



University of
Dayton

Towards Safer Roads: **Benchmarking Object Detection Models in** **Complex Weather Scenarios**

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Outline

01	Introduction
02	Proposed method
03	Experimental Result
04	Conclusion

Outline

01

Introduction

02

Proposed method

ADCD Dataset Collection

Weather-centric Data Augmentation

Evaluating Object Detection Models

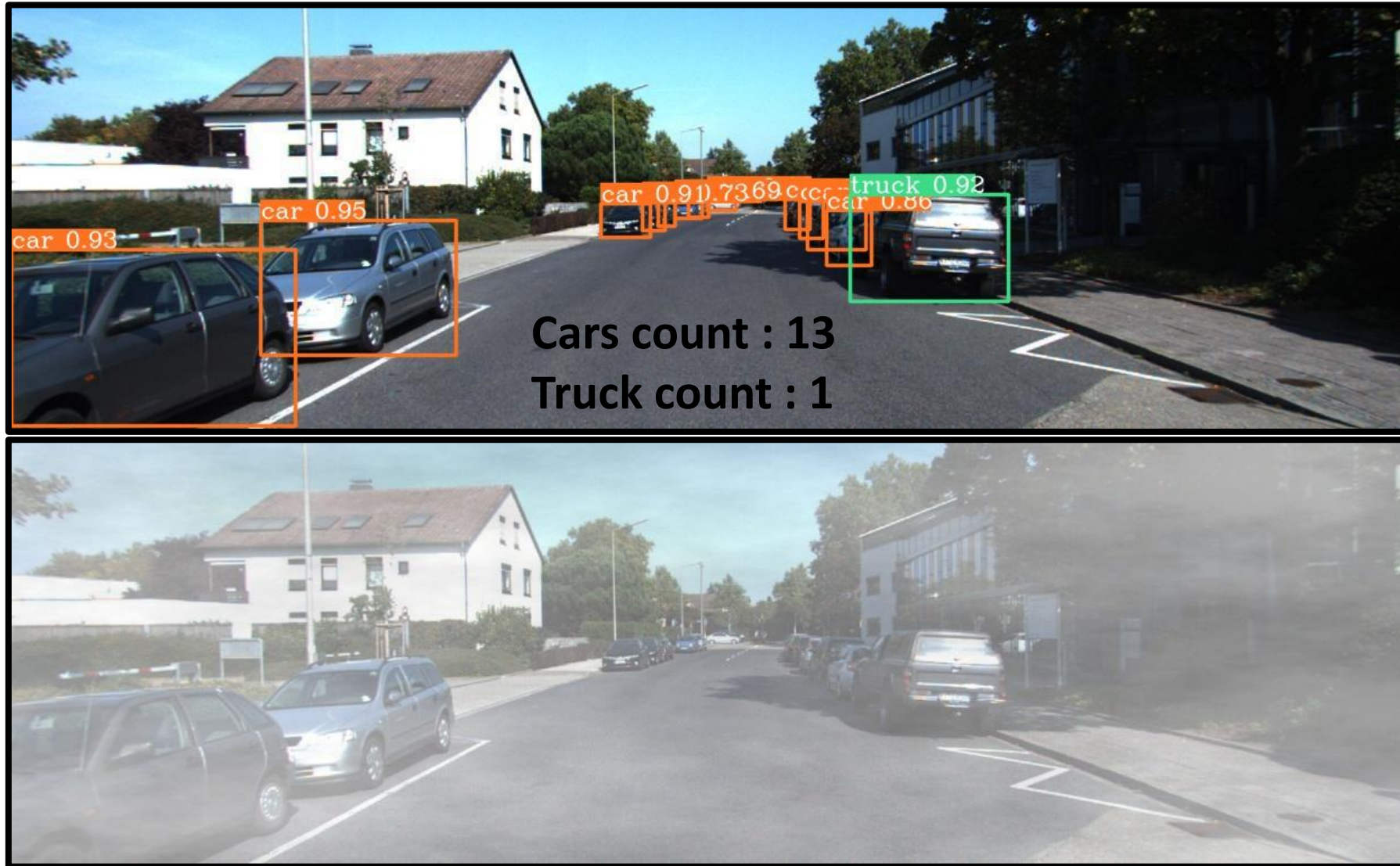
03

Experimental Result

04

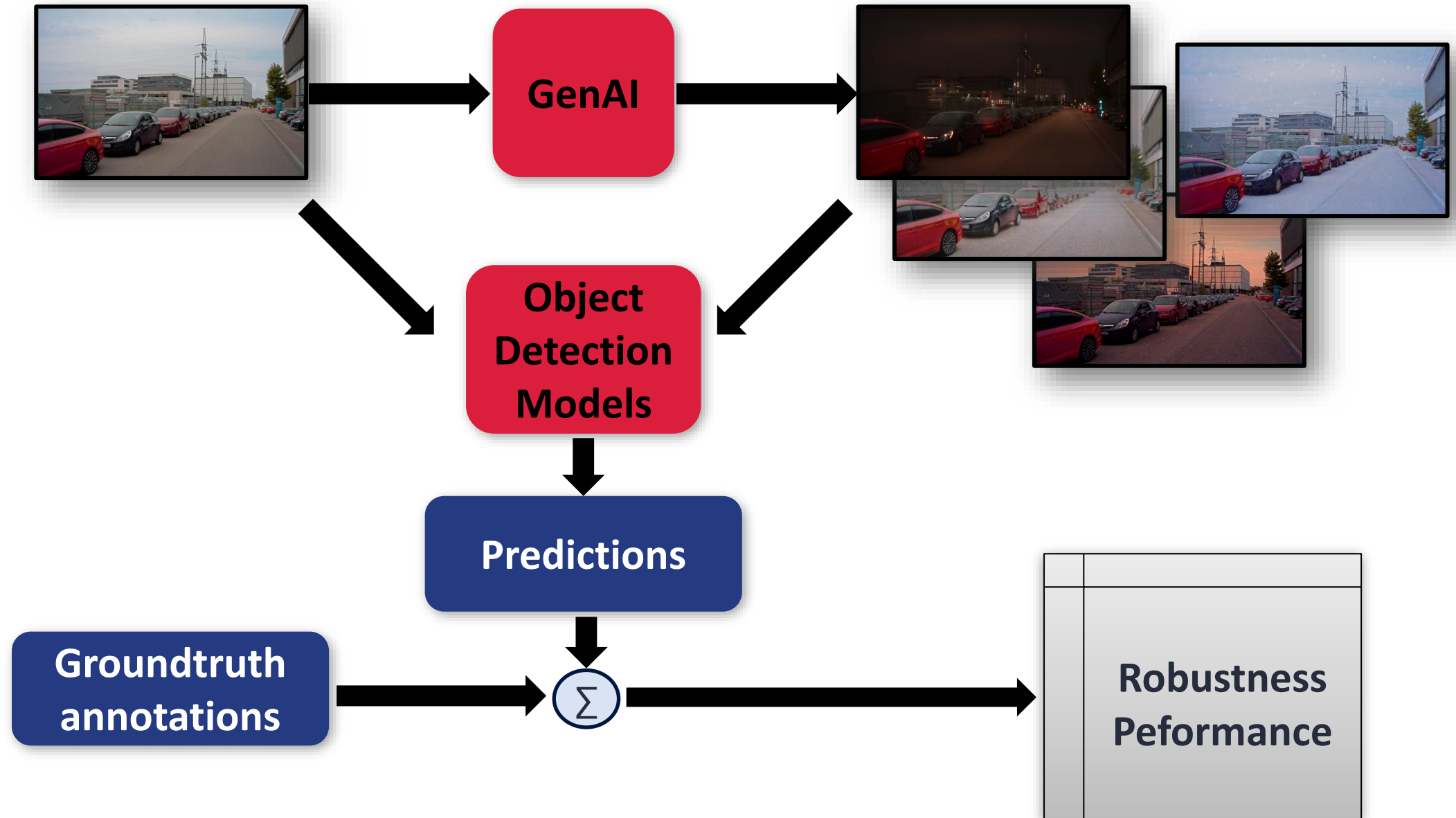
Conclusion

Introduction - Motivation



How many vehicles can current AI models see in the foggy environment?

Introduction - Problem Statement



Introduction - Contribution

- **A synthetic dataset with twelve weather conditions.** Our Adverse Driving Conditions Dataset (ADCDC) comprises a curated collection of 50,000 traffic images sourced from well-established sources and the newly developed Dayton Driving Dataset (DDD)
- **Weather synthesis methodology.** Our approach focuses on preserving the exact positions of all objects within the images while altering only the weather effects.
- **Benchmark evaluation.** We provide critical insights into the limitations of current approaches and suggest pathways for developing more resilient algorithms.



Proposed method

ADCD Dataset Collection

Weather-centric Data Augmentation

Evaluating Object Detection Models



Proposed method



ADCD Dataset Collection

Weather-centric Data Augmentation

Evaluating Object Detection Models

Proposed Method - ADCD Dataset Collection

Dataset	Location	Year	Images
Udacity	Mountain View, United States	2016	24007
ApolloScape	China	2018	7040
IDD	India	2019	5713
A2D2	Germany	2020	12469
DDD	Dayton, United States	2024	755

**Total Dataset size:
50,000 images**

Proposed Method - ADCD Dataset Collection

ApolloScape



Location: China

Conditions: Urban and highway; mostly clear

Size: 7,040 labeled images

Creation: Vehicle with LiDAR, GPS, stereo cameras; diverse driving scenarios

Udacity



Location: C.A., USA

Conditions: Daytime, often in sunny weather

Size: 24,007 labeled images

Creation: cameras mounted on a car

Proposed Method - ADCD Dataset Collection

IDD (Indian Driving Dataset)



Location: Indian cities

Conditions: Urban and semi-urban; varied lighting/weather

Size: 5,713 images

Creation: Car-mounted cameras; diverse Indian road scenarios, unique road elements.

A2D2



Location: Germany

Conditions: Urban and highway; cloudy/clear weather.

Size: 12,496 images

Creation: Cameras, Lidar, Radar, GPS

Proposed Method - ADCD Dataset Collection

Our Extra Dataset Dayton Driving Dataset (DDD)



Location: OH, USA

Conditions: Urban, and semi-urban; mostly clear

Size: 744 images

Creation: Car dash-camera



Proposed method



ADCD Dataset Collection

Weather-centric Data Augmentation

Evaluating Object Detection Models



Proposed method

ADCD Dataset Collection



Weather-centric Data Augmentation

Evaluating Object Detection Models

Proposed Method - Weather-centric Data Augmentation

IMAGE WITH NO EFFECTS



IMAGE WITH DIFFERENT EFFECTS



8 single conditions:

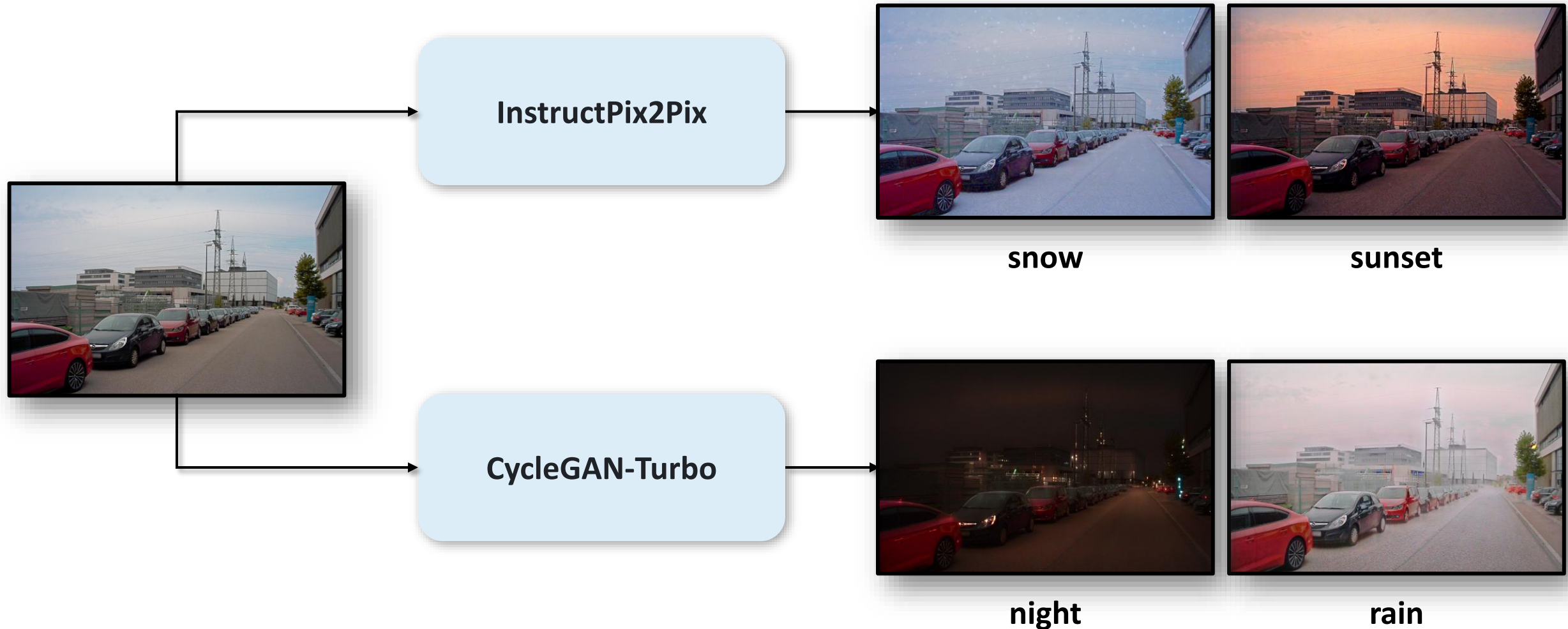
snow, sunset, night, rain, crack, flare (sunny), fog, raindrop

4 mixed conditions:

fog + raindrop, crack + flare, rain + raindrop, night + fog

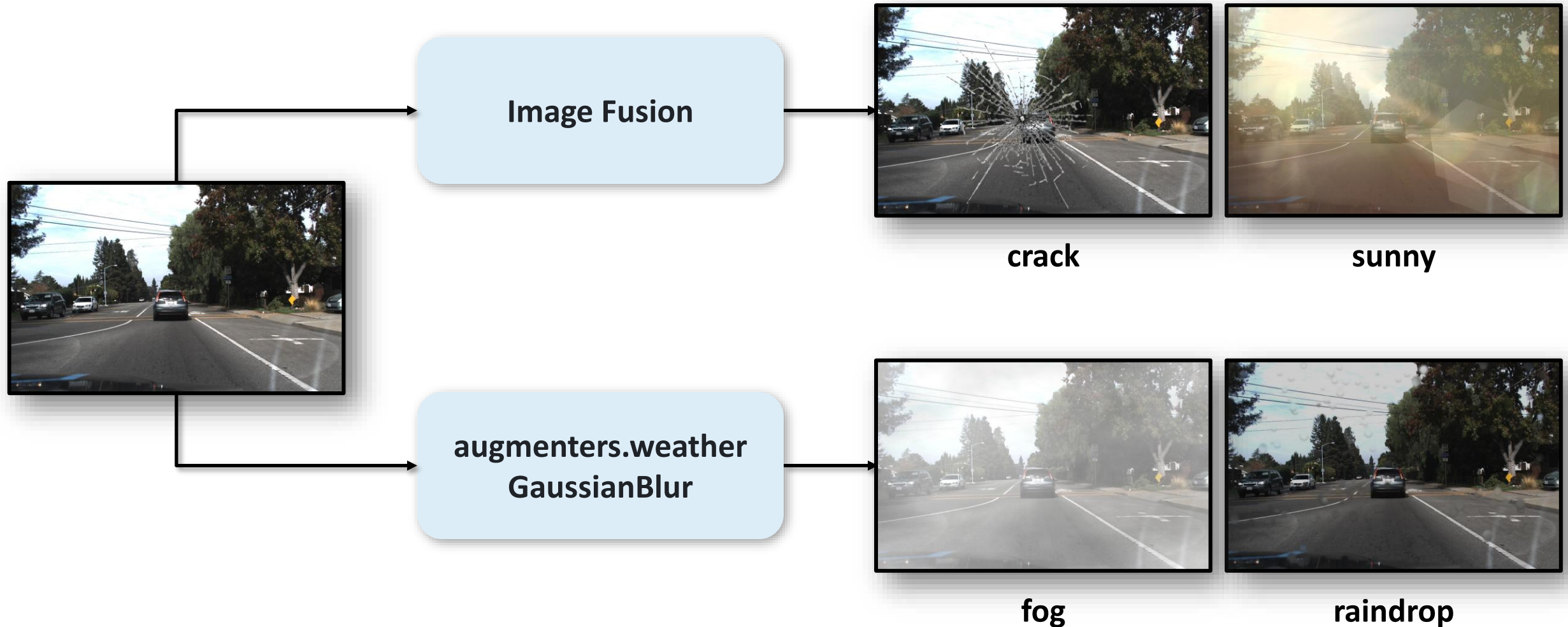
Proposed Method - Weather-centric Data Augmentation

Deep learning-based approach



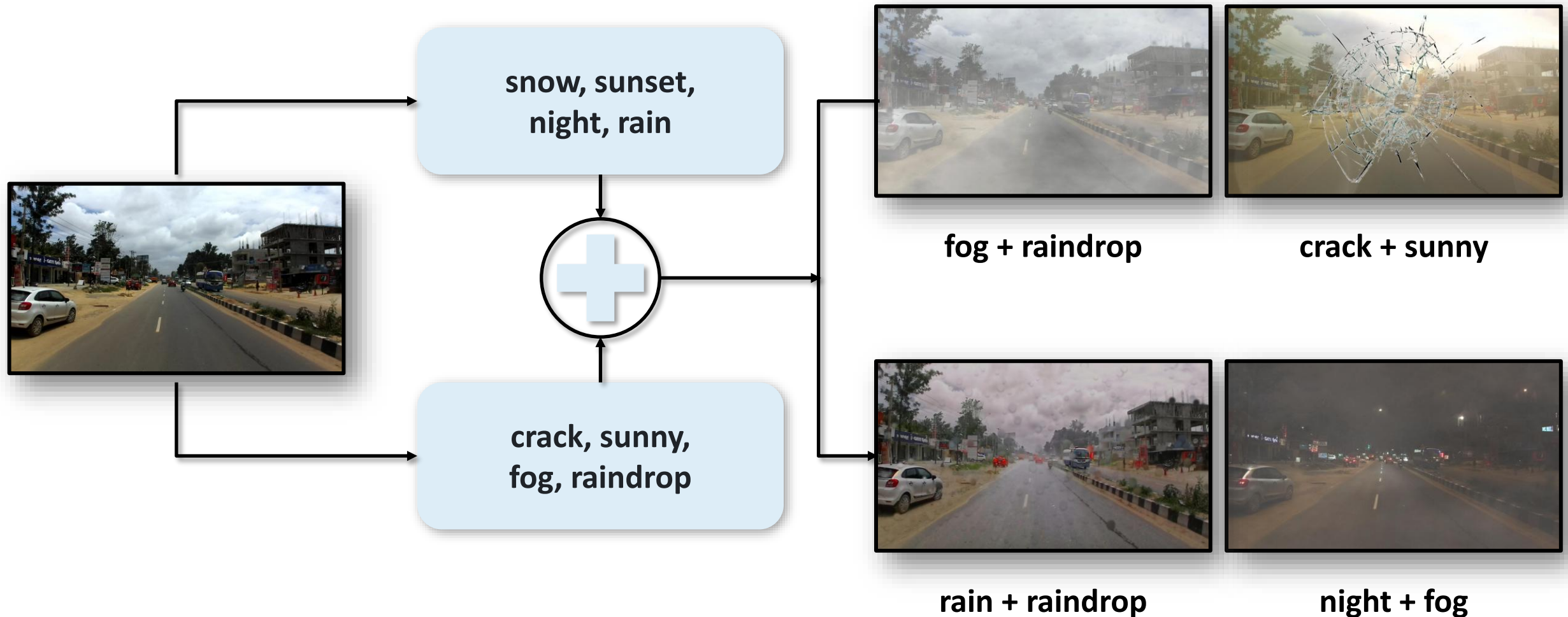
Proposed Method - Weather-centric Data Augmentation

Traditional approach



Proposed Method - Weather-centric Data Augmentation

Combined approach





Proposed method

ADCD Dataset Collection



Weather-centric Data Augmentation

Evaluating Object Detection Models



Proposed method

ADCD Dataset Collection

Weather-centric Data Augmentation

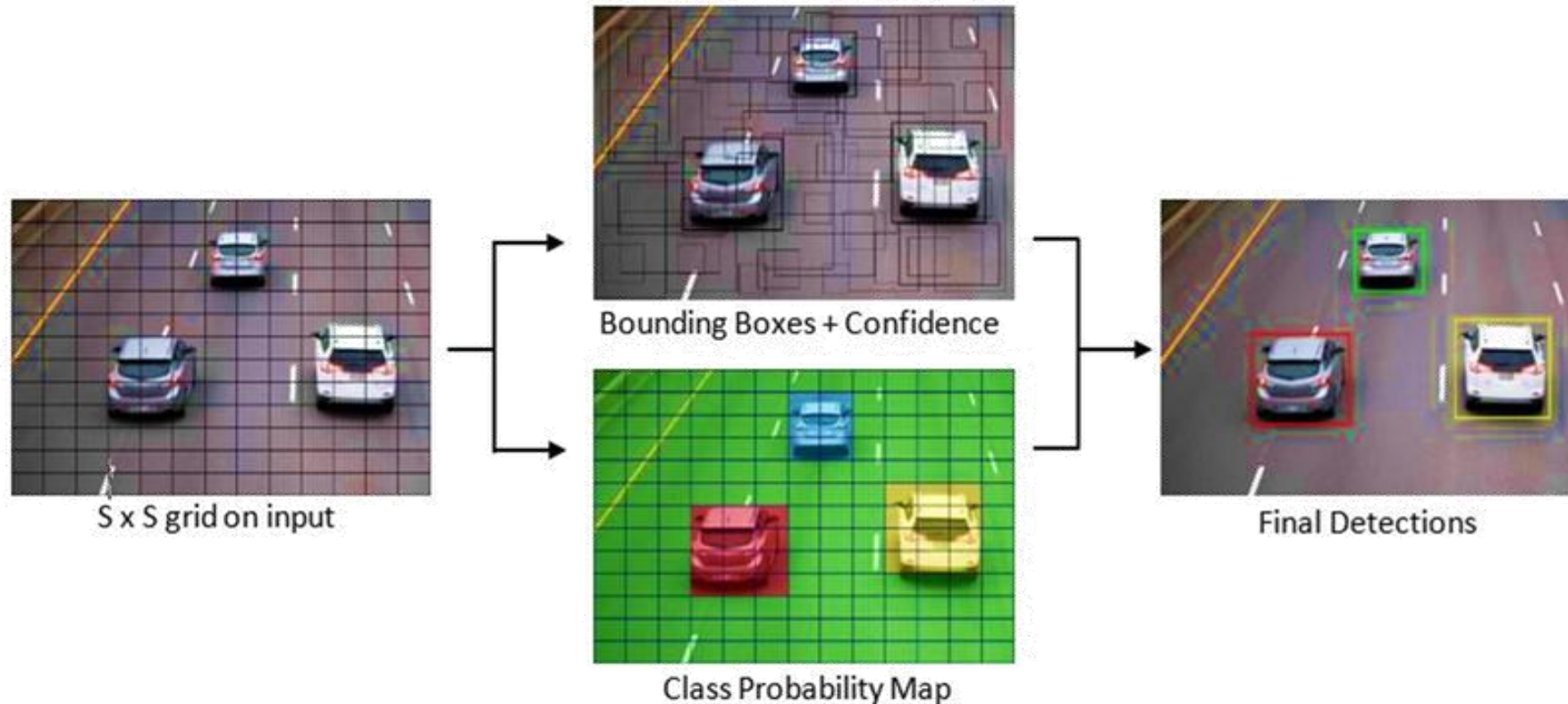


Evaluating Object Detection Models

Proposed Method - Evaluating Object Detection Models

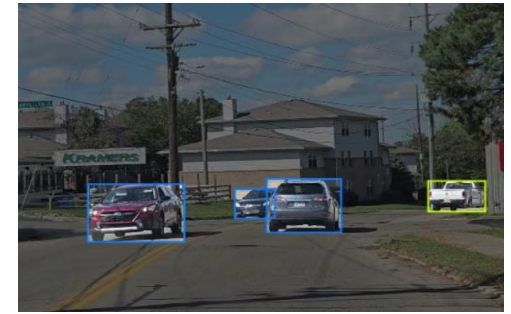
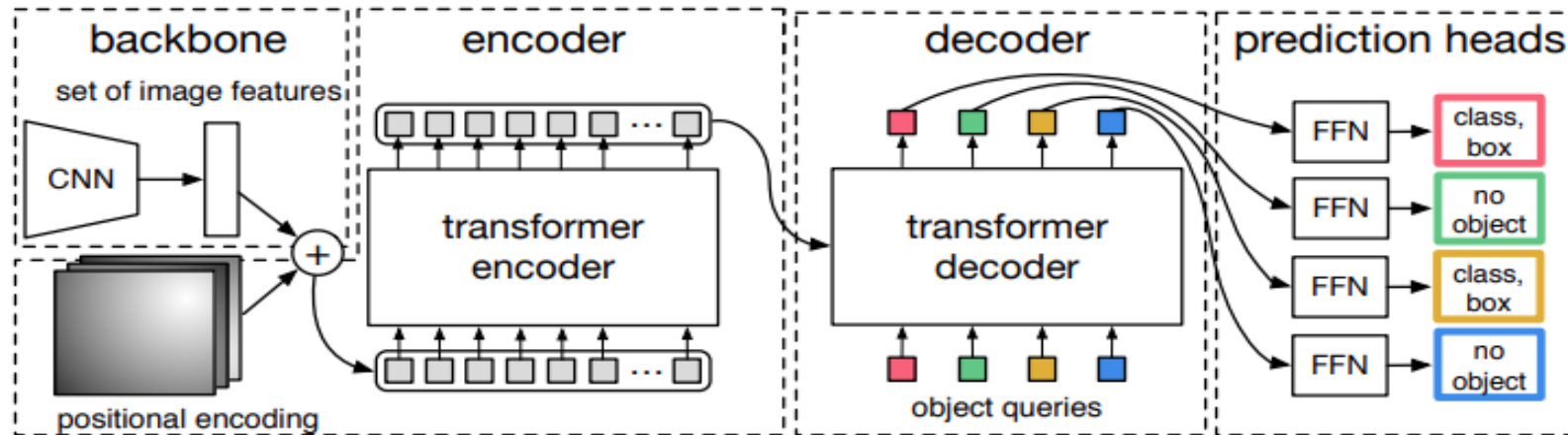
Object Detection models

You look only once (Yolov5-v11)



Proposed Method - Evaluating Object Detection Models

Object Detection models

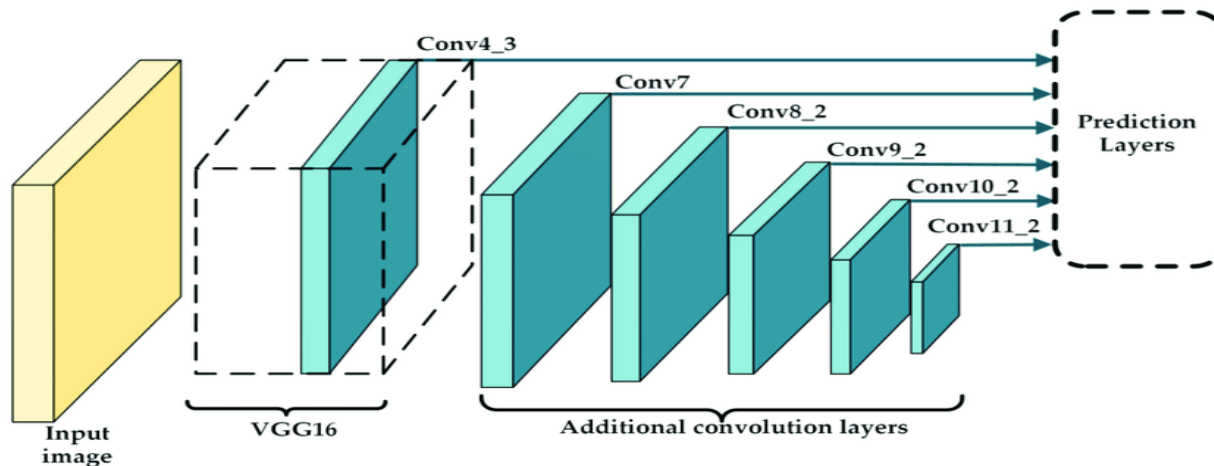
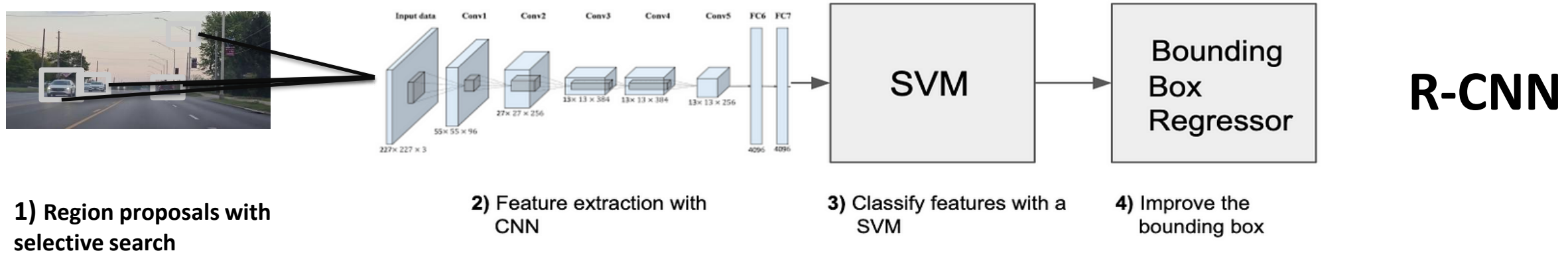


DETR (Detection Transformer)

- Introduced by Facebook AI
- Integrates **transformers** with **convolutional neural networks**
- High computational cost and time

Proposed Method - Evaluating Object Detection Models

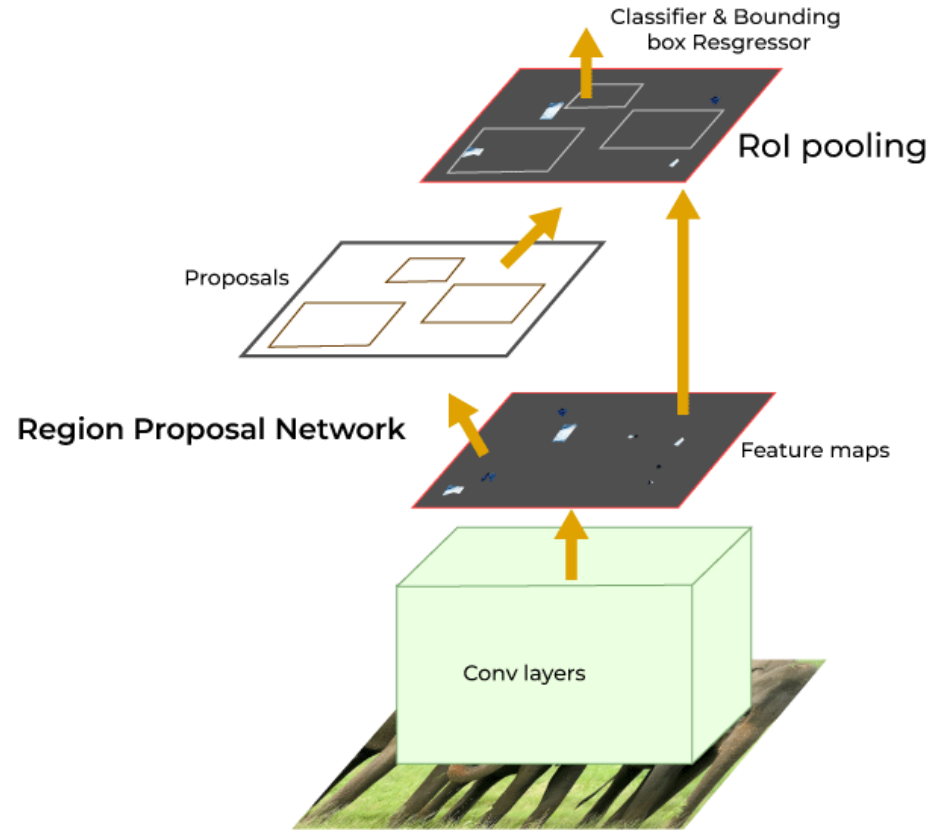
Object Detection models



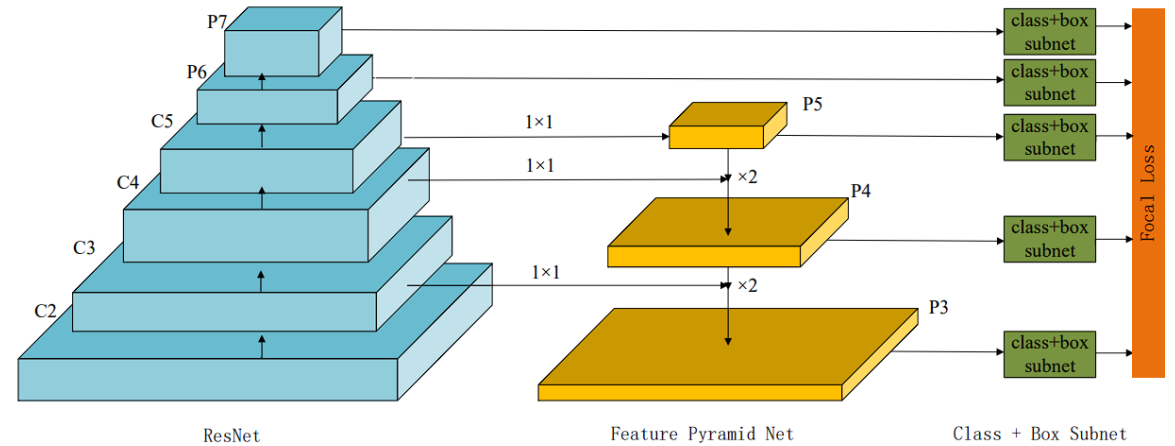
**Single Shot MultiBox
Detector (SSD)**

Proposed Method - Evaluating Object Detection Models

Object Detection models



Faster R-CNN

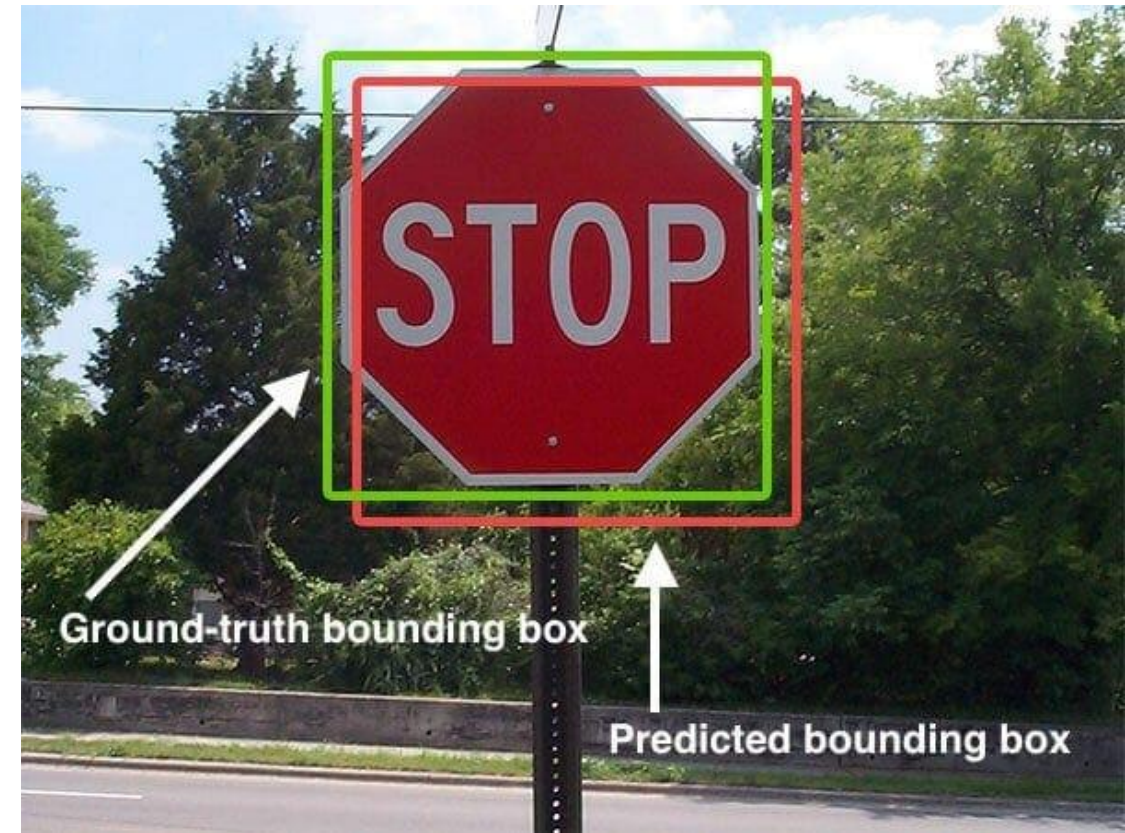
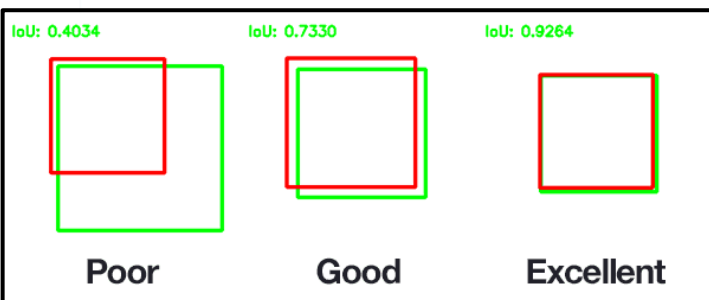


RetinaNet

Proposed Method - Evaluating Object Detection Models

Metrics

$$\text{IoU} = \frac{\text{Area of Overlap}}{\text{Area of Union}}$$

Intersection over Union

Proposed Method - Evaluating Object Detection Models

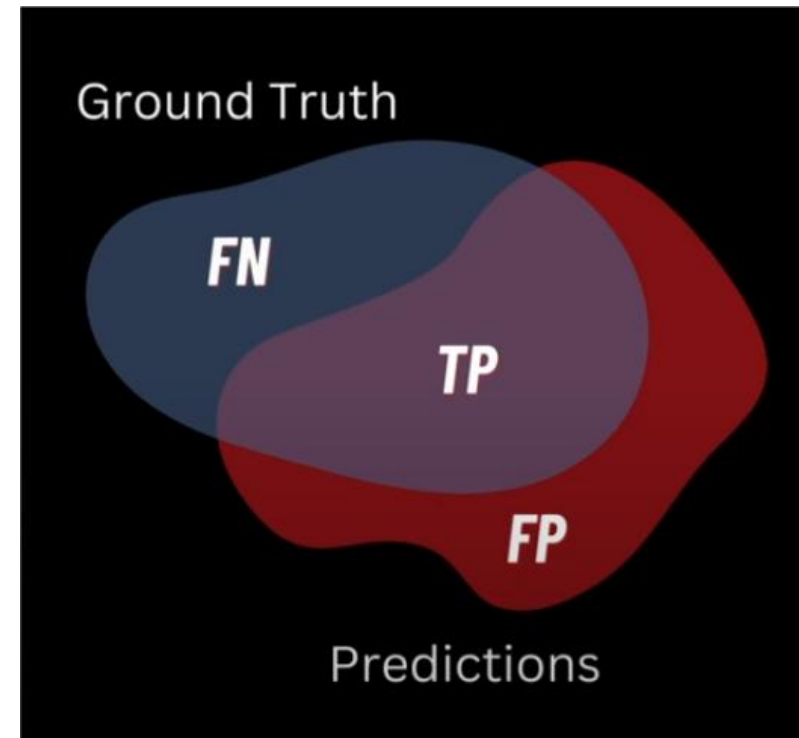
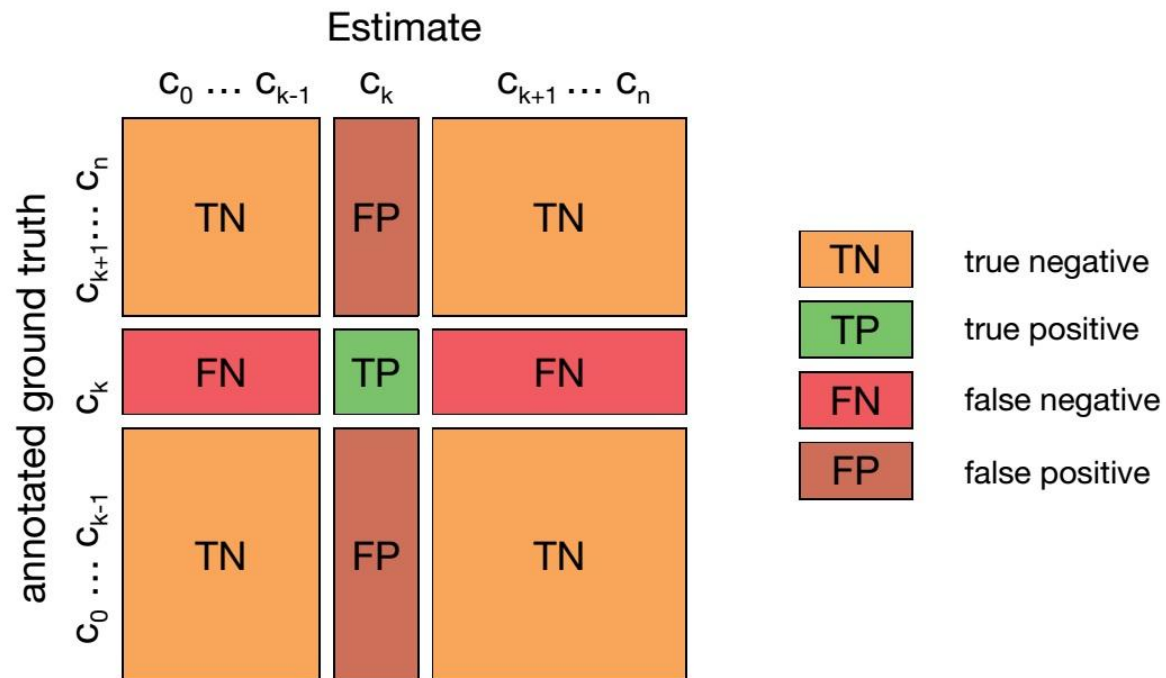
Metrics

True Positives (TP), False Positives (FP), False Negatives (FN)

Precision: $TP / (TP + FP)$

Recall: $TP / (TP + FN)$

→ AP score





Experimental Result

Experimental Result - Overall mAP score

	Base	Crack	Flare	Fog	Raindrop	Snow	Sunset	Night	Rain
Yolov5-x6	43.52	35.99	41.45	38.92	41.28	41.72	40.16	35.30	35.23
Yolov6-l6	46.91	39.70	45.00	42.99	45.02	45.68	44.63	39.43	39.46
Yolov7-e6e	37.74	31.32	35.01	34.15	36.19	36.91	35.77	30.28	32.82
Yolov8-x	38.35	31.53	36.09	34.93	36.64	37.53	36.45	30.14	33.27
Yolov9-e	39.23	32.01	35.98	34.62	37.24	37.95	37.27	31.11	33.59
Yolov10-x	37.17	30.91	34.81	33.45	35.58	36.36	35.19	28.46	31.90
Yolov11-x	38.82	32.00	36.48	34.62	36.80	37.74	36.17	29.60	32.84
DETR	34.91	27.10	16.25	15.95	29.60	33.00	32.65	11.65	21.43
RCNN	40.32	34.45	33.54	31.69	38.05	35.94	38.18	30.88	32.90
Faster-RCNN	39.69	33.78	32.70	31.29	37.35	36.30	37.54	30.58	32.38
RetinaNet	32.00	26.44	24.95	23.66	29.20	26.47	28.70	22.08	24.42
SSD	5.44	4.81	3.13	3.07	5.19	4.04	4.82	3.84	4.50

	Base	Fog Raindrop	Fog Night	Rain Raindrop	Crack Flare
Yolov5-x6	43.52	39.25	33.91	32.95	30.40
Yolov6-l6	46.91	43.23	38.40	37.42	33.74
Yolov7-e6e	37.74	34.52	28.98	30.91	24.89
Yolov8-x	38.35	35.12	28.19	30.87	25.25
Yolov9-e	39.23	34.94	29.15	31.30	24.83
Yolov10-x	37.17	33.80	26.67	29.47	24.85
Yolov11-x	38.82	27.35	28.31	30.27	26.41
DETR	34.91	16.38	7.89	15.42	8.43
RCNN	40.32	33.11	27.96	29.17	21.60
Faster-RCNN	39.69	32.57	27.26	28.16	20.93
RetinaNet	32.00	24.36	19.77	20.35	15.20
SSD	5.44	3.37	2.39	4.14	2.07

Experimental Result - Overall degradation (% mAP)

	Crack	Flare	Fog	Raindrop	Snow	Sunset	Night	Rain	Fog Raindrop	Fog Night	Rain Raindrop	Crack Flare
Yolov5-x6	17.3	4.76	10.57	5.15	4.14	7.72	18.89	19.05	9.81	22.08	24.29	30.15
Yolov6-l6	15.37	4.07	8.36	4.03	2.62	4.86	15.95	15.88	7.84	18.14	20.23	28.08
Yolov7-e6e	17.01	6.7	7.23	4.32	2.04	5.64	16.91	16.24	8.53	23.21	18.1	34.05
Yolov8-x	17.78	5.89	8.92	4.46	2.14	4.95	21.41	11.55	8.42	26.49	19.5	34.16
Yolov9-e	18.4	8.34	11.88	10.12	6.53	9.02	21.18	20.04	10.94	25.69	20.21	36.71
Yolov10-x	16.84	6.35	9.66	6.91	2.07	5.38	23.43	16.06	9.07	28.25	20.72	33.15
Yolov11-x	17.39	6.18	11.75	5.56	2.78	6.34	21.66	15.51	29.55	27.07	22.02	31.97
DETR	15.07	18.05	18.68	7.24	3.57	13.35	21.47	26.64	48.67	75.27	51.68	73.58
RCNN	20.7	13.71	22.56	14.42	5.72	16.47	26.15	24.27	19.09	31.67	28.71	47.21
Faster-RCNN	14.89	17.61	21.16	5.9	8.54	5.42	22.95	18.42	17.94	31.32	29.05	47.27
RetinaNet	17.38	22.03	26.06	8.75	17.28	10.31	31	23.69	23.88	38.22	36.41	52.5
SSD	11.58	42.46	43.57	4.6	25.74	11.4	29.41	17.28	38.05	56.07	23.9	61.95

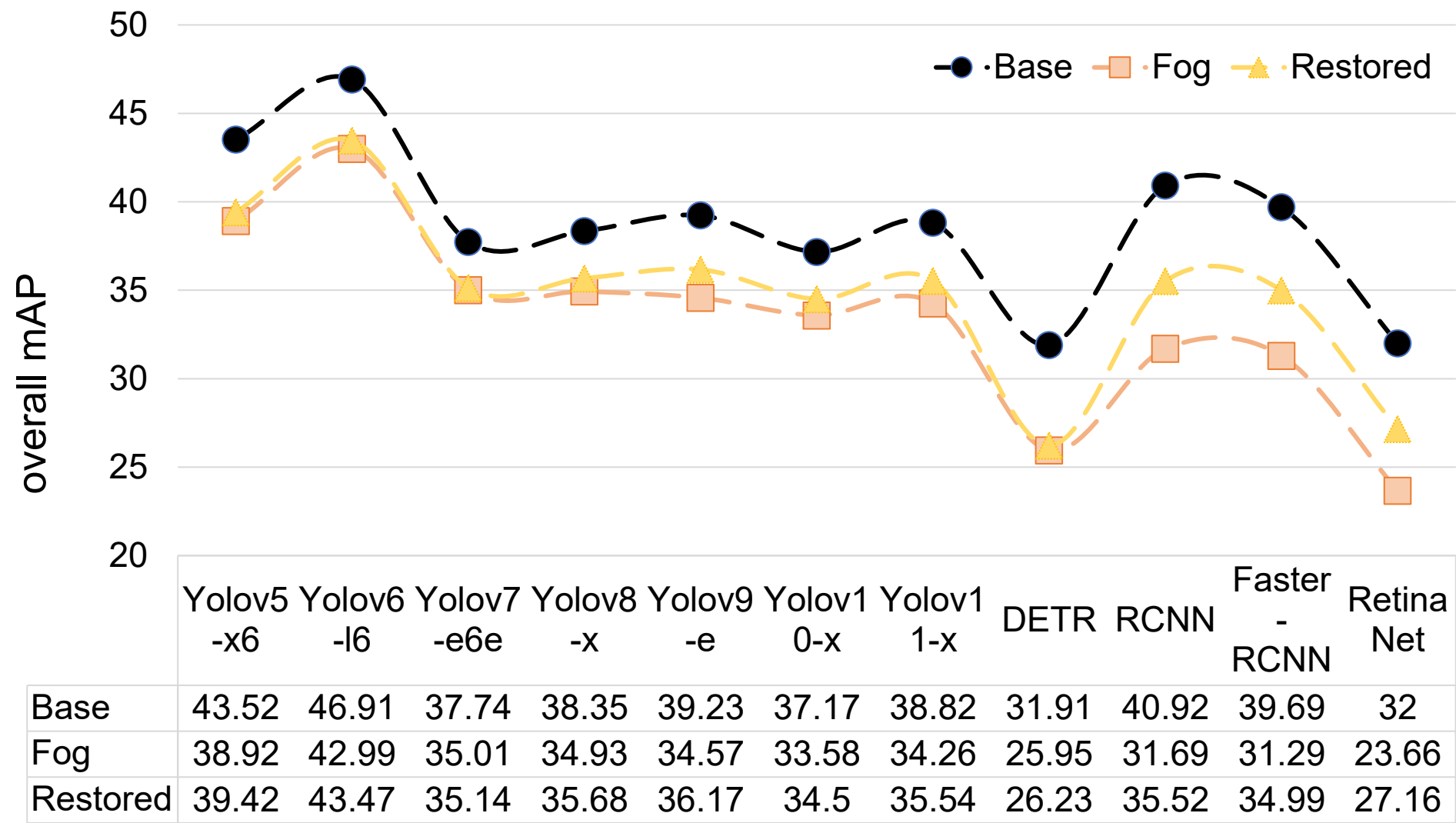
- All models experience performance degradation compared to the base dataset's score, emphasizing the need for reinforcing the dual importance of **advanced architectures and high-quality datasets** in developing robust object detection systems in the real world
- Certain effects can cause specific models to degrade significantly, even if those models perform well under other conditions, indicating that **performance may be condition-specific**

Experimental Result - Class-wise AP score

	Model	Base	Crack	Flare	Fog	Raindrop	Snow	Sunset	Night	Rain											
Car	Yolov5-x6	65.45	59.15	64.89	62.66	64.10	62.78	64.48	62.52	61.40	Motorcycle	Yolov5-x6	47.14	35.09	44.45	39.87	42.89	44.67	41.48	38.45	34.57
	Yolov6-l6	69.12	63.45	68.90	67.10	68.27	67.37	68.69	66.67	66.10		Yolov6-l6	51.85	39.71	48.58	45.07	48.11	49.36	46.70	42.65	38.95
	Yolov7-e6e	65.09	57.83	64.00	62.49	63.59	62.72	64.67	61.47	59.89		Yolov7-e6e	35.28	26.98	31.97	30.46	33.32	35.32	33.11	29.81	29.43
	Yolov8-x	64.25	56.97	63.57	61.37	62.63	61.84	63.85	60.03	58.80		Yolov8-x	38.27	28.60	34.82	32.89	36.22	37.38	35.21	30.70	31.28
	Yolov9-e	64.10	57.16	63.68	61.42	62.57	62.05	63.89	60.72	59.10		Yolov9-e	39.11	29.36	35.33	33.00	36.83	38.10	36.69	32.92	32.26
	Yolov10-x	63.05	56.43	62.48	59.82	61.61	60.66	62.74	58.26	57.48		Yolov10-x	35.79	27.54	33.07	30.83	34.09	35.24	33.52	29.08	28.93
	Yolov11-x	64.07	57.11	63.50	60.96	62.33	61.94	63.59	59.92	58.31		Yolov11-x	38.95	29.38	36.01	33.16	35.93	37.59	35.27	30.91	31.27
	DETR	60.32	51.04	40.18	37.27	56.05	59.02	58.28	27.01	49.54		DETR	32.88	23.12	6.78	7.80	24.36	24.07	33.46	10.01	14.46
	RCNN	62.54	55.87	61.14	58.32	60.61	56.22	62.24	63.14	57.39		RCNN	35.26	29.09	26.38	23.20	31.62	29.44	32.05	29.79	26.33
	Faster-RCNN	62.90	56.29	61.81	59.60	61.14	58.26	62.41	62.50	57.78		Faster-RCNN	34.67	28.15	24.96	22.86	31.19	30.94	30.86	29.57	24.93
	RetinaNet	60.35	51.28	56.11	54.08	57.30	51.05	58.32	54.34	50.41		RetinaNet	23.12	18.78	15.43	13.24	20.13	18.88	20.22	17.86	16.44
SSD	16.14	14.75	12.41	11.91	15.55	13.66	15.21	14.08	14.30	SSD	3.98	3.49	0.86	0.92	3.53	2.44	3.54	2.56	2.78		
Truck	Yolov5-x6	39.82	31.87	38.75	37.35	38.29	37.73	34.65	30.89	33.02	Person	Yolov5-x6	49.60	40.90	46.61	42.85	45.71	45.56	45.00	36.39	38.10
	Yolov6-l6	42.12	34.92	40.74	40.01	40.77	40.09	38.14	35.24	36.91		Yolov6-l6	55.51	46.89	53.17	49.31	52.12	52.72	53.17	43.13	44.36
	Yolov7-e6e	37.24	29.33	35.98	35.24	36.37	35.06	34.64	29.55	32.58		Yolov7-e6e	41.08	34.33	37.17	36.12	39.13	39.87	39.13	30.36	35.35
	Yolov8-x	36.41	28.20	35.88	35.13	35.37	35.74	32.73	27.84	31.41		Yolov8-x	42.50	35.40	38.92	37.32	39.72	40.40	40.17	30.87	35.56
	Yolov9-e	37.71	28.78	34.73	34.05	36.22	35.10	34.29	28.57	32.02		Yolov9-e	42.51	35.18	38.57	36.61	39.73	39.64	39.81	31.01	36.51
	Yolov10-x	35.89	28.10	34.87	34.28	34.68	34.46	32.32	27.70	31.47		Yolov10-x	39.64	33.28	36.06	34.28	37.31	37.92	37.21	27.70	33.29
	Yolov11-x	36.51	28.33	35.96	34.44	35.69	34.44	32.02	29.05	30.65		Yolov11-x	41.67	34.44	37.97	35.88	38.65	39.36	38.66	29.14	34.48
	DETR	27.01	17.71	5.38	7.59	21.49	22.73	21.40	5.61	11.36		DETR	42.61	33.83	25.93	23.22	37.32	43.43	39.80	19.27	31.36
	RCNN	37.79	29.90	31.34	31.28	36.49	33.18	33.83	23.64	31.08		RCNN	46.86	40.18	39.32	35.53	43.18	42.94	44.51	34.38	38.77
	Faster-RCNN	38.18	29.83	31.20	31.69	36.81	34.14	33.93	26.21	32.69		Faster-RCNN	46.76	39.96	38.83	35.10	42.98	42.72	44.61	33.81	38.33
	RetinaNet	31.54	23.72	24.52	25.42	30.19	27.22	26.38	18.15	26.16		RetinaNet	33.55	27.97	27.02	24.44	29.87	27.70	29.79	21.41	27.33
SSD	7.44	6.12	2.68	2.73	7.29	4.00	5.98	3.77	5.37	SSD	3.89	3.38	2.54	2.49	3.57	3.21	3.34	2.09	3.50		
Bicycle	Yolov5-x6	25.62	20.82	24.02	22.47	25.15	25.43	20.89	21.74	18.04	Traffic light	Yolov5-x6	33.48	28.12	29.98	28.33	31.55	34.17	34.43	21.83	26.22
	Yolov6-l6	24.77	20.71	23.21	22.36	24.71	25.81	21.37	21.37	19.00		Yolov6-l6	38.06	32.51	35.42	34.12	36.14	38.75	39.73	27.52	31.44
	Yolov7-e6e	17.95	14.67	16.34	15.87	17.10	18.16	13.73	12.41	14.67		Yolov7-e6e	29.78	24.78	24.62	24.74	27.61	30.32	29.31	18.05	25.03
	Yolov8-x	17.97	14.79	16.87	16.69	17.51	18.70	14.65	13.25	15.72		Yolov8-x	30.72	25.25	26.48	26.18	28.39	31.13	32.12	18.14	26.86
	Yolov9-e	18.83	15.06	17.61	16.89	17.87	19.93	15.45	13.89	15.05		Yolov9-e	33.12	26.51	25.96	25.77	30.25	32.90	33.49	19.58	26.61
	Yolov10-x	17.19	14.36	16.48	15.87	16.91	18.25	13.89	12.32	14.68		Yolov10-x	31.44	25.75	25.92	25.63	28.89	31.63	31.47	15.72	25.53
	Yolov11-x	18.55	15.48	17.71	17.02	18.27	19.57	14.78	13.03	15.63		Yolov11-x	33.20	27.23	27.72	26.28	29.92	33.55	32.68	15.54	26.69
	DETR	18.18	15.58	6.76	6.94	15.68	16.86	12.20	4.52	4.70		DETR	28.44	21.31	12.49	12.85	22.72	31.89	30.73	3.46	17.13
	RCNN	19.33	17.60	15.94	15.37	19.53	18.96	15.14	12.30	15.69		RCNN	40.16	34.08	27.14	26.45	36.90	34.88	41.31	22.04	28.14
	Faster-RCNN	17.60	16.06	14.17	13.36	17.55	18.00	13.38	11.28	13.87		Faster-RCNN	38.00	32.37	25.22	25.14	34.42	33.77	40.03	20.14	26.69
	RetinaNet	13.89	12.70	10.40	8.94	13.49	13.03	9.01	7.27	10.16		RetinaNet	29.52	24.16	16.20	15.82	24.25	20.97	28.50	13.44	16.03
SSD	1.14	1.01	0.29	0.38	1.12	0.90	0.83	0.55	0.92	SSD	0.06	0.13	0.00	0.00	0.07	0.04	0.02	0.01	0.14		

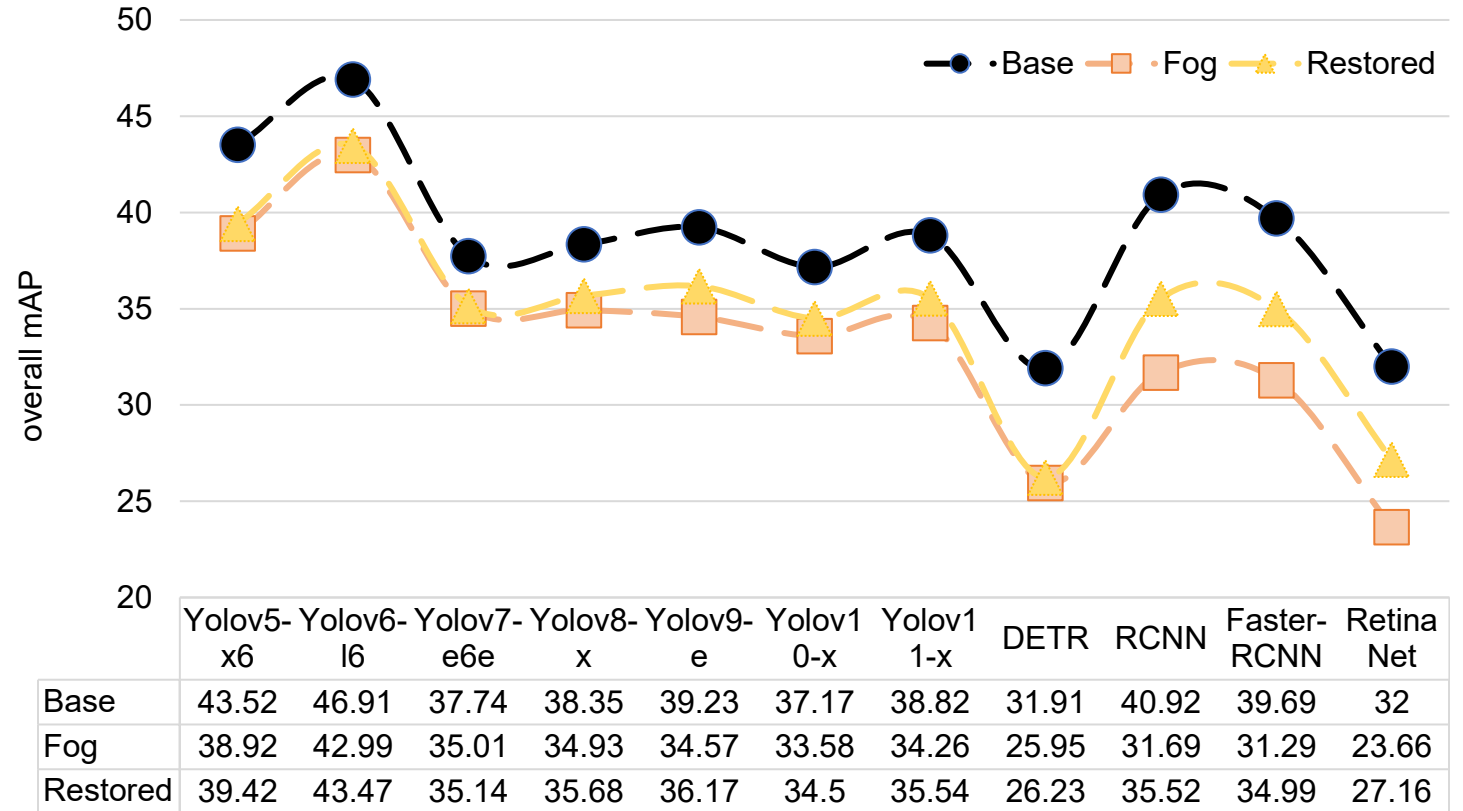
→ under night conditions, models may falsely detect light spots, such as headlights or reflections, revealing **class-specific vulnerabilities** that could be masked when only considering overall metrics.

Experimental Result - Restoration



Experimental Result - Restoration

- image restoration improves detection performance compared to foggy data
- it **does not fully recover the accuracy** of the Base dataset
- performance on the Restored images remains **closer to Fog's than to the Base's**, indicating that **this approach is insufficient to bridge the gap**



→ information loss during the image restoration, domain shifts introduced by restoration artifacts, and visual inconsistencies such as unnatural lighting or contrast



Conclusion

Conclusion

- We collected the Adverse Driving Conditions Dataset (ADCD), which comprises 600,000 images augmented with 12 unique weather effects.
- We proposed adaptable methodology for dataset construction, contributing to advancing the safety and reliability of computer vision systems in critical applications such as autonomous vehicles and traffic monitoring.
- We assessed the robustness of state-of-the-art object detection models under adverse weather conditions.

Conclusion - Future work

- Expanding with additional effects, such as sand to simulate dusty conditions, snow-covered vehicles, or complex combinations such as snow at night, can help challenge object detection models further.
- Dataset construction methods can be adapted to build other diverse datasets for other real-world challenges. For example, tasks like wildlife object detection often involve capturing images under adverse conditions such as rain, fog, or night surveillance.

Thank you



