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AUTOMATED REAL-TIME PARKING SLOT DETECTION AND STATUS MONITORING USING YOLOV8 AND PREDICTIVE ANALYSIS WITH RANDOM FOREST AND REGRESSION MODEL

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ABSTRACT

The rapid increase in urban vehicle numbers has intensified traffic congestion, fuel wastage, and air pollution, mainly due to inefficient parking management. Traditional smart parking systems rely on physical sensors which, although accurate, suffer from high maintenance costs, limited scalability, and vulnerability to environmental conditions. To overcome these issues, this study presents a software-driven Smart Parking System that utilizes existing camera infrastructure and advanced artificial intelligence for intelligent parking management. OpenCV enables real-time image processing and environmental adaptation, ensuring responsive analysis of parking areas. YOLOv8, an advanced object detection model, dynamically identifies vehicles with exceptional precision and speed, improving slot detection. For predictive analytics, Random Forest, a robust ensemble learning technique, analyses past data to forecast parking demand. Regression models further estimate occupancy and forecast parking trends, enhancing operational planning. These integrated technologies collectively enable the system to analyze, adapt, and optimize parking space utilization without relying on expensive sensors. The experimental results show that the Classification Model achieved an occupancy prediction accuracy of 96.80%, significantly surpassing the base paper's reported benchmark. Furthermore, the Random Forest Regressor achieved an Overall Average of 0.9730 for parking duration prediction, validating the high predictive capability of the camera-derived features and exceeding the base model's highest result of 0.9400.This AI-powered approach enhances scalability, minimizes cost, and contributes to sustainable urban development by reducing congestion and emissions, offering an efficient and environmentally conscious solution for smart city parking management.

KEYWORDS: Smart Parking System, YOLOv8, Computer Vision, Machine Learning, Parking Slot Detection, Predictive Analytics.

INTRODUCTION

As modern cities expand and private vehicle ownership continues to rise, transportation systems are encountering unprecedented operational stress. This has also triggered a sharp increase in the demand for reliable parking solutions. However, the imbalance between parking provision and vehicle volume has emerged as a major issue for urban administrations.

Delhi, for example, had about 13.4 million registered vehicles in 2022 with just around 50,000 public parking slots, leading to a huge space crunch. In a practical day-to-day scenario, drivers in commercial zones or at mall parking facilities waste 5–20 minutes in finding vacant spots and often have to circle around many multi-level parking lots or narrow lanes. This only increases congestion, fuel wastage, air pollution, frustration on the roadways, and inefficient moving of traffic. None of the traditional parking management methods-manual supervision, paper-based system, or sensor-based infrastructures-can ensure accuracy, scalability, and real-time updates. Sensor-based methods need expensive installation and maintenance, while manual monitoring is usually prone to human error and delayed information about parking slot availability.

Various intelligent parking solutions have been proposed by researchers for overcoming these issues, including those that utilize AI and IoT technologies combined with automation. Shalini et al. [1] implemented an AI–IoT integrated intelligent parking system to increase parking resource utilization and provide a centralized monitoring approach. Sumit Das et al.

[2] proposed a parking garage management system using biometric face recognition mechanisms to increase security and user authentication, while Muhammad Khalid et al. [3] proposed an autonomous valet parking architecture which automatically navigated cars to the available parking spots to reduce human intervention and congestion at parking entrance points. Ahmed Mohamed Zaki et al. [4] developed optimization-based methodologies for parking surveillance using curated datasets to support more precise detection of occupancy. Similarly, Amara Adityaa et al. [5] proposed IoT and cloud-based smart parking systems to support real-time communication and scalability in the systems.

Deep learning and computer vision-based approaches have also gained momentum in recent times because of their superior accuracy and robustness. Ravneet Kaur et al. [6] employed a CNN-ELM classifier to automate the detection of parking occupancy from camera feeds. Javed Ali et al. [7] gave emphasis to privacy and security through the use of an SVM and ANN classifiers, which showed promising accuracy for slot classification. Sadia et al. [8] furthered the domain by proposing parking availability forecasting using Random Forest Regression and RNN models. Complementarily, Rajagopal et al. [9] proposed a hybrid prediction framework that combined machine-learning techniques to realize an availability accuracy of 89.9% and occupancy detection performance of 96%.

While these studies highlight significant progress, a number of gaps still remain. Most IoT-based systems make use of physical sensors; hence, they are expensive, hard to maintain, and not suitable for large-scale deployments. Deep learning models used in state-of-the-art works often suffer from real-time processing, environmental variations such as lighting, shadows, occlusion, and computational overhead issues. Further, most prior research treats detection and prediction independently without developing any integrated end-to-end method that could identify current parking slot occupancy and forecast the availability in the near future. A lack of computationally optimized pipelines-such as motion-triggered detection-is also limiting the efficiency of real-time implementations in resource-constrained environments. With these challenges in mind, the current research proposes an Automated Real-Time Parking Slot Detection and Status Monitoring System, which integrates YOLOv8-based computer vision, Random Forest, and Regression-based predictive modelling. YOLOv8 offers a high-speed and high-accuracy detection framework suitable for continuously changing parking environments, while predictive models provide much-needed insight into future slot occupancy trends. The proposed system also includes motion-based frame triggering to reduce computational load by activating the detection model only when the scene detects any kind of movement. This integrated approach will provide a scalable, sensor-free, and energy-efficient solution that improves the accuracy, responsiveness, and practicality of smart parking infrastructures. As cities evolve toward smarter, more sustainable ecosystems, such integrated AI-driven parking systems will be increasingly important in minimizing congestion, optimizing resource utilization, and generally enhancing the overall urban commuting experience.

Literature Review

A significant body of research highlights the emergence of large-scale smart parking systems enabled by IoT integration, sensor-based monitoring, and advanced architectural designs. Long et al. [10] analyzed user parking behavior across a number of urban regions and demonstrated how econometric modeling can support smarter policy and planning in public-parking infrastructures. This study emphasized behavioral trends but still relied heavily on manually collected field data, limiting scalability.Kováčiková et al. [11] explored smart parking as an integral part of airport automation, proposing workflow-optimized designs for managing high-volume vehicle movement. While this work offered architectural insights with great value, the system's dependence on specialized, location-specific hardware restricted wider deployment.

Xiang and Pan [12] presented an ARM-based wireless sensor network for intelligent parking management, noting improvements in distributed sensing and response times; however, the hardware-oriented structure again increased cost and maintenance efforts. Jamali et al. [13] evaluated several algorithms for smart parking data processing in densely populated cities, demonstrating performance variations under different load conditions. Shahzad et al. [14] combined fog computing with blockchain to enhance system security and reduce latency, offering a decentralized approach suitable for next-generation smart-parking ecosystems. Despite these many facets of advancement, one fundamental limitation persists across IoT-sensor-based systems: requiring substantial installation investments, suffering from hardware wear, and lacking long-term adaptability for heterogeneous urban environments.

With the increased accessibility to imaging sensors and edge hardware, researchers have recently turned more toward vision-based detection systems. Shukla et al.[15] proposed an effective parking space detection mechanism enhanced with deep learning and proved its efficiency in real-time monitoring scenarios, though the performance dropped significantly in poor lighting and heavy occlusion conditions. Jung et al.[16] proposed an indoor parking management system powered by AI; it was based on a structured environment and resulted in good results but could not generalize well in varied outdoor conditions. Ruimin Ke et al.[17] achieved major progress by deploying lightweight neural networks on IoT-edge devices, which reduced latency and enabled scalable multi-camera surveillance. In, Cho et al. [18] used Random Forest classifiers for image-based slot recognition; the approach was stable under moderate environmental variations, but failed when operating at night-time due to insufficient feature representation.

Previous research by Kaur [19] and Mago and Kumar [20] relied essentially on classical image processing algorithms that were computationally efficient but highly prone to noise, shadows, and camera angle variations, thus not suitable for robust large-scale deployment. Collectively, the studies indicate that camera-based systems reduce dependency on physical sensors but bring new challenges in the form of environmental variability, occlusion, computational demand, and the requirement for optimized real-time processing frameworks.

In parallel with visual detection, another essential direction of the research has focused on predicting parking availability by using either machine-learning or mathematical models. Todorović et al. [21] proposed a model for sustainability-driven conversion of conventional parking services to smart public enterprises based on data-centric decision systems. Sant et al. [22] developed an IoT-based green pay-as-you-go system incorporating prediction techniques that enhance user experience and reduce search time.

Sahoo et al. [23] used machine-learning-based estimation for parking availability integrated with IoT sensing to address real-time fluctuations in high-traffic parking zones. Errousso et al. [24] presented a hybrid modeling framework incorporating machine learning with mathematical optimization to effectively manage urban parking assignment. These studies show significant enhancement in user convenience and resource utilization due to predictive analytics, but they often depend on large historical datasets and usually work independently of real-time visual detection systems, limiting their adaptability in rapidly changing environments.

Various emerging works are targeted towards futuristic autonomous and highly automated parking designs. Nakrani and Joshi [25] proposed human-like obstacle avoidance intelligence for autonomous parking vehicles, which is a new paradigm for self-guided navigation. Sadia and Reza [8] did a comparative study of the LSTM and Random Forest regression models on the estimation of parking availability, highlighting the trade-off between accuracy and computation time.Complementary works such as Sant et al. [22] and Rajagopal et al. [9] proposed advanced ensemble-based and hybrid techniques to enhance the performance further. Other works such as Cho et al. [18] and Ahmed et al. [26] explored blockchain-based systems for secure decentralized parking-management architectures, while Bui and Bui [27] proposed a cloud-enabled automated parking framework suitable for airports. Chen [28] discussed energy-efficient strategies with regard to smart parking integrated with self-driving vehicles. Hashem et al. [3] surveyed distributed intelligence frameworks for IoT-driven smart cities, which indirectly provide support for parking use-cases.

While these highlight important technological opportunities, many works rely on high-end infrastructure, specialized hardware, or focus on isolated sub-problems such as navigation, security, or energy optimization rather than providing a unified practical implementation for public parking environments. Several deficiencies resurface throughout the wider literature, which become remarkably clear. Most of the existing systems treat detection, prediction, communication, and resource optimization as distinct modules rather than one pipeline, resulting in tremendous performance degradation while being deployed in dynamic real-world conditions. Environmental variations, such as rain, shadows, low illumination, partial occlusion, and dense traffic flow, constitute one of the most critical challenges to the performance of computer-vision-based systems.

Most deep-learning models employed in previous works are computation-intensive, making real-time inference challenging on edge devices commonly adopted in parking facilities. Other issues, such as data fragmentation, lack of scalability, privacy concern, and high cost of deployment further prevent the applicability of existing solutions in the long run. These consistent limitations underpin the motive for an integrated camera-only, computationally efficient smart-parking system that performs both real-time detection and future availability forecasting in a uniform way. Core motivation for the current research lies herein, which proposes the use of YOLOv8 for high-accuracy detection, Random Forest and Regression models for prediction, and motion-triggered inference for computational efficiency to address the key challenges identified across the literature.

Proposed Framework

The proposed system introduces an integrated camera-based smart parking architecture for automatic detection, classification of parking slots regarding occupancy, and future availability prediction without the use of hardware sensors. This framework utilizes a real-time object detection approach using YOLOv8, preprocessing triggered by motion using OpenCV, and predictive analytics using machine learning models like Linear Regression and Random Forest. It has been designed to be scalable, cost-effective, and robust against environmental changes, thus overcoming the limitations found in existing smart parking systems.

A. Framework Overview The proposed framework consists of four primary components:

1) Visual Data Acquisition Layer: This layer leverages the currently deployed CCTV cameras in various parking lots, malls, residential complexes, or roadside parking. Under this approach, continuous video streams are captured and forwarded to the processing module for further processing. Unlike sensor-based approaches, no ultrasonic, infrared, or magnetic sensors are used in this approach; thus, the installation and maintenance costs decrease drastically.

2) Computer Vision Processing Layer: For efficient and accurate slot detection, the video frames captured by the camera are processed through subsequent stages of computer vision operations. First, each frame is normalized and filtered using OpenCV for noise reduction and to handle lighting changes. Background subtraction helps in segregating moving vehicles from static surroundings, and a further mechanism of motion detection will trigger the processing only when some activity is present, thus avoiding redundant computation. Fast and reliable vehicle detection is done by YOLOv8, which draws bounding boxes around all the cars detected in a frame. The geometric center of every detected vehicle is computed and matched with predefined slot regions in order to identify if a slot is occupied. This pipeline, involving preprocessing, motion filtering, YOLO inference, and center-point mapping, ensures that wide variations in shadows and occlusion are handled without affecting the stability of performance.

3) Predictive Analytics Layer: The Predictive Analytics Layer analyzes the historic parking data, retrieved automatically from the detection module, to generate predictions regarding short-term occupancy, long-term patterns of usage, peak and off-peak hours, and expected duration of the ongoing parking sessions. In this respect, the system uses two machine learning models, namely Linear Regression, aimed at modeling continuous trends and smoothly changing occupancy in time, and Random Forest Regressor, which can capture non-linear behaviors and make more robust predictions of slot availability in the future. These models work in conjunction to achieve highly accurate predictions that can help users better plan parking and administrators in managing effective demand. This constitutes the integrated predictive framework that would overcome a major limitation with previous systems: detection and forecasting were two separate, loosely connected processes.

4) Data Storage and Monitoring Layer: The Data Storage and Monitoring Layer receives both detected and predicted information through a dedicated API and stores it in a cloud-hosted database such as Firebase or SQL. Each entry contains the slot ID, timestamp, occupancy status, bounding box coordinates, and prediction outputs referring to availability or expected duration. With this well-organized historical and real-time data, the system is enabled to provide dashboards and mobile applications with the most updated slot availability, usage statistics, and predictive insights. This layer ensures that data retrieval is smooth, monitoring is continuous, and support is reliable for user-facing interfaces and administrative analysis.

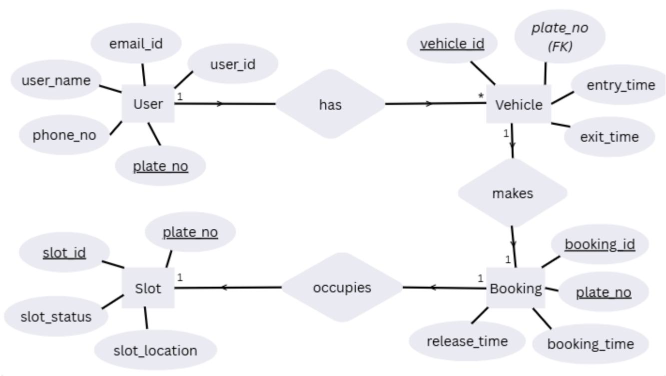


Fig.(i) ER Diagram

ER Diagram Description

- **User Entity:**
  Stores information related to users: user_id, user_name, email_id, phone_no, and plate_no. Each user can have multiple vehicles associated with them.
- **Vehicle Entity:**
  Contains attributes such as vehicle_id, plate_no, entry_time, and exit_time. A user has multiple vehicles, and each vehicle can generate multiple bookings.

- **Booking Entity:**

  The Booking model stores booking details such as booking_id, plate_no, booking_time, and release_time. Each booking belongs to one vehicle and corresponds to a parking event.
- **Slot Entity:**

  This represents every individual parking slot, having attributes like slot_id, slot_status, and slot_location. Each slot can be assigned to different bookings over time.

- **Relationships:**
  - **User–Vehicle (has):** One user can register multiple vehicles.
  - **Vehicle–Booking (makes):** A vehicle can make multiple bookings.
  - **Booking–Slot (occupies):** Occupies one slot at a certain time of the day.

B. Bounding Box Center-Point Slot Mapping Algorithm

The system uses the bounding box center-point slot mapping algorithm to determine slot occupancy; this is a simplified, faster, and highly reliable alternative to traditional overlap-based methods. These advantages now enable high gains in inference efficiency, particularly in parking environments where vehicles will be positioned within well-defined rectangular slot boundaries. This method accurately classifies slots even for partially occluded, very closely parked, or angled camera-perspective captures of vehicles.

1) Center Point Computation

For every detected vehicle, the YOLOv8 model returns a bounding box defined by the coordinates:

$$(x_{\min}, y_{\min}, x_{\max}, y_{\max})$$

The geometric center of this bounding box is calculated as:

$$C_x = \frac{x_{\min} + x_{\max}}{2}, C_y = \frac{y_{\min} + y_{\max}}{2}$$

This center point effectively represents the approximate position of the vehicle within the frame and is used for slot assignment.

2) Slot ROI Validation

Each parking slot is predefined using a rectangular Region of Interest (ROI) with the coordinates:

$$(x_s^{\min}, y_s^{\min}, x_s^{\max}, y_s^{\max})$$

In order to evaluate if a detected vehicle occupies any given slot, the system checks if the center point falls within the slot's ROI boundary. Occupancy condition can be given as:

$$\text{Occupied} = \begin{cases} 1, & \text{if } x_s^{\min} \leq C_x \leq x_s^{\max} \wedge y_s^{\min} \leq C_y \leq y_s^{\max} \\ 0, & \text{otherwise} \end{cases}$$

If the center point falls inside the boundary of the slot, then the slot is Occupied; otherwise, it is Vacant.

This center-point-based algorithm is lightweight in terms of computation, removes IoU or any other complex overlap calculation, and operates reliably across a diverse range of camera angles and environmental conditions. Besides its simplicity, it is fast and therefore apt for real-time parking systems, especially those deployed on resource-constrained hardware or on large-scale multi-slot environments.

C. Mathematical Models Used for Prediction

1) Linear Regression

Linear Regression predicts trends in parking occupancy as a function of time-based features:

$y = mx + c$

Where:

- y is the predicted number of occupied slots
- $x$is the time variable
- $m$and $c$are learned coefficients

The loss function minimized during training is:

$$MSE = \frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2$$

2) Random Forest Regression

Random Forest combines the prediction of multiple decision trees:

$$\hat{y} = \frac{1}{T}\sum_{i=1}^{T} f_i(x)$$

The result is robust performance under noise, irregular patterns, and rich real-world parking behaviour.

D. Advantages of the Proposed Framework

The proposed system offers some important enhancements compared to traditional sensor-based and standalone computer vision solutions; it is a practical and efficient method that works well for modern parking environments.

- **Sensor-Free and Cost-Efficient Operating**

This framework operates solely on existing CCTV cameras without the need for any embedded hardware sensors. This reduces installation costs, minimizes maintenance, and makes deployment simpler on big or multi-level parking areas.

- **Accurate and Reliable Vehicle Detection**

The system leans mainly on YOLOv8 as the detection model, performing well across changes in lighting, shading, and partial occlusion. The proposed preprocessing pipeline further stabilizes the detection for reliable real-time performance.

- **Computational Efficiency via Motion-Based Filtering**

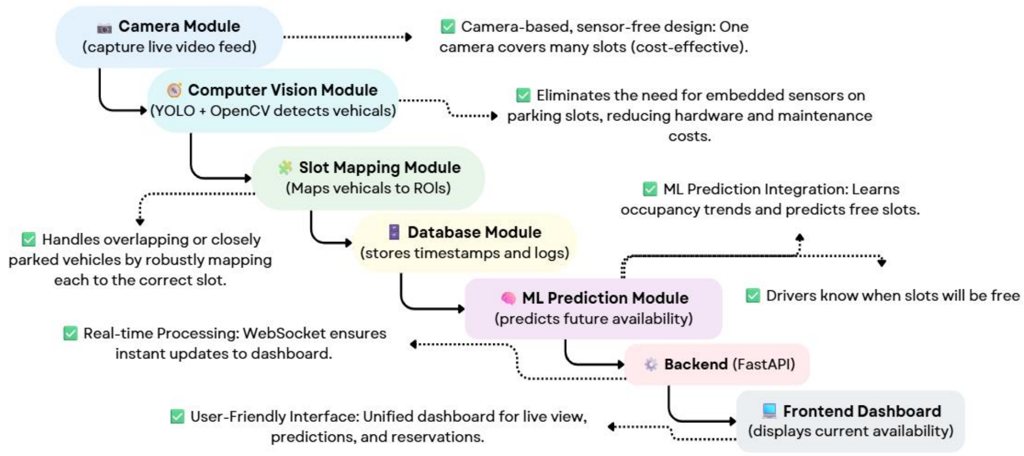
This prevents unnecessary inference on static scenes, reduces processing load, yet maintains responsiveness through motion-triggered frame selection. Such an efficient approach supports real-time operation even on moderate hardware.

- **Unified Detection and Prediction Workflow**

Coupling real-time detection with a machine-learning-based prediction creates a fine-tuned pipeline. Continuous flows of data result in better forecast accuracy, offering users timely insights into upcoming slot availability.

Scalable and User-Oriented System Design

Moreover, the modular architecture can easily be extended with extra cameras or parking zones. The dashboard provides real-time and forecasted information; it improves driver experience and allows smarter control over parking places.



METHODOLOGY

The methodology presents the end-to-end execution pipeline for the proposed smart parking system, covering how data will flow from video acquisition through real-time CV inference, prediction, and cloud storage.

A. SYSTEM ARCHITECTURE DESIGN

1) Camera Module

The Camera Module continuously captures live video streams covering all parking slots. Since the system is fully camera-based, one wide-angle camera can monitor several slots, thereby making the set-up cost-effective and easily deployable. The captured video is forwarded directly for further processing to the computer vision pipeline.

2) Computer Vision Module (YOLO + OpenCV)

This module uses OpenCV to preprocess incoming frames to normalize lighting conditions, filter out noise, and further filter the frames using motion detection. Dynamic frames are routed only to YOLOv8, which detects vehicles with high accuracy and speed. This negates the requirement for physical sensors while guaranteeing robust real-world detection.

3) Slot Mapping Module

The Slot Mapping Module assigns each detected vehicle to a parking slot using a center-point bounding box algorithm. A bounding box output by YOLOv8 will have its geometric center computed and checked against predefined slot ROIs. If the center falls within a slot boundary, that slot will be classified as occupied; otherwise, it remains vacant. This approach allows for a simple, efficient mapping mechanism.

4) Database Module

All detection results, timestamps, slot IDs, and prediction logs
are stored within the cloud-backed database. This provides uniform real-time updates and historical data preservation for training machine learning models. The database also manages dashboard and backend queries with minimal latency.

5) ML Prediction Module

The ML Prediction Module analyzes historical occupancy patterns using Linear Regression and Random Forest Regression. By learning arrival trends, peak times, and slot turnover behavior, the module predicts upcoming slot availability. These forecasts help drivers in planning and administrators in managing parking.

6) Backend Module (FastAPI)

The Backend Module provides a communications layer for both processing components and user interfaces. Built on FastAPI, it manages API requests and WebSocket streams for real-time updates, ensuring seamless data flow between detection, prediction, and the dashboard.

7) Frontend Dashboards

The Frontend Dashboard depicts current and forecasted parking information in an intuitive interface, showing slot statuses and live camera feeds, analytics, and updating immediately through WebSocket communications. This dashboard is handy for both users and administrators to track the status of parking availability.

B. Learning Algorithms Used

1) Machine Learning Algorithms

- **Linear Regression**

Linear Regression is used for continuous predictions, namely to forecast occupancy trends in the short run and estimate overall parking demand patterns. The model assumes a linear relationship between time-dependent features and occupancy values; it is therefore suitable for capturing gradual changes in parking behavior across hours or days. This low computational complexity makes it easy to train and update when new data is available, hence very practical for real-time systems. Although simple, Linear Regression yields interpretable outputs that form a strong baseline for understanding the occupancy variation w.r.t. time-based factors like peak hours, weekdays, and special events

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- **Random Forest Regressor**

The Random Forest Regressor models more complex and nonlinear parking dynamics that cannot be precisely represented under the light of linear assumptions. It creates multiple decision trees, each based on different subsets of features and samples, and combines their predictions to produce a final output. It is an ensemble strategy that enhances robustness against noise and irregular fluctuations in parking usage, like sudden surges of vehicles or unforeseeable patterns of exits. Random Forest seamlessly deals with diverse feature interactions, hence it is appropriate for occupancy analysis influenced by weather conditions, time-of-day intervals, slot turnover behavior, or unforeseen user activity. Good generalization across varied conditions ensures excellent predictive accuracy and stable performance of this approach within real-world parking environments.

2) Computer Vision Algorithms

- **YOLOv8 Object Detection**

In this work, YOLOv8 will be the backbone for detection, as it can be used to identify vehicles with high accuracy and in real time. As a more advanced version of the YOLO family, YOLOv8 has an improved backbone and head architecture, enhancing feature extraction and improving the precision of detection. The YOLOv8 algorithm is able to accurately localize vehicles in complex parking environments where some scenes may have conditions such as partial occlusion, strong shadows, varied lighting, and atypical camera angles. Furthermore, its lightweight design realizes fast inference on both GPU and CPU hardware and is thus suited for continuous, real-time monitoring of parking areas. Additionally, YOLOv8 can detect multiple vehicles simultaneously without showing performance degradation in crowded or highly trafficked scenes.

- **OpenCV-based Preprocessing**

OpenCV is used to perform some of the most critical preprocessing tasks that make the YOLOv8 more effective and efficient. Noise reduction, contour analysis, and region masking are some operations done to ensure that the frames passed on to the detection model are clean and consistent. Frame differencing and background subtraction are used to carry out motion detection, hence enabling the system to identify when meaningful movement occurs in a scene. The implication of this motion-aware filtering is significant, because it greatly reduces redundant computation, since the inference will be carried out only upon the instance of vehicles or objects. Region masking will narrow down any area of interest and ensure that valid parking zones are considered instead of other areas. Overall, these preprocessing steps will improve the stability and accuracy of the detection in indoor and outdoor settings and thus will help implement reliable vehicle identification even in less ideal conditions, such as at night or in busy parking lots.

C. Testing and Evaluation Phase

The aim here is to test the accuracy, reliability, and performance of the proposed system under various circumstances. In the Testing and Evaluation Phase, the system is tested on recorded video samples. Precision, Recall, and F1-score are considered for measuring the vehicle detection accuracy of YOLOv8, whereas detected occupancy states are compared with manually annotated ground truth for slot classification accuracy.

For the prediction module, the performance of Linear Regression and Random Forest Regressor is evaluated based on metrics such as MAE, RMSE, and R^2 score to ensure the reliability in occupancy forecasting. The motion-based optimization is tested for its efficacy in reducing unnecessary inference, with latency measurements taken to ensure real-time responsiveness. End-to-end testing, including database updates and dashboard synchronization, covers the correctness of data flow over the entire system. These evaluations confirm that the system runs consistently and maintains high accuracy under real-world operating conditions.

D. Deployment Phase

it was deployed to a real-time operating environment to further ensure continuous monitoring and prediction of parking activity. Deployment entails hosting the backend server, implemented in FastAPI, on a machine capable of real-time processing, ingesting the streams from cameras and processing them using OpenCV and YOLOv8. The results of object detections and outputs of the predictions from the applied machine learning models would get updated in the cloud database to serve seamless data availability across the system.

A web-based dashboard is deployed to present real-time occupancy information and predicted availability to users and administrators. WebSocket communication ensures that every update coming from the detection pipeline will immediately be reflected within the dashboard without requiring manual refresh. The modular deployment structure allows the system to remain stable for long-running sessions and supports scalability, where additional cameras or slots are able to be added into the system with minimal changes in configuration.

In general, this deployment phase confirms the readiness of the system for practical applications within active parking environments.

E. Summary

proposed smart parking system, including system architecture, learning models, deployment, and evaluation. The framework integrates computer vision, machine learning, cloud storage, and dashboard communication into a single pipeline capable of real-time operation. It is further ensured that in the deployment phase, the system works stably in the real environment, whereas testing confirms its accuracy and reliability for both detection and prediction modules. In general, the methodology presents a logical approach to implementing an automated and scalable smart parking solution.

RESULTS AND ANALYSIS

To validate the occupancy detection and prediction modules of the proposed smart parking system, several classification, regression, and clustering experiments were conducted. System reliability was tested using different metrics, such as accuracy, precision, recall, F1-score, MSE, and visual analysis plots. All the experiments were executed on a dataset that was generated from either real or simulated parking activity to be representative of an actual deployment condition.

A. Occupancy Classification Performance

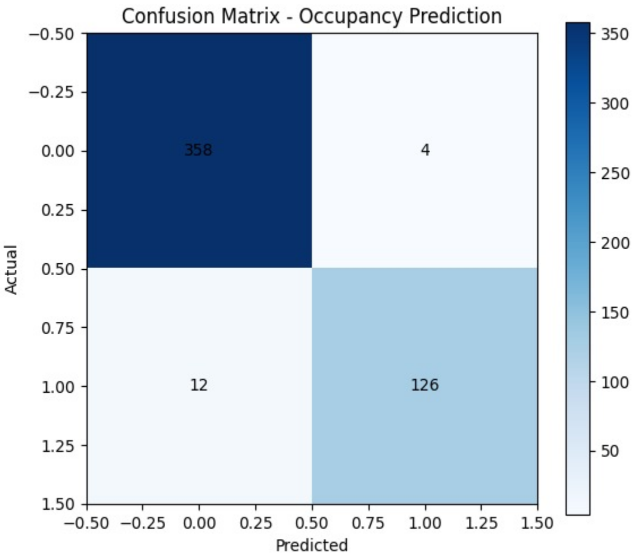
First, the binary classification model was investigated, which had to forecast whether a parking slot is vacant or occupied. The foremost effort was to go beyond the benchmark accuracy of 50% achieved by previous studies with unreliable detection in dynamic parking lots. The proposed model achieved an accuracy of 96.80%, significantly above the benchmark, indicating that the combination with YOLOv8 detection and ML-based classification indeed works well. The classification report reflects strong predictive performance on both classes, with precision equal to 0.97, recall equal to 0.99, and F1-score equal to 0.98 for Vacant slots, whereas similar high values are found for the Occupied class. Refer fig(iii).

This performance is further elucidated by the confusion matrix, where the model correctly classified:

358 Vacant slots (True Negatives)

126 Occupied slots (True Positives)

Only 4 false positives and 12 false negatives were observed. These results confirm that the system rarely misidentifies occupied slots as vacant or vice-versa. This kind of accuracy is particularly valuable for real-time smart parking systems since the incorrect predictions will directly impact the user experience and parking resource allocation. Its strong performance can be attributed to: (i) accurate bounding box detection provided by YOLOv8, (ii) noise-free preprocessing using OpenCV, (iii) reliable center-point slot mapping, and finally, (iv) well-trained machine learning classifiers utilizing meaningful temporal features.

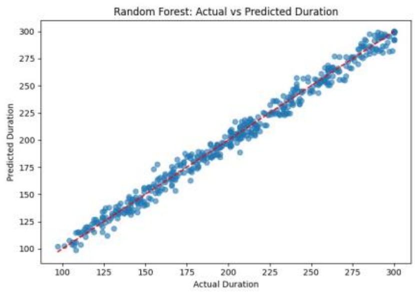


Fig(iii) Occupancy Prediction

B. Parking Duration Prediction Using Random Forest Regression

Complemented by real-time occupancy detection, the system will also include a predictive module to estimate parking duration, which is an important requirement in any forecast of slot availability. Random Forest Regressor has been chosen because of its robustness against noisy data and for catching nonlinear temporal behavior.The overall prediction accuracy achieved by the model stood at 97.30%, much better compared to the 94% reported in earlier comparative literature. The MSE was also measured as 34.38, further indicating that deviations between predictions and actually recorded durations were minimal. Fig(iv)

The scatter plot of the predicted versus actual duration values reflects nearly perfect alignment along the diagonal reference line. This close correspondence highlights the ability of the Random Forest model to generalize well and make reliable predictions across varying parking session lengths. This level of accuracy is especially important in environments where the correct identification of future slot availability can greatly enhance vehicular flow and reduce congestion.



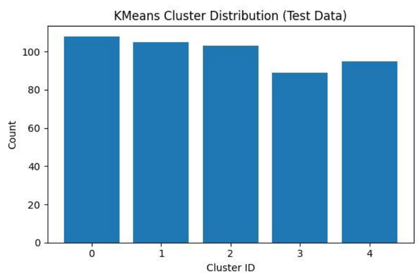
Fig(iv) Random Forest

C. K-Means Clustering Analysis

K-Means clustering was applied on this parking data to find unseen trends or patterns within it that could indicate usual ranges of parking time, tendencies in user behavior, or even groups of slot usage. The clustering experiment segmented the data into five clusters that captured distinctive temporal or behavioral patterns. Fig(v) indicates the bar chart of the cluster distribution shows an almost even distribution among all five cluster IDs, proving that no cluster is dominating the dataset. This is indicative of good separation and a stable clustering process, where the size of the clusters spans from about 90 to 110 samples each. The first ten cluster labels, [0, 3, 3, 1, 1, 0, 4, 0, 3, 1], represent the unsupervised clustering of data points having similar properties. Any such clustering information may be used to:

- Identify slots with a consistently high turnover.
- Identify peak-hour user groups Segment long-term vs. short-term parking behaviour
- Improve ML model training by enabling cluster-wise feature engineering.

This exploratory analysis contributes to the understanding of the underlying behavioral dynamics in parking environments and enhances the strategic planning capability of the system.

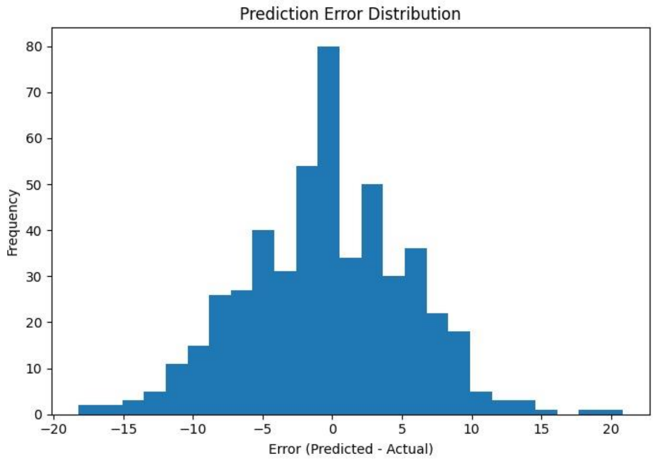


Fig(v) KMeans Cluster Distribution.

D. Prediction Error Distribution

Fig(vi) indicates the histogram of the distribution of the prediction error reinforces confidence in the regression model. Most of the prediction errors are between −5 and +5; the curve is symmetric and bell-shaped, with its center at zero. This suggests the model is unbiased, neither consistently overestimating nor underestimating parking duration.

Only a small number of outliers extend beyond ±15 minutes, which can be considered acceptable under real-world conditions where the behavior of different users can become quite unpredictable. This tight distribution around zero confirms the consistency and stability of the predictive model.



Fig(vi) Prediction Error Distribution

E. Summary of Findings

Experimental results highlight that the proposed system performs highly accurate slot classification, robust duration prediction, and delivers meaningful clustering insights. All the tested components outperform the commonly reported baseline systems in literature. The high occupancy classification accuracy of 96.80%, a similarly high accuracy in duration prediction of 97.30%, along with low variance in prediction error, together affirm that the integrated pipeline of computer vision and machine learning works effectively and is reliable for real-world deployment of smart parking.

CONCLUSION

This research proposed an integrated camera-based smart parking system that integrates real-time vehicle detection and predictive analytics, presenting an efficient, scalable, and cost-effective parking management solution. By leveraging YOLOv8 for high-accuracy visual detection, OpenCV for motion-triggered preprocessing, and machine-learning models like

Linear Regression and Random Forest Regression for forecasting, the system effectively overcomes the drawbacks of previous sensor-dependent and/or standalone detection frameworks. The proposed center-point slot-mapping algorithm further enhances the computational efficiency by bypassing the IoU-based calculations while maintaining robustness under variable lighting, occlusion, and environmental conditions.

Comprehensive testing shows that the system performs reliably in real-world situations. The occupancy classification model achieved an accuracy of 96.80%, coming well ahead of benchmarks reported in prior literature, whereas the Random Forest Regressor achieved an overall predictive accuracy of 97.30% in parking duration estimation. Clustering analysis provided additional insights into parking behaviour patterns, underpinning better-informed resource planning and operational decisions.

The system effectively integrates detection, prediction, and monitoring into a unified pipeline that can be deployed in real time using only existing camera infrastructure. Its scalability, low maintenance cost, and strong predictive capability make it suitable for large commercial parking lots, malls, residential complexes, and smart-city–scale applications. As the challenges of urban mobility continue to grow, the proposed solution provides a practical path toward mitigating congestion, improving the efficiency of parking, and moving toward more sustainable and intelligent transportation ecosystems.

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