Advanced International Journal for Research (AIJFR)
E-ISSN: 3048-7641 ● Website: www.aijfr.com ● Email: editor@aijfr.com

# Smart park AI: Development of an Intelligent Parking Location and Navigation System

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**Abstract**
Urban drivers often circulate to find vacant parking, which increases congestion, fuel consumption, and stress. This study aimed to design SmartPark AI, a real-time parking location and navigation system with short-horizon availability forecasting and transparent recommendations. A modular architecture was implemented using spatio-temporal prediction, transfer learning, explainable artificial intelligence (XAI), and simulation-based stress testing. In semi-synthetic city-zone experiments, SmartPark AI achieved 85–90% prediction accuracy, maintained under 2 s response time, and reached an ≈88% successful recommendation rate with improved decision traceability.

**Keywords:** smart parking, intelligent transportation systems, spatio-temporal prediction, transfer learning, explainable AI

## 1. Introduction

Rapid urbanisation and increased private vehicle ownership have intensified pressure on limited parking infrastructure in dense city centres. A substantial portion of urban traffic is attributed to drivers searching for parking, which extends travel time and elevates fuel use and emissions. The resulting inefficiency affects commuters and complicates municipal traffic management.

Conventional parking guidance, including static signage and basic occupancy displays, is frequently delayed, incomplete, or not integrated with routing. Many Internet of Things (IoT) parking deployments remain siloed and react to current occupancy rather than anticipating near-future availability. Additionally, parking recommendations are often opaque, which reduces user trust and limits operational auditing.

This work addressed the need for fast, accurate, and explainable parking guidance under dynamic, multi-zone urban conditions. SmartPark AI was developed to forecast short-term availability, recommend suitable zones, provide navigation-ready outputs, and maintain traceable decision logs while supporting rapid adaptation across districts.

## 2. Literature Review

Smart parking research has evolved from local occupancy detection to city-scale services that combine sensing, cloud or fog computing, and artificial intelligence (AI). Cloud-based allocation can reduce search time, but practical deployments often show limited robustness, incomplete security treatment, and insufficient citywide validation. Fog-based approaches can reduce latency, yet evaluations are commonly constrained to single sites and narrow communication assumptions.

Recent methods have increasingly emphasised prediction and optimisation, but explainability and cross-city portability are rarely integrated into one framework. Transfer learning has been established as a mechanism to reduce cold-start cost across domains, while model-agnostic explainability methods have been shown to increase trust in AI decisions. However, systematic stress testing of parking intelligence pipelines under extreme demand and abrupt regime shifts remains limited.

| Study | Main Focus | Key Strength | Limitation / Gap Addressed by SmartPark AI |
|---|---|---|---|
| Channamallu et al. (2026) [1] | Review of AI/IoT smart parking | Consolidated challenges and architectures | Limited unified, traceable, explainable operational pipeline |
| Pham et al. (2015) [2] | Cloud-based smart parking | Reduced waiting time via allocation logic | Limited security and large-scale urban validation |
| Balfaqih et al. (2021) [3] | Fog-based prediction and routing | Lower latency; dynamic operation | Single-site scope; limited stress testing across zones |
| Ribeiro et al. (2016) [4] | Model-agnostic explanations | Improved interpretability of AI outputs | Not integrated with parking forecasting and decision logging |

**Table 1:** Literature Comparison

## 3. Methodology

SmartPark AI was implemented as an intelligent parking location and navigation framework that fused real-time occupancy inputs, traffic context, and spatio-temporal forecasting. A layered design was adopted to support continuous data ingestion, unified storage, model-serving services, and device-agnostic access from web, mobile, and in-vehicle clients. Structured data and logs were persisted in a relational store, while lightweight real-time synchronisation supported interactive updates.

The core intelligence combined (i) an Always-On Urban Parking Intelligence Engine for short-horizon availability forecasting, (ii) transfer learning to adapt pretrained models to new zones using limited local data, (iii) a simulation module that generated controllable demand and congestion scenarios for evaluation, and (iv) an explainable AI (XAI) recommendation component. Recommendations were computed using a multi-criteria scoring function that integrated predicted availability, estimated driving time, walking distance, and model confidence.

A traceable decision pipeline was enforced to log input snapshots, preprocessing outputs, model version identifiers, intermediate scores, and final recommendations. This design enabled reproducibility, auditing, and rapid diagnosis of anomalies during stress tests and iterative tuning.

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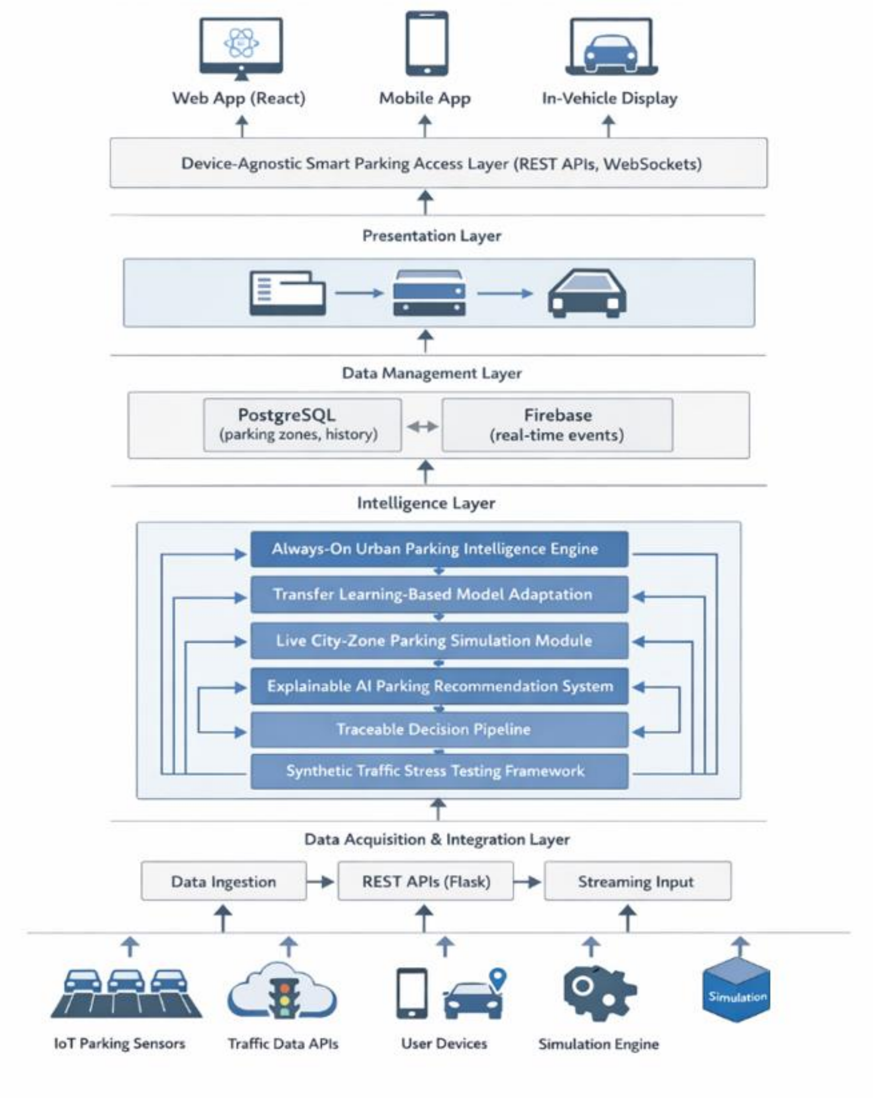


**Fig1:** System Architecture Diagram

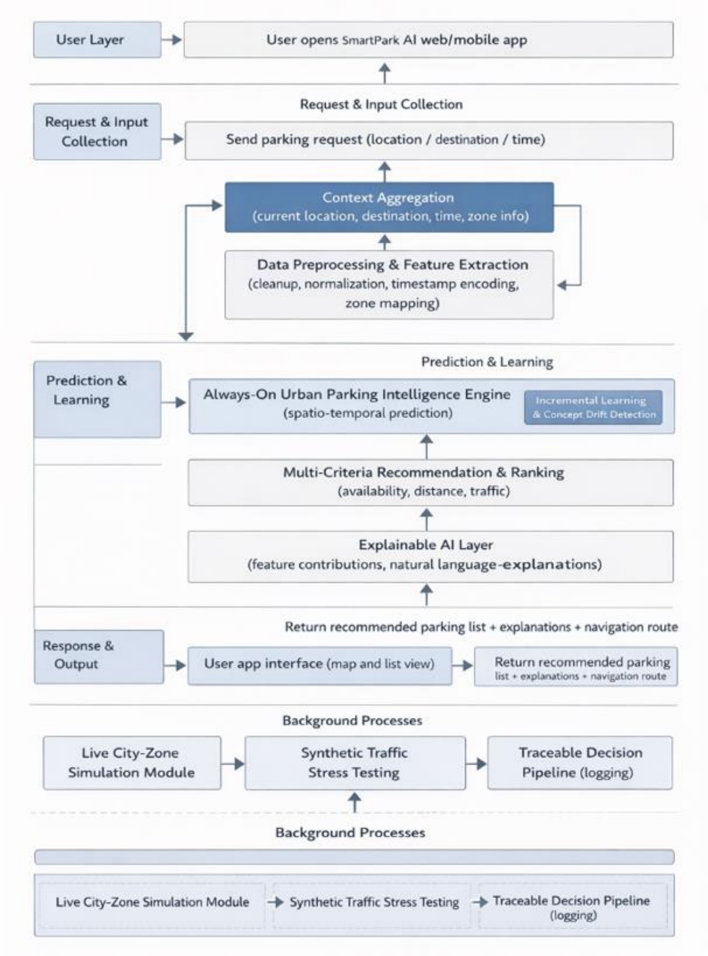


**Fig 2:** Workflow Diagram

## 4. Results and Discussion

SmartPark AI was evaluated in a semi-synthetic testbed that combined historical parking observations with simulated data generated for 20 heterogeneous parking zones across several months. Services were implemented in Python-based APIs with machine learning inference, and the user interface was validated on desktop and smartphone browsers. Performance was assessed using hold-out validation, end-to-end latency measurement, and synthetic stress testing with elevated arrival rates and abrupt occupancy changes.

The forecasting models achieved 85–90% short-horizon accuracy for 5–10 min prediction windows, and mean end-to-end response time remained below 2 s, including during stress scenarios. The observed successful recommendation rate of approximately 88% indicated that predicted availability could be translated into practically useful guidance through the ranking function. Trace logs reduced investigation time for rare mispredictions by preserving model inputs, confidence values, and scoring contributions.
User feedback from controlled tasks indicated that concise XAI statements increased willingness to follow recommendations, particularly when explanations referenced availability and reduced travel or walking distance. Accuracy degradation was observed during highly volatile event-driven surges that were under-represented in training data; however, confidence scores declined in these cases, which improved the appropriateness of user expectations.

| Metric | Observed Value |
|---|---|
| Prediction accuracy (5–10 min horizon) | 85–90% |
| Average response time (end-to-end) | < 2 s |
| Successful recommendation rate | ≈ 88% |
| Stability under stress testing | High (no outages) |

**Table 2:** System Performance

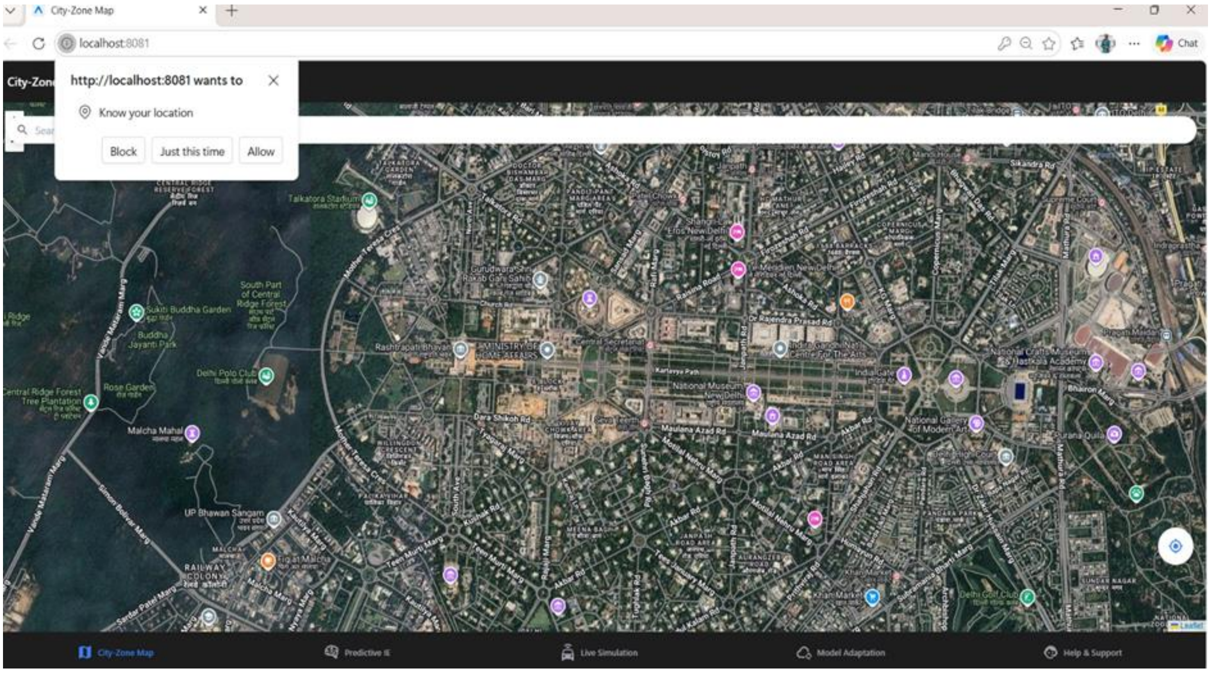


**Fig 3:** Application Screenshot – Home Page

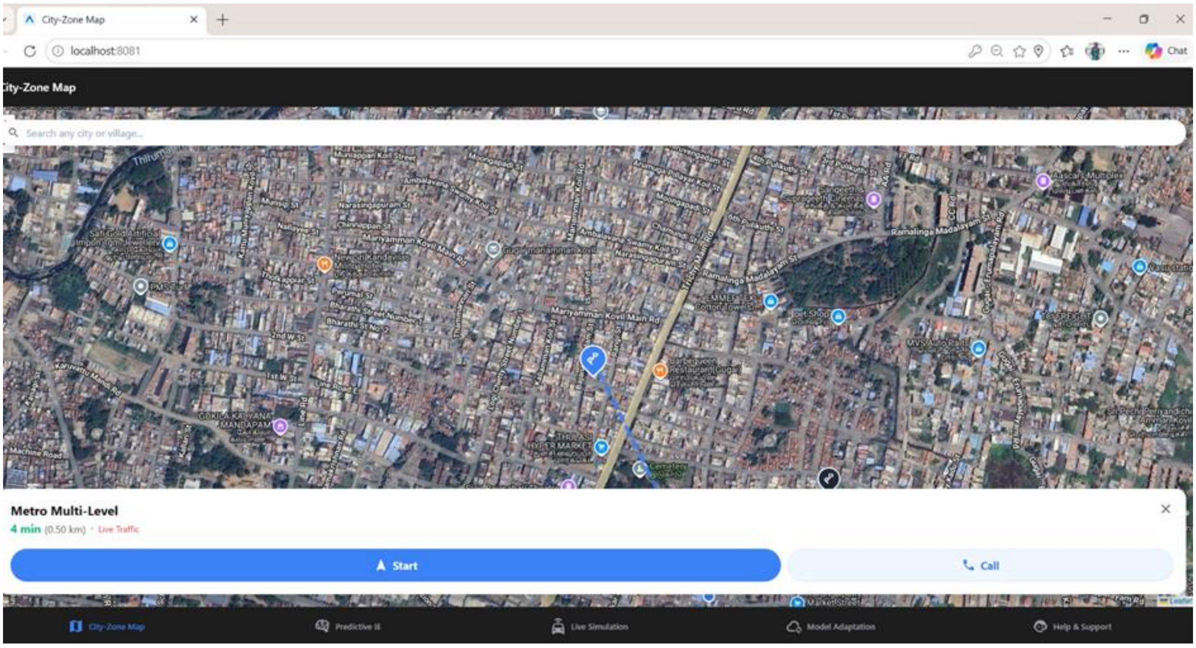


**Fig 4:** Application Screenshot – Results Page

## 5. Conclusion

SmartPark AI was developed to reduce urban parking search time by combining spatio-temporal forecasting, transfer learning-based adaptation, explainable recommendations, and a traceable decision pipeline within a modular architecture. Semi-synthetic evaluation across multiple zones demonstrated 85–90% prediction accuracy, interactive response time below 2 s, and an ≈88% successful recommendation rate, while maintaining stability under stress. Future work should prioritise field trials with live sensors, stronger privacy controls, and integration of payment, reservation, and edge-enabled sensing.

## 6. Acknowledgement

The authors acknowledge the institutional support and computing resources provided by the host department and organization. The authors also thank the volunteer participants who assisted with interface testing and feedback.

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