Smart Parking System Using Artificial Intelligence and IoT with Convolutional Neural Network Algorithm

[1]Amreen Fatima ,[2]Dr. Harikrishna Bommala
[1]*M. Tech Scholar, Department of CSE, KG Reddy college of Engineering and Technology*
[2]*Professor, Department of CSE, KG Reddy college of Engineering and Technology*

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Abstract—Rapid urbanization and the exponential rise in vehicle ownership have intensified parking-related challenges in metropolitan areas, resulting in traffic congestion, fuel wastage, and environmental degradation. This paper presents the design and development of an intelligent parking management framework that integrates Artificial Intelligence (AI), Internet of Things (IoT), and Convolutional Neural Networks (CNN). Deployed IoT sensors and surveillance cameras continuously capture occupancy data from parking slots, which is transmitted through an edge gateway to a cloud server for storage and analysis. A trained CNN model processes camera imagery to accurately determine slot availability even under adverse lighting or weather conditions. Users interact with the system via a mobile or web application that provides real-time slot status, advance reservation, turn-by-turn navigation, and automated digital payments. An administrative dashboard offers comprehensive monitoring, analytics, and revenue management capabilities. System evaluation encompassed unit, integration, white-box, black-box, and acceptance testing, all demonstrating high accuracy and reliability. The proposed architecture is modular, scalable, and extensible to smart city ecosystems, contributing to reduced urban congestion, lower carbon emissions, and enhanced driver convenience.

Index Terms—Smart Parking, Convolutional Neural Network, Internet of Things, Artificial Intelligence, Real-Time Monitoring, Urban Mobility

I. INTRODUCTION

The proliferation of motor vehicles in urban environments has created a persistent challenge for city planners and commuters alike: the scarcity of accessible parking. Conventional parking systems—typically manual, ticket-based, or equipped with elementary boom-barrier

mechanisms—lack the intelligence to relay real-time slot availability, leading to circuitous vehicle movement, fuel loss, and elevated greenhouse gas emissions. Studies indicate that a significant fraction of urban traffic congestion is attributable to drivers searching for vacant parking spaces [1].

Advances in three converging technological domains—Artificial Intelligence (AI), Internet of Things (IoT), and deep learning-based computer vision—present a compelling opportunity to transform parking infrastructure into responsive, data-driven systems. IoT devices embedded within parking bays can relay occupancy signals at near-zero latency; CNN-based detectors can classify slot states from camera feeds with high accuracy regardless of ambient conditions; and cloud-backed application interfaces can aggregate this intelligence into user-facing services such as advance booking, guided navigation, and cashless settlement.

This paper describes the end-to-end architecture, implementation, and evaluation of a Smart Parking System (SPS) that synthesises these three paradigms. Section II reviews related literature. Section III elaborates the proposed system architecture and module design. Section IV details the software and hardware specifications. Section V covers the UML and database design. Section VI discusses implementation outcomes. Section VII presents the testing strategy and results. Section VIII concludes with future research directions.

II. RELATED WORK

Early IoT-based parking solutions relied exclusively on ultrasonic proximity sensors to detect vehicle presence and update occupancy databases [2]. While effective under controlled conditions, such systems exhibited performance degradation when sensors were obscured by dirt, water ingress, or hardware faults, motivating a hybrid sensing approach.

The application of computer vision to parking management was explored by Huang et al. [11], who demonstrated that camera-derived occupancy classification outperforms sensor-only approaches in heterogeneous real-world environments. Subsequent studies incorporated deep CNNs—particularly adaptations of VGGNet and ResNet architectures—to achieve classification accuracies exceeding 97% on benchmark datasets such as PKLot [13].

Parallel research focused on predictive analytics: recurrent neural network (RNN) and long short-term memory (LSTM) models were trained on historical occupancy logs to forecast demand patterns and enable proactive resource allocation [18]. Integration of such predictive capabilities with live IoT feeds remains an open area of investigation.

Cloud-connected parking platforms with mobile interfaces were proposed in [17], yet these implementations lacked the CNN-based detection layer, relying instead on manual check-in or RFID-triggered state transitions. The present work addresses this gap by unifying real-time CNN inference, IoT telemetry, cloud orchestration, and a full-featured user application within a single coherent system.

III. PROPOSED SYSTEM ARCHITECTURE

The SPS adopts a four-tier layered architecture that cleanly separates physical sensing, edge preprocessing, cloud processing, and application delivery.

A. IoT and Hardware Layer

Each parking bay is instrumented with an ultrasonic proximity sensor and an IP camera. Sensors deliver a binary occupied/vacant signal, while cameras supply continuous MJPEG streams. Both classes of device are connected via Zigbee mesh or Wi-Fi to a Raspberry Pi 4-based IoT gateway deployed per parking zone.

B. Edge / Gateway Layer

The gateway aggregates raw sensor readings and periodically samples camera frames. A lightweight preprocessing pipeline applies histogram equalisation, gamma correction, and noise suppression before packaging data into MQTT messages directed to the cloud broker. Edge-based preprocessing reduces uplink bandwidth by approximately 60% compared to raw-stream forwarding.

C. Cloud and Processing Layer

A cloud server (deployable on AWS, Azure, or GCP) hosts the central database (MySQL/MongoDB), the REST API backend (Python/Flask), and the CNN inference service. The CNN model—a fine-tuned MobileNetV2 trained on the PKLot dataset augmented with locally captured images—processes incoming frames and updates slot state records in near real-time. The cloud layer also handles user account management, booking transactions, payment gateway integration, and analytics aggregation.

D. Application and User Layer

End-users interact with a cross-platform mobile application (React Native) or a responsive web interface. Features encompass slot availability visualisation, advance reservation with calendar integration, in-app navigation powered by mapping APIs, and digital payment via credit/debit card or UPI. A dedicated admin dashboard provides real-time monitoring, occupancy heatmaps, revenue analytics, and system health alerts.

IV. MODULE DESIGN

The system is decomposed into four loosely coupled modules, each with well-defined interfaces.

Table I: System Module Summary

Module	Primary Responsibility
Data Acquisition	Sensor polling, camera capture, preliminary edge preprocessing, MQTT telemetry dispatch

AI Processing	CNN inference for slot classification, sensor-vision fusion, anomaly flagging
Communication	MQTT/HTTPS data relay, API routing, push notification dispatch, payment gateway bridging
User Interface	Slot discovery, reservation workflow, navigation, payment, admin analytics dashboard

V. CNN-BASED DETECTION ENGINE

The detection engine constitutes the analytical core of the SPS. Raw camera frames are first subject to a preprocessing pipeline: contrast-limited adaptive histogram equalisation (CLAHE) normalises illumination variations, followed by bilinear resizing to 224×224 pixels and per-channel mean subtraction consistent with the ImageNet distribution used during MobileNetV2 pre-training.

MobileNetV2 was selected over heavier architectures (VGG16, ResNet50) on account of its inverted residual structure and linear bottlenecks, which jointly reduce parameter count while retaining representational capacity. The final classification head was replaced with a two-node softmax layer (vacant / occupied) and fine-tuned for 50 epochs on a combined dataset of 12,416 labelled slot images spanning daylight, dusk, and artificial-light conditions. The model achieved a validation accuracy of 98.3% and an inference latency of 14 ms per slot on a cloud GPU instance, satisfying the sub-30 ms real-time requirement.

A confidence threshold of 0.85 is enforced: slots for which neither class probability exceeds this threshold are flagged as 'uncertain' and resolved via the co-located ultrasonic sensor reading, implementing a sensor-fusion fallback that handles occlusion, glare, and sensor obstruction gracefully.

VI. DATABASE DESIGN

The relational database schema is normalised to third normal form (3NF) to eliminate transitive dependencies and ensure data integrity. Core tables include: Users (user_id PK, name, email, phone, password_hash, user_type, status), ParkingLocations (location_id PK, name, address, city, coordinates), ParkingSlots (slot_id PK, location_id FK, slot_number, slot_type, floor, status ENUM, sensor_id FK), Bookings (booking_id PK, user_id FK, slot_id FK, vehicle_id FK, booking_time, start_time, end_time, status ENUM, total_amount), Payments (payment_id PK, booking_id FK, amount, method, status ENUM, transaction_id, paid_at), Sensors (sensor_id PK, slot_id FK, sensor_type, last_status ENUM, last_updated), and SystemLogs (log_id PK, admin_id FK, action, table name, record_id, ip_address).

Foreign key constraints with CASCADE rules maintain referential integrity across booking and payment lifecycles. Indexes are maintained on slot_id, user_id, booking_time, and payment_status to support sub-millisecond query response for the real-time dashboard. All monetary values are

stored as DECIMAL (10,2) and datetime fields use the UTC DATETIME type to prevent timezone inconsistencies in multi-region deployments.

VII. SYSTEM TESTING

A multi-level testing strategy was employed to validate correctness, performance, and reliability across all system components.

A. Unit Testing

Individual modules—sensor polling functions, CNN inference wrappers, database access objects, and payment processing routines—were tested in isolation using pytest (Python) and JUnit (Java). Mock objects simulated sensor hardware and external payment gateways. Achieving 94% code coverage confirmed that edge cases including sensor timeout, malformed MQTT payloads, and duplicate booking attempts were handled correctly.

B. Integration Testing

Incremental integration testing verified data flow across module boundaries: sensor→gateway→cloud→database and user-request→API→database→notification. All 12 integration scenarios passed, confirming correct serialisation, protocol compliance, and database transaction integrity under concurrent access.

C. Black-Box and White-Box Testing

Black-box test cases covered equivalence partitions (valid/invalid credentials, available/occupied slot booking, successful/failed payment) and boundary values (zero available slots, maximum booking duration). White-box techniques—branch coverage and path coverage—verified the CNN inference conditional logic and the billing calculation loops. All 12 documented test cases (TC01–TC12) returned a Pass status matching expected outputs.

Table II: Test Case Summary (TC01–TC12)

TC ID	Module	Scenario	Input	Expected Output	Actual Output	Status
TC01	Login	Valid credentials	Username + PW	Access granted	As expected,	Pass
TC02	Login	Invalid credentials	Wrong PW	Error shown	As expected,	Pass
TC03	Register	New user signup	User details	Account created	As expected,	Pass
TC04	Detection	Empty slot	No vehicle	Slot = Vacant	As expected,	Pass

TC05	Detection	Occupied slot	Vehicle present	Slot = Occupied	As expected,	Pass
TC06	Booking	Book free slot	Select free slot	Slot reserved	As expected,	Pass
TC07	Booking	Book occupied slot	Select occupied	Error displayed	As expected,	Pass
TC08	Payment	Successful payment	Valid card	Payment success	As expected,	Pass
TC09	Payment	Failed payment	Invalid details	Failure message	As expected,	Pass
TC10	Navigation	View location	Location request	Map displayed	As expected,	Pass
TC11	Database	Store booking	Booking info	Data stored	As expected,	Pass
TC12	Notification	Booking confirm	Booking request	Notification sent	As expected,	Pass

VIII. RESULTS AND DISCUSSION

Functional evaluation across all twelve test cases confirmed full compliance with specified requirements. The CNN-based detection engine sustained 98.3% classification accuracy on the held-out test set, representing a 4.7% improvement over a traditional background-subtraction baseline applied to the same image corpus. Real-time slot state propagation from sensor event to mobile UI update was measured at an average end-to-end latency of 1.8 seconds under a simulated load of 500 concurrent users, within the 3-second threshold specified in the non-functional requirements.

Reservation throughput reached 230 bookings per minute without degradation, and the payment module processed transactions with a 99.6% success rate during load testing. User acceptance testing conducted with a representative cohort of 20 participants returned a mean System Usability Scale (SUS) score of 82.4, classifying the interface as 'Excellent'. Administrators noted a 35% reduction in manual monitoring effort attributable to the automated alert and dashboard subsystems.

IX. CONCLUSION AND FUTURE WORK

This paper has presented a comprehensive Smart Parking System that unifies IoT sensing, CNN-based image classification, cloud orchestration, and a multi-role application layer into a cohesive, testable architecture. The system demonstrably reduces the time drivers spend locating parking,

lowers fuel consumption and associated emissions, and equips parking operators with actionable data analytics. The modular design accommodates incremental enhancement without architectural disruption.

Future work will investigate three principal directions. First, integration of LSTM-based demand forecasting to anticipate peak occupancy and support dynamic pricing. Second, deployment of Automatic Number Plate Recognition (ANPR) to enable frictionless entry/exit and personalised service history. Third, federation with broader smart-city platforms—including adaptive traffic signal control and public transit information systems—to optimise multi-modal urban mobility at city scale.

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