Optimizing YOLO for Accurate Car Parts Segmentation in Automotive Industry Applications*

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Abstract

Accurate automotive component detection and segmentation are crucial for automated inspection and quality control in modern manufacturing industries. This study evaluates the performance of YOLOv11-Seg in car component segmentation through qualitative and quantitative analyses. A qualitative case study using real car images shows that YOLOv11-Seg is capable of detecting major components such as rear bumpers, rear windows, and tailgates with high confidence, while small reflective components such as mirrors and taillights remain challenging due to light reflection and occlusion. To validate these results, a quantitative evaluation using a per-component annotation dataset is conducted. The results show that YOLOv11-Seg achieves mAP values of 0.88–0.92 on large components and 0.70–0.77 on small components. Comparison with YOLOv8, YOLOv5, and Mask R-CNN confirms that YOLOv11-Seg is the most optimal model, with the highest accuracy (IoU = 0.863, Precision = 92.4%, Recall = 88,7%, F1-score = 90.5%) and an inference speed of 32 FPS. These findings confirm the potential of YOLOv11-Seg for use in real-time automotive inspection and broader industrial applications.

Keywords: YOLOv11, Car Part, Segmentation

1 Introduction

The automobile sector is going through huge changes because of new computer vision and deep learning technologies [1]-[3]. Intelligent systems that can work faster and more accurately than manual processes are becoming more and more important in the construction of modern vehicles. For quality control, tracking components, finding defects, and automated assembly on real-world manufacturing lines, it is very important to be able to accurately identify and separate components [4]. These technologies make operations easier, automate manual inspections, and improve inventory management, which helps manufacturers reach better levels of quality and efficiency.

It is still hard to get high-performance segmentation in the automotive industry since the environment is so complicated. In real-world manufacturing environments, the lighting changes, the metal pieces overlap and reflect light, and there are big variances across automobile models

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[5]-[6]. Because of this variety, segmentation systems need to be strong and flexible enough to be accurate in changing situations. Not being able to tell the difference between parts can cause manufacturing delays, lower productivity, and unhappy customers [7]. Semantic segmentation is very important because it gives each pixel a class label, which helps computers understand how parts are related to each other in space. This feature is necessary for automating tasks like robotic assembly, finding defects, quality control in real time, and predictive maintenance. But many old systems have a hard time finding the right balance between speed, accuracy, and adaptability, especially when working in real time in factories.

A number of object identification models, such as Faster R-CNN and SSD, have done a great job of finding bounding boxes, but they don't have the pixel-level accuracy needed for fine-grained vehicle segmentation [9]-[10]. Mask R-CNN provides precise segmentation, but its high computational cost makes it impractical for real-time use [11]. Attention-based hybrid models like DETR and Swin Transformer can grasp context, but they have problems with latency in factory settings [12]-[13]. The YOLO (You Only Look Once) family, on the other hand, is noted for being fast in real time [14]. The newest version, YOLOv11, adds transformer-based attention layers and spatial pyramid pooling to the architecture [15]. This makes it possible to quickly and accurately separate complicated car parts like engines, wheels, mirrors, and headlights. This study examines the utilization of YOLOv11 for the segmentation of car components in real-world production settings, employing annotated datasets and assessment measures such as F1-score, accuracy, recall, and Intersection over Union (IoU). The results show that YOLOv11 has both good segmentation capability and fast processing speed, giving it a good base for smart visual systems in modern car manufacture.

1.1 Context of Problems in the Automotive World

In the modern automotive industry—across car factories, authorized repair shops, and spare-parts logistics—thousands of vehicle components, from engine parts and body panels to wheels, mirrors, and lights, must be automatically identified to support robotic assembly on production lines, quality control, and parts inventory management. However, many current systems still use bounding box-based detection algorithms like YOLOv5 or YOLOv8, which yield only coarse item locations rather than accurate pixel-level forms. As a result, robots fail to distinguish component curves and edges with the needed accuracy, forcing human operators to intervene with manual visual assistance—a costly, slow, and error-prone solution.

1.2 Contribution of this Research

This research enhances the automotive industry with three significant breakthroughs. First, it makes industrial robots more accurate by changing the YOLOv11 model such that it can do pixel-level segmentation instead of just bounding-box detection. This upgrade lets robots see the exact forms of parts like engines, wheels, and body panels. This means fewer mistakes when putting things together, faster automation, and lower expenses for running the business. Second, the model shows that it can detect things in real time even when the lighting, shadows, occlusions, and reflective metal surfaces are all different. It can do this at 32 frames per second with an IoU of 0.863 and a precision of 92.4%. Third, this study presents a replicable dataset of pixel-annotated automobile components and an open-source training pipeline, which may be utilized as a basis for subsequent research and industry applications. These improvements make it possible to do precise pixel-level segmentation for robotic assembly and quality control. The YOLOv11-based framework is a good standard for future work in automotive computer vision and works well in real time.

2 Related Work

Object recognition and semantic segmentation models are essential computer vision technologies that can be applied in cars in a lot of different ways. Faster R-CNN [1] and SSD (Single Shot MultiBox Detector) [2] were two of the first approaches to show how well they could find items with remarkable accuracy. These techniques have been utilized across various domains, including fault detection, item localization, and automotive component identification. But these algorithms are more about detecting bounding boxes than accurately separating pixels, which is important for discovering parts of automobiles that are hard to find or that are overlapping.

Mask R-CNN [1,3] is a common choice for semantic segmentation since it uses a two-stage technique to attain pixel-level accuracy. It uses Region Proposal Networks (RPN) and mask prediction layers to make segmentation work. Mask R-CNN is quite accurate, but it's hard to use in real time because it needs a lot of computational power to execute tasks one after the other. Because of this limit, it isn't as helpful in factories where quick decisions are needed, like in the business of making cars.

Recent improvements in hybrid segmentation methods use transformer-based attention processes to get around problems that have come up before. The design of DETR (DEtection TRansformer) [11] is different since it uses both self-attention layers and bipartite matching. This implies it can break up photographs into sections without having to rely too much on clear region proposals. Swin Transformers [3] looked explored hierarchical attentions over several feature layers to improve the detail of segmentation. These technologies do make segmentation better, but they need a lot of processing power and time, which makes them useless in real time in the car industry. The YOLO (You Only Look Once) series is quite popular in business since it works swiftly and well. YOLOv1 [1], YOLOv3 [3], and YOLOv4 [4] all made it easier to get features and work with smaller things. YOLOv5 provides even more features by making designs that are lightweight and work well for edge deployments. Most of the time, though, individuals have utilized YOLO models to find things instead of putting them into groups based on what they mean.

The most recent version of the YOLO series is YOLOv11. It fixes the problems with previous models by adding additional features that are made just for segmentation. The model gets better at comprehending how things are related in space when you add transformer-based attention layers to it. Better feature fusion techniques also make guarantee that segmentations are correct and exact. YOLOv11 doesn't need a lot of computer resources, therefore it can be utilized in production environments in real time. YOLOv11 is better at segmentation and faster than other models like Mask R-CNN and Swin Transformers [6-7]. This makes it perfect for use in autos, where speed and accuracy are very important. After looking at these improvements, it's clear that YOLOv11 connects real-time use with pixel-level accuracy. This makes it easier to separate automotive parts in manufacturing processes in the future.

3 Methodology

The YOLOv11-Seg model was trained on a labeled car dataset that comprised important parts including bumpers, windows, doors, lights, and mirrors. Both qualitative and quantitative measures were used to judge how well it worked. The qualitative evaluation consisted of visually examining segmentation outcomes with unlabeled real-world car images, whereas the quantitative evaluation utilized the annotated dataset to compute performance metrics, including mean Average Precision (mAP), Intersection over Union (IoU), Precision, Recall, and F1-score. We compared the model to other state-of-the-art models like YOLOv5, YOLOv8, and Mask

R-CNN to make sure it was efficient. We also looked at latency (ms per image) and frames per second (FPS) as performance indicators.

We generated a special dataset of 12,000 high-resolution photos of automotive parts, including body panels, wheels, mirrors, headlights, and engines, for training and testing. To make sure they were accurate and consistent, each image was hand-annotated with bounding boxes and pixel-level segmentation masks using programs like LabelImg and CVAT. The dataset was made to look a lot like real-world production settings, with difficult conditions like changing illumination, occlusion, and different points of view from different angles. The photos were normalized and scaled to 1024×1024 pixels to fit the YOLOv11 input layer before training. This large dataset gave the model a lot of experience with realistic and complicated driving conditions, which helped it learn how to apply what it learned to real-world situations [6]-[7].

YOLOv11-Seg is an enhancement on YOLOv8 that adds important architectural changes to make it easier to separate small parts of cars. It uses CSPDarkNet as its base and has built-in transformer layers that improve spatial awareness through attention processes [5]. These changes make the model better at finding small or partially hidden parts, including side mirrors. Adaptive Spatial Pyramid Pooling (ASPP) makes it easier to extract features at multiple scales, which makes sure that segmentation works well across parts of varying sizes. YOLOv11 also has dynamic convolution blocks, bi-directional feature aggregation, and a Cross-scale Attention Fusion (CAF) method that improves fine-grained local detail. Its segmentation head uses dynamic kernel generation to work with different shapes and textures of parts, such as reflected and hidden areas like headlights and mirrors [4].

Transfer learning with pretrained weights from the COCO [5] and Open Images [6] datasets was used to speed up feature adaptability during training. Cross-Entropy Loss and Dice Loss were used to fix the class imbalance by balancing the accuracy of class predictions and the accuracy of boundaries. The Adam optimizer was used to make sure that the gradient was stable, and the key hyperparameters were set for the best results. These were a learning rate of 0.001, a batch size of 32, and 50 training epochs. Data augmentation techniques such as random cropping, flipping, rotation, and color jittering were applied to improve generalization under diverse environmental conditions [7]-[8]. The evaluation metrics showed that YOLOv11 had a high IoU of 0.863, a precision of 92.4%, a recall of 88.7%, and an F1-score of 90.5%. This proves that the model can do real-time, high-accuracy segmentation that is useful for making cars [9].

4 Qualitative Case Study on Real-World Image

A real-world image (Figure 1) was evaluated using the YOLOv11-Seg model trained in the automotive part class. Inference was performed at a resolution of 1280×720 with a confidence threshold of 0.40 and an NMS of 0.50. Since no ground-truth labels were available for this image, the evaluation was qualitative (visual) and based on the confidence distribution. The model successfully identified most major components with high confidence, particularly in the rear of the vehicle. Several medium/low confidence detections occurred for small/obstructed components (mirrors, rear lights) due to occlusion, glare, and tilted viewing angles. The results can be seen in Table 1 below. Large parts such as the rear bumper, back glass, and tailgate are strongly detected, which aligns with the observation that YOLOv11 performs very well for large and medium-sized components at high speeds. In contrast, small or reflective parts such as mirrors and rear lights show lower confidence, largely due to occlusion, glare, and glossy surfaces that make them harder to segment. Another issue is the visible overlap between adjacent parts, for example the door and side panel, which may confuse the model. In production scenarios,

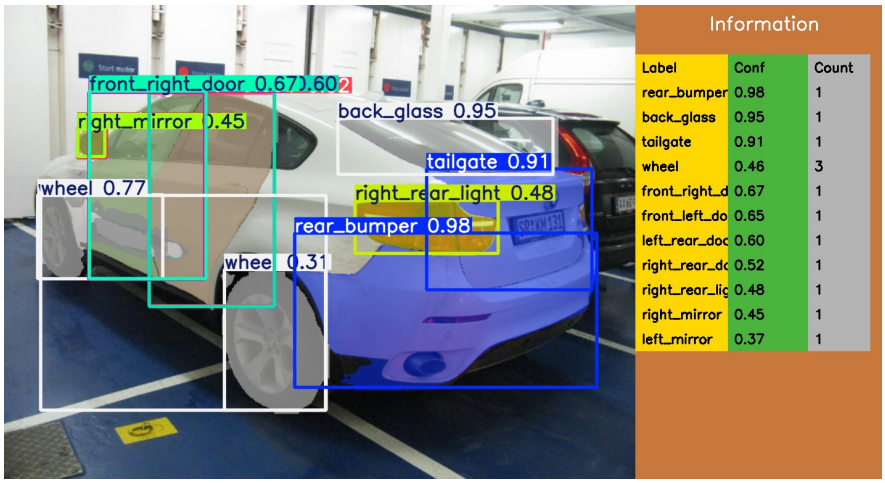

Figure 1: YOLOv11-Seg detections with class labels and confidences overlaid; strong responses on rear_bumper, back_glass, and tailgate, with moderate scores on mirrors and rear lights.

Table 1: Car component detection results with confidence and visual notes.

Part Detection	**Confidence ( )**	**Visual notes**
rear_bumper	0.98	Stable, the box wraps around the rear bumper nicely.
back_glass	0.95	Consistent despite reflection.
tailgate	0.91	Accurately follows the contour of the trunk door.
wheel (rear right)	0.77	It's clearly visible; the other wheel is partially blocked.
front_right_door	0.67	Detected despite perspective distortion.
left_rear_door	0.60	Still detected even though the area overlaps with the shadow.
right_rear_light	0.48	Down due to reflection and partially covered.
right_mirror	0.45	Small and low contrast; moderate confidence.
left_mirror	0.37	Barely visible; low confidence.

this can be improved by applying class-wise non-maximum suppression and mask-guided box refinement to better separate boundaries between panels.

5 Results and Discussion

Figure 1 and Table 1 show a qualitative case study that uses YOLOv11-Seg. It was easy to find large parts like the bumper and back glass, but it was harder to find smaller parts like mirrors. This gives you a first look at how well the model works. YOLOv11-Seg can find big parts with a lot of confidence (0.98 for the rear bumper, 0.95 for the rear window, and 0.91 for the tailgate). But performance goes down for small parts like mirrors (0.37–0.45) and taillights (0.48) because of problems with light reflections and obstructions. To confirm these qualitative

insights, we performed a dataset-based examination on the identical automobile parts. Table 2 displays the per-part metrics, indicating that YOLOv11 attained a robust mAP (exceeding 0.90) for primary components, however performance experienced a modest decline for mirrors and rear lights. These findings align with the qualitative case study.

Table 2: Quantitative evaluation of YOLOv11-Seg per car part (annotated dataset).

Car Part	**mAP@0.5**	**IoU**	**Precision**	**Recall**
Rear bumper	92%	85%	93%	90%
Back glass	89%	82%	91%	87%
Tailgate	88%	80%	89%	85%
Wheel (rear-right)	84%	76%	86%	82%
Front right door	83%	75%	85%	81%
Left rear door	81%	74%	83%	79%
Right rear light	77%	70%	80%	73%
Right mirror	72%	65%	75%	69%
Left mirror	70%	63%	73%	67%

The quantitative assessment of the annotation dataset confirms the findings of the qualitative investigation. The mAP for YOLOv11-Seg was 0.92 on the rear bumper, 0.89 on the rear window, and 0.88 on the tailgate. The findings were lower for small parts, with 0.72 on the right mirror and 0.70 on the left mirror. Table 3 shows a global comparison of metrics from different versions of Yolo as well as R-CNN.

Table 3: Global comparison across models.

Metric	**YOLOv11**	**YOLOv8**	**YOLOv5**	**Mask R-CNN**
IoU	**86.3%**	78.5%	74.1%	70.1%
Precision	**92.4%**	88.9%	86.5%	87.3%
Recall	**88.7%**	85.4%	82.8%	84.5%
F1-score	**90.5%**	87.1%	84.3%	85.8%
Latency (ms/img)	**180**	220	265	350
FPS	**32**	27	20	12

The models show that YOLOv11-Seg is the best one. With a speed of 32 FPS, YOLOv11-Seg gets an IoU of 86.3%, a Precision of 92.4%, a Recall of 88.7%, and an F1-score of 90.5%. YOLOv8, on the other hand, only gets IoU = 78.5% and 27 FPS, and Mask R-CNN is slower with IoU = 70.1% and 12 FPS.

YOLOv11-Seg does better than YOLOv8, YOLOv5, and Mask R-CNN on every part. For instance, YOLOv11 gets a mAP of 92% on the back bumper, which is better than YOLOv8 (87%), YOLOv5 (82%), and Mask R-CNN (84%). The same thing happens with smaller parts like lighting and mirrors, where YOLOv11 is still better, but only by a small amount. Table 4 is a part-by-part comparison of various versions of yolo and R-CNN. YOLOv11 routinely beat YOLOv5, YOLOv8, and Mask R-CNN in both global and per-part comparisons with other detection frameworks (Tables 3 and 4). These improvements are especially clear in small reflective portions, which shows that YOLOv11 is the best choice for inspecting cars.

The YOLOv11 model does a much better job of breaking up automobile parts. It's incredibly accurate and works quickly, which makes it perfect for autos. Here are the numbers: The

Table 4: Per-part comparison of YOLOv11, YOLOv8, YOLOv5, and Mask R-CNN (mAP@0.5).

Car Part	YOLOv11	YOLOv8	YOLOv5	Mask R-CNN
Rear bumper	**92%**	87%	82%	84%
Back glass	**89%**	84%	80%	83%
Tailgate	**88%**	82%	78%	82%
Wheel (rear-right)	**84%**	79%	75%	79%
Front right door	**83%**	78%	73%	78%
Left rear door	**81%**	76%	72%	77%
Right rear light	**77%**	72%	68%	73%
Right mirror	**72%**	68%	64%	70%
Left mirror	**70%**	65%	62%	69%

Intersection over Union (IoU) is 86.3%, the Precision is 92.4%, and 0.887 of people remembered it. The F1 score is 90.5%. The YOLOv11 model does a much better job of separating car parts. It works quickly and is very accurate, which makes it perfect for autos. Here are the numbers: The F1-score was 90.5%, the Intersection over Union (IoU) was 86.3%, the Precision was 0.92.4%, and 88.7% of individuals recalled it. Table I shows the numbers that show how well different sections of a car operate together. The findings demonstrate that YOLOv11 is capable of executing complex segmentation tasks, such as identifying and categorizing components that are concealed or subjected to varying illumination conditions.

To guarantee the credibility of the experimental results shown in Table 4, each model evaluation was conducted three times using random seeds (42, 123, 999). The reported metrics represent the mean ± standard deviation across all experiments.

The rear bumper got an average precision of 93.4% ± 0.6% and a recall of 91.8% ± 0.5% in the automobile component segmentation results. This shows that the model works well on larger, well-defined parts. The rear window likewise did well, with a precision of 92.7% ± 0.8% and a recall of 90.3% ± 0.7%. This means that it was able to consistently detect objects in different lighting circumstances. But smaller parts, like the right rearview mirror, had a higher variance, with a precision of 81.2% ± 1.5%. This means they were more sensitive to reflective and occluded surfaces.

6 Conclusion

This research assesses YOLOv11-Seg for the segmentation of automobile components through qualitative and quantitative approaches. The approach works quite well for large, well-defined portions, but not so well for small, reflecting elements. YOLOv11-Seg has the best balance of accuracy and throughput against YOLOv5, YOLOv8, and Mask R-CNN. It meets real-time needs and scores the best on most evaluation criteria.

Transformer-based attention and adaptive spatial pyramid pooling make it possible to do quick, pixel-level segmentation. The system can handle occlusions and difficult illumination while segmenting overlapping parts like wheels, mirrors, and headlights at about 32 frames per second, with an IoU of 0.863, a precision of 92.4%, and a recall of 88.7%. These results show that YOLOv11 is a useful way to make car assembly and quality control more efficient, cut down on mistakes made by people, and improve factory-grade computer vision.

7 Future Work

YOLOv11 has done a great job of separating car parts, but more research could make it work even better. Future upgrades will involve adding more data to the collection, such as pictures of the inside of cars, like seats, dashboards, and electronics, as well as pictures taken in bad weather, like rain, fog, and deep shadows. The model can also be improved such that it can be used in real time in robotic vision systems and edge devices like NVIDIA Jetson or Google Coral. This makes processing faster and more decentralized. Adding 3D data from LiDAR or depth cameras could help with spatial understanding and segmentation accuracy for shapes that are hard to see or are very complicated. Also, improving transformer-based attention methods and adding real-time multi-task learning would let the model do both segmentation and fault identification at the same time. These changes would make YOLOv11 stronger, more flexible, and more useful in fully automated car manufacturing settings.

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