# Title: Automatic Vehicle Damage Detection

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**Introduction**:

The detection of vehicle damage through automated systems is essential for improving the accuracy, efficiency, and reliability of insurance claim processing and fleet management. Manual inspection methods are often time-consuming, subjective and difficult to document all the information, particularly when there is a flow of large volumes of insurance claims. By leveraging machine learning and computer vision, we aim to develop a robust automatic vehicle damage detection system that can locate and classify damage types, enhancing accuracy and operational efficiency.

**Dataset**:

We are utilizing the "Vehicle Dataset - Automatic Vehicle Damage Detection" available on Kaggle:

* URL: <https://www.kaggle.com/datasets/hendrichscullen/vehide-dataset-automatic-vehicle-damage-detection>
* Data size: Approximately 2 GB
* Inputs/Variables:
  + Images of vehicles (JPG format) - About 13.4k images
  + Annotation files indicating the type of damage and locations
* Target Variables:
  + Damage classification labels (Paint scratch, Dent, Missing parts, Torn, Puncture, Broken Glass, Broken Lamp, No Damage)
  + Localization bounding boxes (coordinates specifying the area of damage)

**Research Problems**:

* Damage Type Classification: Vehicles can exhibit a wide variety of damages (e.g., scratches, dents, broken glass), which often appear visually similar or partially occluded in real-world images. Manually identifying and labeling each type is labor-intensive and prone to inconsistency. There is a need for a scalable method that can accurately and consistently classify these damage types from images.
* Damage Localization: Detecting the exact location of damages on a vehicle in an image is challenging due to varying lighting conditions, backgrounds, viewing angles, and overlapping vehicle components. Bounding box annotations are available but building a system that can replicate this detection with high precision is a key challenge.

**Potential Solutions**:

The goal is to locate and classify one or more damages on the vehicle, so we use object detection techniques that can achieve this in a single pipeline.

* We consider approaches such as Fast R CNN, YOLOv8 etc. for this task.
* Experiment with transfer learning to improve accuracy and reduce training time.
* Tune model hyperparameters to enhance performance and compare different architectures to find the right balance between high accuracy and fast inference times, depending on the practical deployment needs.

**Evaluations**:

* We will use a train-validation-test split (e.g., 70%-15%-15%) to evaluate model performance.
* Classification Metrics: Accuracy, Precision, Recall, F1-score.
* Localization Metrics: Mean Average Precision (mAP), Intersection over Union (IoU).

These metrics provide a balanced evaluation of the model’s classification performance.

**Expected Outcomes**:

* A functional prototype capable of accurately classifying and localizing vehicle damages with high precision.
* A comparative analysis of various object detection techniques to determine the best-performing model.

**Evaluation Questions**:

1. Objective/goal clarity: Yes, the objectives are clearly outlined with practical, solvable problems.
2. Solution validity: Proposed solutions align well with identified problems, clearly dependent on the dataset.
3. Clear evaluation approach: Yes, clear metrics and methods for evaluating solutions have been detailed.
4. Comprehensibility: The proposal provides sufficient details for readers to understand problem and solution clearly.
5. Difficulty and novelty: The project addresses relevant challenges in vehicle damage detection with practical implications and complexity in model evaluation.