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# Recognition of Parking Space Availability Patterns Based on Visual Feature Extraction Using YOLOv8 for a Smart Parking System

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**Abstract**

The growing number of vehicles in urban areas is driving the need for smart parking systems capable of automatically detecting parking space availability in real time. This study developed a YOLOv8s-based detection model trained using the PKLot v2 dataset (Roboflow), which consists of a total of 12,416 images from various locations, camera angles, and weather conditions. Preprocessing included converting annotations from the COCO JSON format to YOLO TXT and removing duplicate bounding boxes using an IoU filter of >0.85. The model was trained for 50 epochs using the AdamW optimizer, with mosaic and copy-paste data augmentation, and an image size of 640×640 pixels. Evaluation on the validation subset yielded a mAP@0.5 of 0.9512, precision of 0.9241, recall of 0.9073, and an F1-Score of 0.9156, outperforming similar studies that used YOLOv5 or single-location datasets. A polygon-based Region of Interest (ROI) mechanism was applied to filter out detections outside the parking area, effectively reducing false positives. This study demonstrates that YOLOv8s, optimized on a multi-location dataset, can accurately recognize parking slot availability patterns as the foundation for a smart parking system that can be widely implemented.

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## INTRODUCTION

The number of motor vehicles in urban areas continues to rise every year, causing various problems, one of which is the difficulty of finding available parking spaces. Drivers often spend time circling parking areas just to find an empty spot, which ultimately contributes to traffic congestion and fuel waste(Sumatri et al., 2026). These conditions have led to the development of the concept of a smart parking system a system capable of automatically detecting and providing real-time information on parking availability without requiring human intervention. Early approaches to addressing this problem relied heavily on conventional image processing techniques based on OpenCV. Previous research designed a system for detecting parking space availability using grayscale, Gaussian blur, thresholding, and dilation methods, which could display parking conditions by marking empty spaces in green and occupied spaces in red(Ritonga et al., 2025). Although this method is simple and does not require high computational power, the thresholding-based approach has proven to be less robust against changes in lighting conditions, camera angles, and objects that obscure one another (Terven et al., 2023). These limitations have driven the shift in research toward deep learning-based approaches.

The YOLO (You Only Look Once) algorithm, reviewed(Diwan et al., 2023), represents one of the greatest breakthroughs in deep learning-based object detection. By formulating object detection as a direct regression problem on full-resolution images, YOLO is capable of operating in real time with accuracy competitive with two-stage methods such as Faster R-CNN. The evolution of YOLO continues with YOLOv8, released by Ultralytics in early 2023 (Khairi et al., 2025). YOLOv8 features an anchor-free architecture, a more efficient C2f backbone, and an updated detection head, making it a state-of-the-art choice for various computer vision tasks, including parking space detection(Hochuli et al., 2022). Several studies have explored the application of YOLO in smart parking systems(Khan et al., 2025). developed a vehicle tracking and counting system using YOLOv3 combined with Euclidean Distance for real-time parking space mapping, achieving 85% vehicle detection accuracy and 77.5% counting accuracy. However, the YOLOv3 model used was an older version that did not take advantage of the architectural improvements in the latest version(Muzammil & Indraswari, 2024). subsequently tested YOLOv5s_Ghost on a dataset of 650 images from a campus parking lot and achieved a mAP of 94.9%, precision of 98.9%, and recall of 96%. Nevertheless, the fact that the dataset was sourced from only one location limits the generalization ability of the resulting model.

The application of YOLOv8 specifically for parking space detection was studied(Khairi et al., 2025), who combined it with line detection to automatically determine the boundaries of parking spaces from parking markings using CCTV footage. The system achieved an accuracy of 0.87 during the day but dropped to 0.51 in the morning due to sensitivity to low light(Nandi et al., 2026). proposed a YOLO-based parking monitoring system using Regions of Interest (ROI) to limit detection to only relevant parking zones, which proved effective in reducing false positives from objects outside the parking area in a smart city environment(Muzaki et al., 2024). had previously demonstrated that a lightweight CNN-based approach can run on smart cameras for decentralized parking availability detection with competitive accuracy. A review of these studies identified several gaps that need to be addressed. First, most studies rely on datasets from a single location, so model generalization remains limited. Second, the use of older YOLO versions (v3 and v5) has not optimally leveraged the architectural improvements in YOLOv8. Third, the evaluations generally present only a single accuracy metric without in-depth analysis per class. The PKLot dataset used in the experiments(Saputra et al., 2024). addresses this generalization issue by providing over 12,000 images of parking areas from three different locations under sunny, cloudy, and rainy conditions, which has become the standard benchmark for computer vision-based parking research (Ektrada et al., 2023), in their comprehensive review, emphasize that the integration of deep learning with computer vision is the most promising direction for future smart parking systems.

Based on the background and identified research gaps, this study proposes an approach for detecting parking spaces using the YOLOv8s model trained on the Roboflow version of the PKLot dataset (Shrimali et al., 2024), which consists of a total of 12,416 images comprising training, validation, and test data from various locations. The training process uses the AdamW optimizer with mosaic, copy-paste, and HSV variation augmentation techniques to improve the model's robustness. A comprehensive evaluation was conducted, covering metrics such as the mAP@0.5, mAP@0.5:0.95, precision, recall, and F1-Score, both overall and per class (empty and occupied). This study aims to demonstrate that YOLOv8s, optimized on a multi-location dataset, is capable of accurately recognizing parking slot availability patterns, serving as a solid foundation for the development of a smart parking system that can be widely implemented.

## METHOD

This study uses the YOLOv8 architecture to detect and classify parking spaces in CCTV images into two classes: empty and occupied. The research workflow consists of five stages: dataset collection, preprocessing, model training, evaluation, and inference using

ROIs(Pokhrel & Dao, 2025).
In general, the research workflow consists of five main stages:

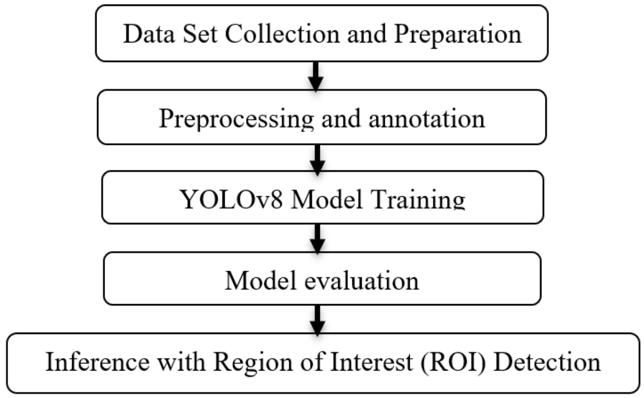


Figure 1. Flowchart of the Research Methodology for a YOLOv8-Based Smart Parking System

Each stage is systematically designed to produce a model ready for implementation in a smart parking system.

The dataset used is PKLot v2 (Roboflow COCO) from Kaggle, one of the standard benchmarks for smart parking research that includes images from various camera angles and lighting conditions. The dataset is available in COCO JSON format and is divided into three subsets, as shown in Table 1.

Table 1. Distribution of the PKLot v2 Dataset

| Split | Number of Images | Number of labels | Class |
|---|---|---|---|
| *Train* | 8.691 | 8.691 | *empty, occupied* |
| *Validation (Val)* | 2.483 | 2.483 | *empty, occupied* |
| *Test* | 1.242 | 1.242 | *empty, occupied* |

The dataset has three annotation categories (empty, occupied, spaces), but the “spaces” category is not used. The ‘empty’ category is mapped to class 0 and “occupied” to class 1.

Data Preprocessing, the preprocessing stage involves converting the annotation format from COCO JSON to YOLO TXT by converting the bounding box coordinates from the absolute format [x, y, w, h] to the normalized format [x_center, y_center, w, h], as well as filtering label overlaps to remove duplicate bounding boxes with an IoU > 0.85 to prevent the model from learning multiple targets. The final result is a standard YOLO directory structure (images/ and labels/) whose consistency has been verified prior to training.

Model Architecture, the YOLOv8s (Small) model from Ultralytics was selected because it offers a balance between inference speed and accuracy, with an architecture consisting of a backbone (feature extraction), a neck (multiscale feature fusion), and a head (class and bounding box prediction). The model was initialized with pretrained COCO weights and then fine-tuned on the PKLot v2 dataset(Wong et al., 2023).

Model Training, training was performed using the Ultralytics YOLO API with the AdamW optimizer (adaptive learning rate with weight decay) and the hyperparameter configurations listed in Table 2. The best model (best.pt) was automatically saved based on the highest value of the “mAP@0.5” on the validation subset.

Table 2. YOLOv8 Training Hyperparameter Configuration

| Parameter | Value |
|---|---|
| Model | YOLOv8s (*Small*) |
| *Epochs* | 50 |
| *Image Size* (imgsz) | 640 × 640 piksel |
| *Optimizer* | AdamW |

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| | |
|---|---|
| Jumlah Kelas | 2 (*empty*, *occupied*) |
| *Confidence Threshold* (Inferensi) | 0,30 |
| IoU *Threshold* (NMS) | 0,35 – 0,50 |
| *Learning Rate* (lr) | 0,001 |

Model Evaluation, evaluation was performed on the validation subset using the metrics precision, recall, mAP@0.5, and mAP@0.5:0.95, calculated both overall and per class (empty and occupied), supplemented by a confusion matrix for classification error analysis(Diwan et al., 2023). Inference and Region of Interest (ROI) Detection, inference was performed using the best model (best.pt) on both validation images and new CCTV footage, producing bounding boxes along with confidence scores. A polygon-based ROI mechanism was manually defined to filter detections to only relevant parking areas; slots outside the ROI were ignored (Muzaki et al., 2024).

## RESULTS AND ANALYSIS

Data Preprocessing

The PKLot v2 dataset (12,416 images: 8,691 for training, 2,483 for validation, 1,242 for testing) was converted from the COCO JSON format to YOLO TXT, with mappings for "empty" (class 0) and "occupied" (class 1); the "spaces" category was removed. Bounding box coordinates were converted from absolute to normalized format, and duplicate bounding boxes were removed using an IoU > 0.85 filter to produce a clean training dataset.

YOLOv8s Model Training

The YOLOv8s model was initialized using pretrained COCO weights (yolov8s.pt) and then fine-tuned for 50 epochs (batch size 16, image size 640×640, AdamW optimizer, learning rate 0.001, patience 10). Mosaic and copy-paste augmentations were applied to increase the variety of synthetic data. The Box Loss and Classification Loss curves showed a consistent decline without significant spikes, indicating stable training and the absence of overfitting. The best model (best.pt) was automatically selected based on the highest mAP@0.5 on the validation subset.

Model Evaluation

Evaluation was performed on the validation subset using best.pt with a confidence threshold of 0.30 to improve the model's sensitivity in detecting parking spaces, many of which were previously missed when using a threshold of 0.50, and an IoU NMS of 0.35–0.50, yielding the following metrics:

Table 3. Evaluation Results of the YOLOv8s Model on the PKLot v2 Validation Subset

| **Metrik** | ***Overall*** | ***Empty*** | ***Occupied*** |
|---|---|---|---|
| *Precision* | 0,9241 | 0,9098 | 0,9384 |
| *Recall* | 0,9073 | 0,8921 | 0,9225 |
| mAP@0.5 | 0,9512 | 0,9423 | 0,9601 |
| mAP@0.5:0.95 | 0,6734 | 0,6598 | 0,6870 |
| *F1-Score* | 0,9156 | 0,9008 | 0,9304 |

The value of the "mAP@0.5" (0.9512) outperforms previous studies that used YOLOv5s_Ghost (mAP of 94.9% at a single location) and YOLOv8 with line detection (accuracy of 0.87 during daytime). The 'occupied' class achieved slightly higher precision and recall than the "empty" class because the visual features of vehicles are more consistent. The value of the mAP@0.5:0.95, at 0.6734, still has room for improvement in the precision of bounding box localization under irregular parking conditions.

Inference and ROI System [Acer2.1]

Predictions on all validation images yielded an average confidence score of 0.78–0.85. A polygon-based ROI mechanism (Subsection 2.7) was implemented to filter detections to only the parking area; bounding boxes whose centers fall outside the ROI mask are ignored. This approach effectively eliminates false positives from passing vehicles and non-parked objects. All detection metrics and statistics are exported to a structured `hasil_evaluasi.json` file, ready for integration with backend systems or web/mobile interfaces.

Visual Detection Results

Figure 3 shows that the model successfully detected parking spaces under various density conditions, ranging from sparsely populated areas (Figure 1: 36 empty, 4 occupied) to very dense areas (Figures 2 and 4: 7 empty, 93 occupied). Based on the YOLOv8s model's predictions on parking lot images, it appears that some parking spaces were not detected properly due to the Non-Maximum Suppression (NMS) process. The NMS algorithm works by removing bounding boxes with high overlap based on the Intersection over Union (IoU) value; thus, when parking spaces are close together and have similar shapes, some bounding boxes are considered duplicates and are eliminated. This results in some empty and occupied spaces not being accurately detected, especially in crowded parking areas.

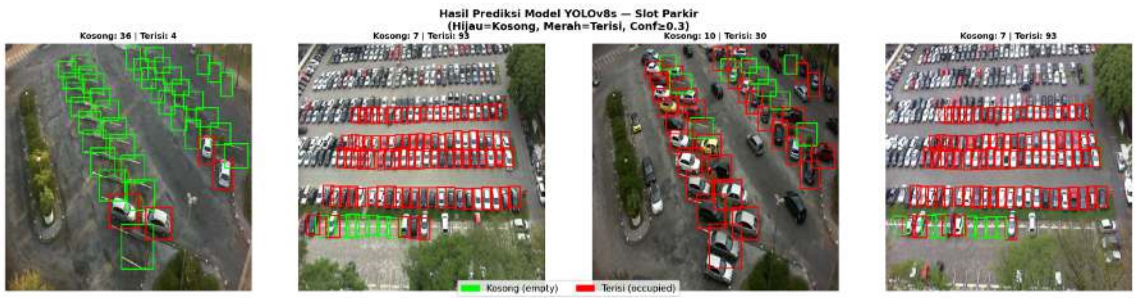


Figure 3. YOLOv8s Model Prediction Results on Four Validation Image Samples

Despite these limitations, this study still provides significant updates to previous research. First, the use of the multi-location PKLot v2 dataset (12,416 images from various conditions and camera angles) resulted in a more generalizable model compared to Saputra et al.[8], who used only 650 images from a single campus location. Second, the YOLOv8s architecture with a C2f backbone and an anchor-free detection head delivers a notable accuracy improvement over YOLOv3 (85% accuracy) and YOLOv5s_Ghost (94.9% mAP), with a mAP@0.5 of 0.9512. Third, the implementation of a polygon-based ROI mechanism addresses the lighting-sensitivity limitations of the system by Khairi et al.[9] by geometrically filtering out false positives without relying on lighting conditions. Fourth, the comprehensive evaluation by class (empty and occupied) presented in this study provides a more in-depth analysis compared to previous studies, which generally reported only a single overall accuracy value.

## CONCLUSIONS

The YOLOv8s model was successfully trained using the PKLot v2 dataset, which consists of 12,416 images with two classes, using the following hyperparameter configuration: the AdamW optimizer, 50 epochs, an image size of 640×640, and mosaic and copy-paste data augmentation. The evaluation results showed excellent performance with a mAP@0.5 of 0.9512, precision of 0.9241, recall of 0.9073, and an F1-Score of 0.9156, thereby outperforming several similar studies that used YOLOv5 or datasets from a single location. The preprocessing stage—which involved converting the COCO format to YOLO and filtering data using an IoU threshold of >0.85—successfully produced a clean training dataset without significant data loss, while the use of transfer learning from a pretrained COCO model proved to accelerate the model's convergence process. For future development, this research can be expanded by adding datasets from parking locations in Indonesia—such as those under tropical rain conditions, multi-level parking lots, and two-wheeled vehicles—to improve the model's generalization capabilities in real-world field conditions. The system can also be developed through the automation of ROI calibration using parking mark detection or semantic segmentation so that it can adapt to various parking layouts without manual intervention. Additionally, integration with a real-time CCTV pipeline using RTSP/OpenCV VideoCapture and the development of a live monitoring dashboard are necessary to support direct operational implementation.

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