Optimizing YOLOv11 for Accurate Car Parts Segmentation in Automotive Industry Applications

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Abstract—We study the application of the YOLOv11 (You Only Look Once version 11) model for automotive component segmentation. Computer vision technologies are becoming increasingly important to the automobile industry. They help to improve manufacturing, improve quality control and make inventory management easy. To automate these operations, it is required to be able to segment automotive parts accurately. This means you can correctly identify and sort out parts in images. The proposed study uses a dataset of different images of car parts with annotations for training the YOLOv11 model. The research aims to improve the architecture and training parameters of the model to achieve high accuracy and efficiency in the segmentation of various automotive parts including engine, wheels and body panels. We can see how well the model works using performance metrics like Intersection over Union (IoU), precision, recall and F1-score. Expected results of this study are a powerful segmentation model which can be integrated into existing automotive systems to improve operational efficiency and reduce human error in recognition of car parts.

Keywords— YOLOv11, Car Part Segmentation, Semantic Segmentation, Automotive Industry, Deep Learning, Computer Vision

I. INTRODUCTION

The field of computer vision and deep learning technologies is revolutionizing the automotive industry at a rapid pace [1]-[3]. The modern manufacturing process demands intelligent systems that can perform tasks with unprecedented accuracy and speed. In practical applications, the ability to locate and segment parts accurately is of great importance for quality control, component tracking, defect detection, and automating the assembly process [4]. These technologies improve operations, automate manual tasks, and reduce errors in inventory management. This allows manufacturers to achieve higher standards in both quality and cost. Since the environment is so complicated, it is difficult to achieve high-performance segmentation, especially in the automobile field. In real world, lighting conditions may change, pieces may overlap and block each other, metal parts may reflect light, different car models may look different [5]-[6]. These problems require robust and flexible segmentation methods that work under a wide variety of conditions. Mistakes in the identification of car parts can cause problems on the production line which can reduce throughput and customer satisfaction [7]. Semantic segmentation, the task of assigning a label to every pixel in an image, is especially important to enable machines to understand spatial relationships between different parts of a picture [8]. This feature is critical to automating operations like robotic assembly, defect detection, real-time quality control and predictive maintenance. But with many of the older methods, getting the right balance between speed, accuracy and flexibility is sometimes a big problem, particularly when processing needs to happen in real time. Object recognition in images has been shown to be very promising by object detection models such as Faster R-CNN and SSD [9]-[10]. These models are good at detecting bounding boxes but not as good at tasks that require pixel level segmentation. Meanwhile, Mask R-CNN provides detailed segmentation, but its computational requirements restrict its use in real-time manufacturing processes [11]. Hybrid methods, incorporating attention mechanisms

such as DETR and Swin Transformers, can improve the contextual understanding, but they usually suffer from latency in industrial environments [12]-[13].
The YOLO (You Only Look Once) series has become popular because it can perform object detection quickly and effectively [14]. YOLO looks at the entire image in a single forward pass, making it particularly well-suited for real-time applications, unlike traditional methods. However, earlier YOLO models, although suitable for object detection, do not meet the demands of detailed pixel-level segmentation needed for complex automotive components. YOLOv11 builds upon the existing YOLO framework, alleviating its limitations through architectural improvements, such as the addition of transformer-based attention layers and spatial pyramid pooling [15]. The improvements allow YOLOv11 to do precise segmentation while keeping the speed high. Moreover, the improved feature fusion techniques help the model to achieve accurate segmentation results so that the model can better recognize the overlapping or complex car parts such as engines, wheels, mirrors, and headlights. In this paper we present the use of YOLOv11 for automotive parts segmentation in complex real-world scenarios. A diverse annotated dataset of tagged car photos was created for training and testing of YOLOv11. The accuracy of the segmentation model was verified by quantitative indicators such as Intersection over Union (IoU), precision, recall and F1 score. Qualitative visual comparisons further verify the capability of YOLOv11 to analyze data in real time, yet still offer high-quality segmentation. YOLOv11 is a viable solution for improving computer vision applications in the automotive industry due to its strong segmentation capabilities and flexible design. Technology application in the industrial process can lead to smooth operations, reduce human errors and enhance productivity in intelligent vehicle part recognition systems.

II. RELATED WORK

Object detection and semantic segmentation models are important computer vision technologies with a large applicability in the automotive domain. Early work such as Faster R-CNN [1] and SSD (Single Shot MultiBox Detector) [2] demonstrated the ability to localize objects with high accuracy. These methods have been used in different industries such as defect detection, localization and car parts recognition. However, these methods are more concentrated on bounding box detection rather than pixel-wise segmentation, which is crucial for overlapping or complex automobile parts.
Semantic segmentation is usually done by Mask R-CNN [1,3] that uses a two-stage method to get pixel-level accuracy. It allows for robust segmentation by integrating Region Proposal Networks (RPN) and mask prediction layers. Mask R-CNN is pretty accurate, but it is hard to run in real time due to its heavy processing needs for sequential tasks. This limitation reduces its utility in industrial applications needing fast decision making like in the automotive manufacturing industry.
To overcome the above problems, recent advances in hybrid segmentation methods have utilized transformer based attention processes. DETR (DEtection TRansformer) [11] is an architecture which uniquely combines self-attention layers with bipartite matching. This makes it quite good at segmenting images without needing to rely too much on explicit region proposals. Swin Transformers [3] considered hierarchical attentions over several feature layers to increase the detail of segmentation. These methods do enhance the segmentation, but they require a lot of processing power and time, making it difficult to use them in real time in the automotive industry.
The YOLO(You Only Look Once) series is quite popular in industry due to its fast and efficient. YOLOv3 [3] and YOLOv4 [4] have made some improvements in the feature extraction and processing of smaller objects from YOLOv1 [1]. YOLOv5 introduced even

more features. It created designs that were lighter and better for edge deployments. But most of the time, YOLO models are used for object detection rather than semantic segmentation.

YOLOv11, the latest version of the YOLO series, addresses the problems in previous models by adding extra features specially designed for segmentation. Adding transformer based attention layers improves the capability of the model to learn spatial relationships, and better feature fusion approaches guarantee that segmentations are detailed and correct. YOLOv11 is also not computationally intensive, which means that it can be used in real-time production environments. YOLOv11 is better than Mask R-CNN and Swin Transformers in both speed and quality of segmentation [6-7]. This makes it ideal for automotive applications where speed and accuracy are critical. With these improvements, it can be said that YOLOv11 successfully combines real-time use with pixel-level accuracy. This provides a good way for future improvements of auto part segmentation in production systems.

III. METHODOLOGY RESULTS AND DISCUSSION

A. DATASET

A custom dataset of 12000 high-resolution images of car parts was created to train and test the YOLOv11 model. The pictures showed many car parts such as engines, wheels, mirrors, headlights and body panels. Semantic segmentation Each image is annotated with manually labeled bounding boxes and pixel-wise labels. The dataset was built to mimic real car production scenarios, involving challenging conditions such as varying lighting (dim light, overexposed areas), overlapping parts hiding each other, and different viewpoints, from front to side. To improve diversity and robustness, we captured images of real production lines and added artificial conditions.

We used industry standard technologies such as LabelImg and CVAT for annotating the data . For labeling, we prioritized the accuracy during training so that the classification and segmentation were done correctly. The dataset was also well pre-processed, including normalization and downsizing to 1024×1024 pixels resolution, so it would work perfectly with the input layer of YOLOv11. This diversity ensured the model was tested in a wide range of situations similar to real-life driving situations [6]-[7].

This section gives the results of the research and at the same time gives the comprehensive discussion. The results can be presented in figures, graphs, tables and others to make it easy for the reader to understand [2], [4]. Figures are centered as below and are cited in the manuscript.

B. YOLOv11 Architecture

YOLOv11 is based on CSPDarkNet, which is used to extract features. It adds to the architectural improvements that are specific to splitting out detailed automobile pieces. Transformer layers were added to the backbone to better help the model understand context. These layers use attention mechanisms to focus on the relevant spatial features [5]. By using the transformer layers of YOLOv11, it can pay attention to small regions of the image that were important for locating small and hidden parts like side mirrors.

In addition, adaptive spatial pyramid pooling (ASPP) modules were added to allow feature extraction at different scales. This modification enabled YOLOv11 to capture the features at different resolutions, which made the segmentation efficient on automobile parts of different sizes. We fine-tuned the layers of the neck and head of the network to enable pixel-wise segmentation. It transforms features into dense spatial representations for semantic categorization. All of these structural changes combine to make YOLOv11 very accurate at segmentation, while also being efficient with its computing power. The speed-detail combination is a response to the requirements of real-time automotive manufacturing procedures [4].

C. Training Strategy

The training method was transferring learning with pretrained weights from the

COCO [5] and Open Images [6] datasets. This approach allowed the YOLOv11 model to leverage the prebuilt feature extraction tools, which sped up the fine-tuning process. In order to solve the problem of class imbalance, which is a usual problem in segmentation tasks, Cross-Entropy Loss and Dice Loss functions were used. Cross-Entropy Loss ensured the probability of correct classification were correct, whereas Dice Loss made boundary-level accuracy better for parts with small spatial footprint, like mirrors. The key to getting the best results was hyperparameters: The learning rate is 0.001 and we employ a scheduler to gradually decrease the rates during training. Batch Size: 32 photos per batch. Epochs: 50, which is sufficient for the model to learn how to work with different types of segmentation. Optimizer: We chose Adam optimizer as it works fine on varying gradients. To increase the robustness of the model, data augmentation techniques were used, including random cropping, flipping, rotation and colour jittering. The modifications introduce the model to a variety of scenarios, similar to real world usage of cars [7]-[8].

D. Evaluation Metrics

We utilized four important indicators to see how well YOLOv11 did, Intersection over Union (IoU): This measures how much the predicted and ground-truth segmentations overlap. Precision, shows how accurate positive forecasts are. Recall, this measures how well the model can find all the important pieces. F1-score, this metric measures how well something works by balancing precision and recall. Mean Average Precision (mAP), this number shows how accurate all of the classes and thresholds are on average.

The numbers showed that YOLOv11 was better, with an IoU of 0.863, a precision of 92.4%, a recall of 88.7%, and an F1-score of 90.5%. These numbers show that YOLOv11 is a strong and dependable choice for real-time segmentation tasks [9].

IV. RESULT AND DISCUSSION

The YOLOv11 model demonstrates significant advancements in car part segmentation, achieving It has a high level of accuracy and efficiency, which makes it perfect for use in cars. The numbers are as follows, Intersection over Union (IoU): 0.863, Precision 92.4%, and 88.7% of people remembered it, F1-score: 90.5%

Table I shows the quantitative data, which show how well different automotive parts work together. The results show that YOLOv11 can handle difficult segmentation tasks, like finding and categorizing portions that are hidden or under different lighting situations.

Table 1. Segmentation Performance by Car Part

Car Part	IoU	Precision	Recall	F1-Score
Engine	0.872	93.1%	89.5%	91.2%
Wheel	0.854	91.6%	87.2%	89.3%
Headlight	0.878	94.0%	90.1%	92.0%
Mirror	0.841	90.8%	85.4%	88.0%
Body Panel	0.859	92.0%	89.3%	90.6%

A. Technical Analysis of Metrics

1. Intersection over Union (IoU):

The IoU of 0.863 shows that YOLOv11 is better at accurately separating parts in real-world situations. YOLOv11 does a better job of drawing lines than YOLOv8 (IoU = 0.785) and Mask R-CNN (IoU = 0.701). This is important for sections like headlights and mirrors, where it's easy to be confused about where the lines are [10].

2. Precision and Recall:

YOLOv11 is reliable since it has a high precision rate of 92.4%, which means it can reduce false positives and make sure that the segmented areas are in the right class. Its recall rate of 88.7% shows that it can capture all critical parts even when there are obstructions and other problems. These measures show that YOLOv11 performs well overall, while YOLOv8 has an accuracy of 88.9% and a recall of 85.4% [12]-[13].

3. F1-Score:

The 90.5% F1-score shows that YOLOv11 can segment well, finding the right balance between precision and recall better than earlier models. This statistic is especially important in real-time applications, since

false negatives could mess up the production process [14].

B. Comparative Analysis: Performance vs. Other Models

Table 2 shows how YOLOv11 stacks up against YOLOv8, YOLOv5, and Mask R-CNN in terms of speed, accuracy, and detail.

YOLOv11 is unique in that it can segment with high accuracy, yet still run in real time, an important capability for practical industrial systems. YOLOv11 has improved pixel-level segmentation, especially at small, complex parts such as mirrors and wheels, through transformer-based attention and spatial pyramid pooling. Efficiency: The model runs at 32 frames per second (FPS) and 180 milliseconds (ms) latency per image, better than Mask R-CNN's 350 ms latency and 12 FPS [15]-[16].

Table 2. Comparison Across Models

Metric	YOLOv11	YOLOv8	YOLOv5	Mask R-CNN
IoU	0.863	0.785	0.741	0.701
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 per img)	180 ms	220 ms	265 ms	350 ms
FPS	32 FPS	27 FPS	20 FPS	12 FPS

C. Addressing Weaknesses: Reflective Surfaces and Shadows

YOLOv11 has strong segmentation abilities, but failure analysis found two major problems, reflective Surfaces, sometimes, parts like mirrors and chrome accents cause contour inaccuracies because light spreads out and its intensity changes. Grad-CAM visualizations showed that the model's focus moved away from reflective areas, which led to more false negatives [17]. Strong Shadows: Body panels and other parts that were in strong shadows had lower recall because it was harder to see features in areas that were blocked.

D. Technical Solutions and Grad-CAM Insights

The Grad-CAM study indicated that the attention was not aligned in the many reflections and shadows setting. In particular, reflective surfaces have scattered attention areas, which means that transformer layers need to be improved to focus better on features. Extreme shadows required two additional preprocessing steps: intensity normalization and adaptive augmentation. Some of the recommended recommendations include, dataset Diversity and Augmentation, using advanced augmentation methods to provide more reflective surfaces and photos with a lot of shadows during training. Model Refinement: Adjusting the transformer layers to improve attention in difficult lighting situations without sacrificing processing speed.

IV. FUTURE WORK

YOLOv11 has shown great results in isolating car parts but more research and development could make it even more useful. The following directions are suggested for future work,

Add interior car parts including seats, dashboards and electronic parts to the dataset . Expand the Dataset's Scope To make the model more robust, gather data that simulates more extreme weather conditions like heavy rain, fog and deep shadows. Robotic Vision Systems Integration Implement YOLOv11 into robotic vision systems to enable automated assembly, inspection, and defect detection on real-time manufacturing lines. Edge Devices Deployment, improve YOLOv11's performance on edge devices like the NVIDIA Jetson or Google Coral AI accelerators to enable decentralized production systems to perform inference with minimal latency. If you want to look into 3D Segmentation Techniques, you can use 3D image data (like LiDAR or depth cameras) to improve the accuracy of your segmentation for complex shapes and occluded parts, which helps you better understand space. Improving Attention Mechanisms, make transformer-based layers perform better so that the model can better handle reflective surfaces and low-visibility situations like shadows. This will

lessen the chance of segmentation failures. Real-Time Multi-Task Learning, combine YOLOv11 with multi-task learning frameworks to segment car parts, detect defects and classify them all at once in a single inference process. The suggested improvements will help YOLOv11 to deal with a wider variety of automotive problems, improving its scalability and its usefulness in real-world manufacturing environments. These actions can help to establish its role as a key component of automated car part detection and segmentation systems.

V. CONCLUSION

The YOLOv11 model has been a major step in the automotive applications for the separation of the automobile parts. YOLOv11 is an improvement over previous models such as YOLOv5, YOLOv4 and Mask R-CNN, using transformer-based attention mechanisms and adaptive spatial pyramid pooling. It achieves better accuracy (IoU: 0.863) and speed (32 FPS). The model is really good with pixel level segmentation, which is important for parts which are complicated and overlap like headlamps, mirrors and wheels. It hits a sweet spot of accuracy (92.4%) and recall (88.7%) and is also resilient in various real-life situations such as occlusion or complex illumination. Also, the latency of 180 ms of YOLOv11 makes it a good choice for real-time manufacturing applications where fast decisions are needed. However, it is still a little less accurate to distinguish things like mirrors and body panels, as it is difficult to work with reflective surfaces and really dark shadows. The use of Grad-CAM for failure analysis has helped us better understand these issues and work to fix them.In conclusion, YOLOv11 is a good and high-performance way to improve automobile manufacturing workflows and reduce human-made mistakes. It is an important step forward in computer vision systems for use in factories, because it can adapt and grow. Conclusion There is a compatibility between the statement expected as stated in the chapter “Introduction” and that discussed in the chapter “Results and Discussion”. Moreover, the possibility of development of results and prospects of further studies into the next (based on result and discussion) can be added.

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