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Comparison of the Use of YOLOv11 Variations in the Empty Parking Spaces Detection System

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Abstract

The Indonesian government continues to encourage technology-based innovation in public services, including the development of smart cities and smart parking that utilize sensor technology. The development of a smart parking system using the You Only Look Once (YOLO) model has improved the efficiency of parking management by providing real-time vehicle detection and availability of parking spaces. This study compared three variants of YOLOv11-Nano (YOLOv11n), YOLOv11-Small (YOLOv11s), and YOLOv11-Medium (YOLOv11m) to determine the most effective model in detecting empty parking spaces. The experiment was carried out using a dataset consisting of 5725 images of parking areas with various conditions such as angles, lighting, and distance. In addition, the researcher also used a 6-second parking lot timelapse video for the test material of the model that had been trained. The results show that each variant of YOLOv11 has its own advantage. YOLOv11s has the highest mAP50 (0.967), the YOLOv11m has the highest precision and recall and YOLOv11n has the highest FPS (62.14). With an accuracy range of 7.4% - 17.9% , YOLOv11s gets the highest accuracy. The findings of this study aim to determine the most effective YOLOv11 variant for smart parking implementation.

Keywords: computer vision, deep learning, object detection, smart parking, YOLOv11

INTRODUCTION

The Indonesian government continues to oversee innovations that are integrated with technology to improve the quality of public services (Afrilia, Asy'Ary, Muhdiarta, Mayasari, & Anangkota, 2024). This is linear with the development of smart cities that use innovation and technology-based infrastructure. *Peraturan Presiden Nomor 132 Tahun 2022* or Presidential Regulation Number 132 of 2022 concerning the *Sistem Pemerintahan Berbasis Elektronik* (SPBE) or Electronic-Based Government System. which is expected to form a clean, effective, transparent, and accountable government *(Peraturan Presiden Nomor 132 Tahun 2022)*. SPBE is also a guideline in the implementation of data and information integration, applications, infrastructure, and security in SPBE to optimize national government services in an integrated manner through transformation towards electronic government (e-government) and smart city (Hamjen, 2023). *Badan Perencanaan Pembangunan Nasional* (BAPPENAS) or National Development Planning Agency stated that effective governance transformation is collaboration between progressive leadership, technological innovation, and sustainability (Mungkasa, 2024). To build a sustainable city, smart cities in Indonesia are very important to be developed (Aisyah & Pratama, 2023). Not only focusing on technology, but smart cities also prioritize social and environmental integration as an improvement in the quality of life of the community (Wahyudi, Widowati, & Nugroho, 2022). Since 2017, Indonesian government has the "Movement Towards 100 Smart Cities" program as a commitment to implement smart cities (Atmaheni, Atmaheni, & Adianto, 2024).

One of the smart city implementations is smart parking, which is able to overcome parking management problems in urban areas. The development of smart parking shows the influence of technology in parking management so that it can save time searching for parking spaces and minimize congestion by applying sensor technology based on mobile applications that present real-time information to drivers regarding the availability of parking spaces (Zhang, Liu, & Wang, 2023). This system can increase security through the application of police number recognition as vehicle verification for parking facility users (Kishor, 2024). Rachman et al. (2024) emphasize the influence of important integration between public transportation systems and smart parking management in improving mobility efficiency in big cities. In addition to improving the user experience, smart parking also plays a role in efforts to reduce carbon emissions through time effectiveness (Zhang, Liu, & Wang, 2023).

The development of smart parking by applying the You Only Look Once (YOLO) model has given significant results (Kishor, 2024). Research by Alif (2024) shows that the YOLOv11 method is able to detect the availability of parking spaces with 98% accuracy which is included in the high accuracy category with a real-time video analysis process in identifying parked vehicles and empty parking spaces (Alif, 2024). Application of YOLOv11 to parking lot monitoring systems can accelerate the decision-making process in parking management (Kishor, 2024). YOLOv11 can detect parking space vacancies and provide information and directions to drivers to the available parking spaces. The accuracy shows 97%, which means that the system is optimal in providing routes for drivers in real-time (Cahyo, 2024). The use of YOLOv11 is growing as evidenced by the significant speed and accuracy of the results (Sharma, Kumar, & Longchamps, 2024). Variations such as YOLOv11-Nano (YOLOv11n), YOLOv11-Small (YOLOv11s), YOLOv11-Medium (YOLOv11m), YOLOv11-Large (YOLOv11l), and YOLOv11-Xtra Large (YOLOv11x) have their own advantages and are used according to user needs in the application of the YOLOv11 method (Alkhammash, 2025).

This research compares YOLOv11 variants (n, s, m) to determine their effectiveness in solving smart parking cases. The reseacher compares YOLOv11 variants (n, s, m) because they have a file size that tends to be smaller and can be used on devices with low specifications. The aim of this research is to recommend the most effective YOLOv11 variant in the future development of smart parking so that the accuracy is maximized, and the benefits are even greater.

METHODS

The variants of YOLOv11 need to be compared to evaluate object detection tasks. Each iteration of YOLOv11 can bring innovation and optimization to its architecture, so it is important to understand the advantages and limitations of each variant. The existence of this model variant comparison is intended to identify and offer the effective model according to the assessment matrix studied. In addition, the conduct of this case study can provide insight into the evolution of the YOLOv11 model and assist practitioners in determining the choice of model according to their specific needs. To achieve this goal, the researchers conducted an experimental approach using YOLOv11n, YOLOv11s, and YOLOv11m on specific datasets.

Data Used

In this research, the researcher used two datasets used for training and testing. The training dataset was in the form of a collection of images processed by Almutasem Bellah Enad with the title *Real-time Car Parking Computer Vision Project*. This dataset contained 5725 images of parking lots and their vehicles, captured from various positions, angles, lighting conditions, and distances.The dataset was divided into 5094 train set images, 361 valid set images, and 270 test set images. The large number of images in this dataset allowed for the development of more advanced detection technologies and contributed to achieve higher precision in object recognition. Moreover, the diverse image conditions within the dataset provided a comprehensive representation of real-world scenarios, making the detection model more adaptable to different environments. The inclusion of various lighting conditions and perspectives ensured that the model could effectively generalize its predictions beyond the training data. Furthermore, by incorporating multiple angles and distances, this dataset enhanced the robustness of the detection system in recognizing vehicles under different circumstances. A sample dataset from the first dataset is shown in Figure 1.

Figure 1. Sample from Real Time Car Parking Computer Vision Project (Resource: [https://universe.roboflow.com/almutasem-bellah-enad/real-time-car-parking/dataset/4 link](https://universe.roboflow.com/almutasem-bellah-enad/real-time-car-parking/dataset/4))

The testing data used was a 6-second video of parking lot activity from the acceleration results. This video comes from GitHub with the username Arpitpatel1706. The researcher only took the raw video with the title parking1.mp4 on GitHub. This video has several conditions, namely dark and light. The researcher used testing data in the form of a video to see the variants of YOLOv11 in detecting moving and real objects. The sample dataset testing video footage is shown in Figure 2.

Figure 2. Video Footage from Arpitpatel1706

(Resource: Personal Document, 2025)

YOLOv11 Architecture

YOLO (You Only Look Once) is one of the deep learning architectures used for object detection in imagery and video (Zoubaydat & Mao, 2021). First introduced by Redmon et al. in 2016, YOLO offers a fast and efficient object detection approach by simultaneously performing bounding box prediction and object classification in a single stage of a convolutional neural network (CNN) (Redmon, 2016). Since then, YOLO has undergone various iterations and improvements, including YOLOv2, YOLOv3, and so on, with improvements to accuracy and detection speed.

The You Only Look Once version 11 (YOLOv11) model is relied upon as a new architecture in YOLO modelling known for its high level of efficiency and precision. The YOLOv11 architecture consists of three main components, namely Backbone, Neck, and Head (Wang, Jiang, Xu, Xiao, & Zhao, 2025). The backbone plays a role in extracting features from the input image. YOLOv11 uses C3k2 (Cross Stage Partial with kernel size 2) which is a variant of Cross Stage Partial (CSP) with a smaller kernel size (Khanam & Hussain, 2024), so that processing can take place quickly without compromising the performance of the model. Neck plays a role in combining features of different resolution levels, in YOLOV11 use Spatial Pyramid Pooling Fast (SPPF) to improve efficiency in the feature extraction process and Cross Stage Partial with Spatial Attention (C2PSA) mechanism to improve spatial in the feature map so that the model can focus on important areas in the image (Agustin, Ayub, & Liliawati, 2024). Head is in charge of predicting bounding boxes and object classification directly, (Mujahidin, Kamil, & Abdullah, 2024), in YOLOV11 anchor-free is implemented to increase flexibility and adapt to different types of datasets without complex configurations (Alif, 2024). With these innovations, YOLOV11 is expected to present better performance in detecting vehicles in real-time in the form of images and aerials. The YOLOv11 architecture can be seen in Figure 3.

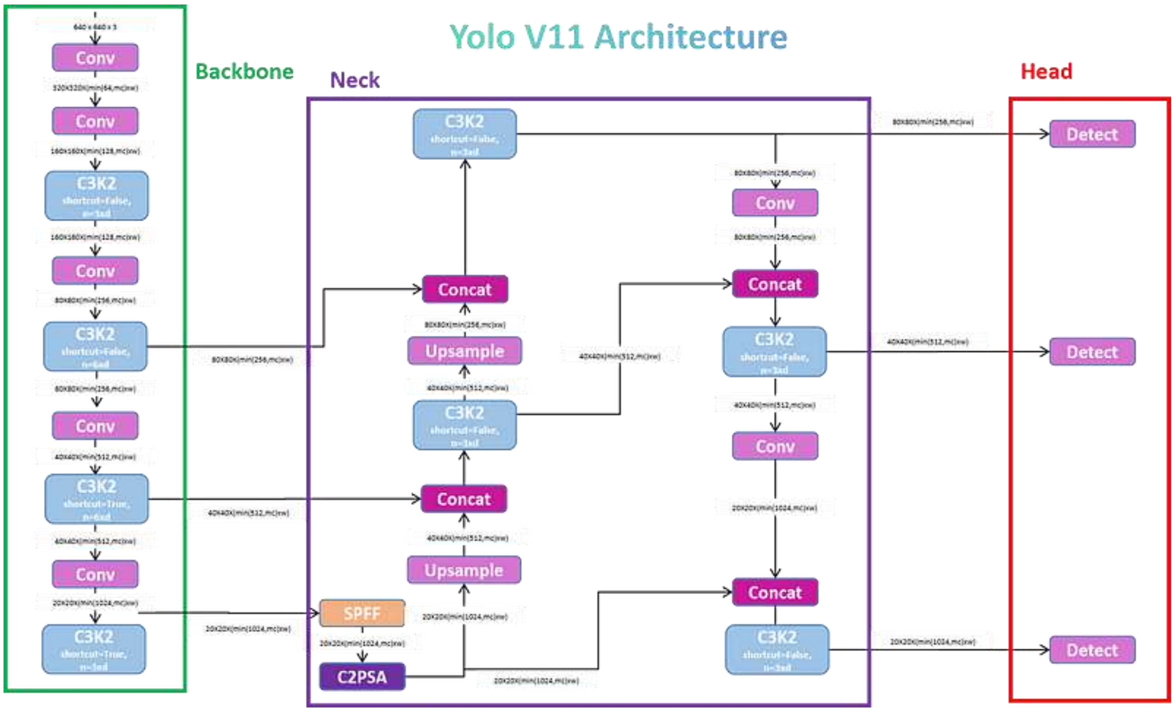

Figure 3. YOLOv11 Architecture
(Resource: https://medium.com/@nikhil-rao-20/yolov11-explained-next-level-object-detection-with-enhanced-speed-and-accuracy-2dbe2d376f71)

One of the main advantages of YOLOv11 is its ability to perform real-time object detection without sacrificing accuracy (Khanam & Hussain, 2024). This is achieved through architecture optimization that allows for high-speed image processing. In addition, the use of modern techniques in deep learning makes YOLOv11 more robust to variations in data, such as lighting changes and occlusion. (Li, Yan, Li, & Wang, 2024). YOLOv11 has been applied in various fields, including surveillance systems, autonomous vehicles, and mobile applications. Its ability to detect objects in real-time makes it ideal for applications that require fast response and high accuracy. In addition, the computing efficiency of YOLOv11 allows implementation on devices with limited resources, such as smartphones and embedded systems (Radovan, Mršić, Đambić, & Mihaljević, 2024).

Despite its many advantages, YOLOv11 also faces challenges, such as difficulty in detecting very small-sized objects or in severe overlapping conditions. More research is needed to address these limitations, including the exploration of more adaptive architectures and integration with other techniques such as semi-supervised learning. In addition, efforts to improve computing efficiency without sacrificing accuracy remain a major focus in further development.

Implementation of YOLOv11 Variants

The implementation of the YOLOv11n, YOLOv11s, YOLOv11m models was carried out in development using Python version 3.11. In the process of training and testing the model, researchers used the Graphics Processing Unit (GPU) in Google Colab to speed up the computing process. The libraries used in this experiment include Ultralytics YOLO as the main framework for deep learning, PyTorch and OpenCV as image and video processing tools, as well as Matplotlib and Seaborn to visualize the results of the evaluation.

Training and testing used the same dataset, which was the first dataset containing 5725 images with various conditions. The dataset was divided into 5094 train set images, 361 valid set images, and 270 test set images. The researcher did not perform the augmentation or preprocessing process on the dataset because the dataset had been evaluated by the creator. The configuration of the experiment carried out using the Ultralytics YOLO training pipeline was 100 epochs, batch size is 16, with the image used is 640 x 640 pixels and 8 workers to speed up the data loading process. The tested model consisted of three variants, namely YOLOv11n (nano) which is the lightest version and suitable for limited devices, YOLOv11s (small) which has higher accuracy but is still efficient, and YOLOv11m (medium) which is larger and accurate but requires more computing resources.

Figure 4. Sample Result of Train dan Validation
(Resource: Personal Documents, 2025)

After the testing process was completed, the researchers provided a real-time video of vehicle activity in the parking lot with a duration of 6 seconds. The video had been sped up to show the activity from day to night. This video was used to evaluate the model's performance in detecting parking slots in various light conditions. The model generated a boxed bounding that marked the detected parking slot, along with a confidence score that shows the level of certainty of the model against the detection results. The detection results of each model variant were compared based on several evaluation metrics, such as loss function (box loss, classification loss, and DFL loss), mAP50, precision, recall, FPS (frames per second), and confidence score. From the test results, performance differences between models were assessed to determine the advantages of each variant in the context of parking lot detection.

Evaluation of YOLOv11 Variants

At the evaluation stage, tests were carried out on the three YOLOv11 variants, namely YOLOv11n, YOLOv11s, and YOLOv11m to assess the ability to detect parking slots in a 6-second video. This evaluation aims to measure how well each model recognizes empty and filled parking areas, as well as assess the inference speed of each model. Some of the metrics used in the evaluation included mAP50, mAP50-95, precision, recall, and inference rate (latency per frame). In addition, to understand the detection performance of each category (empty and filled parking slots), precision, recall, and mAP50 measurements were carried out specifically for each class.

The evaluation was carried out using a confusion matrix to measure the accuracy of the model's classification of parking conditions. In addition, analysis of precision and recall values was used to determine whether the model was more likely to produce false positives or false negatives in detecting parking status. All of these metrics were calculated based on the detection results applied to an accelerated 6-second test video, so that it could represent parking activity from morning to night.

RESULT AND DISCUSSION

In this section, an analysis of the performance of the YOLOv11 model with three variants, namely YOLOv11n, YOLOv11s, and YOLOv11m, in detecting parking lots was based on a 6-second test video. The evaluation was carried out by comparing several key metrics, such as mAP50, Precision, and Recall, as well as FPS Comparison and Confidence Score Comparison. Testing of this 6-second video resulted in 189 frames with ground is 17 parking slots.

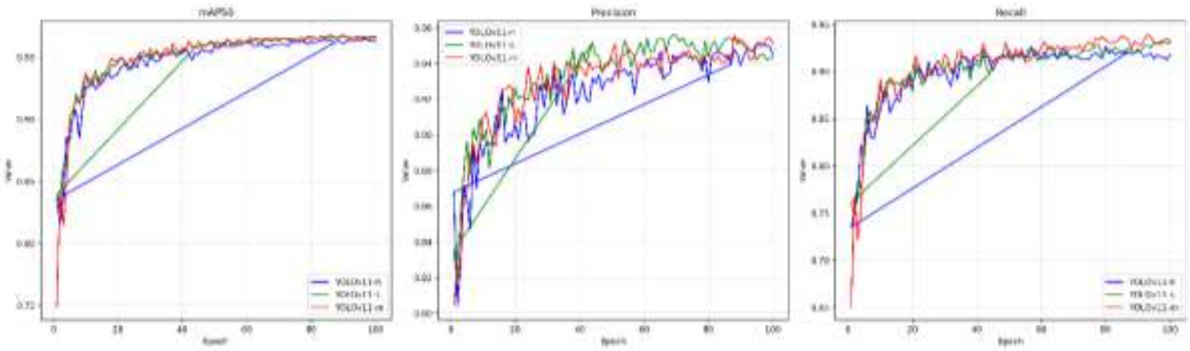

Figure 5. Comparation Result of YOLOv11n,YOLOv11s, and YOLOv11m (Resource: Personal Documents, 2025)

The comparison image shows that in terms of mAP50, the difference between the three models is quite small, with YOLOv11s recording the highest mAP50 at 0.967, followed by YOLOv11m and YOLOv11n which have a value of 0.965. In terms of Precision and Recall, the results show that YOLOv11m and YOLOv11s have higher precision and recall values than YOLOv11n. However, the difference is not too significant, especially in detecting empty and filled parking slots. This indicates that while more complex variant (YOLOv11m) have better overall performance, lighter variant such as YOLOv11s can still deliver competitive results.

Inference speed (latency per frame) is one of the important factors in selecting a model for real-time implementation. From the FPS Comparison results, it can be seen that YOLOv11n has the highest FPS (62,14), followed by YOLOv11s (56,50), and YOLOv11m which has the lowest FPS (37,67). This suggests that while YOLOv11m has the best performance in the detection aspect, its use in real-time applications may be more limited due to its higher latency. This is shown in figure 6.

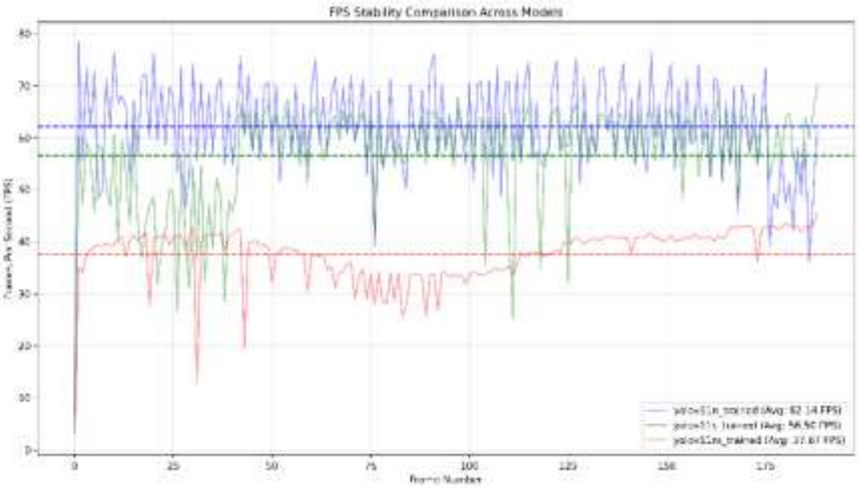

Figure 6. FPS Stability of YOLOv11n, YOLOv11s, and YOLOv11m
(Resource: Personal Documents, 2025)

In addition, the Confidence Score Comparison shows that YOLOv11m has the highest confidence score (0.706), followed by YOLOv11s (0.704) and YOLOv11n (0.692). This indicates that variant with larger sizes tends to have higher confidence in detecting objects, but with a compromise in inference speed.

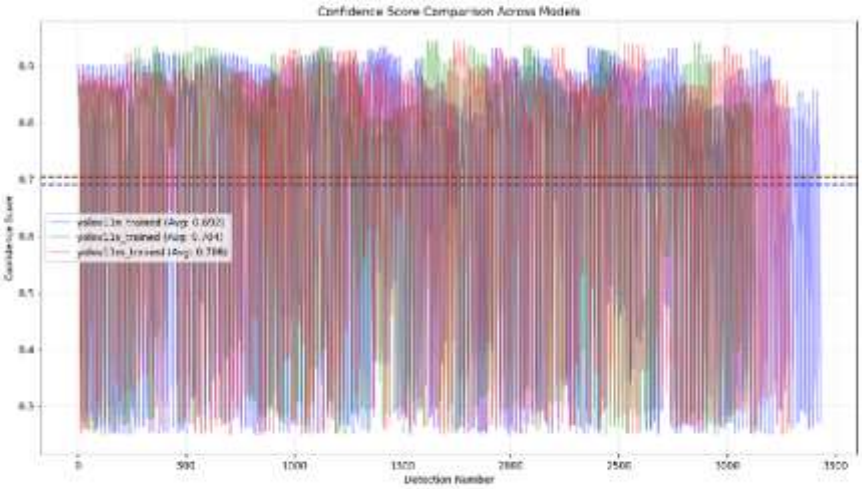

Figure 7. Confidence Score of YOLOv11n, YOLOv11s, and YOLOv11m
(Resource: Personal Documents, 2025)

In addition, the researcher also observed the results of the confusion matrix for testing on a 6-second video. The 6-second video that became the test material produced 189 frames. In the video the researcher assumed that there were 17 parking slots which became the ground truth. Each model had produced an average number of detections equal to ground. The third image of the confusion matrix obtained by each model is shown in Figure 8.

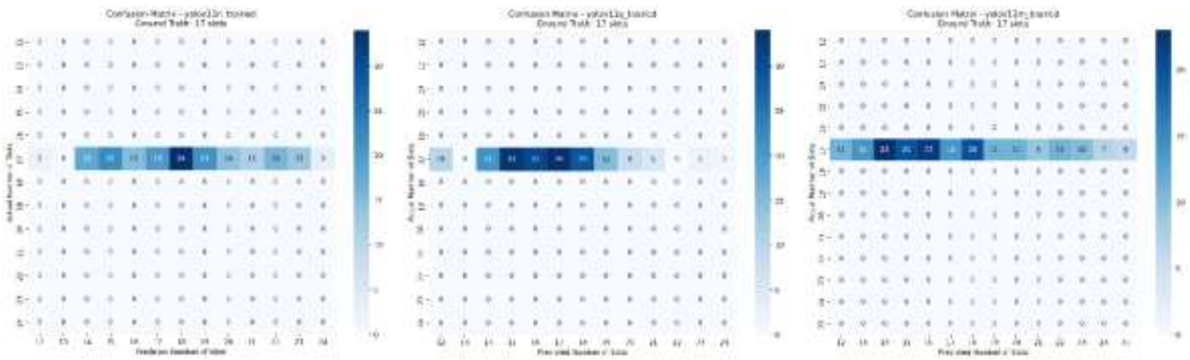

Figure 8. Confusion Matrix of YOLOv11n, YOLOv11s, and YOLOv11m
(Resource: Personal Documents, 2025)

From the results of the confusion matrix, YOLOv11n can correctly detect the number of parking spaces by 20, YOLOv11s can detect 34 parking spaces correctly, and YOLOv11m can detect 14 parking spaces correctly. Although on average the n, s, and m variants can have an average detection value of 18.15343915, 16.53439153, and 17.42857143, if you calculate the accuracy, all variants still have low accuracy. YOLOv11n gets 10.5% accuracy, YOLOv11s gets 17.9% accuracy, and YOLOv11m gets 7.4% accuracy. This can happen because of a number of reasons. The researchers assume that the model is poorly trained to distinguish parking slots, vehicles in certain lighting conditions and adjustments. In the sample footage, it can be seen that under certain color conditions, the model fails to detect the presence of cars or parking lots. In certain frames, the model detects vehicles that shouldn't.

Figure 9. Sample Footage Analysis of Detection Result
(Resource: Personal Documents, 2025)

In the context of real-time parking spot detection implementations, the choice of model is highly dependent on specific needs. If the system requires fast detection with minimal latency, YOLOv11n can be a more appropriate choice. However, if accuracy is a top priority, YOLOv11m is more recommended. YOLOv11s can be the most effective variant if you want to get a balance between these two aspects.

CONCLUSION

After comparing the three YOLOv11 variants, namely YOLOv11n, YOLOv11s, and YOLOv11m in detecting parking spaces in video tests that have color, lighting, and angle conditions that make parking spaces not clearly visible, researchers found that YOLOv11s has the highest mAP50 (0.967), indicating that this model provides the most accurate detection results compared to the other two variants. Meanwhile, the YOLOv11m has the highest precision and recall, which means that this model is better able to detect parking slots with fewer errors than the YOLOv11n. YOLOv11n has the highest FPS (62.14), followed by YOLOv11s (56.50), and YOLOv11m (37.67). This means that YOLOv11n is better suited for real-time applications because of its lower latency.If the top priority is real-time detection speed with minimal latency, YOLOv11n is the best choice. Based on these results, the selection of the YOLOv11 variant should be tailored to the specific needs of the application, whether it prioritizes accuracy, speed, or resource efficiency.

For further research, it is recommended to focus on improving the accuracy of the model in detecting empty and filled parking slots. Based on the test results, the accuracy of the model is still relatively low, which is likely due to the model's lack of ability to distinguish parking slots from vehicles in certain lighting conditions. Therefore, it is necessary to make adjustments to the training data, such as adding more image samples with different lighting variations, shooting angles, and environmental conditions. In addition, the model also needs to be better trained, for example by increasing the number of epochs or fine-tuning hyperparameters to reduce detection errors. Errors in detecting objects that are not vehicles as cars, or vice versa, are also a concern, so the use of additional data augmentation or preprocessing techniques can be considered to improve the model's resilience to variations in parking conditions. In addition, further validation can be carried out with testing on longer videos to ensure that the model can work stably in real-world scenarios. With this improvement, it is hoped that the YOLOv11 model can be more optimal in detecting parking slots accurately and efficiently.

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