Car Damage Detection

Instance Segmentation on car damages

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***Abstract*—In recent years, the advancement of computer vision techniques, particularly deep learning algorithms, has revolutionized various fields, including automotive safety and insurance assessment. This project proposes the implementation of Mask R-CNN (Region-based Convolutional Neural Network) for the detection and segmentation of car damages in images. The objective is to develop an efficient and accurate system capable of automatically identifying and delineating different types of damages such as scratches, dents, and cracks on car surfaces.**

I. Introduction

Automobiles play a pivotal role in modern society, serving as indispensable assets for transportation and mobility. However, the wear and tear experienced by vehicles over time, compounded by various environmental and human factors, often lead to damages that compromise their aesthetic appeal and structural integrity. In this context, the ability to swiftly and accurately detect and assess car damages is crucial for ensuring safety, maintaining asset value, and facilitating timely repairs.

Car damage detection represents a multifaceted challenge in computer vision, encompassing the identification and segmentation of various types of damages, including scratches, dents, and dings. As such, it falls within the domain of instance segmentation, wherein the goal is to delineate individual instances of objects within an image while categorizing them into distinct classes.

In recent years, advancements in deep learning and neural network architectures have revolutionized the field of computer vision, offering powerful tools for automating complex tasks such as car damage detection. Among these, Mask R-CNN (Region-based Convolutional Neural Network) and YOLOv8 (You Only Look Once version 8) have emerged as prominent frameworks for instance segmentation, providing state-of-the-art performance and efficiency.

This report explores the application of Mask R-CNN and YOLOv8 in the domain of car damage detection, aiming to leverage their capabilities to accurately identify and segment various types of damages in car images. By harnessing the capabilities of these advanced neural network architectures, we endeavor to streamline the process of damage assessment, enabling efficient maintenance and restoration of vehicle fleets while minimizing downtime and associated costs.

Through a comprehensive examination of methodologies, experimental results, and practical considerations, this report seeks to provide insights into the challenges, opportunities, and implications of employing deep learning techniques for car damage detection. Ultimately, our goal is to contribute to the development of robust and scalable solutions that enhance safety, reliability, and cost-effectiveness in the automotive industry.

II. Motivation

Car accidents are a common occurrence, resulting in millions of dollars in damages and numerous injuries annually. Timely and accurate assessment of vehicle damage is crucial for insurance claims processing, accident investigations, and vehicle maintenance. Traditional manual inspection methods are often time-consuming, subjective, and prone to errors. Moreover, with the increasing volume of vehicles on roads, there is a growing need for automated solutions that can efficiently analyze and assess car damages. Deep learning techniques such as Mask R-CNN and YOLO, have shown remarkable success in various computer vision tasks, including object detection and segmentation. By leveraging the power of deep neural networks, we can develop a robust system capable of automatically detecting and segmenting different types of damages on cars, such as scratches, dents, and cracks, with high accuracy and efficiency. Here are some detailed points for the motivation behind using deep neural network for car damage detection and segmentation:

1) Efficiency in Insurance Claims Processing:
   - Traditional methods of assessing car damages for insurance claims often involve manual inspection by adjusters, which can be time-consuming and labor-intensive.
   - By automating the process using computer vision techniques, such as Mask R-CNN and YOLO, insurers can significantly reduce the time and resources required for claims processing.
   - This increased efficiency can lead to faster claims settlements, improved customer satisfaction, and reduced administrative costs for insurance companies.
2) Objective and Consistent Assessments:
   - Manual inspection of car damages can be subjective and prone to human error, leading to inconsistencies in assessment results.
   - With Mask R-CNN, damage detection and segmentation are performed objectively based on predefined

criteria, ensuring consistency and accuracy in assessments.
- This objective approach helps eliminate biases and disputes in the claims settlement process, leading to fairer outcomes for both insurers and policyholders.

3) 3. Enhanced Safety and Maintenance:
   - Identifying and repairing car damages promptly is essential for ensuring vehicle safety and maintaining its resale value.
   - By automating the detection and segmentation of damages, Mask R-CNN enables timely repairs and maintenance interventions, minimizing the risk of accidents and breakdowns caused by unnoticed damages.
   - This proactive approach to vehicle maintenance can contribute to improved road safety and reduced repair costs for vehicle owners in the long run.
4) Scalability and Adaptability:
   - With the increasing volume of vehicles on roads and the growing complexity of car damages, there is a need for scalable and adaptable solutions that can handle diverse scenarios.
   - Mask R-CNN offers scalability by leveraging deep learning techniques to learn from large-scale datasets and adaptability through fine-tuning on specific tasks, such as car damage detection and segmentation.
   - This scalability and adaptability make Mask R-CNN well-suited for addressing the evolving challenges in car damage assessment across different environments and conditions.
5) Technological Advancements in Computer Vision:
   - Recent advancements in computer vision, particularly deep learning, have significantly improved the accuracy and efficiency of object detection and segmentation tasks.
   - Mask R-CNN and YOLO with their ability to simultaneously localize objects and generate pixel-level segmentation masks, represents a state-of-the-art solution for complex visual recognition tasks like car damage detection.
   - By leveraging these technological advancements, we can develop sophisticated systems that offer reliable and robust solutions for car damage assessment, benefiting various stakeholders in the automotive industry.

III. Literature Review and Background

Researchers provide a generic, versatile, and conceptually simple framework for segmenting object instances. Their method creates an excellent segmentation mask for each instance of an object while also effectively detecting objects in an image. The technique, known as Mask R-CNN, adds a branch for object mask prediction to Faster R-CNN in tandem with the branch for bounding box identification that already exists. Running at 5 frames per second, Mask R-CNN is easy to train and adds very little overhead to Faster R-CNN. Furthermore, Mask R-CNN can be easily extended to other applications, such as estimating human poses within the same framework. They demonstrate best-in-class performance in the instance segmentation, bounding-box object detection, and person keypoint detection tracks of the COCO suite of challenges. [1]

YOLO has developed into a key real-time object identification platform for robots, autonomous vehicles, and video surveillance. Researchers offer a thorough examination of the development of YOLO, looking at the improvements and contributions made in each iteration from YOLOv8 to the original. The basic measurements and postprocessing are covered first, followed by the main modifications to the network architecture and the best practices for training each model. In conclusion, we offer an overview of the key takeaways from Yolo's evolution and offer an outlook on its future, pointing out possible avenues for study to improve real-time object identification systems. [2]

Employing Unmanned Aerial Vehicles (UAV) along with instance segmentation for monitoring construction sites (including machinery and operational surfaces) represents a substantial advancement in efficiency compared to conventional manual supervision methods. Nonetheless, identifying individual objects in UAV-captured images poses challenges due to the intricate details of construction machinery and the similarities in image features among different operational surfaces. In response, this research introduces an innovative instance segmentation model based on the YOLOv8-seg architecture. Tailored to address these hurdles, the proposed model incorporates three key enhancements to the original YOLOv8-seg framework. Firstly, the study integrates the FocalNext module, which expands the convolutional kernel's perception field to encompass contextual information and incorporate multilevel features, thereby enhancing the detection of local intricacies. Secondly, it incorporates the Efficient Multiscale Attention (EMA) module, which improves feature refinement by highlighting spatial-channel interactions and effectively discerning patterns across different scales, aiding in the identification of similar construction operation surfaces. Lastly, recognizing the complexity of construction site imagery, the Context Aggregation module is introduced to elevate pixel analysis by dynamically adjusting feature weights to emphasize crucial global contexts. Ablation experiments demonstrate the effectiveness of these enhancements within the YOLOv8-seg framework. Comparative analysis against existing instance segmentation models reveals that the enhanced model significantly surpasses them in terms of performance, complexity, and inference speed. [3]

IV. METHODOLOGY

By following the below methodology, we aim to develop robust and reliable solutions for car damage detection, leveraging state-of-the-art deep learning techniques to enhance safety, efficiency, and cost-effectiveness in the automotive industry

1) **Data Collection and Preprocessing:**
   - Acquire a diverse dataset from the internet comprising images of damaged cars.

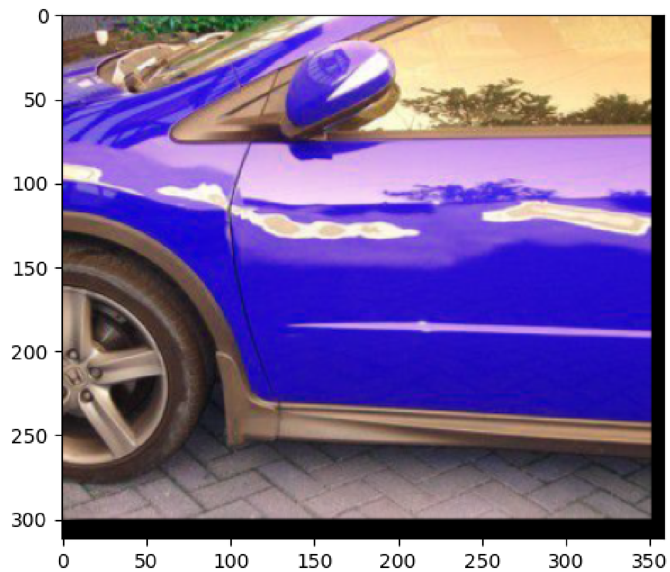

Fig. 1. Training and testing image sample

   - Annotate the dataset to delineate instances of car damages, such as scratches, dents, and other imperfections, using bounding boxes and segmentation masks.
     - Acquire a diverse dataset from the internet comprising images of damaged cars.

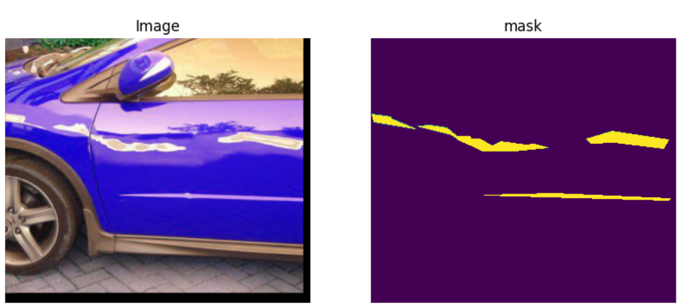

Fig. 2. Original image and damage mask

   - **Model Selection and Training:**
     - Choose Mask R-CNN and YOLOv8 as the primary neural network architectures for instance segmentation, given their proven efficacy in similar tasks.
     - Initialize the network weights with pre-trained models on large-scale datasets, such as COCO (Common Objects in Context), to expedite convergence and improve generalization.
     - Fine-tune the models on the annotated car damage dataset using transfer learning, adjusting hyperparameters and regularization techniques to mitigate overfitting and enhance performance.
     - Employ data augmentation strategies, including random rotations, flips, and translations, to augment the training dataset and improve the models' robustness to variations in viewpoint and lighting conditions.

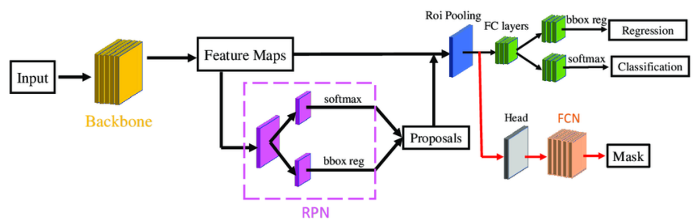

Fig. 3. Mask R-CNN model

   - **Evaluation:**
     - Assess the performance of the trained models for instance segmentation.
     - Divide the dataset into training, validation, and test sets to facilitate unbiased evaluation of the models' performance on unseen data.
     - Conduct cross-validation experiments to validate the robustness and generalization capabilities of the models across different subsets of the dataset.
   - **Model Interpretation and Visualization:**
     - Visualize the model predictions alongside the ground truth annotations to qualitatively assess the accuracy and efficacy of the instance segmentation algorithms.
     - Investigate failure cases and misclassifications to identify potential sources of error and areas for improvement in the training data and model architecture.

V. RESULTS

The study assessed 15 car damage images using YOLO and Mask RCNN for detection. It tackled instance segmentation, revealing Mask RCNN's higher rate of False Negatives and False Positives compared to YOLO in identifying and segmenting car damages. Overall, YOLO demonstrated relatively superior performance.

Fig. 4. Test images

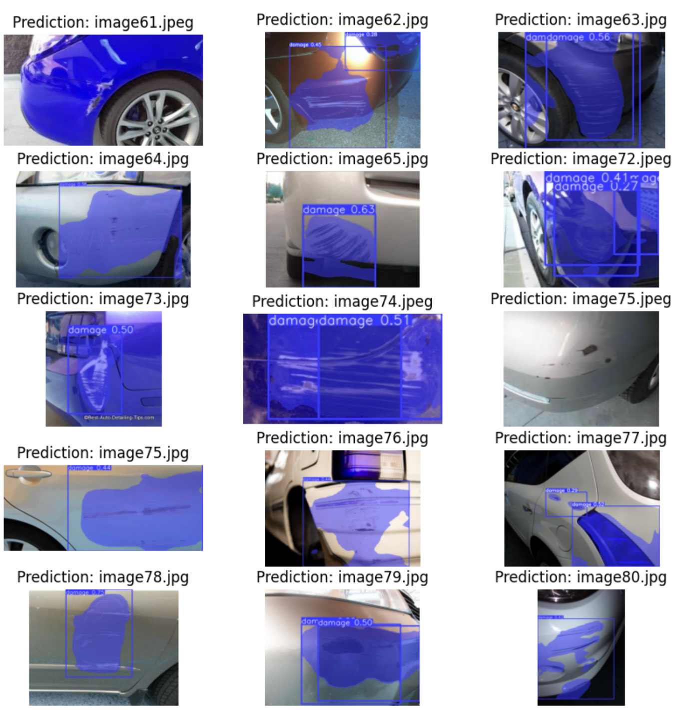

Fig. 5. Mask R-CNN model predictions on test images

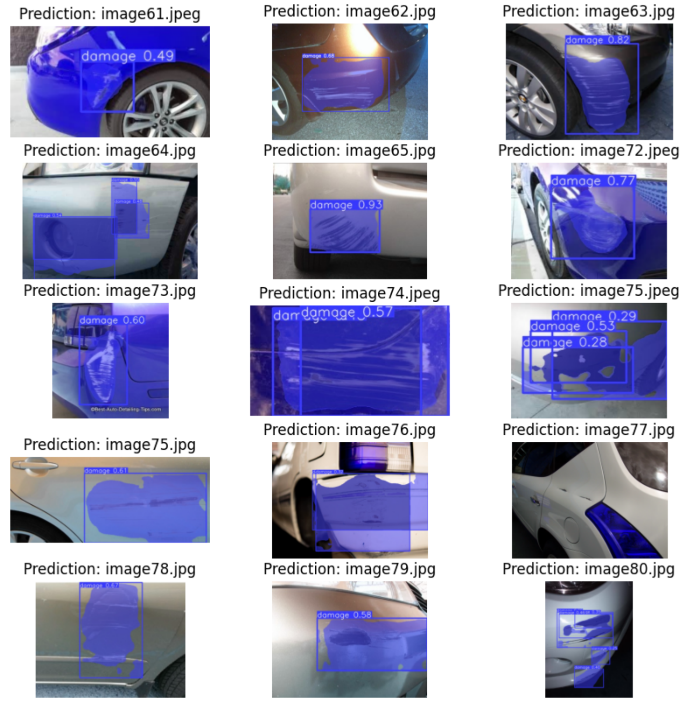

Fig. 6. YOLOv8 model predictions on test images

VI. Conclusion

In conclusion, the implementation of deep learning algorithms, specifically Mask R-CNN, presents a promising approach for automating car damage detection and segmentation. This technology addresses the critical need for efficient and accurate assessment of vehicle damages, crucial for insurance claims processing, safety assurance, and timely maintenance. The study showcases the effectiveness of Mask R-CNN and YOLOv8 in identifying and delineating various types of car damages. Despite Mask R-CNN exhibiting higher rates of False Negatives and False Positives, YOLOv8 demonstrates superior overall performance. By leveraging advanced neural network architectures, we aim to enhance safety, reliability, and cost-effectiveness in the automotive industry, paving the way for scalable and adaptable solutions that streamline damage assessment processes and mitigate associated risks. Further research and refinement of these techniques hold the potential to revolutionize car damage detection, benefiting stakeholders across the automotive sector.

References

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[3] R. Bai, M. Wang, Z. Zhang, J. Lu and F. Shen, "Automated Construction Site Monitoring Based on Improved YOLOv8-seg Instance Segmentation Algorithm," in IEEE Access, vol. 11, pp. 139082-139096, 2023