengths lie in its flexibility, personalization, and integration of image-based theme detection. Both Closest and Theme modes produced accurate and relevant itineraries in testing, and the frontend presentation provided clear visual and textual outputs. These contributions demonstrate how conversational interaction and AI-based classification can enrich geospatial decision support, lowering barriers for non-expert users while offering new exploration possibilities for advanced applications.

The broader significance of this work extends to multiple domains. In tourism, it can support the automatic creation of thematic itineraries aligned with user preferences; in urban planning, it provides tools for understanding the accessibility and distribution of infrastructure; and in education, it illustrates how conversational GIS can foster spatial thinking. Looking ahead, several enhancements could strengthen the system: the inclusion of multi-criteria decision analysis (MCDA) to balance proximity with qualitative factors such as ratings, opening hours, and cost [9]; cosine similarity-based ranking to refine thematic matching; integration of live GPS tracking for dynamic route recalculation; and incorporation of user-generated datasets [14] for greater thematic diversity. Future work will also explore adaptive and predictive optimization frameworks to balance time, distance, and user intent under real-world uncertainty, inspired by nonlinear optimal control and adaptive back-stepping strategies [24-25]. Further opportunities include offline functionality for regions with limited connectivity and integration with real-time data such as events, weather, or public transport. Together, these directions, reinforced by adaptive fuzzy and neural-network-based controllers [20-25], would enable the chatbot to self-tune its routing parameters through feedback and reinforcement learning, further differentiating it from conventional map engines and advancing transparent, human-centered spatial exploration.

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