DEEP LEARNING BASED CAR DAMAGE DETECTION AND SEGMENTATION

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ABSTRACT

This project proposes an innovative strategy focused at advancing the the automation of damage detection and segmentation for vehicle damage assessment processes in the automotive industry. By leveraging the advanced capabilities of Mask Region-based Convolutional Neural Network (Mask R-CNN), the study aims to develop a system capable of autonomously detecting and accurately segmenting various types of car damages, such as scratches and dents. This technology promises to transcend traditional manual inspection methods, offering a more streamlined, accurate, and scalable solution for repair assessments and insurance claims. The methodology comprises data collection, annotation, and model training phases, specifically focusing on scratches and dents from different vehicle orientations. The expected outcomes include detection accuracy, precise damage localization, and the establishment of a new benchmark for future research in automated vehicle damage assessment.

1 INTRODUCTION

In the current evolving world, the automotive industry is continuously searching for different solutions to make their business processes more efficient while increasing their customer's satisfaction. A key challenge in this industry is the accurate and efficient assessment of vehicle damages, which is essential for handling insurance claims and performing repairs. Traditionally, these assessments have been done manually by human experts within the insurance companies. But this manual inspection-based method has different limitations and also can lead to a wide range of evaluations due to its reliance on personal judgment. This traditional approach tends to be slow and filled with subjective opinions and prone to inconsistencies/human errors which makes the insurance claiming process more time consuming. This highlights the need for a shift towards a more efficient method, which is where the potential of deep learning becomes apparent, promising an automated and uniform approach to evaluating vehicle damage.

This project focuses on utilizing Mask Region-based Convolutional Neural Network (Mask R-CNN) (He et al., 2017), a forefront model in deep learning known for its exceptional ability to identify objects and their precise boundaries. Applying this model to car damage assessment, we envision a system capable of autonomously recognizing different types of damage such as scratches, dents, and shattered glass, and then accurately delineating these damages. Our goal is not merely to digitize an existing manual process but to completely transform how the auto industry manages repair assessments and insurance claims, making these processes more streamlined, accurate, and expandable.

The broader implications of successfully implementing this project are significant. For insurance companies, it could lead to quicker claims processing, decreased operational expenses, and a more impartial evaluation method. Repair shops might benefit from more prompt and accurate damage

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assessments, which in turn could lead to more efficient repair processes. Additionally, the application possibilities of this technology are extensive, ranging from its integration into mobile apps for instant damage evaluation, its use in autonomous vehicles for immediate damage detection, to its application in routine maintenance checks to identify potential issues before they escalate.

In a nutshell, this project aims to do more than just introduce a new approach; it seeks to pave the way towards a future where technological advancements significantly enhance efficiency and reliability across the automotive industry, making services better for everyone involved.

The subsequent sections will discuss the background 2, related works 3, proposed methodology 4, experiment design 5, expected results 6 and finally the references, setting the stage for a detailed discussion on how deep learning can revolutionize the assessment of vehicle damage in the automotive industry.

2 Background

The use of deep learning in computer vision has revolutionized numerous fields, especially when it comes to tasks like object detection, classification, and segmentation from images. Mask R-CNN is one of the most notable achievements in this field; it is a model that goes beyond object identification in images and further capable of localizing the objects within the image. Because of its dual capabilities, it is highly suitable for tasks that need a precise grasp of the shape and location of each object, such as segmenting different parts of an image with precision.x

The motivation for this study comes from seeing how these advances in deep learning might be applied to a specific challenge, the segmentation and detection of vehicle damages. This is a significant problem in industries like as insurance and auto repair, where proper damage identification and classification are essential to business operations and client happiness. These industries have always depended on manual inspections, a method with drawbacks including subjectivity, consistency, and time consumption.

By applying Mask R-CNN's capabilities to car damage identification, this project aims to significantly improve how damages are detected and analyzed. The model's ability to precisely segment damages offer a level of detail previously unattainable with manual inspections, promising a shift towards more accurate, efficient, and consistent assessments. This not only has the potential to streamline insurance claim processing and vehicle repairs but also to enhance the overall reliability of damage evaluation, contributing to better customer experiences and operational practices within the automotive industry.

3 Related Work

Vehicle damage detection using deep learning techniques has emerged as a crucial area of research with applications in insurance claim processing, vehicle inspection, and safety assessment. Various studies have been conducted to develop efficient frameworks for automatic vehicle damage detection and classification. This literature review synthesizes findings from a range of papers focusing on different aspects of vehicle damage detection using deep learning methodologies.

Parhizkar et al. (2022) proposed an automated recognition system for damaged surface parts of cars in real scenes based on a two-path convolutional neural network (CNN). This study contributes to the development of models capable of identifying specific damaged areas on vehicles, enhancing the precision of damage assessment processes.

In a comprehensive research study, Li et al. (2021) introduced a deep learning and transfer learning approach for vehicle damage detection, utilizing a CNN model to classify vehicles based on the presence of damages. Their work highlights the significance of transfer learning in improving the accuracy of damage detection systems by leveraging pre-trained weights from large datasets.

Zhang et al. (2020) presented an automatic car damage assessment system that reads and understands videos to assess damages akin to professional insurance inspectors. Their work involves advanced techniques such as improving MASK R-CNN for detecting damaged components and accurately segmenting component boundaries simultaneously. This level of sophistication in segmentation is crucial for precisely localizing and assessing damages in vehicles.

Fouad et al. (2023) developed an automated vehicle inspection model using deep learning techniques, incorporating fully connected layers for additional damage classification. This model offers a comprehensive pipeline for vehicle damage assessment, streamlining the inspection process and facilitating detailed damage classification. Their model's ability to classify damages into specific categories such as broken glass, headlights, taillights, scratches, and dents showcases the granularity achievable through deep learning algorithms. This level of detail is essential for accurate damage assessment and subsequent repair.

Van Ruitenbeek & Bhulai (2022) explored the use of Convolutional Neural Networks (CNNs) for vehicle damage detection, emphasizing the role of deep learning in enhancing the accuracy of damage identification systems. Their study underscores the effectiveness of CNNs in detecting and classifying vehicle damages with high precision.

Reddy et al. (2022) proposed an automatic vehicle damage detection classification framework using Fast and Mask deep learning, showcasing the potential of advanced deep learning techniques in accurately detecting and classifying vehicle damages . Their framework incorporates the use of Fast R-CNN (Girshick, 2015) and Mask R-CNN, which are popular models for object detection and segmentation tasks, respectively. This indicates a robust methodology for identifying and categorizing vehicle damages.

In another research, Jamal & Arefeen (2022) employed transfer learning and an upgraded version of RCNN for vehicle damage identification, achieving superior results compared to other pre-trained models. This approach highlights the importance of leveraging transfer learning and advanced models for enhancing the performance of vehicle damage detection systems.

Gustian et al. (2023) developed a method for detecting damaged car bodies using the YOLO deep learning algorithm, emphasizing the significance of preprocessing and segmentation in identifying damaged car parts. Their approach contributes to the development of robust systems for detecting and localizing vehicle damages effectively.

Patil et al. (2017) focused on deep learning-based car damage classification, highlighting the role of transfer learning in improving the accuracy of damage classification models. Their study underscores the importance of leveraging deep learning techniques for precise damage assessment and classification.

Dhieb et al. (2019) introduced a very deep transfer learning model for vehicle damage detection and localization, emphasizing the benefits of transfer learning in enhancing the performance of damage detection models. Their research showcases the potential of transfer learning in improving the accuracy and efficiency of vehicle damage detection systems. Transfer learning allows models to leverage knowledge from pre-trained models, enhancing performance, especially in scenarios with limited data. This approach is crucial for tasks like vehicle damage detection, where annotated datasets may be scarce.

Sruthy et al. (2021) explored car damage identification and categorization using various transfer learning models, showcasing the versatility of transfer learning in developing robust damage detection frameworks. Their study highlights the effectiveness of transfer learning in categorizing and localizing vehicle damages accurately.

Kyu & Woraratpanya (2020) focused on car damage detection and classification, emphasizing the role of transfer learning and artificial intelligence in developing sophisticated damage assessment systems. Transfer learning used as it plays a vital role in adapting models trained on large datasets to the specific task of vehicle damage detection. Additionally, the incorporation of regularization techniques aids in improving model generalization and performance.

In conclusion, the integration of deep learning techniques, transfer learning, and advanced CNN models has significantly enhanced the accuracy and efficiency of vehicle damage detection and classification systems. These studies collectively underscore the importance of leveraging cutting-edge technologies to develop robust frameworks for automated vehicle damage assessment, thereby improving safety standards and streamlining insurance claim processes.

4 Proposed Methodology

The proposed solution adopts a strategic approach to enhance the precision and efficiency of car damage detection and segmentation, focusing on the use of Mask R-CNN. I've structured the methodology to tackle the challenge methodically, with particular attention to specific orientations of cars and types of damage, such as scratches and dents. Below, we detail each step in our process, from data collection to the optimization of our deep learning model.

4.1 Data Collection, Validation and Annotation

4.1.1 Data Collection

The initial step involves gathering a diverse set of images that specifically represent vehicles from various orientations - front, right, and left sides. This targeted approach ensures that our model can accurately recognize damage regardless of the vehicle's angle in the image.

4.1.2 Focus on Specific Damages

Mainly concentrate on collecting images that depict clear examples of scratches and dents. By focusing on these specific types of damage, I aim to fine-tune my model's detection capabilities, making it highly effective in identifying these common issues.

4.2 Data Annotation

4.2.1 Detailed Annotation

Following the data collection, each image will undergo a detailed annotation process. This step is vital for accurately training the model. I will use tools like Labelme (Russell et al., 2008) to draw bounding boxes and segmentation masks around the damage, paying close attention to the nuances that differentiate scratches from dents.

4.2.2 Damage Localization

The annotation process will not only label the type of damage but also localize it with precision. This means indicating exactly where on the vehicle the damage has occurred, whether on the front, right, or left side. This detailed localization is crucial for the model to learn from the specific orientations and damage types.

4.3 Model Selection and Training

4.3.1 Model Adaptation

I will use a Mask R-CNN model pre-trained on a broad dataset like COCO (Lin et al., 2014) as our starting point. This choice is based on Mask R-CNN's proven capability in object detection and segmentation tasks.

4.3.2 Training on Custom Annotated Data

The model will then be fine-tuned on our specially collected and annotated dataset. This training phase will adjust the model to our specific needs - recognizing and segmenting scratches and dents on cars. Throughout the training process, we'll implement continuous validation checks to monitor the model's performance. This approach helps in identifying any overfitting or underfitting, ensuring the model generalizes well to new, unseen images.

4.4 Hyperparameter Tuning and Optimization

Through a series of experiments, we will tweak the model's hyperparameters to find the optimal settings for our task. Adjustments may include changing the learning rate, batch size, and the specific layers of the network we choose to fine-tune. The focus will be on optimizing the model to enhance its accuracy in detecting and segmenting the predefined damage types on specific car orientations. Techniques like transfer learning will be key in leveraging the model's pre-trained knowledge for our specific application.

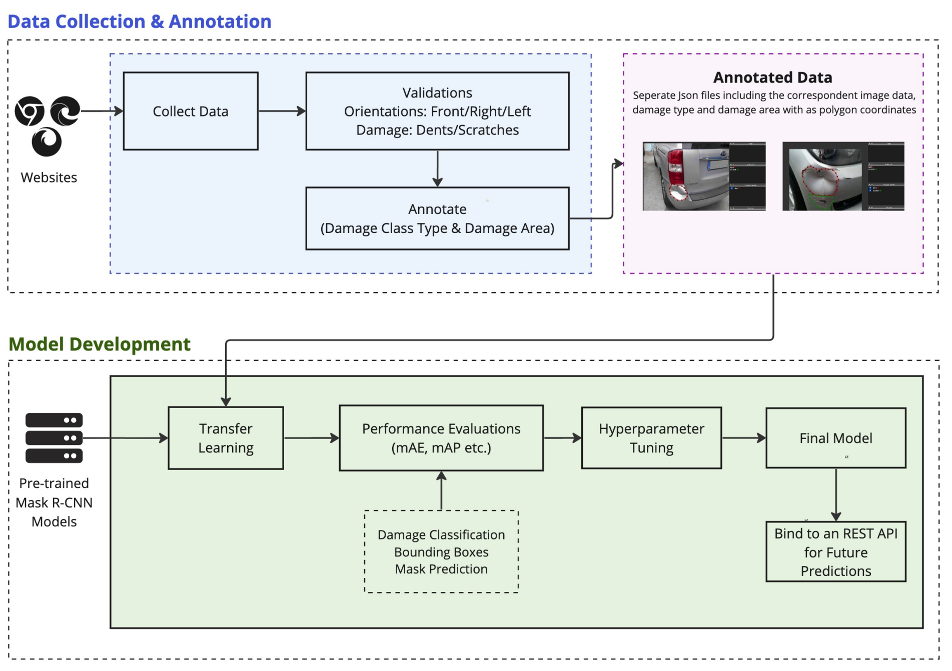


Figure 1: High-Level Design Diagram

5 Experiment Design

In our approach to evaluating the effectiveness of the Mask R-CNN model for car damage detection and segmentation, we aim to conduct a detailed analysis covering various aspects of model performance. This includes the detection accuracy, the precision of bounding box placements, and the accuracy of mask detection for identifying specific damages. To ensure a thorough evaluation, we will employ standard metrics commonly used in similar problem domains, such as Mean Average Precision (mAP) for detection accuracy, and Mean Absolute Error (MAE) for assessing the precision of bounding boxes and segmentation masks.

5.1 Performance Evaluation Metrics

5.1.1 Detection Accuracy

We'll measure how accurately our model detects the presence of damage using mAP. This metric is essential for understanding how well our model identifies damaged areas across different vehicle orientations.

5.1.2 Bounding Box Precision

The precision of bounding box placements around detected damages will be evaluated using MAE. This will help us gauge how accurately the model locates and outlines the damaged areas.

5.1.3 Mask Detection Accuracy

For the segmentation masks that delineate the extent of damages, we'll also use MAE to measure the accuracy of these masks, ensuring that the model precisely captures the shape and size of the damage.

5.2 Customized Evaluation Approach

Given the specialized focus of our project on specific car orientations (front, right, and left sides) and damage types (dents and scratches), and the lack of a benchmark dataset tailored to these parameters, our evaluation will need to account for the customized nature of our dataset and objectives. This poses a unique challenge, as it limits our ability to compare our results directly with existing methodologies or datasets.

To address these challenges, our experiment design includes:

5.2.1 Creating a Custom Dataset

Given the project's specific focus, we will compile a unique dataset that reflects the variety of damages and orientations we aim to detect. This dataset will serve as the basis for training, validating, and testing our model.

5.2.2 Tailored Evaluation Metrics

While employing standard metrics like mAP and MAE, we will adapt our evaluation criteria to focus on the model's performance relative to our project's specific goals. This means paying particular attention to the model's ability to detect and segment dents and scratches accurately in the specified orientations.

5.2.3 Comparative Analysis

Without a benchmark dataset for direct comparison, we will benchmark our model's performance against manual assessments to highlight improvements in accuracy, speed, and consistency. This comparison aims to demonstrate the advantages of automating the damage assessment process through deep learning.

5.2.4 Future Benchmarking Opportunity

By documenting our dataset creation process and evaluation methodology, we aim to provide a foundation for future research in this area. Our project could serve as a benchmark for similar studies focusing on automated vehicle damage assessment in specific contexts.

6 Expected Results

The primary objective of this project is to leverage the capabilities of Mask R-CNN for the targeted detection and segmentation of specific car damages, namely scratches and dents, on distinct orientations of vehicles (front, right, and left sides). Drawing on the foundational principles of deep learning, and considering the advanced functionalities of Mask R-CNN highlighted in existing research, I anticipate several key outcomes from this endeavor.

6.1 Enhanced Accuracy in Damage Detection

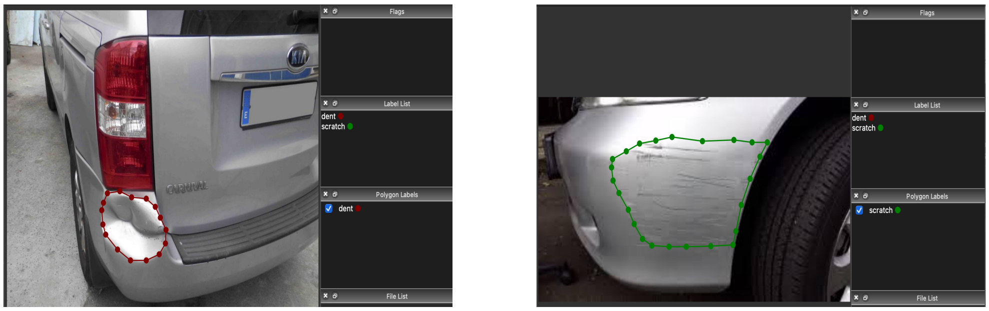
I expect a significant improvement in the accuracy of detecting and classifying car damages. By focusing on specific types of damage and car orientations, the model can learn detailed features relevant to these conditions, leading to a higher precision rate. This outcome is supported by studies that have demonstrated Mask R-CNN's effectiveness in distinguishing subtle nuances in object features, making it particularly suited for our primary purpose.

6.2 Precise Localization of Damages

Another predicted result is the precise localization of damages, facilitated by the segmentation capabilities of Mask R-CNN. The annotated dataset, specifically tailored to include various instances of scratches and dents from different vehicle orientations, will enable the model to not only identify the presence of damage but also accurately outline its extent. This precision is crucial for assessing the severity of damages and determining appropriate repair actions.

6.3 Sample Results (Expected)

The below are the sample images which showcase the correct damage label and the exact damage area within the car images. Similar to this, the expected output images should also contains the predicted class, localized area and also the bounding boxes.



(a) For ”dent” damage type

(b) For ”scratch” damage type

Figure 2: Images containing ”dent” or ”scratch” damage types

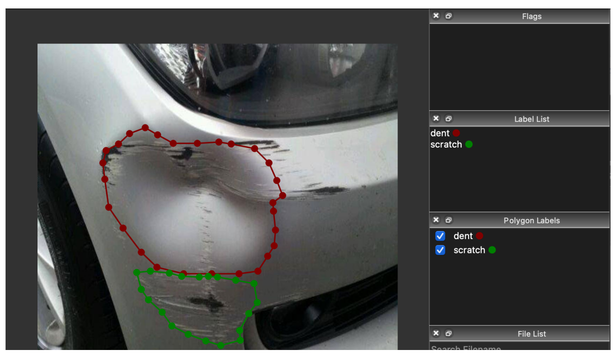


Figure 3: Image contains both ”dent” and ”scratch” damage types

The project's expected outcomes strongly correspond with the exploration of the theoretical foundations and real-world applications. By applying these principles to this real-world problem, I aim to not only validate the effectiveness of Mask R-CNN for yet another solution but also contribute to the ongoing evolution of automated systems in the automotive industry.

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