Lens Contamination in Autonomous Vehicles

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Project Task Description

Problem Statement & I/O

Identify and segment objects (vehicles, pedestrians, cyclists) in contaminated ADAS (KITTI) images, outputting bounding boxes/segmentation masks with confidence scores.

Novelty

- Synthetic lens contamination using generative models.
- Systematic YOLO testing & fine-tuning on contaminated data.
- Analysis of degradation by dirt location/coverage.

Motivating Use Case

Real-World Challenge

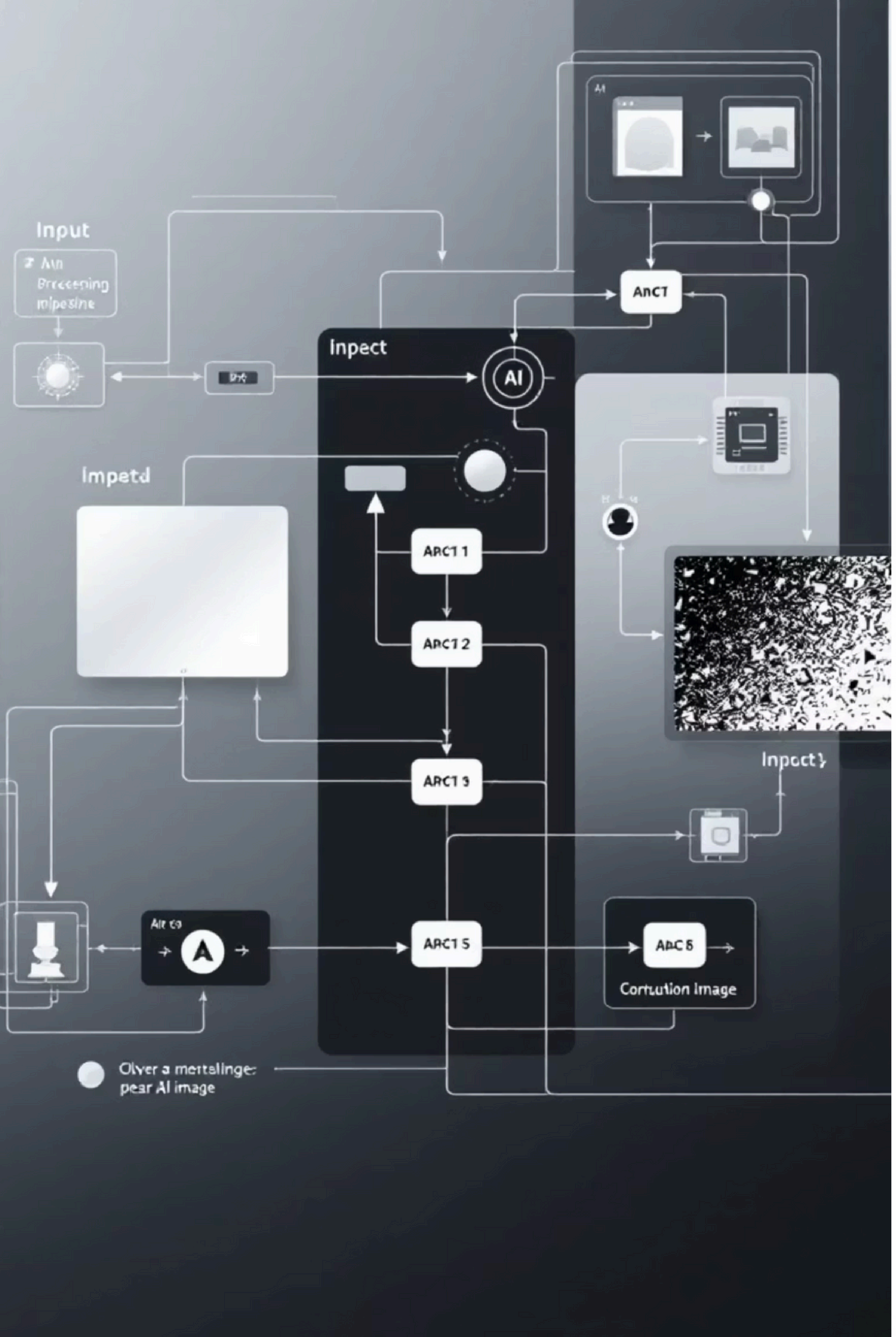
ADAS cameras, crucial for autonomous vehicles, frequently face lens contamination from elements like mud, dust, and rain.

Why It's Important

Contamination impairs vision, causing detection failures and safety risks. Most models, trained on clean images, are highly vulnerable.

Why It's Challenging

Collecting diverse real-world contaminated data is difficult. Partial occlusion further complicates detection, leading to false negatives.



Models and Methods

Pipeline Overview

01

Load Clean KITTI Images

Start with pristine images for baseline.

02

Create Contamination Masks

Generate masks for insect splatter, mud drops, and smudges.

03

Generate Realistic Contamination

Use Stable Diffusion Inpainting to "synthesize" dirt.

04

Integrate Contaminated Images

Add synthetic contaminated images to the dataset.

05

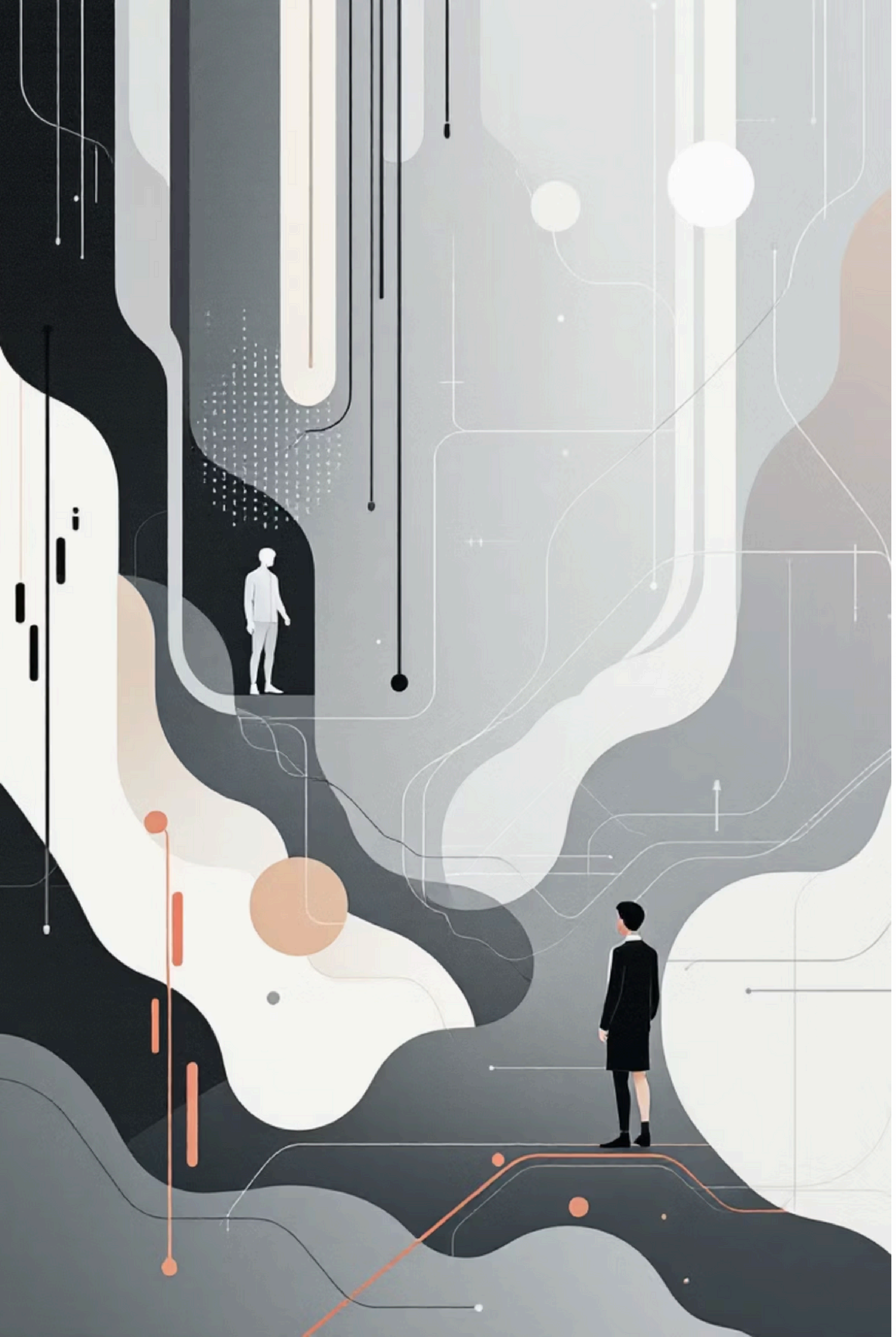
Train YOLO Models

Train YOLO for object detection and segmentation.

06

Compare & Analyze

Evaluate performance: Clean vs. Contaminated vs. Fine-tuned models.



Models and Techniques

Models Utilized:

- YOLOv8 / YOLOv9: For robust detection & segmentation
- Runwayml/stable-diffusion-v1-5: Generative model for realistic contamination
- runwayml/stable-diffusion-inpainting: Generate Realistic Contamination via SD Inpainting

Key Techniques:

- Synthetic augmentation
- Mask-based inpainting
- Strength control + severity levels
- Training with mixed data for robustness

Data Specification & Generation

Dataset

KITTI Object Detection + Segmentation: A widely used benchmark for autonomous driving research.

Categories: Car, Pedestrian, Cyclist.

Synthetic Data Generation

Creating realistic contamination across **three severity levels**:

Low: A few drops/insects.

Medium: Wider spread, slight blur.

Heavy: Significant coverage, especially at the image center.

Generation Steps

1

Generate Contamination Mask

Using Gaussian blobs or insect splatter shapes.

2

Define Prompt

"ADAS camera view obscured by insect remains, dirt, mud splashes – realistic lens contamination."

3

Stable Diffusion Inpainting

Adding natural-looking dirt to masked areas.

4

Save & Reuse YOLO Labels

Objects remain in original positions, no re-labeling needed.

Labeling Efficiency

No re-tagging is necessary as contamination does not alter object locations. Only contaminated versions are generated alongside the clean dataset.

Metrics & KPIs

Evaluation Metrics

- mAP@0.5
- mAP@[0.5:0.95]
- IoU for segmentation
- Error analysis:
  - Drop-rate per class
  - Miss-rate for occluded objects
  - Comparison per severity level

Key Performance Indicators (KPIs)

- Performance drop from Clean → Contaminated data.
- Improvement after fine-tuning on contaminated data.
- Robustness curve based on lens coverage percentage.
- Impact of fine-tuned model on clean image quality (avoiding degradation).