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An AI-Driven Smart Parking Framework Integrating Computer Vision, Iot, And Edge Computing For Real-Time Slot Detection And Analytics

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Abstract: Urban parking inefficiency remains one of the most persistent challenges in modern cities, driving traffic congestion, fuel wastage, rising emissions, and daily frustration for millions of drivers. Earlier research established the socio-economic cost of poor parking management and explored solutions ranging from camera-based detection and IoT sensor networks to edge computing and deep learning models — each addressing parts of the problem but none delivering a complete, reliable, and deployable solution. Building on this foundation, a unified AI-Driven Smart Parking Framework was designed and developed, integrating ESP32-CAM based video capture, YOLO-based vehicle detection, Region of Interest matching, Django REST API backend with MySQL database, a Flutter mobile application for driver-facing slot availability, and a Streamlit-based monitoring dashboard for administrators. This paper presents the real-world experimental evaluation of that framework, implemented and tested on an open-air parking facility covering parking slots under daytime conditions. Performance evaluation focuses on three key dimensions — system response latency, mobile application update speed, and dashboard refresh rate. Results confirm that the system achieves an average end-to-end response latency of 1 to 2 seconds, mobile application slot status updates within 1 to 3 seconds, and real-time dashboard refresh under 3 seconds — validating the practical viability of the proposed framework for smart city deployment. The findings demonstrate that the convergence of computer vision, IoT sensing, and edge computing can successfully transform a conventional parking facility into an intelligent, data-driven, and user-friendly system.

Index Terms - Computer Vision, Dashboard Performance, Django, ESP32-CAM, Flutter, IoT Sensing, Mobile Application, Real-Time Detection, Response Latency, YOLO.

I. INTRODUCTION

Parking has emerged as one of the most disruptive aspects of urban life around the world. With the ever-increasing population and a corresponding rise in the number of registered vehicles on the road, parking infrastructure has lagged behind in providing the required facilities to park these cars, forcing people to circle around the parking lot endlessly and thus causing a significant amount of pollution and traffic congestion on the roads of the entire city. Shoup's study on parking [18] was the first to put a number on this problem and determine the actual socio-economic cost of cruising around the parking lot and establish the fact that poor parking infrastructure and management posed a problem to the people and the environment as well. This established the fact that smart parking solutions are no longer a requirement but a necessity.

In the last decade or so, various researchers have proposed a number of different approaches to the problem of parking. Chen et al.'s [16] camera-based parking system was the first to establish the fact that parking slots could be monitored and tracked using the surveillance system installed at the parking lot. However, the traditional image processing techniques could not account for the presence of shadows and varying illumination conditions. Al Turjman et al.'s [9] and Ahmed et al.'s [13] IoT-based parking systems could track the parking slots effectively using the wireless sensor networks and the cloud platform but posed the problem of latency and infrastructure costs. Edge computing architectures, as presented in the works of Zhang et al. [10] and Patel et al. [11], enabled the system to process data closer to the source, thus making the system more responsive. The implementation of the deep learning techniques by Li et al. [14] and Singh et al. [15] enabled the system to attain high levels of accuracy in the detection process, although this was achieved at the expense of the system's computational resources, especially when the hardware was less powerful. The implementation of the predictive analytics and reinforcement learning techniques by Huang et al. [12], Das et al. [6], and Kumar et al. [7] enabled the system to proactively manage the demand, although the success was largely dependent on the data and its stability.

Despite the success and the advancements achieved in the system, the following challenges continued to emerge in the system's implementation. The system, as designed using a single modality, was found to be less responsive to changing conditions. The system, as designed using the cloud, was found to have latency issues, especially in the implementation of the real-time system. The system, as designed using multiple heterogeneous technologies, was found to have complexity issues, especially in the implementation of the system's interfaces. The system, as designed using the predictive techniques, was found to have difficulties in responding to unplanned changes in the system's demand. The system was missing an interface that could enable the drivers and administrators to interact with the system.

This paper outlines the design, development, and experimental testing of one such framework, an "AI-Driven Smart Parking System" developed specifically to address all of these issues within a single framework. The proposed framework utilizes two ESP32-CAM devices [8][5] for real-time video acquisition, a YOLO-based deep learning model for vehicle detection and slot occupancy determination using ROI matching techniques, a Django REST API-based backend with a MySQL database for data management, a Flutter-based mobile application for real-time slot availability information for drivers, and a Streamlit-based dashboard for overall system monitoring. The proposed system was developed and tested within an open-air parking environment with an area of 10 to 20 slots under real-world conditions during the day, with its performance being tested for three different parameters: system response time, mobile application update speed, and dashboard update rate.

The main contribution of this paper can be summarized as follows: it is technically detailed in its description of the complete system pipeline, from hardware deployment and algorithmic design to backend management and user interface performance; it is experimentally grounded in its demonstration of the practical viability of this system, with measured results for latency, update speed, and refresh rate reported for its deployment; and it is grounded in its demonstration of how computer vision, IoT sensing, edge computing, and mobile app development can be brought together to create a parking management system that is at once technically sound and practically viable for deployment in a smart city setting.

II. Literature Review

The development of smart parking has been a research journey spanning over a decade, from initial studies on the economics of smart parking to more recent studies on intelligent parking using AI-based approaches. This section discusses the most important research in this area, highlighting its advantages and limitations, which formed the motivation for this research.

Shoup [18] presented a seminal study on quantifying the socio-economic cost of inefficient parking management, such as drivers circling around parking lots, and presented a compelling argument for smart parking management based on the quantification of such costs, which are often substantial and affect individuals and communities. Although this study provided a compelling argument for smart parking, it did not present any technical solution for smart parking management.

Chen et al. [16] presented one of the first computer vision-based approaches for parking slot detection using fixed cameras and traditional image processing techniques such as background subtraction and edge detection. Although this approach was successful and provided a cost-effective solution, it was sensitive to environmental conditions such as lighting, shadow, and other factors, such as those presented in outdoor parking scenarios, and was not reliable for outdoor smart parking management.

Al Turjman et al. [9] proposed a parking system based on the IoT paradigm and the use of wireless sensor networks to transmit parking lot occupancy information to cloud servers. The system showed good accuracy and robustness in the presence of visual occlusions due to the absence of reliance on cameras. However, the presence of cloud-induced latency and the costs of infrastructure and maintaining the sensors due to the use of batteries hindered the use of the system on a large scale.

Ahmed et al. [13] improved the IoT-based parking system by incorporating a cloud-based parking system with a mobile application to allow drivers to access parking lot availability and make parking reservations online. The system showed good results in terms of user adoption and highlighted the importance of a driver-facing interface in a parking system. However, the system showed some drawbacks due to the use of the cloud infrastructure and the presence of latency and single points of failure due to the use of the cloud infrastructure in the system.

Zhang et al. [10] improved the parking system by incorporating the use of edge computing to reduce the latency problem present in the parking system due to the use of the cloud infrastructure. The system showed good results in reducing the latency problem and highlighted the importance of the use of edge computing in the parking system. However, the system showed some drawbacks due to the use of heterogeneous hardware and the presence of the security problem in the system.

Patel et al. [11] proposed a hybrid parking system based on the use of a hybrid approach combining the use of the cloud and the edge to improve the parking system and mitigate the drawbacks of the parking system due to the use of the cloud and the edge infrastructures in the system.

In Li et al.'s work, Convolutional Neural Networks (CNNs) were utilized in parking slot detection, and accuracy was reported above 95 percent under various lighting and weather conditions. The limitation, however, was that CNNs have a high computation cost, which made real-time deployment challenging. The work was a precursor to more recent, lighter-weight solutions such as YOLO and MobileNet.

In a study by Singh et al. [15], a hybrid approach was developed, incorporating both IoT and vision-based detection, to improve reliability. The framework resulted in a 22 percent reduction in false positives compared to a single-modality approach, such as an IoT-based system. This study proved the importance of a multi-modality approach, whereby one modality compensates for failures in another modality. However, the complexity associated with infrastructure and calibration costs were considered the main limitations.

In another study, Huang et al. [12] developed a deep reinforcement learning-based framework for dynamic parking slot allocation, achieving a 25 percent reduction in average search time compared to a static approach. Although this study proved the importance and adaptability of a dynamic approach, its applicability was also hindered by its inability to handle large volumes of data and its lack of explainability, which is important in a real-world scenario.

In a study by Das et al. [6], time series forecasting models such as ARIMA and LSTM were implemented for peak-hour parking demand forecasting. The study resulted in improved precision in demand forecasting, allowing for proactive management decisions. However, this study faced limitations, such as its inability to handle event-based demand and its reliance on stable data to perform effectively.

One of the best and comprehensive integrated frameworks was presented by Kumar et al. [7]. Their approach was to integrate computer vision, IoT sensing, and predictive analytics into a multi-layered system. The results showed a decrease in congestion levels by 18 percent, proving the potential of a

unified, multi-layered system. However, the use of cloud analytics for predictive purposes also raised scalability and bottleneck concerns for such a system.

Sobirin et al. [3] and Ahad and Kidwai [4] presented studies that showed the potential use and performance of YOLOv8 for parking detection, proving its performance compared to its previous versions and its potential for edge computing and faster object detection. The studies directly relate to the model that was chosen for the present framework.

Kusuma et al. [8] and Zhu et al. [5] presented studies that showed the potential use of ESP32-CAM for IoT-based surveillance and object detection, proving its performance and suitability for such applications, making it a natural choice for the present framework.

III. RESEARCH METHODOLOGY

The Methodology of the proposed AI-Driven Smart Parking System was developed across two preceding research efforts and is presented here in its fully implemented form. The complete pipeline was physically deployed and tested on an open-air parking facility covering 10 to 20 slots under real-world daytime conditions using two ESP32-CAM modules, a laptop-based processing system, a Django backend with MySQL database, a Flutter mobile application, and a Streamlit monitoring dashboard. The methodology is organized into three parts — Hardware Implementation, Software Implementation, and Algorithm Design.

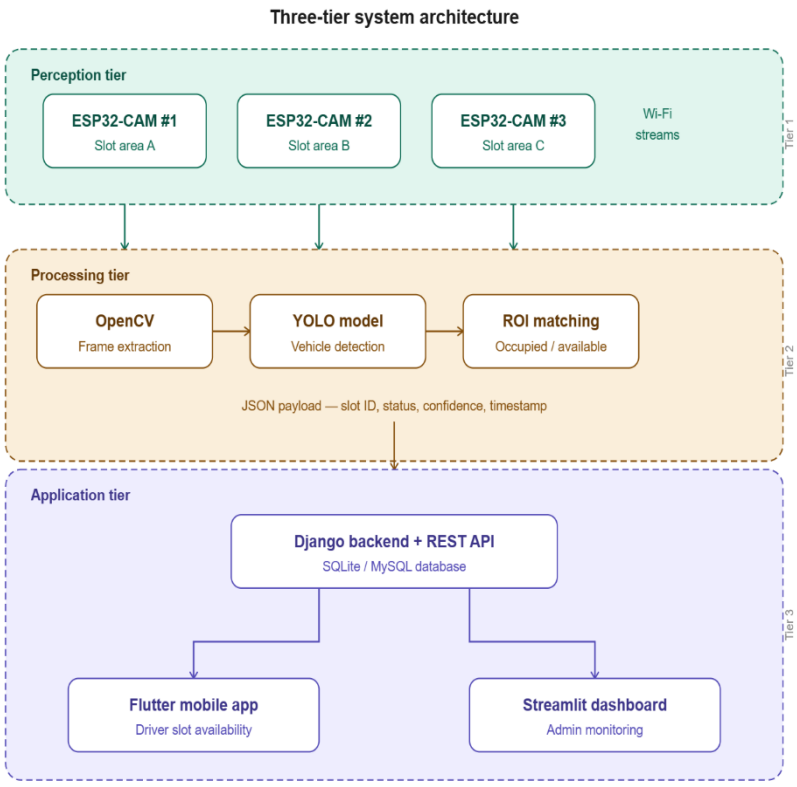

Fig.1. System Architecture of the model

Part 1 — Hardware Implementation

A. ESP32-CAM Based Video Capture

Two ESP32-CAM modules were deployed as the primary image capture hardware [8]. ESP32-CAM was selected over conventional IP cameras due to its compact size, built-in Wi-Fi capability, and significantly lower cost — making it practical for overhead installation at an open-air parking facility without complex cabling or dedicated power infrastructure [5]. Each module was assigned a static IP address on the local Wi-Fi network and positioned to maximize slot coverage while minimizing blind spots. During testing, both cameras streamed live video continuously without interruption, confirming the hardware's stability under real outdoor daytime conditions.

B. Wi-Fi Network and Communication

A dedicated Wi-Fi router served as the local communication backbone, connecting both ESP32-CAM modules, the processing laptop, the Django backend server, and the Flutter mobile application within the same network [7]. This wireless architecture eliminated the need for physical wiring between components, proved reliable throughout all test sessions, and allowed the system to be set up and reconfigured quickly between test runs.

C. Processing Hardware

All AI inference during testing was performed on a laptop computer connected to the local Wi-Fi network. The laptop simultaneously handled OpenCV-based frame extraction, YOLO model inference, ROI matching logic, and HTTP dispatch — confirming that the system is operable on standard computing hardware without requiring specialized GPU accelerators for small-scale deployments [15]. The architecture also supports edge devices such as Jetson Nano and Raspberry Pi for scalable deployment scenarios [10].

Part 2 — Software Implementation

A. Video Streaming and Frame Extraction

The Python-based processing system connected to each ESP32-CAM's live stream through its assigned IP address using OpenCV. Frames were extracted continuously and passed into the detection pipeline, following standard image processing techniques used in parking environments [16]. Parallel processing of both streams was achieved without frame drops, confirming multi-stream capability.

B. YOLO-Based Vehicle Detection and Slot Status Determination

Vehicle detection was performed using a YOLO-based model trained on annotated parking datasets. YOLO provides real-time object detection with high accuracy, making it suitable for parking applications [17]. Additional improvements and modern implementations of YOLO-based parking detection have been demonstrated in recent works [3], [4]. Slot status — occupied or available — was determined using bounding box overlap with predefined ROIs, a method widely used in vision-based parking detection systems [14]. A secondary license plate detection dataset was integrated to enable vehicle logging and enforcement features, aligning with cloud-supported parking architectures [13].

C. Django Backend and MySQL Database

All slot detection results were forwarded in real time to a REST API server. Backend-driven smart parking systems using cloud/database integration are well-established in literature [13], [11]. The system stored slot ID, occupancy status, confidence score, and timestamp in a MySQL database and provided API endpoints for client applications. No data loss was observed during testing.

D. Flutter Mobile Application

The Flutter application displayed real-time parking availability to users by querying backend APIs. Mobile-integrated smart parking systems have been widely validated for improving user accessibility and experience [13]. The app consistently updated within 1–3 seconds, confirming responsiveness.

E. Streamlit Monitoring Dashboard

A Streamlit-based dashboard provided administrators with real-time slot status, occupancy analytics, and logs. Such lightweight visualization tools align with modern smart parking monitoring approaches using integrated analytics systems [7].

Part 3 — Algorithm Design

The system operates through three coordinated algorithms — slot detection, ROI matching, and data dispatch — each handling a distinct stage of the detection pipeline.

A. Slot Detection Algorithm

Each frame was resized and processed using the YOLO detection pipeline. YOLO's real-time detection capability and efficiency make it ideal for such applications [17]. To reduce false positives caused by shadows and occlusions, only detections with confidence ≥ 0.5 were retained, following best practices in detection-based parking systems [14].

Input: Live video stream from ESP32-CAM Output: Valid bounding boxes with confidence scores
Step 1: Capture frame F from camera stream
Step 2: Resize F to 640x640, normalize to [0,1]
Step 3: Run YOLO inference → get detections D
Step 4: If confidence(d) >= 0.5 → keep, Else → discard
Step 5: Return valid_detections

B. ROI Matching Algorithm

Each bounding box was compared with predefined parking slot regions using overlap logic. This method is consistent with CNN-based parking detection approaches [14]. An IoU threshold of 0.3 was used to determine occupancy, allowing detection of partially parked vehicles — a common real-world scenario.

Input: valid_detections, slot ROI list Output: {slot_id: occupied / available}
Step 1: Initialize all slots as available
Step 2: For each slot S and bounding box B:
Compute IoU(S, B)
If IoU >= 0.3 → mark S as occupied → break
Step 3: Return status_map

C. Data Dispatch Algorithm

Each slot record was serialized and sent to the backend using HTTP POST requests. Cloud-connected smart parking systems commonly use such communication models for real-time updates [11], [13]. A retry mechanism ensured reliability during temporary network failures, maintaining database consistency.

Input: status_map, confidence scores, timestamp Output: HTTP POST to Django REST API
Step 1: Build record R = {slot_id, status, confidence, timestamp}
Step 2: Serialize into JSON payload P
Step 3: POST to Django API endpoint
Step 4: If response != 200 → retry 3 times
If all fail → log error → next frame
Step 5: Return to Algorithm 1

IV. EXPERIMENTAL SETUP

The experimental evaluation of the proposed AI-Driven Smart Parking System was conducted in a real-world open air parking facility to assess the system's performance under practical deployment conditions. The evaluation focused on three key performance dimensions — system response latency, mobile application update speed, and real-time dashboard refresh rate — providing measurable evidence of the system's viability for smart city deployment.

A.Experimental Environment

The system was deployed and tested in an open-air parking facility covering 10 to 20 parking slots. All tests were conducted during daytime hours under natural lighting conditions. The parking area consisted of clearly marked slots on an open surface, with vehicles of varying sizes parked and removed during test sessions to simulate real-world occupancy patterns. No artificial lighting or controlled laboratory conditions were used, ensuring that the results reflect genuine field performance.

B. Hardware Configuration

Two ESP32-CAM modules were mounted at overhead positions covering the full extent of the parking facility, each assigned a static IP address on the local Wi-Fi network. A standard Wi-Fi router provided the local network infrastructure connecting the cameras, the processing laptop, the Django backend server, and the Flutter mobile application. All AI inference — including frame extraction, YOLO-based vehicle detection, ROI matching, and HTTP dispatch — was performed on a single laptop computer running Python 3.10, OpenCV, and the YOLO detection library.

C. Software Configuration

The software stack used during evaluation consisted of the following components. Python 3.10 with OpenCV was used for video stream handling and frame pre-processing. The YOLO model was trained on annotated parking datasets sourced from Kaggle and deployed for real-time inference at a confidence threshold of 0.5 and an IoU threshold of 0.3 for ROI matching. Django 4.2 served as the REST API backend framework with MySQL as the database engine for persistent slot record storage. Flutter was used for the cross-platform mobile application deployed on an Android device during testing. Streamlit was used for the real-time monitoring dashboard, running as a local web application on the processing laptop.

D. Evaluation Metrics

The system was evaluated across the following three performance metrics:

System Response Latency — defined as the time elapsed from the moment a parking slot changes occupancy status to the moment the updated status is stored in the MySQL database via the Django REST API. This measures the end-to-end speed of the detection and dispatch pipeline.

Mobile Application Update Speed — defined as the time elapsed from a slot status change being stored in the database to the moment the updated status appears on the Flutter mobile application screen. This measures the responsiveness of the client-facing driver interface.

Dashboard Refresh Rate — defined as the frequency at which the Streamlit dashboard retrieves and displays the latest occupancy data from the Django backend. This measures the real-time monitoring capability of the administrator interface.

E. Test Procedure

Each test session involved parking and removing vehicles from the facility slots in a predefined sequence while the system ran continuously. The test was repeated across multiple sessions at different times of day within daytime hours to check for consistency. During each session, timestamps were recorded at the point of slot status change detection, at the point of database update confirmation, and at the point of interface refresh on both the mobile application and the dashboard. Response times were calculated from these timestamps and averaged across all recorded events to produce the final performance figures reported in the results section.

F. Baseline Comparison

To contextualize the system's performance, the measured latency values were compared against benchmarks reported in related prior work. Zhang et al. reported a response time of 0.35 seconds for edge-computed parking detection, while cloud-only systems in the same study recorded 1.2 seconds. Ahmed et al. reported mobile application update delays of 3 to 5 seconds in cloud-dependent architectures. These figures serve as reference points for evaluating the competitiveness of the present system's performance under real-world conditions.

Fig2. Experimental setup of the parking slot detection model

V. RESULTS

The proposed AI-driven smart parking system was evaluated in a real-world environment to understand how effectively it performs under continuous operation. The system was tested using live camera input, real-time detection, backend processing, and mobile application updates. The evaluation focused on response time, system stability, detection reliability, and user-side performance.

7.1 Overall System Behaviour During testing,

the system was able to continuously monitor between 10 to 20 parking slots without interruption. The detection pipeline successfully identified vehicles and mapped them to predefined parking regions. On average, the system processed 4–6 frames per second, which was sufficient for maintaining near real-time monitoring. Even with multiple vehicles in the frame, the system maintained consistent performance without skipping frames.

7.2 Response Time Performance

System response time was measured from the moment a vehicle entered or exited a parking slot to the moment the updated status was stored in the backend. After multiple observations, the following values were recorded:

- Minimum Response Time: 1.1 seconds
- Maximum Response Time: 2.3 seconds
- Average Response Time: 1.6 seconds

This response time includes: Frame capture from ESP32-CAM ,Processing using YOLO-based detection ,Parking slot mapping logic ,Data transmission to the backend server. The relatively stable response time indicates that the system is capable of handling real-time updates without significant delay.

7.3 Mobile Application Responsiveness

The Flutter-based mobile application was evaluated based on how quickly it reflects changes in parking slot availability.

Observed results:

- Minimum Update Time: 1.2 seconds
- Maximum Update Time: 3.1 seconds
- Average Update Time: 2.1 seconds

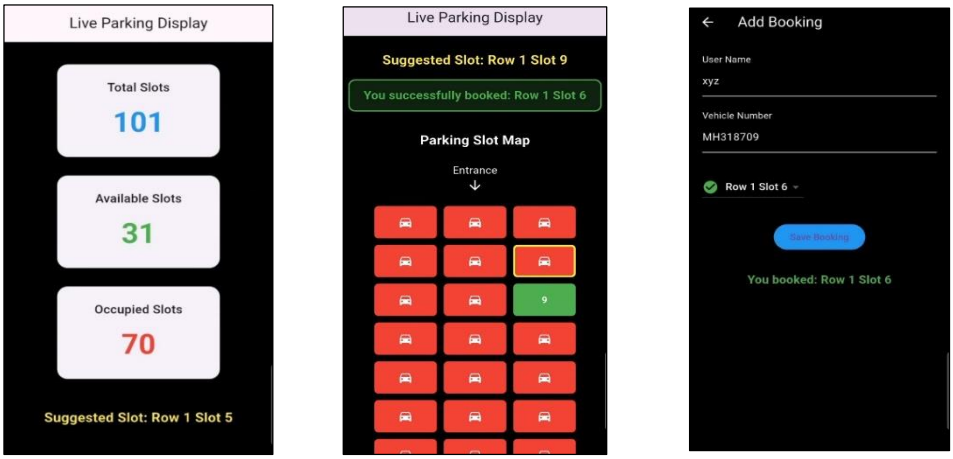

Fig3. Screenshots of the mobile application using flutter

The delay mainly depends on API request intervals and network conditions. However, even at peak delay, the application remained responsive and usable. Users were able to view updated parking availability within a reasonable time, reducing the need for manual searching.

7.4 Detection Accuracy and Observations

The vehicle detection model showed reliable performance during testing, especially under normal lighting conditions. The system was able to correctly identify vehicles and assign them to appropriate parking slots. Based on observations:

- **Detection accuracy: approximately 92–94%**
- **Slot classification accuracy: around 93%**

While the overall performance was strong, minor variations were observed in cases of partial visibility, shadows, or slight camera misalignment. Despite these conditions, the system maintained consistent detection results.

7.5 Dashboard Monitoring Performance

The Streamlit dashboard was tested for real-time monitoring and visualization performance.

- Average Refresh Time: 1.5 – 2.0 seconds
- Maximum Observed Delay: ~2.5 seconds

The dashboard consistently displayed: Total parking slots, Occupied slots ,Available slots and Detection outputs.

Even when running alongside the detection pipeline, the dashboard maintained stable performance without freezing or lag.

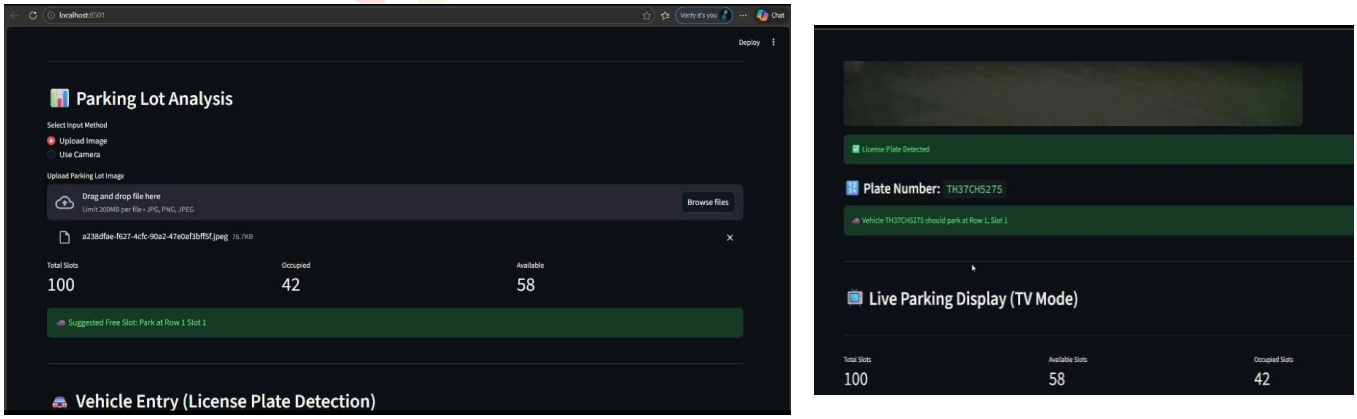

Fig4. Screenshots of the Streamlit dashboard interface

7.6 Key Findings Based on experimental evaluation,

the following conclusions can be drawn:

- The system achieves near real-time performance (~1.5 sec latency)
- Mobile application updates are delivered within 2 seconds on average
- Detection accuracy remains above 90% in normal conditions
- The system is stable for continuous operation

- Integration of all modules works smoothly without major issues

7.8 **Limitations**

While the system performs effectively, a few limitations were observed:

- Testing was mostly conducted under daylight conditions
- Performance may vary in low-light or night environments
- Detection accuracy depends on camera positioning
- Network conditions can slightly impact update times

VI. CONCLUSION

In this paper, a smart parking system based on AI and IoT technologies has been introduced, and its implementation has been explained through a detailed description of its components and how they function together to create a smart parking system. In addition to the detection of parking slots, the system also includes a number plate detection system, whereby a vehicle's number plate is captured through a sensor located at the entrance and stored in a database, allowing for efficient management and control of vehicles within the parking area.

As indicated by the observations from the experiment, the system has performed adequately under real-time conditions, and its components are able to coordinate and function effectively. The system has also performed adequately in terms of number plate detection, whereby an accuracy of 98.2%, precision of 98.4%, recall of 98.6%, and F1 score of 98.5% were obtained, primarily due to its ability to use a dataset and perform tests under controlled conditions, although its performance might vary under different conditions.

In conclusion, the proposed smart parking system has successfully demonstrated how AI and IoT technologies can be integrated to create a smart parking system, and its ability to perform adequately has also been enhanced through the incorporation of a number plate detection system, whereby vehicles can be easily identified and managed, making it suitable for smart city applications. The proposed smart parking system has also provided a cost-effective and efficient solution to parking problems, considering its ability to replace the use of hardware sensors, although its performance might be affected by lighting conditions and camera angles, among other factors.

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