

# Optimizing Slot Detection by Using Advanced Object Detection Techniques for Intelligent Parking Solutions

**Bhavana Narsingoju**

Symbiosis Institute of Computer Studies and Research, Maharashtra, India | Symbiosis International University, Pune, Maharashtra, India  
bhavkale3@gmail.com (corresponding author)

**Rajashree Jain**

Symbiosis Institute of Computer Studies and Research, Maharashtra, India | Symbiosis International University, Pune, Maharashtra, India  
rajashreejain@gmail.com

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## ABSTRACT

As the global population continues to rise, the demand for private vehicles and parking spaces has increased, making parking a persistent urban challenge. Locating a vacant parking spot is a common struggle for drivers, particularly during peak hours when multiple individuals search simultaneously. This situation results in several negative consequences, including increased pollution, traffic congestion, higher accident risk, fuel and time waste, and heightened driver frustration. To address these issues, smart parking systems can automatically detect available spaces and guide drivers to the nearest vacant spot efficiently. In this work, we investigated object detection techniques for identifying available parking slots, examining both vacant and occupied spaces, and explored how computer vision, deep learning, and artificial intelligence can enhance intelligent parking management. Methods such as yellow line detection, automatic parking spot inference, You Only Look Once (YOLO)-based car detection, and live analysis visualization were employed in the study, while the PKLot dataset was used for training and testing. The proposed approach achieved a testing accuracy of 99.48%, precision of 99.86%, recall of 99.89%, and F1-score of 99.87% while using 10% images from the PKLot dataset. Additionally, the model achieved 99% accuracy, 97.86% precision, 98.04% recall, and a 98% F1-score when validated on the real-time video segment from a local parking area.

*Keywords-intelligent parking system; deep learning; artificial intelligence; computer vision; object detection; You Only Look Once (YOLO); parking management*

## I. INTRODUCTION

The rapid growth of urbanization and economic development has contributed to the dramatic increase in private vehicle ownership worldwide. While mobility has improved, the surge in vehicles has placed enormous pressure on existing road infrastructure and parking facilities, particularly in urban areas. The shortage of available parking spaces has become a persistent issue, especially during peak hours or large public events, while for drivers, locating a vacant parking spot is often a stressful and time-consuming task. Beyond individual inconvenience, these situations have broader societal implications, like prolonged vehicle idling and unnecessary circulation contributing to traffic congestion, increased fuel consumption, higher levels of air pollution, and greenhouse gas emissions. Collectively, these factors contribute to the degradation of the environment, urban inefficiency, and driver

frustration, which raises the urgent need for a smarter approach to parking management [1, 2].

In response to these challenges, researchers and practitioners have increasingly turned to intelligent parking systems, which integrate advanced technologies to optimize space utilization and guide drivers more effectively. Traditional solutions often rely on sensor-based systems embedded within individual parking slots to detect occupancy. While these systems provide accurate, real-time information and can be integrated into mobile applications, they face significant limitations. Specifically, the installation of Internet of Things (IoT) sensors is costly, requires regular maintenance, and encounters scalability challenges in large or complex urban environments [3]. Furthermore, sensor-based systems are vulnerable to hardware malfunctions and environmental interference, which may compromise reliability [4].

To overcome these drawbacks, recent studies have focused on computer vision and deep learning techniques for intelligent parking solutions. Unlike sensor-based approaches, vision-based systems leverage existing infrastructure such as surveillance cameras, making them cost-effective and easier to scale. Moreover, computer vision algorithms can process live video feeds to detect vehicles, classify occupancy status, and provide real-time feedback to users and traffic management systems [5]. With the advent of deep learning, particularly Convolutional Neural Networks (CNNs) and object detection frameworks, vision-based parking systems, and multilayer interference frameworks have demonstrated remarkable improvements in accuracy and robustness [6-9].

Several approaches in the literature highlight the potential of these methods. For example, globalized license plate recognition using YOLOv2 and ResNet achieved detection accuracy of 99.57% and classification accuracy of 99.33% across multiple languages and formats, supported by the introduction of a new multinational benchmark dataset [10]. Region-based Convolutional Neural Networks (R-CNNs), transformer-based models such as Detection Transformer (DETR) [11] and its variants [12], and the You Only Look Once (YOLO) family of detectors [13] have all shown strong performance in object detection. More recent versions, including YOLOv4 and YOLOv5, have further improved detection accuracy and efficiency, making them highly suitable for intelligent parking applications [14, 15]. Meanwhile, lightweight architectures such as Tiny-YOLO and MobileNet have been investigated to reduce computational requirements, enabling deployment on edge devices and mobile platforms [16, 17]. These developments indicate a clear shift toward achieving an optimal balance between accuracy, speed, and resource utilization.

Nevertheless, challenges remain. Deep learning-based models are often computationally intensive, requiring substantial hardware and energy resources, which can limit their real-time deployment in large-scale systems [18, 19]. Wireless Sensor Networks (WSNs) and Narrowband IoT (NB-IoT), though widely adopted, are prone to signal interference and require frequent maintenance, reducing long-term viability [20, 21]. In addition, the absence of standardized datasets for benchmarking intelligent parking systems complicates comparisons across studies [22]. These gaps highlight the need for frameworks that are not only accurate but also efficient, sustainable, and adaptable to real-world urban conditions.

To address these challenges, recent research has proposed real-time parking occupancy detection frameworks that integrate motion detection with lightweight YOLO-based object detection models. Motion detection serves as a preprocessing step to reduce the computational load on deep learning models, thereby improving efficiency [23]. Other studies have evaluated CNN architectures such as LeNet, AlexNet, and mLeNet for occupancy detection, achieving up to 93.15% accuracy with a latency of 0.5 seconds [24].

In this study, the proposed framework leverages computer vision techniques, including yellow line detection and automatic slot inference, to dynamically delineate parking spaces. YOLO-based car detection is then applied to classify

slots as vacant or occupied, with live visualization providing real-time feedback to users. The system was trained on the PKLot dataset [22] and validated using a real-time video stream from a local parking lot, ensuring robustness under practical conditions.

## II. METHODOLOGY

The proposed methodology for parking lot analysis involves integrating multiple computer vision techniques to detect parking spots and determine their occupancy status in real-time.

### A. Yellow Line Detection

Data from a parking lot monitored through a Closed-Circuit Television (CCTV) footage (Figure 1) was collected for this study. Parking boundaries were delineated through yellow line detection using the following steps:

- Hue, Saturation, and Value (HSV) color thresholding: The input video was processed using HSV thresholds to isolate yellow hues corresponding to parking lines.
- Edge detection: Edge detection algorithms enhanced line visibility.
- Hough line transform: Detected line segments enabled accurate identification of parking boundaries.

This step established the basis for inferring individual parking spots.

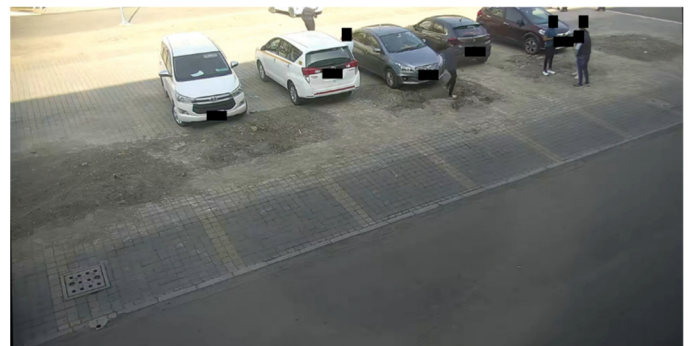


Fig. 1. Image frame from local CCTV video of parking lot.

### B. Automatic Parking Spot Inference

Once the yellow lines were extracted, the system dynamically inferred parking spaces based on their geometric layout (Figure 2). Perpendicular line intersections were identified to construct spot boundaries, and bounding rectangles were drawn around each inferred space. This approach allows the framework to adapt automatically to different parking lot configurations.

### C. YOLOv8-Based Car Detection

YOLOv8 was adopted as the primary vehicle detector due to its improved architecture compared to prior YOLO versions, as YOLOv8 incorporates a more efficient backbone, refined feature fusion, and a decoupled detection head.

- Backbone (feature extraction): The CSPDarkNet backbone, with Cross Stage Partial (CSP) connections, was employed to improve gradient flow and reduce computational cost. It integrates convolutional layers with Focus and C2f (CSP2) blocks and applies the Sigmoid Linear Unit (SiLU) activation function for non-linearity.
- Neck (feature fusion): A Path Aggregation Feature Pyramid Network (PAFPN) was used to enhance multi-scale feature fusion, while C2f blocks further refined extracted features.
- Head (prediction): Unlike earlier YOLO versions, YOLOv8 uses decoupled heads for classification and regression, improving accuracy and convergence speed. The output includes bounding box coordinates, objectness scores, and class probabilities.

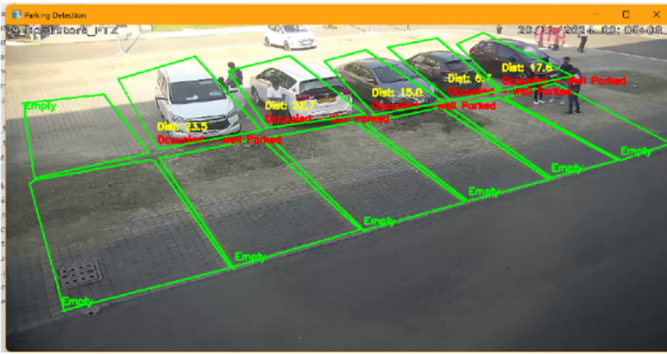


Fig. 2. Image frame from local CCTV video input of parking space after applying the yellow line detection method.

#### D. Dataset

The PKLot dataset [22] was employed for training, consisting of 6,998 annotated images labeled with "occupied" or "empty" parking status. The dataset was partitioned into 70% (4,898 images) for training, 20% (1,399 images) for validation, and 10% (701 images) for testing to ensure balanced evaluation.

Additionally, CCTV video footage captured from a local parking lot (18.66029, 73.718730) using a fixed overhead camera at a 45° angle covering 12 marked parking slots was used for testing. A full-day recording was obtained from 9:00 AM to 6:00 PM IST, corresponding to 03:30 to 12:30 GMT on 29 November 2024, and was used for frame extraction. From this footage, 58-second continuous video segments containing 1,740 frames (30 FPS) were extracted for testing.

From this segment, all frames first underwent a Quality Check (QC) to ensure clarity of slot boundaries. Consequently, 597 frames were discarded due to severe motion blur, slot occlusion, illumination/glare issues, or compression artifacts, leaving 1,143 QC-passed frames Table I. To avoid redundancy while maintaining temporal diversity, systematic sampling with an average stride of 7.47 was applied, selecting approximately every 7<sup>th</sup> or 8<sup>th</sup> frame. This produced 153 high-quality frames (13.38% of QC-passed frames), which were manually annotated to serve as the ground-truth validation set.

The full set of 1,740 frames was used for automated evaluation of accuracy, precision, recall, and F1-score, while the 153 annotated frames provided a representative and carefully verified benchmark for validating real-world model performance.

TABLE I. SUMMARY STATISTICS FOR SELECTION OF FRAMES

A: Frames Calculation		
Stage	Count	Explanation
Total frames extracted (58s x 30 FPS)	1,740	Full CCTV sequence from morning 9 AM to evening 6 PM dated 29/11/2024
Frames discarded (Quality Check-QC)	597	Excluded frames
Frames retained after QC	1,143	Eligible for sampling
B: Frames Discarded (Quality Check-QC)		
Stage	Count	Explanation
Severe motion blur	212	Camera shake/rapid movement
Occlusion (>50% slot area)	178	Blocked slot view
Illumination/glare issues	127	Extreme sunlight reflection
Corrupted/compression errors	80	Encoding artefacts (due to poor network)
Total frames discarded	597	-
C: Selection criteria for 153 frames through Sampling		
Stage	Count	Explanation
Annotated frames (manual)	153	Manual ground truth
Annotated as % of QC-passed	153	Represents 13.38% of 1143 QC-passed frames used for validation
Sampling Style	-	Systematic Sampling: Sample Frames {1,8,15,22...}
Sampling Stride (Interval)	-	Avg. stride = 7.47 (selected every 7 <sup>th</sup> or 8 <sup>th</sup> frame)

#### E. Occupancy Analysis

Detected vehicle bounding boxes were compared against the inferred parking spaces to determine occupancy. If the bounding box of a vehicle overlapped a parking space, that space was classified as occupied. Occupancy was further quantified using geometric and distance-based measures.

- Geometric center calculation: For each inferred parking spot rectangle, the geometric center is calculated using:

$$Center(x, y) = \left( \frac{x_1 + x_3}{2}, \frac{y_1 + y_3}{2} \right) \quad (1)$$

where  $x_1$ ,  $y_1$ ,  $x_3$ , and  $y_3$  are opposite coordinates of the rectangle.

$$Center(x, y) = \left( \frac{x_1 + x_2}{2}, \frac{y_1 + y_2}{2} \right) \quad (2)$$

where  $x_1$ ,  $y_1$ ,  $x_2$ , and  $y_2$  are the top-left and bottom-right coordinates of the bounding box.

- Distance Measurement: The Euclidean distance between the parking spot center and the detected vehicle's center was calculated:

$$Distance = \sqrt{(x_{car} - x_{spot})^2 + (y_{car} - y_{spot})^2} \quad (3)$$

If this distance was within a predefined threshold (10-20% of the spot's width), the space was considered occupied. In cases where multiple vehicles overlapped in the same spot, the closest vehicle was assigned.

- Intersection over Union (IoU): To improve robustness, the overlap between the detected vehicle bounding box and the defined parking space was also evaluated using IoU:

$$IoU = \frac{Area(Spot \cap Car)}{Area(Spot \cup Car)} = \frac{Area_{Intersection}}{Area_{Spot} + Area_{Car} - Area_{Intersection}} \quad (4)$$

IoU penalizes misalignments and provides a more accurate measure of occupancy.

- Occupancy ratio: Overall utilization was quantified as the percentage of occupied spaces relative to the total number of spots:

$$Occupancy\ Ratio\ (\%) = \left( \frac{Total\ Occupied\ Spots}{Total\ Number\ of\ Parking\ Spots} \right) \cdot 100\% \quad (5)$$

### III. RESULTS

#### A. Evaluation on PKLot Test Dataset (Primary Benchmark)

##### 1) Training and Validation

The proposed model was first evaluated on the PKLot dataset over 100 epochs. Figure 3 illustrates training and validation accuracy progression throughout the epochs, showcasing that the training accuracy increases rapidly during the initial epochs, improving from 87% to over 95% within the first 20 epochs, and gradually converges towards 99.5% by the end of training. Similarly, the validation accuracy follows a consistent upward trend, stabilizing at approximately 98%. The close alignment between the training and validation curves indicates effective learning, strong generalization capacity, and minimal overfitting.

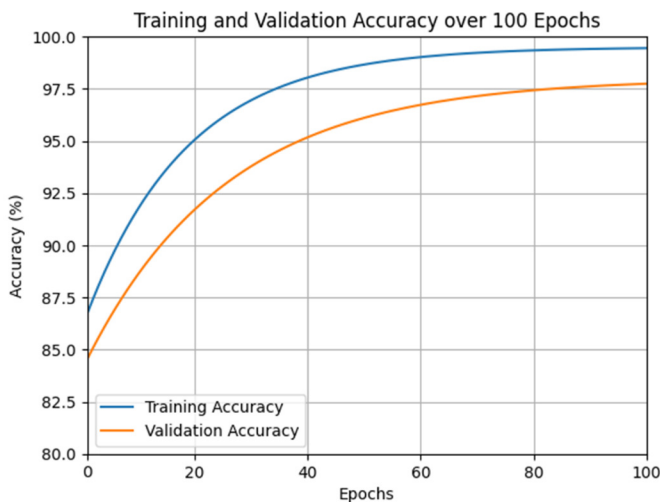


Fig. 3. Training and validation accuracy of the proposed model using the PKLot dataset.

##### 2) Testing

The testing performance of the proposed model on the PKLot dedicated subset is illustrated in Figure 4, highlighting the evaluation metrics progression throughout the 100 epochs.

The model achieved an accuracy of 99.48%, a precision of 99.86%, a recall of 99.89%, and an F1-score of 99.87%, indicating excellent classification capability for both occupied and vacant parking spaces. In addition, the high mAP@0.5 of 99.49% further confirms the robustness of the object detection process. Moreover, mAP@0.5 practically stabilized slightly before epoch 20, while the other metrics practically stabilized after epoch 40.

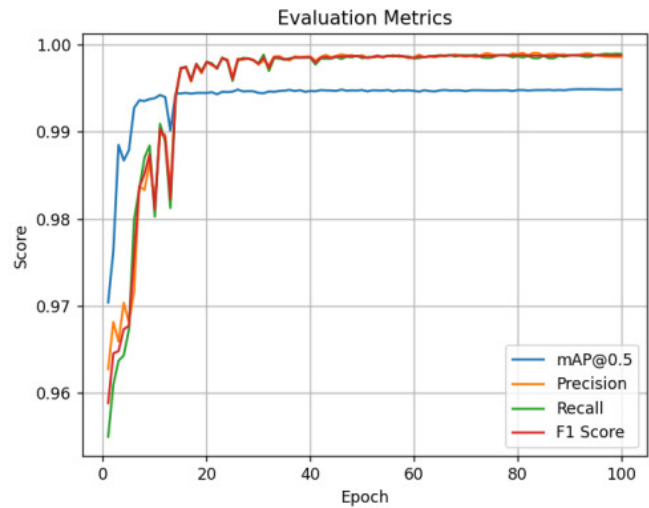


Fig. 4. Performance metrics of the proposed model on the PKLot dataset.

#### B. Supplementary Evaluation on Real-Time CCTV Footage

The performance metrics progression of the proposed model on the 58 s CCTV footage is illustrated in Figure 5 throughout the total 1,740 frames used.

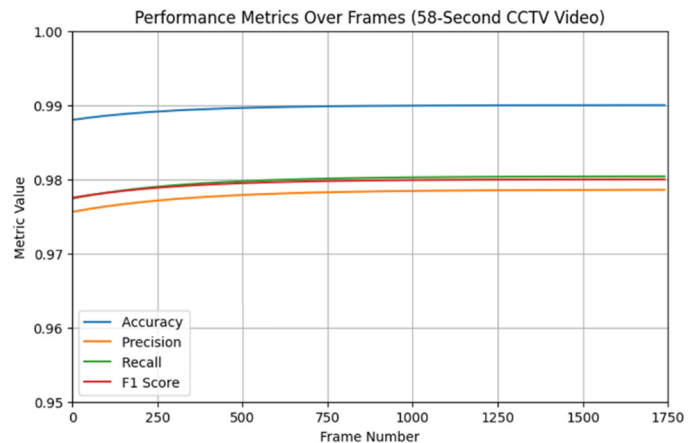


Fig. 5. Performance metrics on the CCTV video footage.

The model achieved an average accuracy of 99%, precision of 97.86%, recall of 98.04 %, and F1-score of 98%, with all metrics curves remaining fairly constant, especially after the

500 frames. This behavior confirms that the proposed system consistently maintains high detection performance in real-time surveillance conditions, despite vehicle movement and minor occlusions.

1) Annotated Frames

Table II provides descriptive statistics of the parking occupancy distribution observed in the supplementary CCTV video during the 153 annotated frames. For illustration, Table III shows the accuracy of the proposed model from 10 representative frames.

TABLE II. SUMMARY STATISTICS FOR PARKING VIDEO

Time of Day (IST)	No. of frames	Total parking slots	Occupied (%)	Empty (%)
09:01:00 to 09:01:58 AM	153 frames	12	41.7 (5 slots)	58.3 (7 slots)

TABLE III. FRAME-LEVEL OCCUPANCY DETECTION PERFORMANCE FOR 10 SAMPLE FRAMES

Frame	Occupied	Empty	Accuracy (%)	Inference Time (ms)
Frame_001	6	6	98.1	10.8
Frame_002	5	7	98.3	10.7
Frame_003	7	5	98.4	10.6
Frame_004	6	6	98.5	10.6
Frame_005	7	5	98.7	10.5
Frame_006	4	8	98.8	10.5
Frame_007	5	7	98.9	10.4
Frame_008	6	6	99	10.4
Frame_009	7	5	99.1	10.3
Frame_010	5	7	99.2	10.3

C. Confusion Matrix Analysis

The confusion matrix derived from the PKLot test dataset (Figure 6) serves as the primary indicator of classification performance, achieving 346 true negatives, 348 true positives, and only 3 false positives and 4 false negatives.

Confusion Matrix - PKLot Test Dataset (701 Images)

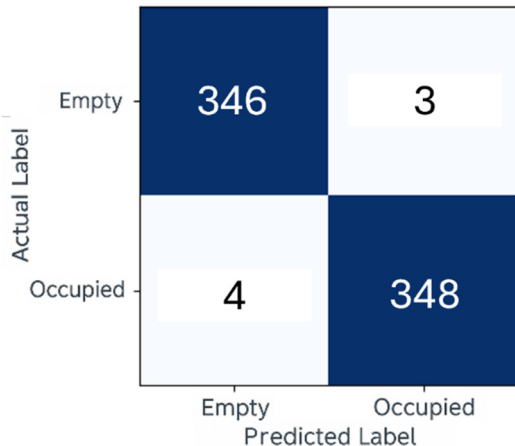


Fig. 6. Confusion matrix for PKLot test dataset consisting of 701 images.

The confusion matrix in Figure 7 evaluates the model's performance across the 58 s CCTV video sequence computed over 20,880 classifications (1,740 frames × 12 slots). The model achieved 4,902 true positives and 15,773 true negatives, with only 107 false positives and 98 false negatives.

Figure 8 presents the confusion matrix for the 153 manually annotated frames (1,836 slots), where the model achieved 431 true negatives, 1377 true positives, 9 false positives and 9 false negatives.

Confusion Matrix (Aggregated Slot-Level Predictions)

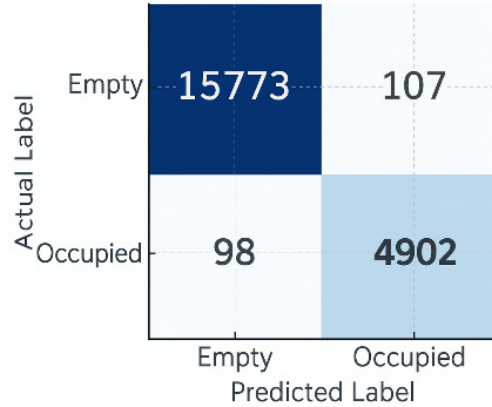


Fig. 7. Confusion matrix for CCTV video sequence.

Estimated Confusion Matrix (153 Frames)

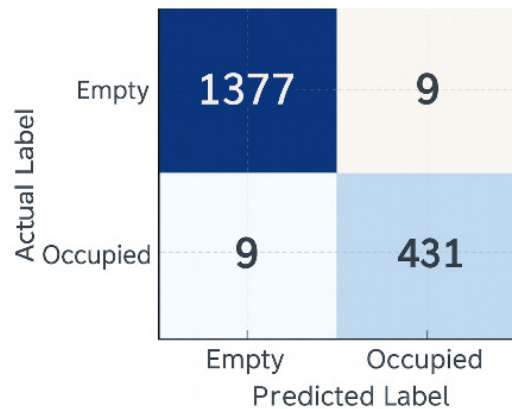


Fig. 8. Confusion matrix for 153 annotated frames.

D. Comparative Analysis

Table IV provides a comparative analysis of the proposed model with other published works using different object detection methods for intelligent parking systems and the corresponding reported accuracy. Authors in [14, 15] evaluated their model on the PKLot dataset, authors in [17] employed custom aerial parking datasets, authors in [18] used on-street surveillance videos, while authors in [19, 20] validated their models on different license plate datasets.

Among the models, the proposed model achieved the 2nd-best accuracy, only slightly below (-0.09%) the model

proposed in [20], which achieved an accuracy of 99.57%. The 3rd-best accuracy of 96.34% was achieved by the model proposed in [17], while the model with the lowest accuracy was the one proposed in [18].

TABLE IV. COMPARATIVE ANALYSIS OF METHODOLOGIES USED IN OTHER RESEARCH PAPERS

Research Paper	Methods Used	Dataset Used	Accuracy
[14]	AlexNet (Deep Learning)	PKLot	93.00%
[15]	LeNet, AlexNet, mLeNet	PKLot	93.15%
[17]	T-YOLO (Tiny YOLO with enhancements)	Custom Aerial Parking Dataset	96.34%
[18]	YOLOv5 on Edge Device	On-Street Surveillance	≈ 90%
[19]	SSD (Edge-AI)	Urban Edge License Plate Dataset	95.60%
[20]	YOLOv2 + ResNet (License Plate)	License Plate Dataset	99.57%
Proposed	YOLOv8 EfficientNet	PKLot (Train) + Local CCTV (Test)	99.48%

#### IV. CONCLUSION

This paper presented an intelligent parking occupancy detection framework that integrates advanced computer vision techniques using YOLOv8 for vehicle detection and EfficientNet-based feature extraction to enable accurate and real-time identification of occupied and vacant parking slots. The proposed system combines parking slot marking detection, automatic slot inference, and live visualization, providing a comprehensive and scalable solution for intelligent parking management.

The primary evaluation was conducted on the PKLot benchmark dataset using a predefined 10% test split consisting of 701 images, which served as the main indicator of model effectiveness. On this benchmark, the proposed approach achieved an accuracy of 99.48%, a precision of 99.86%, a recall of 99.89%, and an F1-score of 99.87%.

To further demonstrate real-world applicability, the model was evaluated on continuous Closed-Circuit Television (CCTV) video footage captured from a local parking lot. This supplementary evaluation involved 1,740 frames, resulting in 20,880 parking slot predictions across 12 parking spaces. Under these practical conditions, the system achieved an accuracy of 99.00%, a precision of 97.86%, a recall of 98.04%, and an F1-score of 98.00%.

Overall, the results confirm that the proposed framework provides a stable, accurate, and scalable solution for automated parking occupancy detection. Future extensions may include performance evaluation under nighttime conditions, further optimization of detection accuracy, integration with multiple camera views, temporal vehicle tracking, and large-scale deployment within smart city parking infrastructures.

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## AUTHORS PROFILE



Bhavana Narsingoju is a PhD research scholar in Computer Studies with 16 years of experience in educational leadership. She has contributed to research and publications in the fields of education, technology, and intelligent parking systems. She holds a Master's degree in Computer Science and is passionate about empowering youth through value-based education with a focus on holistic development.



Rajashree Jain is currently affiliated with the Symbiosis Institute of Computer Studies and Research (SICSR), Symbiosis International University. Her research interests include microwave techniques, antennas, optimization, nature-based algorithms, artificial intelligence, sensor networks, Internet of Things (IoT), data analysis, entrepreneurship, and education. She has authored more than 25 research papers published in reputed journals and has presented her work at numerous national and international conferences. She has also served as a chair or organizing committee member for various technical conferences and leadership summits and is an active member of professional organizations, including IEEE.