RoboDepth: Robust Out-of-Distribution Depth Estimation under Corruptions

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NEURAL INFORMATION PROCESSING SYSTEMS

Motivation & Contribution

TL;DR

❖ RoboDepth is a comprehensive benchmark designed for probing the OoD robustness of monocular depth estimation algorithms. It includes a total of 18 common corruption types, ranging from weather and lighting conditions, sensor failures and movements, and noises during the data processing.

weather & lighting: Brightness, Dark, Fog, Frost, Snow, Contrast

sensor & movement: Defocus Blur, Glass Blur, Motion Blur, Zoom Blur, Elastic, Color Quant

data & processing: Gaussian Noise, Impulse Noise, Shot Noise, ISO Noise, Pixelate, JPEG

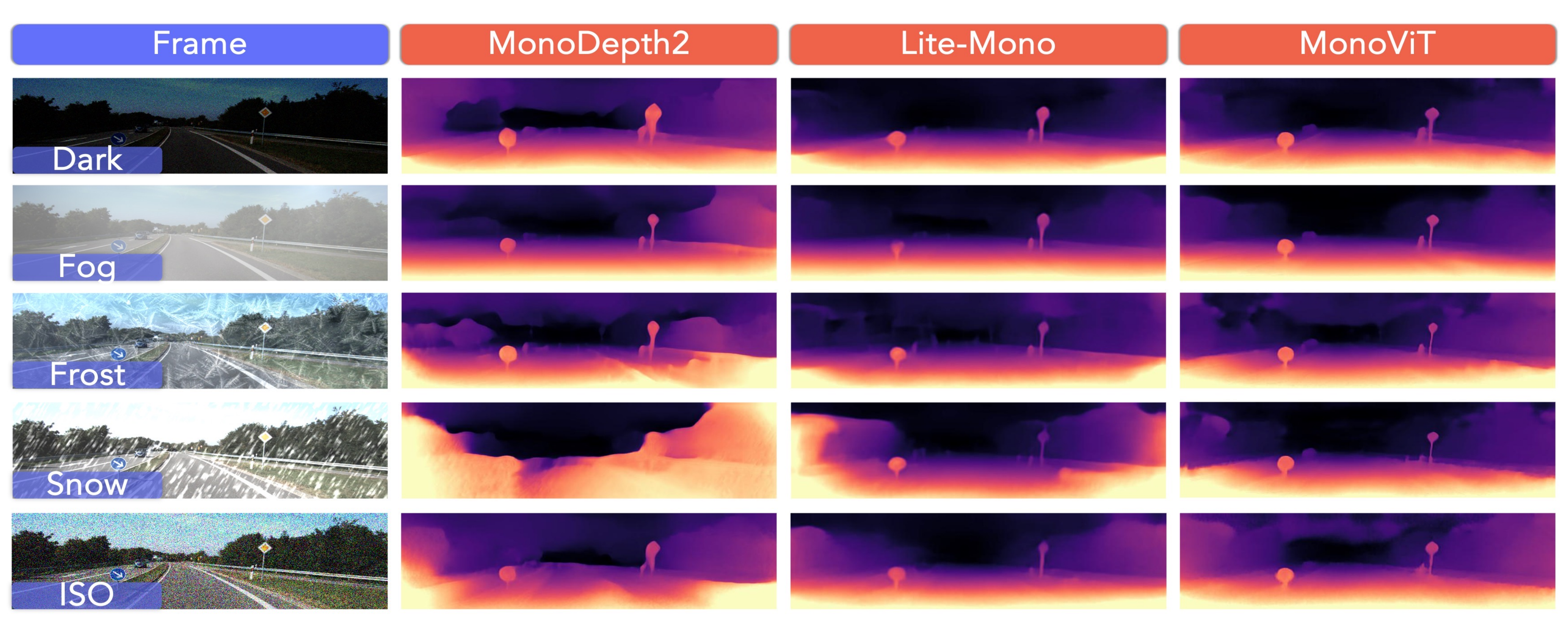
Motivation

❖ Existing supervised & self-supervised learning-based monocular depth estimation algorithms often use "clean" sequences for training. The data captured by cameras in the real world, however, may include distortions, noises, and other artifacts introduced by the environment, sensors, or data processing. In this project, we aim to answer the following questions:

❖ How robust are the existing monocular depth estimation algorithms against the various corruptions that tend to occur in the real world?

❖ What makes an algorithm more robust to certain corruption types?

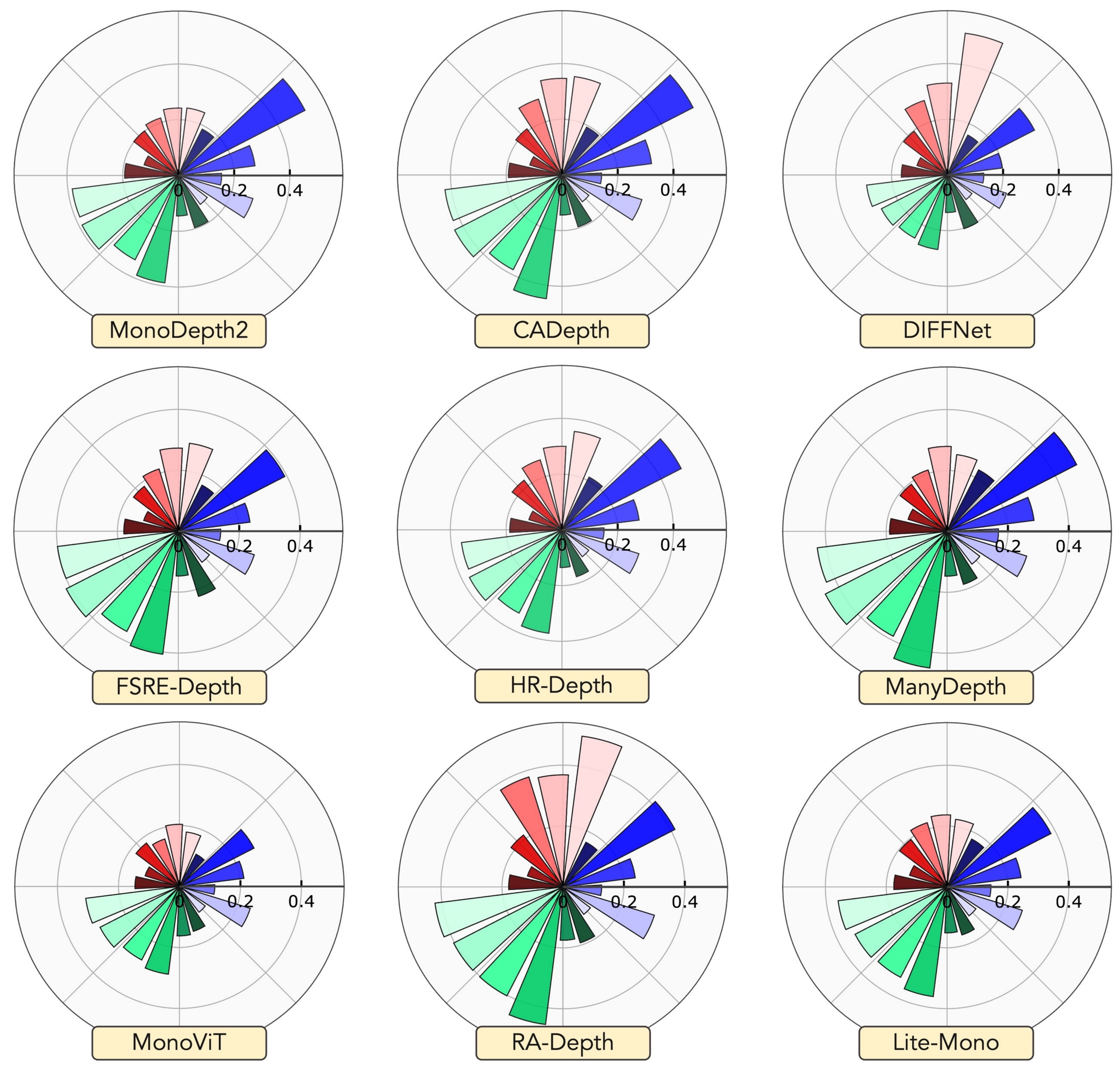
❖ Can we design novel monocular depth estimation algorithms that are robust and reliable across a wide range of common corruptions?



Datasets & Benchmarks

The RoboDepth Benchmark

❖ We benchmarked 42 state-of-the-art monocular depth estimation models from indoor and outdoor scenes, on their robustness against corruptions, via newly established datasets: KITTI-C, NYUDepth2-C, and KITTI-S.



❖ We generate realistic corruptions using clean data to mimic the real-world out-of-training-distribution scenario, which is proven via pixel distributions. This guarantees that our findings and conclusions can be generally applied.

Evaluation Protocol

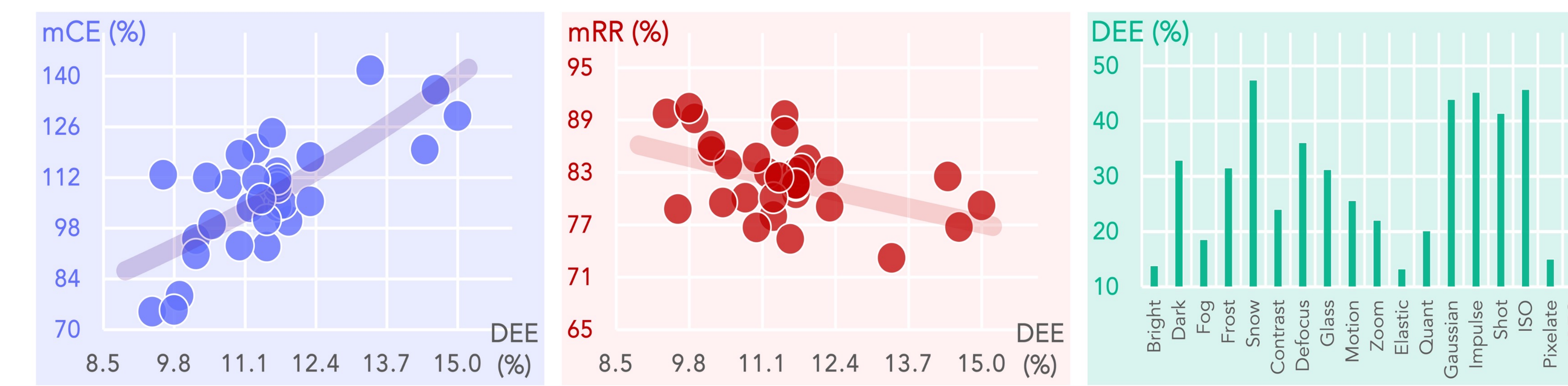
❖ To avoid any unfairness in robustness comparisons, we unified common configurations among different candidate depth estimation models.

❖ This includes the backbones, data augmentations, and post-processing, etc.

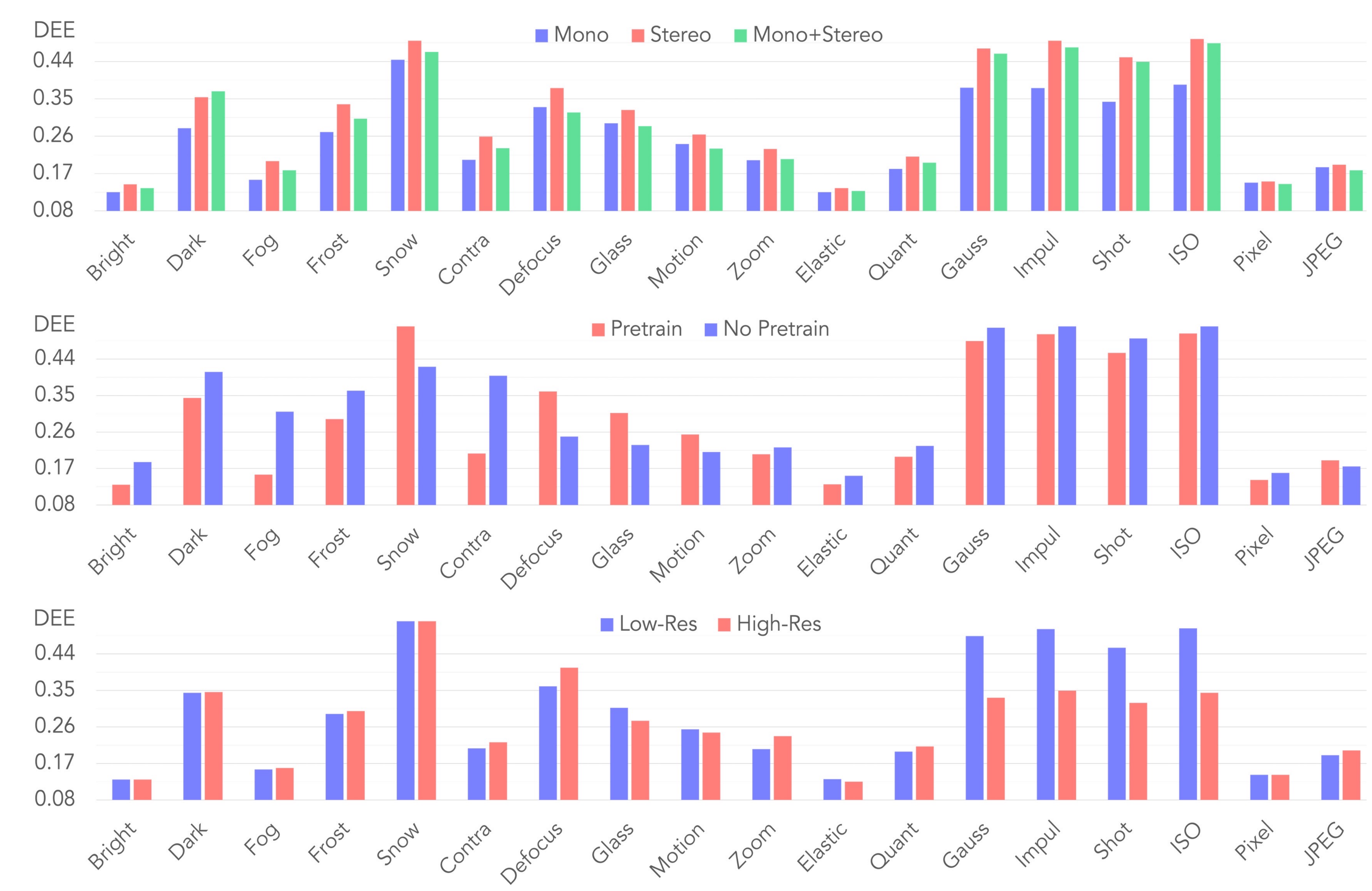
Experiments & Analyses

Benchmark Results

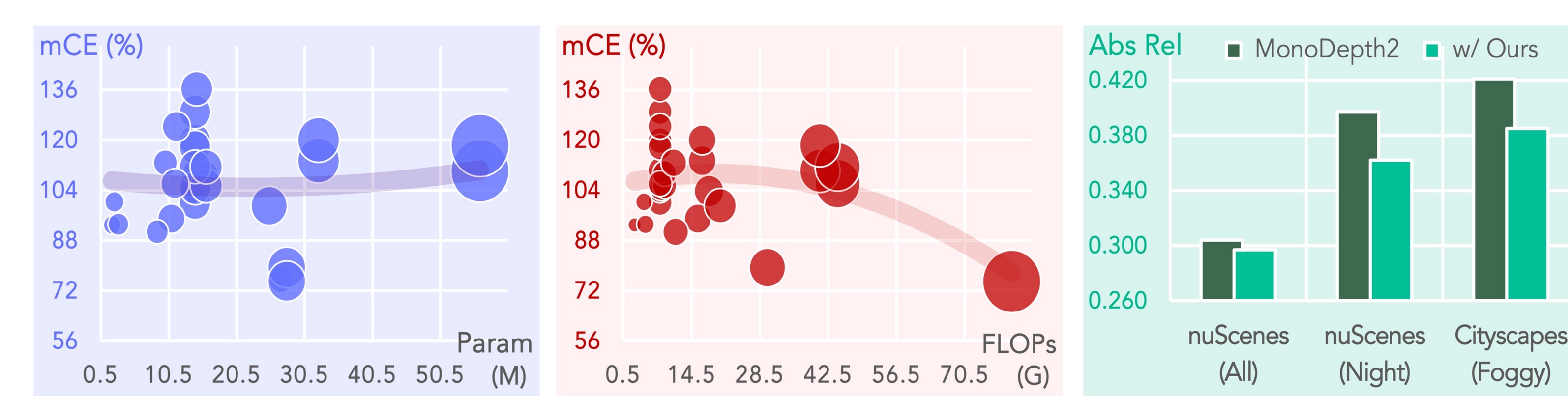
❖ We adopt mean Corruption Error (mCE) and mean Resilience Rate (mRR) to measure the robustness of depth estimation models under corruptions.



❖ We reveal that several factors related to the input modality, resolution, and pretraining strategy can play important roles in robust depth estimation.



❖ We observe that model size and FLOPs show distinct correlations with mCE; meanwhile, robustness finetuning is capable of improving OoD robustness.



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