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Budget Buddy: A Geo-Location Based Budget Activity Recommender

Jawad Khan[1], Sreenivasa Setty[2], Moeez Khan[3], Hemantha M[4]
[1,2,3,4]Department of Computer Science and Engineering, AMC Engineering College, Bengaluru-560083, Karnataka, India.
Email ID: *1am22cs084@amceducation.in[1], Sreenivasasetty66@gmail.com[2], 1am22cs111@amceducation.in[3], 1am22cs074@amceducation.in[4]*

Abstract
Planning travel activities is often a challenging process, as individuals must consider both their geographical lo- cation and financial constraints while exploring available options. Traditional methods, such as online searches, guidebooks, or fragmented platforms, tend to be inefficient, lack personalization, and do not meet budget limits, leading to missed opportunities and suboptimal travel experiences. This project introduces GeoBudget Explorer, an AI-driven application that recommends affordable and location-sensitive activities tailored to a user's budget. The system integrates geospatial filtering, cost-based recommendation algorithms, and machine learning models for activity ranking and personalization. External APIs (e.g., Google Maps, TripAdvisor) provide real-time activity data, while a back-end powered by Flask/FastAPI and a MongoDB/PostgreSQL database ensures secure storage and efficient retrieval of user and activity information. In the front-end, Geo Budget Explorer provides a dynamic activity list, interactive maps, and budget-sensitive dashboards to visualize expenditure trends. A feedback module enables users to share their experiences, which are analyzed using sentiment analysis to refine future recommendations. The primary goal of Geo Budget Explorer is to simplify travel planning by combining location intelligence with budget optimization, making activity discovery more accessible, cost- effective, and user-friendly. This improves user satisfaction, supports better decision making, and fosters more meaningful travel experiences
Keywords: *Location-based services, budget- aware recommendation system, Geo spatial filtering, Activity rec- ommendation, Machine learning, Sentiment analysis, Personalized travel planning*

1. Introduction
In today's fast-paced world, travel and leisure planning arengly influenced by personalization, affordability, and lo- cation location awareness.als often struggle to balance their budget with the range of activities available in a particular location, leading to limited experiences and inefficient plan- ning. Traditional methods such as online searches, guidebooks, or fragmented platforms require significant manual effort, lack personalization, and fail to provide budget-conscious recommendations. Travelers, students, and tourists frequently face challenges in accessing a consolidated and user-friendly system that highlights activities they can afford while considering their geographical location. Similarly, businesses and local tourism agencies lack intelligent tools that connect users to affordable, personalized experiences in real time. The proposed system, GeoBudget Explorer, addresses this gap by introducing an AI-powered activity recommendation platform that integrates location data with individual bud- get constraints. By leveraging geospatial filtering, machine learning algorithms, and real-time APIs, the system generates tailored activity suggestions along with visualizations of ex- penditure trends[1-3]. This project is highly relevant in the context of smart tourism, budget optimization, and digital transformation of travel planning, especially for cost-sensitive users such as students, families, and solo travelers.

2. Literature Review
Location-Based Recommendations: Previous research has applied geo spatial filtering and GPS-based services to suggest nearby activities. APIs such as Google Maps and TripAdvisor have been widely used, but most lack personalized filtering based on user-specific constraints.Budget-Constrained Travel Planning: Existing travel plat- forms focus on listing attractions, but rarely integrate cost- awareness.

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Studies on budget-based recommendation highlight the need to align activity suggestions with the financial limits of a user[4]. Our approach combines affordability checks with geo location to improve practicality. Recommendation Algorithms: Collaborative filtering, content-based methods, and hybrid models have been applied in tourism recommendation systems. We extend this by incorporating budget ranking alongside location-based activity discovery. Sentiment Analysis in Tourism: Tourist reviews and feed- back analysis have been used to evaluate the quality of the destination. Lightweight models such as VADER and Text Blob provide effective opinion classification. Our system applies these techniques to refine activity recommendations through real user sentiment.

3. Methodology

BudgetBuddy's methodology focuses on delivering a com- plete end-to-end system for location-based budget recom- mendations. It integrates backend processing, real-time APIs, database management, and interactive fron-tend modules[5]. Figure 1 shows The system architecture is modular, scalable, and allows for smooth integration of additional features such as feedback analysis or personalized suggestions.

A. System Architecture

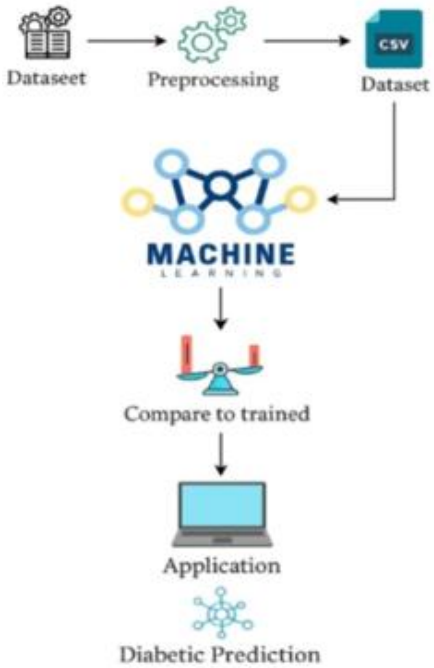

Figure 1 System Architecture

The system is divided into four main modules handled by team members:

Backend API (jawad)

Node.js/Express backend setup

Python scripts for processing activity recommendations MongoDB integration for storing activity and user data REST APIs for frontend data retrieval

Acquisition Budget Filtering (Moeez)

Activity data ingestion from external sources (Google Places API, event APIs)

Geo-location retrieval via GPS Budget-based filtering algorithms

Frontend Interactive UI (Hemantha)

React + HTML/CSS + Tailwind frontend Interactive map with markers for recommended activities

Filters by budget, category, and distance Charts and lists for quick insights

B. Flow of System

- Student opens the app, which retrieves their current geo- location.
- Student enters budget preferences and desired activity category. Figure 2 Shows Flowchart

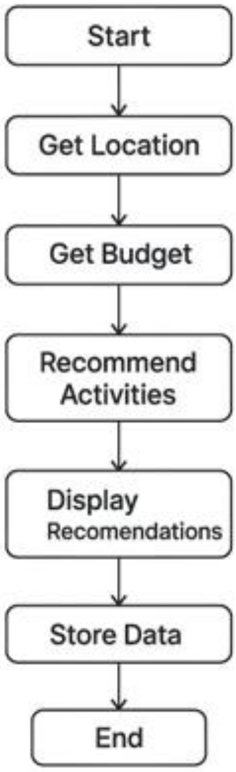

Figure 2 Flowchart

- Backend fetches relevant activities from MongoDB or external APIs.
- BudgetBuddy filters activities based on location proxim- ity and budget.
- Filtered results are displayed on the interactive map and lists[11].
- Student selects activity and optionally provides feedback.
- System aggregates feedback for analytics and future recommendation improvements.

4. Expected Results

- Real-time, location-aware activity recommendations within the user's budget.
- Interactive maps and lists displaying suitable activities[6].
- Personalized suggestions based on budget, preferences, and location.
- Analytics on most popular activities and trends.
- Easy-to-use interface for student engagement.

5. Advantages of Proposed System

- Saves time by automating the search for activities.
- Provides budget-aware recommendations for students.
- Enhances student engagement and city exploration[7].
- Scalable and deployable on cloud platforms (Ren- der/Railway + MongoDB Atlas).
- Offers insights for institutions on popular student activi- ties.

Conclusion

Budget Buddy offers an innovative, geo-location based system for budget-aware activity recommendations. By com- bining real-time APIs, backend processing, and an interactive frontend, it simplifies decision-making for students, enhances engagement, and provides actionable analytics for institutions[8-10]. Future enhancements could include personalized AI sugges- tions, integration with events calendars, and cross-platform support.

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