



# Boosting ADAS Camera Robustness

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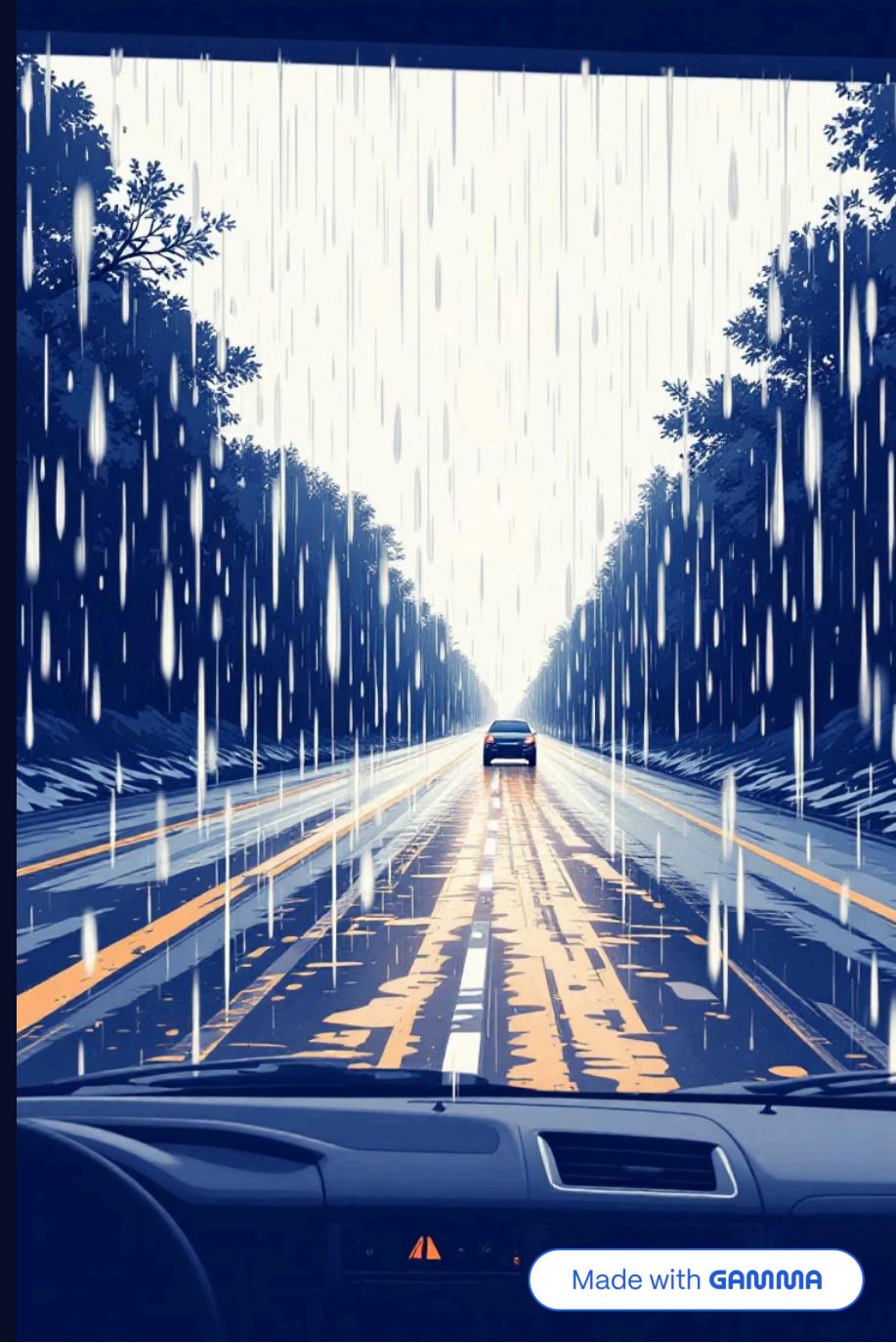
# Novel Approach: Simulating Real-World Obstacles

## Motivation & Specifications

Improve ADAS camera robustness by simulating lens contamination (mud, droplets, dirt) to train object detection models under adverse conditions.

## Key Contributions

- Application of KITTI dataset with realistic multi-type lens contamination.
- Data augmentation simulating real-world environmental conditions.
- Establishing a benchmark for ADAS performance under lens contamination.



# Previous Related Work

Title / Year	Task	Methods	Data	Results	Relation to Project
<b>Effect of Droplet Contamination on Camera Lens Surfaces (2025)</b>	Quantify droplet impact on image quality + detection	MTF/MTF50 + YOLOv8x mAP under controlled droplets	Controlled lens/cover glass; varying droplet coverage; hydrophilic vs hydrophobic	Small-object mAP can drop <b>up to ~90%</b> ; hydrophilic worse	Motivation + guides severity/coverage parameters for our synthetic contamination
<b>Enhancing ADAS Sensor Vision in Rain (2024)</b>	Check if retraining helps under droplet images	Train YOLOv3/YOLOv4 on droplet-influenced images; compare to pretrained	Wind-tunnel rain simulation; single-class (stop sign)	Retrained models outperform pretrained under droplets	Supports training/evaluating on contaminated data (we use a simplified pipeline)
<b>Impact of Raindrops on Camera-Based Detection (2024)</b>	Analyze which raindrop factors hurt detection most	Raindrop-type/density analysis; propose YOLO-RA; optional SR3+YOLO-RA	BDD100K-based rainy data with raindrop categories	Density/coverage most damaging; mitigation improves metrics	Helps choose what to vary (density/coverage) in our contamination generator (no need to implement their model)

# Building the Contaminated Dataset

1

## Dataset Creation

- **Base:** KITTI object detection images.
- **Contaminations:** mud, dirt, water droplets.
- **Labels:** same as KITTI (bounding boxes).

2

## Generation Techniques

- Alpha-blended contamination textures.
- Randomized contamination levels and placement for realism.

3

## Exploratory Data Analysis (EDA)

- Class distribution consistent with original KITTI.
- Balanced contamination distribution across types.

Visualizing the impact of contamination:



# Baseline Performance & Analysis

## Baseline Model: Pretrained YOLOv8

Utilized a pretrained YOLOv8 model on KITTI, with minimal adaptation to contaminated images initially.

## Observation: Significant Accuracy Drop

Performance reduced with heavy contamination, highlighting the need for specialized training.

## Error Analysis: False Negatives

Mostly on objects partially occluded by contamination, confirming the necessity for data augmentation.



# Project Roadmap & Next Steps

1

## Dataset Generation

**Description:** Create full contaminated KITTI dataset (mud, droplets, mixed).

**Outcome:** Complete labeled dataset for training.

2

## Model Training

**Description:** Fine-tune YOLOv8 on the newly contaminated dataset.

**Outcome:** Improved detection under various contamination scenarios.

3

## Evaluation

**Description:** Evaluate model on both contaminated and clean images.

**Outcome:** Quantitative performance analysis and benchmark.

4

## Optimization

**Description:** Adjust data augmentation and hyperparameters.

**Outcome:** Maximized accuracy under all contamination types.

5

## Final Presentation

**Description:** Prepare comprehensive slides & visualizations.

**Outcome:** Showcase results and future implications.