

Next-Park-AI: A Smart Parking Prediction and Recommendation System

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Abstract

Finding an empty parking spot has become a small daily battle for most drivers, and the problem only grows as vehicle ownership climbs faster than the infrastructure built to handle it. Campuses, shopping complexes, and dense city blocks show the same pattern: drivers circle the same stretch of road two or three times before giving up on a spot they can already see, wasting fuel, time, and patience. This review paper looks closely at three recent studies tackling different pieces of this problem: a destination-and-slot recommendation system for shared micromobility riders (U-Park), a comparative study of machine-learning classifiers predicting parking-space availability from IoT sensor data, and an LSTM-based analysis of how a university smart parking rollout affected citation rates. Rather than simply summarising these works, the paper re-analyses them side by side on the dimensions that matter most for a new system: the prediction task each solves, how much data it needs, what it achieves, and whether it could realistically be deployed, and uses that comparison to justify concrete design choices. These choices feed directly into Next-Park-AI, a MERN-stack smart parking prediction and recommendation platform currently being built, bringing together real-time availability tracking, AI-based slot recommendation, occupancy forecasting, online booking, QR-based entry verification, and secure digital payment in one place. The goal is straightforward: take what the research already shows works, pair it with the booking and payment features none of the three reviewed systems offer, and use this analysis as the documented foundation for the prototype now under development.

Keywords

Smart Parking, Machine Learning, Random Forest, LSTM, MERN Stack, Parking Prediction, Slot Recommendation, IoT, Occupancy Prediction

1. Introduction

The domain this work sits in is smart parking management, a specific slice of the broader intelligent transportation and urban mobility field that has grown alongside the steady rise in vehicle ownership across cities, campuses, and commercial complexes worldwide. Its application is easy enough to picture: any place where more cars arrive than there are visible, well-signed spots for them — a university campus during exam week, a mall parking lot on a weekend, a dense city block at rush hour.

The challenge is just as easy to observe from the driver's seat. In the absence of real-time information, drivers routinely circle congested areas searching for a free spot, which adds to traffic congestion, wastes fuel, and increases air pollution — all for something as small as an empty parking bay. Conventional parking management, built around manual attendants, static signage, or at best a simple sensor-based occupancy counter, does not offer predictive insight, personalized recommendations, or integrated digital booking. Drivers are left to guess, and administrators are left with limited data on how their spaces are actually used.

This gap is exactly what has pushed a growing body of research toward applying Internet of Things (IoT) sensing and machine learning (ML) to parking management over the past few years. That overcoming phase has progressed in stages rather than in one leap: early work focused on simply reporting occupancy in real time, later work moved to short-

horizon prediction of how occupancy will change, and the most recent work — the three papers reviewed in this study — pushes further into destination-aware slot recommendation and violation-compliance monitoring. Each stage has closed part of the gap, but, as this review shows, no single stage has closed all of it at once.

That incompleteness is the motivation behind this paper. It is one thing to read that a Random Forest model classifies parking availability at 93–94% accuracy, or that an LSTM network can detect a statistically significant drop in violations after a smart-parking rollout; it is another to ask what it would actually take to build a working, deployable system for a real campus or city block using these ideas — especially when the system in question, like the one this project's authors are building, starts with no historical data of its own and needs to be usable from day one. That practical question is what motivated the present review.

This paper's contribution is twofold. First, it re-analyses three recent, peer-reviewed studies not as isolated summaries but side by side, comparing them on the prediction task each solves, the data each one needs, the performance each reports, and how realistically each could be deployed by a new, data-scarce project — and it uses that comparison to justify a specific set of design decisions rather than simply listing what each paper did. Second, building directly on those decisions, the paper documents Next-Park-AI, a MERN-stack-based smart parking prediction and recommendation system currently under development, which brings together real-time availability tracking, AI-driven slot recommendation, occupancy prediction, online booking, QR-code-based verification, and secure digital payment in a single platform.

The remainder of the paper is organized as follows. Section 2 reviews the related literature as cited in the base project's own literature review; Section 3 re-analyses the three core studies comparatively; Section 4 states the final design decisions drawn from that re-analysis; Section 5 states the problem addressed by this work; Section 6 defines the objectives; Section 7 describes the proposed system's working principle and methodology; Section 8 lists the hardware and software requirements; Section 9 presents the system architecture; Section 10 discusses expected outcomes; Section 11 outlines the project timeline; and Section 12 concludes the paper, along with its limitations.

2. Literature Review

Three peer-reviewed works form the primary basis of this review, spanning micromobility parking recommendation, IoT-based availability prediction, and campus-scale violation forecasting. Table 1 summarizes their methodology, findings, and limitations, followed by a detailed discussion of each.

2.1 U-Park: A User-Centric Smart Parking Recommendation System (Yan, O'Connor & Liu, 2024)

Yan et al. proposed U-Park, a recommendation system designed for Electric Shared Micromobility Services (ESMS) such as shared e-bikes. The system divides a user's journey into pre-journey, in-journey, and post-journey stages, and applies a two-step machine-learning pipeline: an Artificial Neural Network (ANN) predicts the likely destination from historical trip records at the start of a journey, and an Attention-based Recurrent Neural Network (ARNN) refines this prediction using live GPS trajectory data as the trip progresses. Once the destination is

estimated, an ASTGCN-inspired model forecasts parking-space availability at nearby stations and recommends a station using a probability-weighted scheme based on availability at the destination and at nearby alternatives. Tested on real-world data from the MOBY Bikes service in Dublin, Ireland, the system achieved destination-prediction accuracy above 97.60% without requiring explicit user input, and improved the probability of finding an available parking spot by 24.91% on average (up to 29.66% in constrained scenarios). The authors note that the approach was validated only on a shared e-bike dataset, and that parking-availability data had to be approximated from a comparable open dataset because station-level records were unavailable — limiting its direct applicability to private-vehicle or car-park scenarios.

2.2 Machine Learning-Based Prediction of Parking Space Availability in IoT-Enabled Systems (Dahiya et al., 2024)

Dahiya et al. conducted a comparative evaluation of six machine-learning classifiers — K-Nearest Neighbours, Support Vector Machine, Random Forest, Decision Tree, Logistic Regression, and Naive Bayes — for predicting parking-space availability ten minutes ahead, using IoT sensor data collected from car parks in Birmingham, United Kingdom. After hyperparameter tuning via grid search and evaluation at two train/test thresholds (65% and 85%), Random Forest consistently achieved the best performance across precision, recall, accuracy, and F1-score, reaching roughly 93-94% accuracy at both thresholds, while Logistic Regression and Naive Bayes performed weakest. The study also modelled system waiting time using an M/M/c queueing formulation and showed that the proposed Random Forest model reduced average waiting time substantially compared to the other classifiers as vehicle volume increased. While effective for short-horizon occupancy classification, this work is confined to predicting availability at a fixed location; it does not address destination prediction, personalized recommendation, or booking.

2.3 Evaluating the Impact of Smart Parking Systems on Parking Violations (Javaheri et al., 2024) — Base Paper

Javaheri et al. investigated whether the deployment of a Smart Parking System (SPS) — sensor-based real-time occupancy monitoring paired with a 'Parking Finder' web application — measurably changed driver compliance on a university campus. Using five years of parking-citation data (2018-2023), the authors trained a Long Short-Term Memory (LSTM) network to forecast expected violations from historical patterns, then compared these forecasts against actual citations issued after the SPS was introduced in September 2023. Actual violation counts were consistently and significantly lower than the LSTM's predictions, and a Kolmogorov-Smirnov test confirmed that the pre- and post-SPS distributions differed significantly (KS statistic = 0.916, $p = 1.775e-05$), indicating that real-time monitoring measurably improved compliance. Feature-importance analysis further showed that holidays and exam periods were the strongest predictors of violation spikes. The authors acknowledge that the study is limited to a single university campus and does not incorporate weather or trip-origin data, and that it addresses enforcement/compliance outcomes rather than proactive guidance or booking for drivers.

Author(s) & Year	Technology / Method	Key Findings	Limitations / Gaps
Yan, O'Connor & Liu (2024)	U-Park: ANN-based history destination prediction, ARNN trajectory-based prediction, ASTGCN-based parking-space availability prediction	Predicted user destination with over 97.60% accuracy without direct user input; improved probability of obtaining a parking spot by 24.91% on average (29.66% maximum) when availability was limited	Validated only on a shared e-bike (ESMS) dataset from Dublin; relies on approximated parking-availability data from a comparable open dataset rather than direct station-level records; not tested for private-vehicle parking

Dahiya, Mittal, Sharma, Lilhore, Simaiya, Ghith & Tlija (2024)	Comparative ML study: KNN, SVM, Random Forest, Decision Tree, Logistic Regression, Naive Bayes on IoT sensor data	Random Forest consistently outperformed other classifiers, reaching about 93-94% accuracy for predicting 10-minute-ahead parking-space availability in a Birmingham, UK IoT dataset	Focuses purely on availability classification; no destination or route awareness, no booking/reservation, and no user-facing recommendation layer
Javaheri, Channamallu, Kermanshachi, Rosenberger, Pamidimukkala, Kan & Hladik (2024) — Base Paper	LSTM network trained on five years of campus parking-citation data to forecast violations before and after Smart Parking System (SPS) deployment	Actual violations were consistently lower than LSTM-predicted values after SPS rollout (KS statistic 0.916, $p = 1.775e-05$), showing real-time monitoring measurably improved compliance; holidays and exam periods were the most influential features	Confined to a single university campus; excludes weather and trip-origin data; addresses compliance/enforcement rather than proactive slot recommendation or booking

Table 1: Summary of reviewed literature

Beyond the three papers reviewed in depth, related work cited alongside this study in the project's own literature review includes Kotb et al. (2018), who examined the role of IoT-based smart parking in smart cities and demonstrated improved space utilization but without AI-based prediction, online booking, or digital payment; Jiang et al. (2020), who designed a real-time parking-monitoring system that reported live availability but offered no booking or recommendation capability; and Saharan et al. (2023), who proposed DyPARK, a dynamic pricing and allocation scheme for on-street parking. Collectively, this body of work demonstrates that while individual components of a smart parking solution — availability prediction, destination-aware recommendation, and compliance monitoring — have each been studied and validated separately, no single system in the reviewed literature integrates real-time availability, AI-based slot recommendation, occupancy prediction, secure online booking, and digital payment into one unified, deployable platform.

3. Comparative Re-Analysis of Reviewed Studies

Rather than treating the three core papers as independent data points, this section re-analyses them side by side across the dimensions that matter for selecting a design direction for Next-Park-AI: the prediction task each system solves, its data requirements, its demonstrated accuracy, and its real-world deployability. Table 2 presents this comparison.

Dimension	U-Park (Yan et al., 2024)	RF Comparative Study (Dahiya et al., 2024)	LSTM SPS Study (Javaheri et al., 2024)
Prediction task	Destination + parking-station recommendation	Short-horizon (10-minute) space-availability classification	Long-horizon violation-count forecasting
Core technique	ANN (history) + ARNN (trajectory) + ASTGCN-style availability model	Random Forest (best of 6 classifiers tested)	LSTM (single layer, 50 units)
Minimum data needed to train	Multi-trip per-user history + live GPS trajectory stream	Tabular sensor/booking features; no long history required	~5 years of historical citation records
Reported performance	>97.60% destination accuracy; +24.91% avg. parking-spot probability	~93-94% accuracy, precision, recall, F1 at 65%/85% thresholds	KS = 0.916, $p = 1.775e-05$ (distribution shift, not accuracy)
Real-time capability	Yes, updates during in-journey stage	Yes, 10-minute-ahead classification	No — retrospective/periodic forecasting
Booking / payment / verification	Not included	Not included	Not included
Feasibility for a new, data-scarce college project	Low — depends on trajectory history the project does not yet have	High — trainable incrementally from early booking/sensor data	Low at launch — needs years of historical records

Table 2: Comparative re-analysis across the reviewed studies

Three observations follow from this re-analysis. First, on predictive accuracy alone, all three approaches perform well within their own task: U-Park's ARNN exceeds 97% destination-prediction accuracy, Dahiya et al.'s Random Forest reaches roughly 93-94% availability-classification accuracy, and Javaheri et al.'s LSTM is not evaluated on raw accuracy but on its ability to detect a statistically significant behavioural shift (KS = 0.916). These numbers are not directly comparable because the three

systems solve different problems — destination prediction, short-horizon occupancy classification, and long-horizon violation forecasting, respectively — so accuracy cannot be the sole basis for selecting one technique over another.

Second, on data and infrastructure requirements, U-Park's trajectory-based ARNN depends on continuous GPS trajectory streams and a multi-year historical trip history per user, which a new booking platform with no existing user base cannot supply at launch. Javaheri et al.'s LSTM depends on multiple years of historical citation/violation records, which likewise do not exist for a new system. Dahiya et al.'s Random Forest, by contrast, operates on structured, tabular sensor/booking features (time of day, day of week, occupancy counts) that can be generated incrementally from the very first bookings the platform records, and it requires comparatively little hyperparameter tuning (a shallow forest of 100 trees, as reported by Dahiya et al.) to reach strong accuracy — making it the only one of the three techniques that is practically trainable during an early-stage college project with a limited data-collection window.

Third, on system-level completeness, none of the three papers implements booking, payment, or entry/exit verification; each solves one stage of the parking problem in isolation. This confirms that the integration itself — not any single prediction algorithm — is the primary contribution opportunity available to Next-Park-AI.

4. Final Design Decision

Based on the comparative re-analysis above, the following design decisions have been finalized for Next-Park-AI:

Prediction technique: Random Forest (Scikit-learn) is adopted for occupancy/demand prediction, following the strongest evidence of accuracy-versus-data-requirement trade-off among the three studies reviewed (Dahiya et al., 2024). LSTM- and ARNN-style sequence models are noted as a future enhancement once sufficient longitudinal booking data has been collected post-deployment, consistent with the multi-year data volumes those models required in the reviewed literature.

Recommendation logic: The weighted-scoring approach to slot recommendation (distance, availability, charges) is retained from the working principle in Section 7, informed by U-Park's probability-weighted station-recommendation strategy, but simplified to avoid U-Park's dependency on continuous GPS trajectory history, since Next-Park-AI targets general drivers booking in advance rather than in-journey micromobility users.

Compliance and monitoring: The real-time synchronization (Socket.IO) and QR-based verification approach is retained as the practical, deployable analogue of the compliance improvement that Javaheri et al. attributed to real-time monitoring — achieving a similar effect (visibility and enforcement at the point of entry/exit) without requiring years of citation history to demonstrate value.

System scope: Booking, payment, and admin analytics are treated as first-class features from the outset, directly addressing the integration gap common to all three reviewed papers and the broader survey literature.

This decision set is treated as final for the current development phase; it will be revisited once real usage data is available, at which point the feasibility of layering an LSTM-based long-horizon forecasting module on top of the Random Forest baseline can be re-evaluated.

5. Problem Statement

Rapid urbanization and rising vehicle ownership have made parking management a major challenge in smart cities and institutional campuses alike. The reviewed literature confirms that current systems, taken individually, lack at least one of the following: real-time availability visibility, intelligent slot recommendation, online reservation, or secure digital payment — resulting in continued congestion, wasted fuel, and

driver frustration. There is a need for an integrated, AI-based platform that combines real-time data, predictive analytics, and digital booking into a single, user-facing system.

6. Objective

- Develop an AI-based Smart Parking Management System (Next-Park-AI) for efficient, citywide parking management.
- Provide real-time parking availability, online slot booking, and secure digital payment within a single platform.
- Optimize parking-space utilization and reduce traffic congestion through intelligent, data-driven slot recommendations.

7. Working Principle & Methodology

Next-Park-AI is being developed as a full-stack web platform built on the MERN stack (MongoDB, Express.js, React.js, Node.js), combined with a Python/Scikit-learn AI module for prediction and recommendation. The intended workflow is as follows:

- User Authentication:** Secure registration and login implemented with JWT-based tokens and Passport.js.
- Parking Search:** Nearby parking locations displayed on an interactive map using Leaflet (OpenStreetMap).
- Slot Recommendation:** A weighted-scoring approach considers distance, current availability, and parking charges to recommend the most suitable slot.
- Parking Reservation:** Slot booking is handled through the React.js web application.
- Online Payment:** Payments are processed securely via the Razorpay gateway.
- QR Verification:** A QR code is generated for each booking to enable secure vehicle entry and exit.
- Real-Time Updates:** Socket.IO synchronizes slot availability across all connected clients instantly.
- Occupancy Prediction:** A Random Forest model (Python, Scikit-learn) forecasts parking demand, drawing on the comparative evidence from Dahiya et al. (2024) that Random Forest outperforms alternative classifiers for this task.
- Admin Dashboard:** Chart.js visualizations present bookings, occupancy trends, and revenue to administrators.

This methodology is directly informed by the reviewed literature: the destination- and availability-aware recommendation logic draws on the two-stage prediction approach of U-Park, the choice of Random Forest for occupancy prediction follows the comparative results reported by Dahiya et al., and the emphasis on real-time monitoring as a compliance and efficiency driver reflects the findings of Javaheri et al.

8. Hardware / Software Requirements

The system is designed to run entirely on standard commodity hardware and cloud infrastructure, without dedicated IoT sensor deployment at this development stage. The core software components are summarized in Table 3.

Module	Technology Used
Frontend	React.js, HTML, CSS, JavaScript
Backend	Node.js, Express.js
Database	MongoDB Atlas
Authentication	JWT, bcrypt
Cloud Storage	Cloudinary
Maps & Navigation	Leaflet (OpenStreetMap)
Payment Gateway	Razorpay
Real-Time Communication	Socket.IO
QR Code Generation	QRCode (npm package)
Data Visualization	Chart.js
AI / ML Module	Python, Scikit-learn (Random Forest)
Deployment	Vercel (Frontend), Render (Backend)

Table 3: Technology stack used in Next-Park-AI

9. Construction Design / System Architecture

The system follows a client-server architecture. Users interact through the React.js web application, which communicates with a Node.js/Express.js REST API. The API layer reads and writes parking, booking, and user data to a MongoDB Atlas database, invokes the Python-based AI module for slot recommendation and occupancy prediction, and integrates with external cloud services — Cloudinary for media storage, Razorpay for payments, and Leaflet/OpenStreetMap for mapping. Socket.IO maintains a persistent connection between the server and connected clients to propagate real-time occupancy changes without requiring page refreshes.

10. Expected Result and Discussion

Real-time parking-slot availability displayed to users.

Users able to search, reserve, and pay for parking spaces within the application.

AI-based recommendation of the best available slot by availability, distance, and charges.

QR-code verification enabling secure, fast entry and exit.

Continuously accurate availability through real-time synchronization.

An administrator dashboard summarizing bookings, occupancy, revenue, and usage reports.

Taken together, these outcomes are expected to reduce parking search time, traffic congestion, and fuel consumption, addressing the specific gaps — absence of integrated booking, payment, and AI recommendation — identified across the reviewed literature.

11. Project Timeline

Phase	Activity	Duration
Phase 1	Literature Review & Requirement Analysis	Week 1-2
Phase 2	System Design & Database Design	Week 3-4
Phase 3	Frontend Development (React.js)	Week 5-6
Phase 4	Backend Development (Node.js & Express.js)	Week 7-8
Phase 5	AI Module & Integration	Week 9
Phase 6	Testing & Bug Fixing	Week 10
Phase 7	Deployment, Documentation & Final Presentation	Week 11-12

Table 4: Proposed development timeline

12. Conclusion and Limitations

The reviewed literature shows that machine-learning and deep-learning techniques — ANN/ARNN-based destination prediction, Random Forest-based occupancy classification, and LSTM-based violation forecasting — have each demonstrated strong, measurable improvements in specific aspects of parking management, yet no single existing system combines real-time availability, AI-driven recommendation, online booking, secure payment, and compliance verification into one integrated platform. Next-Park-AI is being developed to close this gap by combining a MERN-stack web application with an AI/ML recommendation and prediction module, real-time synchronization, QR-based verification, and integrated payment. The system is expected to improve space utilization, reduce congestion and search time, and deliver a more efficient parking experience for both users and administrators, with future scalability toward smart cities, malls, airports, hospitals, and other commercial parking facilities.

That said, this review has its own limitations, and it is worth being upfront about them rather than overstating what has actually been established. First, the comparative analysis in Sections 3 and 4 is built on three core papers plus a handful of supporting citations; it is not an exhaustive survey of the smart-parking literature, and other relevant

approaches — particularly newer deep-learning or transformer-based methods — may exist outside its scope. Second, the design decisions drawn from that analysis, including the choice of Random Forest for occupancy prediction and a weighted-scoring approach for slot recommendation, are reasoned from the reported results of other systems rather than from any experiments run on Next-Park-AI's own data, since the platform has no historical booking history to train or validate against yet. Third, the accuracy figures and compliance findings quoted throughout this paper (97.60% destination accuracy, 93–94% availability accuracy, a KS statistic of 0.916) belong to the original studies and their specific datasets — Dublin micromobility trips, Birmingham IoT sensors, and a single US university campus — and cannot be assumed to transfer directly to Next-Park-AI's deployment context without independent evaluation once the system is live. Finally, the current design does not incorporate physical IoT occupancy sensors, weather data, or trip-origin information, relying instead on booking-based occupancy records; extending the model with these inputs is left as future work once the platform has real usage data to draw on.

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