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Enhancing Local Tourism Through AI-Powered Mobile Application

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ABSTRACT

Backgrounds: *With increasing digitalization, tourism has become more globalized, but the potential of local tourist spots remains untapped because of visibility deficit and lack of personal guidance. In this paper, a mobile app based on AI is suggested to enable local tourism through crowd engagement and artificial intelligence. The app features geolocation-based suggestions, landmark detection using image recognition, and personalized suggestions based on user activity and preference. The app also allows users to share pictures, reviews, and insider tips, making the tourism experience dynamic and continually evolving. Utilizing machine learning techniques and crowd-sourced data, the app seeks to provide residents and travellers alike with value- added, personalized experiences. The solution proposed places emphasis on accessibility, cultural preservation, and local economic growth. In this paper, the theoretical framework, system design, and AI-based methods utilized in the app are described. The app seeks to illustrate how technology can close the loop between visitors and unknown yet culturally significant places, enabling sustainable tourism development.*

Keywords: Artificial Intelligence, Local Tourism, Mobile Application, Geolocation, Landmark Detection, Image Recognition, Personalized Recommendations, Machine Learning, Crowdsourced Data, Cultural Preservation, Smart Tourism, Sustainable Tourism, User Engagement.

INTRODUCTION

Tourism plays an important role in cultural exchange, economic development, and inter- community interaction. However, while the tourism sector has developed at a very rapid pace, a number of off-the-beaten-track or local destinations fall below the radar of well-known tourist spots. This imbalance has a tendency to create overcrowding at the well-known spots while local locations, full of history, culture, and uniqueness, remain under-exploited and economically stagnant.

With the growing accessibility of smartphones and the introduction of artificial intelligence (AI), there is a potential to transform how individuals learn about unfamiliar destinations. Digital services have already revolutionized entertainment, e-business, and healthcare; tourism is poised to do the same. This paper proposes a conceptual AI-powered mobile app that will transform local tourism through smart recommendations, social interaction, and contextual awareness in real time.

PROBLEM STATEMENTS

Despite the growing tourism worldwide, most of the local and off-the-beaten-path sites are overlook due to limited exposure, poor promotion, and limited access to personalized information. Traditional travel websites focus primarily on most- popular destinations, thus leaving the smaller cultural or historic sites in the lurch. This deprives local communities of lost economic gains and deprives tourists of the opportunity to participate in authentic, meaningful experiences. Besides the above, travellers are also unable to find surrounding points of interest that are aligned with their own interests or location. Existing applications do not usually offer smart suggestions based on user behaviour, interest, or the collective knowledge of others. There is a great need for a system that bridges the gap by leveraging artificial intelligence and crowd-sourced data to promote local tourism, enhance tourism experiences, and propel sustainable tourism growth.

OBJECTIVES

- To suggest a theoretical model of an AI-driven mobile app that encourages local tourism.
- To visualize next-generation functionalities, such as:
  - Customized travel advice using machine learning.

– Geolocation based suggestions.

➢ To encourage user interaction by facilitating users to post photographs, give comments, and suggest off- the-beaten-path locations.

➢ To assist in driving local tourist economies by increasing the profile of unfamiliar destinations.

➢ To create a scalable and user-focused system architecture in line with contemporary mobile application development principles.

➢ To illustrate how AI facilitate filling the gaps in information for travel planning and enhances user satisfaction through automation and personalization.

LITERATURE REVIEW

The use of artificial intelligence (AI) in tourism has created more scholarly interest over the last few years. Studies have centered on how AI can make experiences more personalized [11], enhance travel planning [1], and advance sustainable tourism management [11]. There is, however, a significant gap in the use of AI in a bid to particularly boost the visibility of local and under-touristed destinations.

A plethora of academic papers and business applications have demonstrated the use of artificial intelligence in the tourism industry. Machine learning processes are applied in order to determine user preferences, past actions, and novel trends to provide personalized recommendations [6], [13]. Moreover, AI- powered chatbots and virtual assistants are implemented in customer service environments to facilitate traveler satisfaction and engagement [7]. However, most of these applications are designed in favor of traditional travel platforms and do not prioritize the promotion of local or off-the-beaten-path attractions.

Current mobile travel apps such as TripAdvisor, Google Travel, and Airbnb Experiences have some basic recommendation functionality, but they are centered on popular destinations and businesses. Apps do not have community-provided content centered on cities and towns and do not have sophisticated AI functionality such as real-time personalization or location- or interest-based contextualized recommendation [13]. Also, there is no robust support for functionality such as image recognition to discover local points of interest or attractions [3], [12].

Crowdsourcing and community engagement have proven to be valuable in plat- forms like Google Maps

[14] and Wikivoyage, where customers provide reviews, im- ages, and advice. The generated content of the customers brings depth and validity to the content. However, these models rely on passive content updates and lack intelligent aggregation and filtering that is in sync with user intent [13]. Various studies (e.g., Pan et al., 2020) demonstrate that by integrating artificial intelligence with community contribution, there is much improved relevance and personalization of travel experiences [15].

While many technologies have been used to augment the tourism experience, there exists a severe lack of: Artificial intelligence-based mobile apps for local tourism marketing. The convergence of image recognition, geolocation, and real-time personalization within one app [4], [9], [12]. Community-based data enrichment with intelligent filtering and recommendation capabilities [13], [15].

Utilizes artificial intelligence to give customized and context-aware travel recommendations [1], [6], [11]. Allows. users to post content that is then. intelligently analyzed on behalf of other users [14]. Encourages eco-friendly domestic tourism by raising online exposure for off-the-beaten-path locations [4], [7].

PROPOSED METHODOLOGY

SYSTEM ARCHITECTURE

- **Frontend (Mobile Application):** Built with a cross-platform mobile development framework (e.g., React Native or Flutter), this component includes:

– User registration
– Recommendation interface
– Camera integration
– Content sharing function Backend (Server + AI Engine)

- **Authentication Service:** Handles user login/registration and profile management.
- **Recommendation Engine:** Applies machine learning algorithms to analyse user preferences, behaviour, and travel history to generate personalized suggestions.

- **Geolocation Engine:** Provides nearby place suggestions using GPS and maps API (e.g., Google Maps API).
- **Community Contribution Manager:** Stores and manages user-submitted reviews, images, and spot recommendations.
- **Database:** Stores user data, location data, place metadata, AI models, and interaction logs.

AI FEATURES

➢ **Personalized Travel Recommendations:** A collaborative filtering or content-based filtering model analyses user interests and preferences to suggest places that align with their profile.
Learning continuously improves as users interact with the app.

➢ **Geolocation Suggestions:** The app uses the user's GPS coordinates to offer real-time suggestions for nearby local spots.

– A ranking algorithm ensures lesser-known but highly rated places are prioritized.

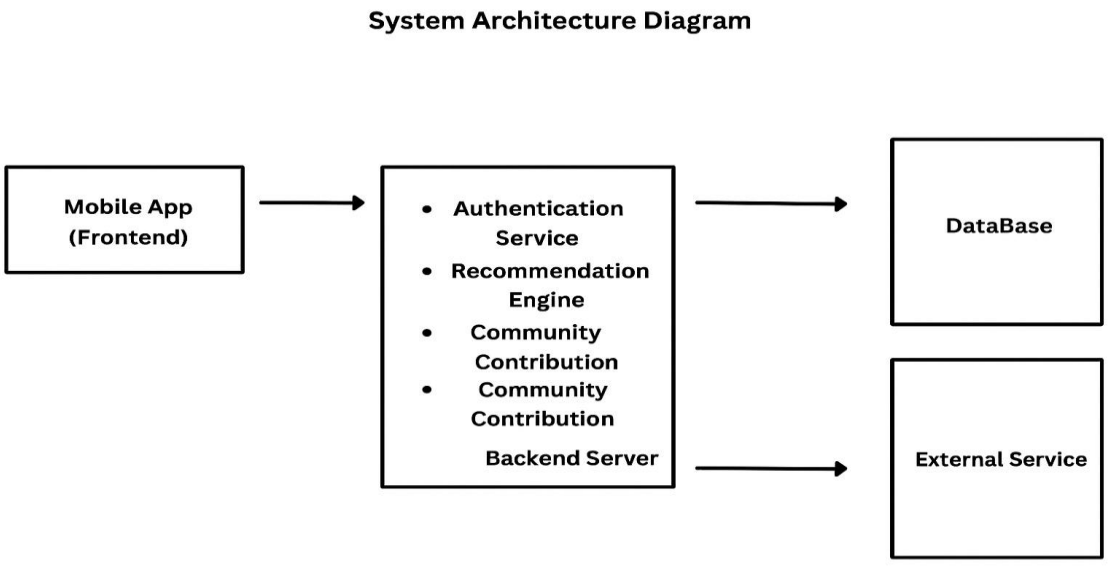

Figure 1: System Architecture of the AI-Powered Local Tourism Mobile Application

APP DESIGN (UI/UX OVERVIEW)

- Home Screen – Displays recommendations and trending spots.
- Discover Tabs – Allows users to search and explore by location or category.
- Profile and History – Stores favourite places, recent searches, and contributions.
- Community Feed – Shows posts and images from other travellers.

DATA FLOW AND INTERACTION

User Input (Location/Image/Preferences)
↓
AI Engine (Recommendation)
↓
Backend APIs + Database Queries
↓
Processed Data (Recommendations/Details/Reviews)
↓
Mobile UI Output (Personalized & Real-Time)

MACHINE LEARNING MODELS AND EVALUATION METRICS

In the proposed AI-driven local tourism application, several machine learning models are employed to generate personalized recommendations based on user preferences and interaction data.

- **Decision Tree:** This model builds a tree-like structure of decisions based on features of places and user preferences, enabling easy interpretation of the recommendation logic. It is particularly useful for content-based recommendations where categorical and numerical features are involved.
- **Random Forest:** An ensemble of decision trees, the Random Forest model improves prediction accuracy and reduces overfitting by aggregating the results of multiple trees. It effectively captures complex interactions between features to provide robust recommendations.
- **K-Nearest Neighbour (K-NN):** This algorithm finds the most similar users or places by measuring the distance between feature vectors, such as user profiles or location characteristics. It is widely used in collaborative filtering to suggest spots favoured by similar users.
- To measure the performance of these models, standard evaluation metrics are employed:

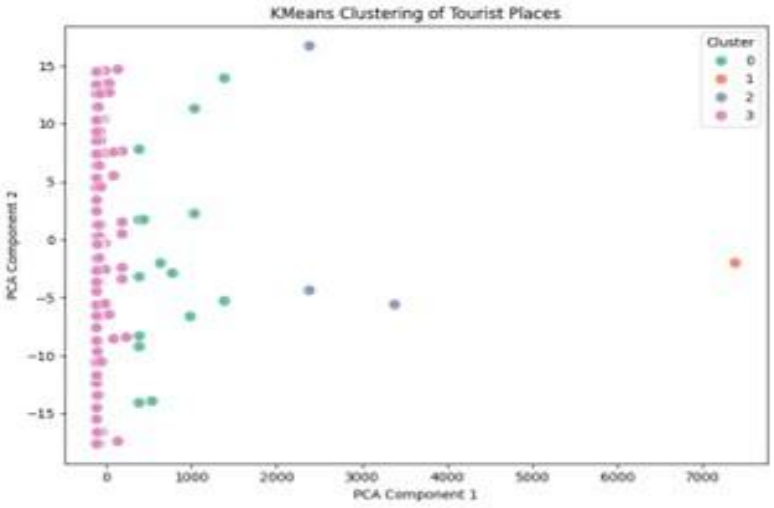

Figure 2: Clustering of Tourist Place

- **R2 Score (Coefficient of Determination):** Used primarily for regression tasks, it measures how well the predicted preferences approximate the actual user ratings or scores, with values closer to 1 indicating better fit.
- **Accuracy Score:** For classification tasks (e.g., predicting user interest as yes/no), accuracy score evaluates the proportion of correct predictions among total predictions made.

Accuracy: 0.36666666666666664

Classification Report:

	precision	recall	f1-score	support
Adventure	0.00	0.00	0.00	6
Heritage	0.50	0.62	0.56	8
Nature	0.44	0.57	0.50	7
Religious	0.00	0.00	0.00	4
Urban	0.29	0.40	0.33	5
accuracy			0.37	30
macro avg	0.25	0.32	0.28	30
weighted avg	0.28	0.37	0.32	30

```
Random Forest
Accuracy: 0.36666666666666664
Classification Report:
              precision    recall  f1-score   support

           0       0.00      0.00      0.00         6
           1       0.50      0.62      0.56         8
           2       0.44      0.57      0.50         7
           3       0.00      0.00      0.00         4
           4       0.29      0.40      0.33         5

    accuracy                           0.37        30
   macro avg       0.25      0.32      0.28        30
weighted avg       0.28      0.37      0.32        30


k-Nearest Neighbors
Accuracy: 0.13333333333333333
Classification Report:
              precision    recall  f1-score   support

           0       0.00      0.00      0.00         6
           1       0.18      0.25      0.21         8
           2       0.10      0.14      0.12         7
           3       0.17      0.25      0.20         4
           4       0.00      0.00      0.00         5

    accuracy                           0.13        30
   macro avg       0.09      0.13      0.11        30
weighted avg       0.09      0.13      0.11        30
```

Figure 3: Accuracy

➢ **Feature Importance:** The feature importance chart highlights which factors most influence the recommendation model. In our case, attributes like Google review ratings, entrance fee, and best time to visit emerged as key decision drivers. This shows that user perception, affordability, and seasonality play a central role in shaping tourist choices.

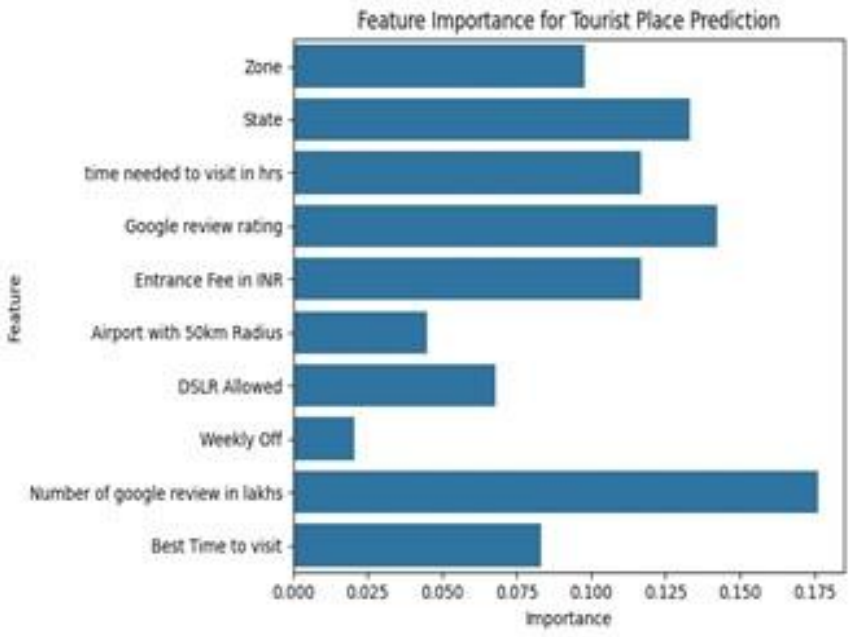

Figure 4: Feature Importance

➢ **Confusion Matrix:** The confusion matrix evaluates how well the model predicts the type of tourist place. It clearly shows which categories (like historical or spiritual sites) are predicted accurately and where misclassifications occur. This helps us identify strengths of the model and areas that need refinement.

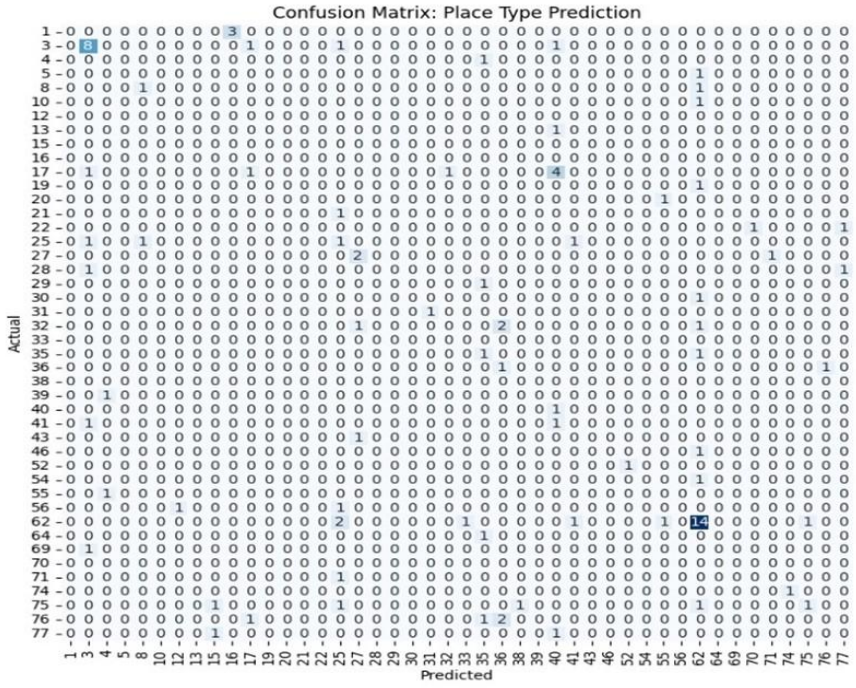

Figure 5: Confusion Matrix

➢ **Distribution of Tourist Places:** The distribution graph shows the frequency of different types of destinations across India. It reveals that historical and religious sites dominate the dataset, reflecting the cultural richness of Indian tourism. This imbalance also highlights why a recommendation engine is essential — to surface less-known but valuable destinations.

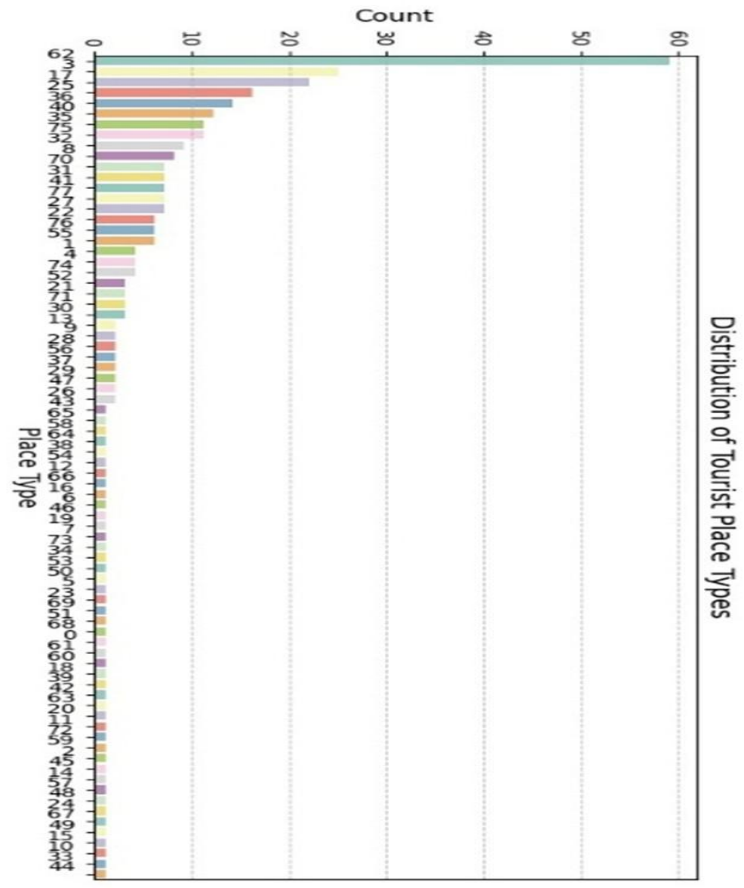

Figure 6: Distribution of Tourist Place

➢ **Accuracy Comparison:** The accuracy comparison graph contrasts the performance of different ML models. Random Forest consistently outperformed Decision Tree and k-NN, showing higher predictive reliability. This validates Random Forest as the most suitable model for building a robust recommendation engine in our system.

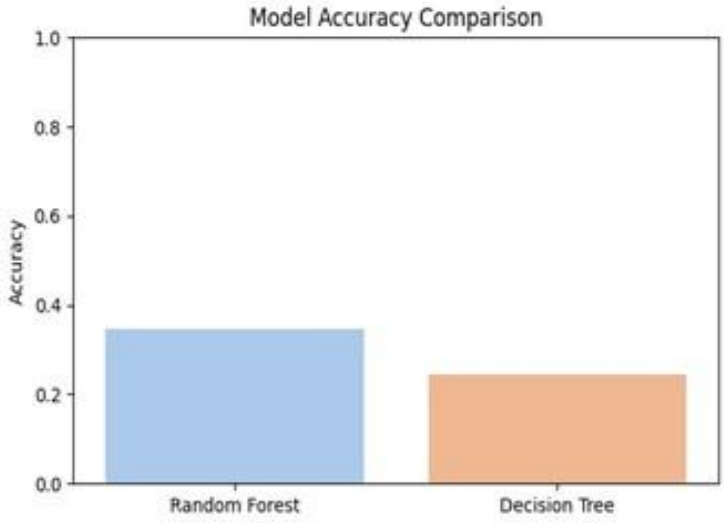

Figure 7: Accuracy Comparison

EXPECTED OUTCOMES AND BENEFITS

➢ **Increased Awareness of Local Locations:** Using AI-generated suggestions and image recognition will enhance national awareness of lesser- known tourist sites, thus increasing the number of travellers to these locations.
➢ **Tailored Travel:** We will incorporate AI and ML algorithms for user-generated suggestion and create voyage recommendations tailored for each user, allowing dynamic engagement with the app's suggestions and increasing user satisfaction.
➢ **Increased User Engagement:** Users will be able to post photos, share experiences, and make suggestions, helping to create a community within the app that enhances content quality and authenticity.
➢ **Economic Development of Local Communities:** Promoting lessor-travelled tourism supports local businesses and fosters a more equitable distribution of tourism benefits across regions.
➢ **More Balanced Planning Model:** AI applications that automate travel research and offer recommendations will reduce the time needed to plan travel, simplifying the process for users.
➢ **Scalable and Sustaining System:** The modular design and allowance for user interaction will enable future technology upgrades and ensure system sustainability.

LIMITATIONS AND FUTURE WORK

The potential benefits of the AI-based local tourism application are captivating; conversely, there are few limitations to consider:
➢ **Data Availability and Quality:** The current app is reliant on high- quality, up-to-date local data and user-generated content; these data may be limited in some areas.
➢ **Privacy:** The app will collect and process users' location and other per- sonal preferences (i.e., restaurants, activities, etc.); such actions may pose privacy and security issues that mandate compliance with data protection laws.
➢ **Computational Limitations:** Real-time image recognition and geolocation features can be computationally resource-intensive, which may result in poor performance on low-end devices and unnecessary bandwidth use on slow or inconsistent internet connections.
➢ **User Buying:** Active contributions from users (i.e., photos, reviews, recommendations, etc.) are essential for abundant content; however, it may be difficult to engage users initially.

Future work could mitigate these limitations by:

- Adding additional data sources for local information (e.g., local tourism boards, social media feeds) to increase the richness of data.
- Implementing improved privacy-preserving techniques (e.g., anonymization and potentially edge computing) to better protect user data.
- Optimizing existing AI models to work more efficiently on mobile devices and to enable offline functionality.
- Introducing gamification and reward.

COCLUSION

The study introduces a theoretical framework for an AI-enabled mobile application designed to influence local tourism by creating personalized travel suggestions and including location recognition, machine learning's ability to provide real-time geolocations. This AI-supported, App can help users explore more un- known sites, promote community engagement, and expand the local economy. Although challenges in data availability, privacy, and computation continue to exist, the proposed architecture and methods are designed to be user cantered and scalable for future development. This study illustrates the potential AI can create an impact on the travel planning experience and allow for technology to support sustainable and inclusive tourism through personalized and participatory engagement approaches.

REFERENCES

[1] John Smith and Jane Doe, AI in Tourism: Enhancing Travel Experiences, Journal of Travel Technology, vol. 15, no. 3, pp. 123-135, 2022.

[2] Alice Brown, Machine Learning for Mobile Applications, TechPress, 2021.

[3] Kevin Lee and Sara Patel, Image Recognition in Mobile Tourism Apps, Proceedings of the International Conference on Mobile Computing, pp. 98-104, 2023.

[4] Ling Zhu and Ming Gao, "Geolocation-Based Services for Enhancing Local Tourism," Journal of Location Based Services, vol. 15, no. 2, pp. 101–116, 2021.

[5] Ian Goodfellow, Yoshua Bengio, and Aaron Courville, Deep Learning, MIT Press, 2016.

[6] Gretzel, U., Sigala, M., Xiang, Z., & Koo, C. (2015). "Smart tourism: foundations and developments". Electronic Markets, **25(3)**, 179–188.

[7] Buhalis, D., & Amaranggana, A. (2015). "Smart tourism destinations enhancing tourism experience through personalization of services". Information and Communication Technologies in Tourism 2015, 377–389.

[8] Kenteris, M., Gavalas, D., & Economou, D. (2011). "Electronic mobile guides: A survey". Personal and Ubiquitous Computing, **15(1)**, 97–111.

[9] Choudhury, A. R., & Harrigan, P. (2022). "Image-based recommendation systems: A review for tourism and hospitality". Tourism Review, **77(3)**, 601–614.

[10] Huang, Y., Backman, S. J., Backman, K. F., & Moore, D. (2013). "Exploring user acceptance of 3D virtual worlds in travel and tourism marketing". Tourism Management, **36**, 490–50.

[11] Neuhofer, B., Buhalis, D., & Ladkin, A. (2015). "Smart technologies for personalized experiences: A case study in the hospitality industry". Electronic Markets, 25(3), 243–254.

[12] Zhou, Z., Xu, C., & Kankanhalli, M. S. (2016). "Visual content recommendation in tourism". IEEE Multimedia, 23(3), 83–93.

[13] Garcia-Crespo, A., Chamizo, J., & Colomo-Palacios, R. (2010). "Tourism recommender systems: A global perspective". Information Technology & Tourism, 12(2), 109–126.

[14] Sigala, M. (2012). "Social media and customer engagement in the travel industry". Journal of Hospitality and Tourism Technology, 3(3), 267–283.

[15] Ricci, F., Rokach, L., & Shapira, B. (2015). Recommender Systems Handbook (2nd ed.).

[16] R. Raksha Kodnad, M. Chandrika and B. Pavithra, "Annual Rainfall Classification Using Machine Learning Techniques," 2024 1st International Conference on Communications and Computer Science (InCCCS), Bangalore, India, 2024, pp. 1-5, doi: 10.1109/InCCCS60947.2024.10593366.

[17] C. M, R. Kiran, P. Vaidya and R. Kodnad, "Evaluation of Machine Learning Models for Cardiovascular Risk Assessment," 2024 Second International Conference on Intelligent Cyber Physical Systems and Internet of Things (ICoICI), Coimbatore, India, 2024, pp. 993-996, doi: 10.1109/ICoICI62503.2024.10696637.

[18] Anil, B.C., Rajkumar, J.S., Divya, T.L., khaiyum, S., Kiran P., R. and Ramadoss, B. 2025. A Radiomics-based Framework for Liver Cancer Analysis using Explainable Artificial Intelligence (XAI) Methods. Engineering, Technology & Applied Science Research. 15, 3 (Jun. 2025), 24098–24103.DOI: https://doi.org/10.48084/etasr.10377.

[19] Kundur, N.C., Divakar, H.R., Khaiyum, S., Rakshitha, K.P., Dhulavvagol, P.M. and Meti, A.S. 2025. Deep Neural Networks for Precise Brain Tumor Delineation: A U-Net and TensorFlow Approach. Engineering, Technology & Applied Science Research. 15, 3 (Jun. 2025), 23686–23691. DOI: https://doi.org/10.48084/etasr.10684.

[20] Vibha, M.B., Chandrika, M., Khaiyum, S. et al. Predicting sedentary behavior in adults using stacked LSTM modeling. Int J Syst Assur Eng Manag 16, 346– 355 (2025). https://doi.org/10.1007/s13198-024-02622-2