

# Unexplored Faces of Robustness and Out-of-Distribution: Covariate Shifts in Environment and Sensor Domains

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# Motivation: Domain shift



- DNN models are widely used recently.
- They, however, often does not perform well when environment changes!
- **Domain shift** is the main reason for the performance drop.
  - *Training data domain  $\neq$  Test data domain*

**Video shows 8-car pileup after a Tesla allegedly using Full Self-Driving stopped in a highway tunnel**

Grace Kay Jan 11, 2023, 8:00 AM GMT+9

Share | Save



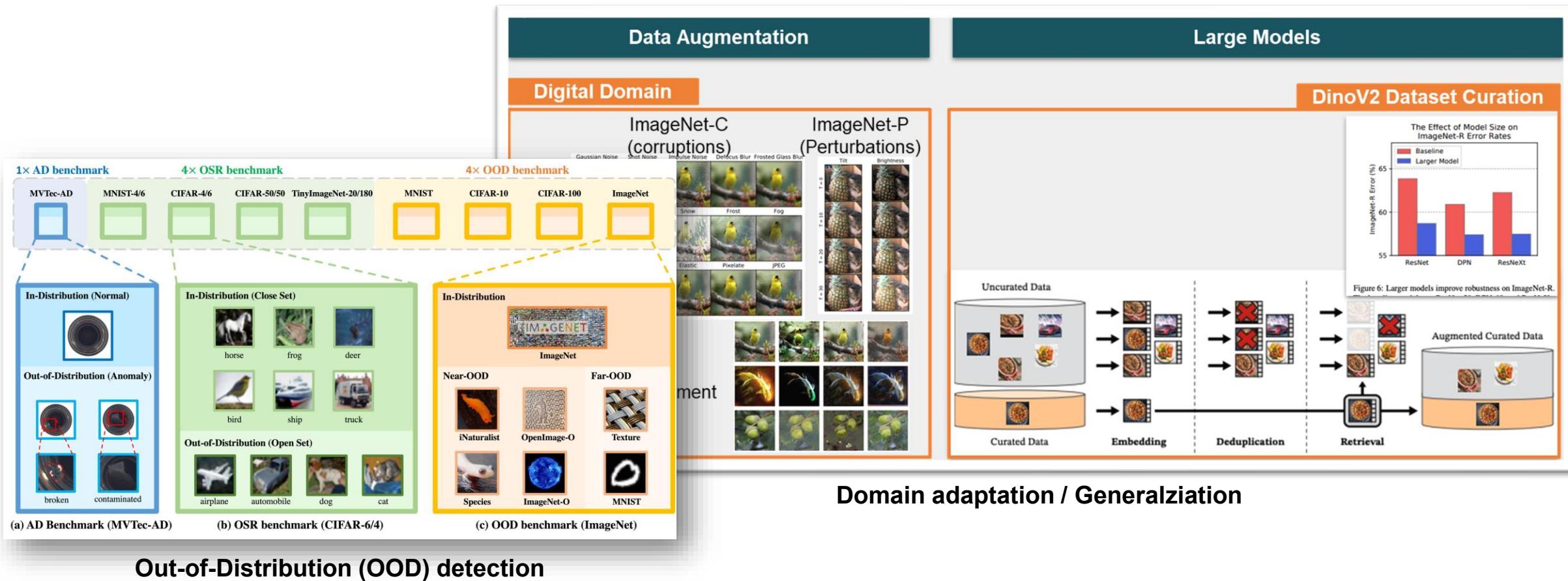
Video obtained by The Intercept appears to show a Tesla causing an 8-car pileup on November 24, 2022. [The Intercept reporter Ken Klippenstein on Twitter](#)

Source: Business insider

# Motivation: Domain shift



- Many approaches to tackle domain shift.

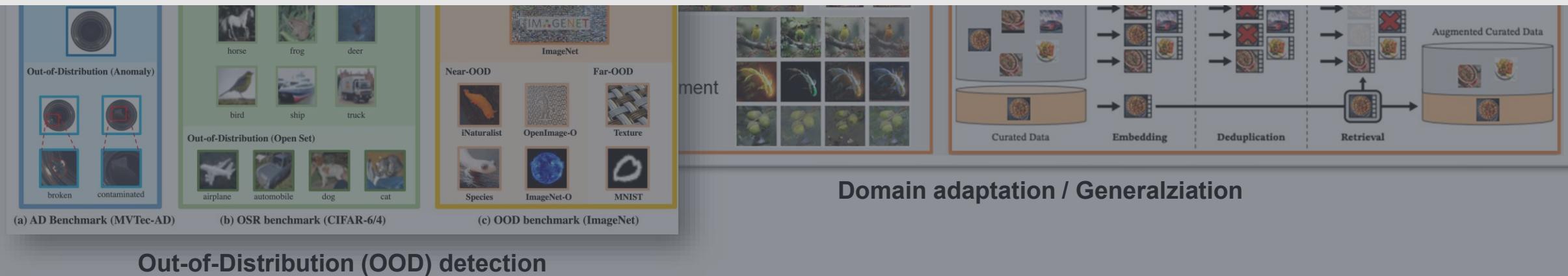


# Motivation: Domain shift



- Many approaches to tackle domain shift.

***Tries to make a smarter DNN model, but is it the best?***



# Motivation: Domain shift

- Human vision system



# Motivation: Domain shift

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# Motivation: Domain shift

- Human vision system

Current

**“Best solution?”**



It's too bright!!  
I can't see anything!!



It's too close!!  
I can't see anything!!

# Motivation: Domain shift

- Human vision system

Current

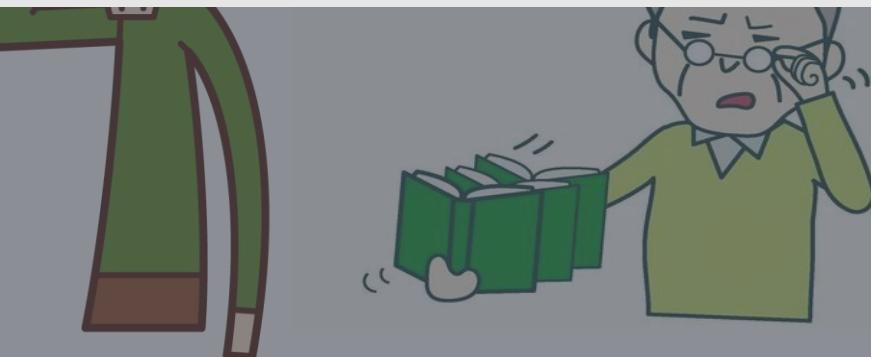
**“Easier and better solution!”**



or



It's too bright!!  
I can't see anything!!

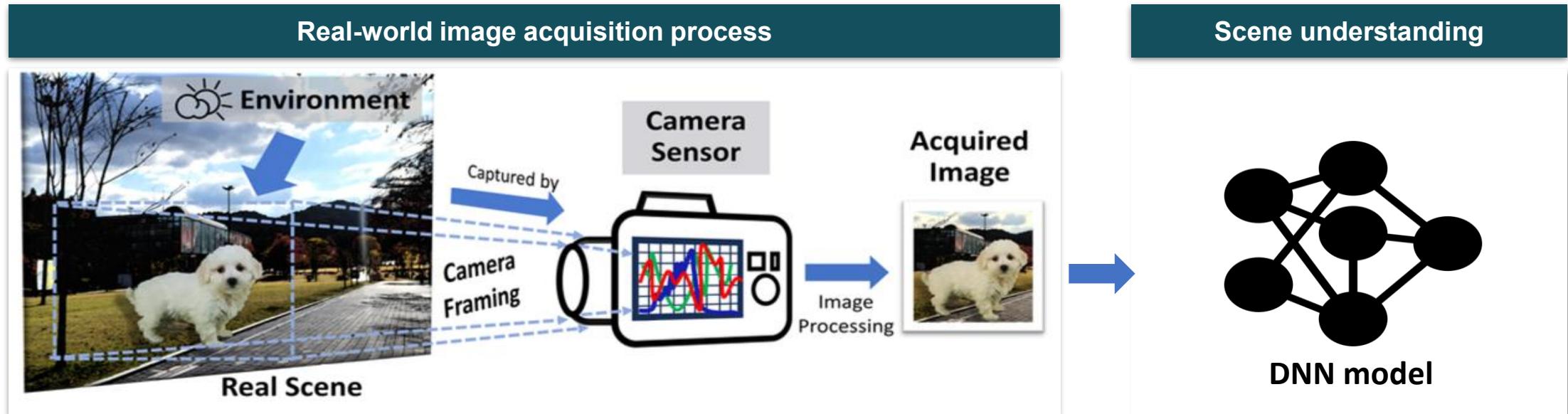


It's too close!!  
I can't see anything!!

# Motivation: Domain shift



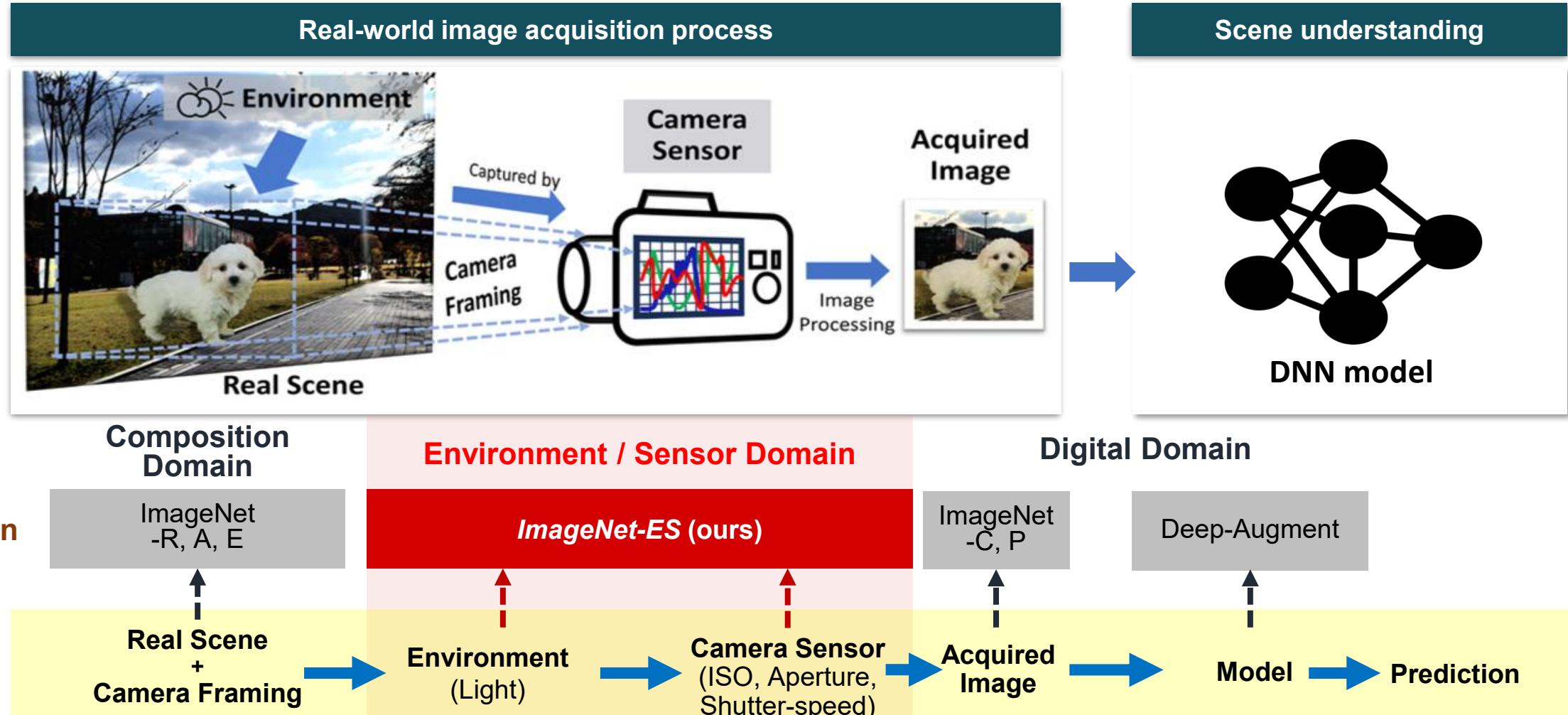
- Computer vision system



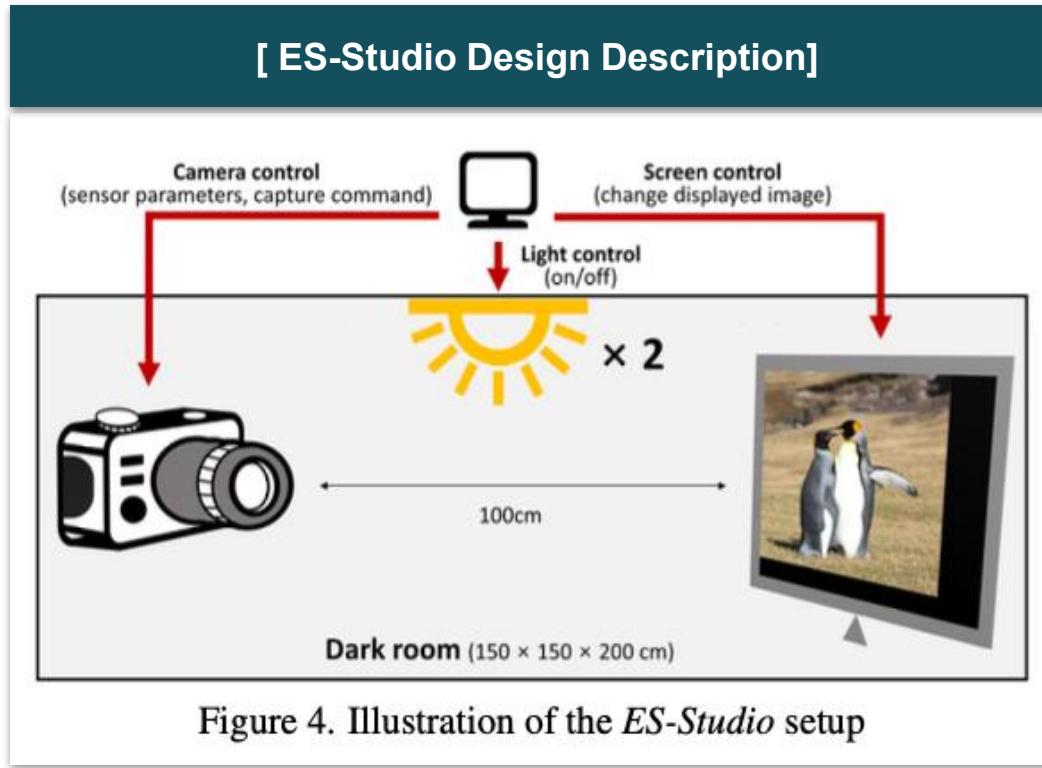
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- Computer vision system



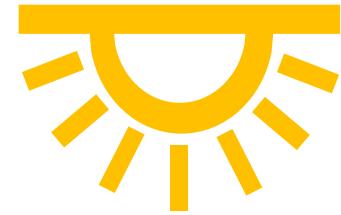
- Controllable testbed for Environment and Sensor domain
  - Capture real-world perturbations related to **light** (On/Off) and **camera parameters** (ISO / Shutter speed / Aperture)
  - Ensure reproducibility



# ImageNet-ES dataset



- Covariate shift datasets from the environment & sensor domain



ISO

Shutter Speed

Aperture

Auto Exposure (5 shots)

**Val. Set** 1000 sampled images from ImageNet  $\times$  2 Light options (On / Off)  $\times$  (64 + 5) Camera parameter options  $=$  138K Images

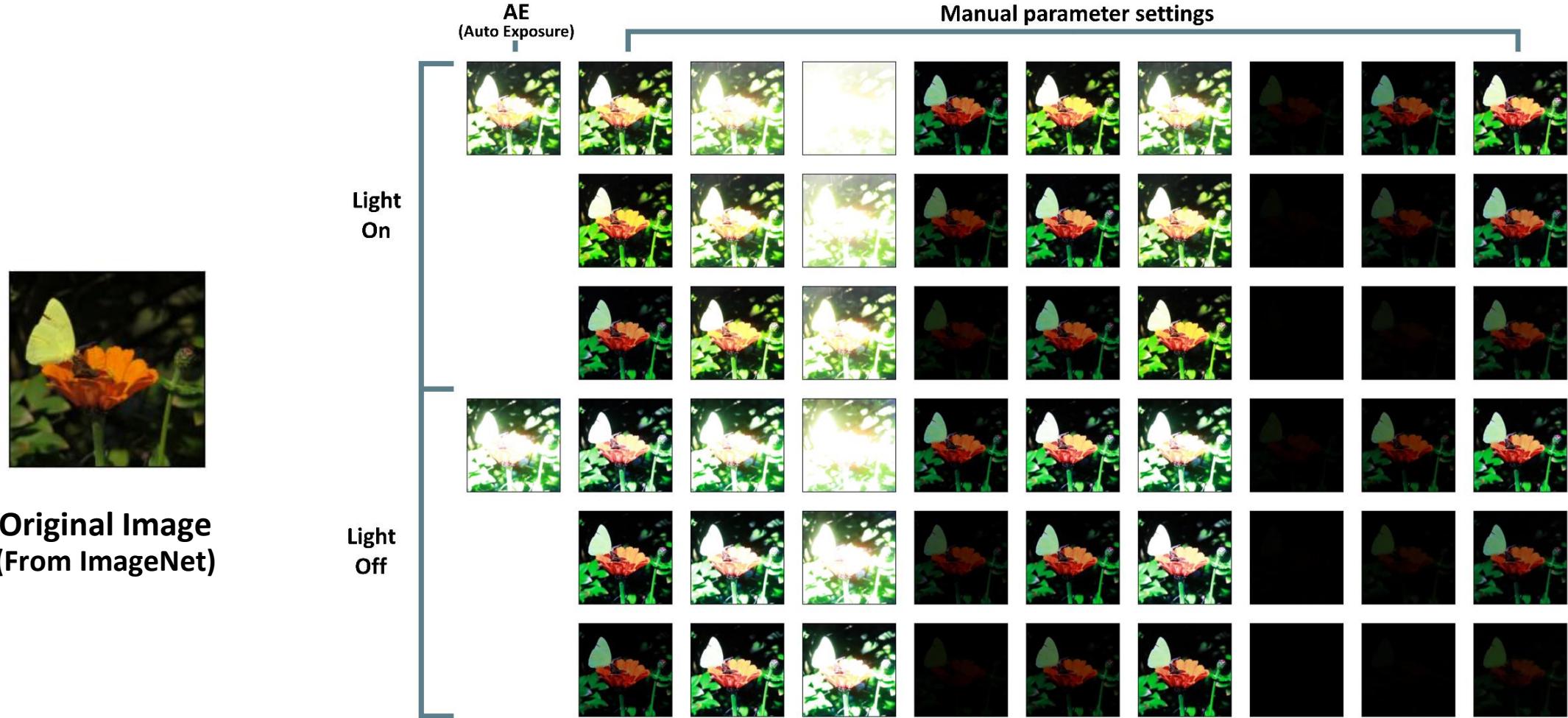
**Test Set** 1000 sampled images from ImageNet  $\times$  2 Light options (On / Off)  $\times$  (27 + 5) Camera parameter options  $=$  64K Images

**Total 202K Images**

# ImageNet-ES dataset



- Sample images from test set:



# Experiments: Out-of-Distribution (OOD) detection

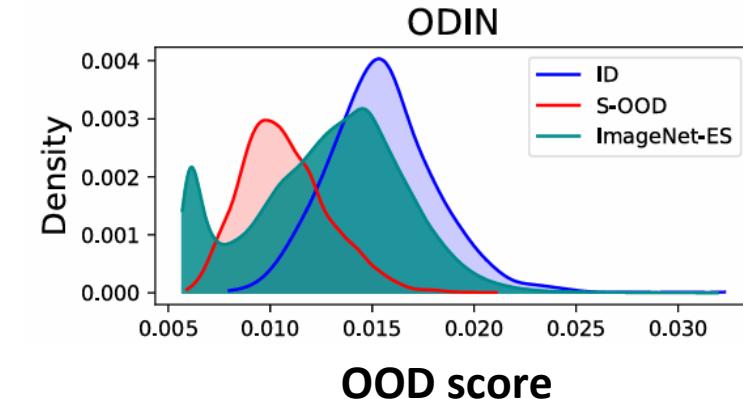
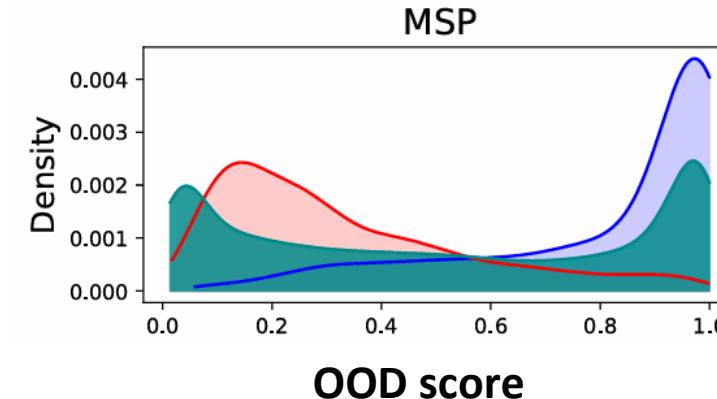
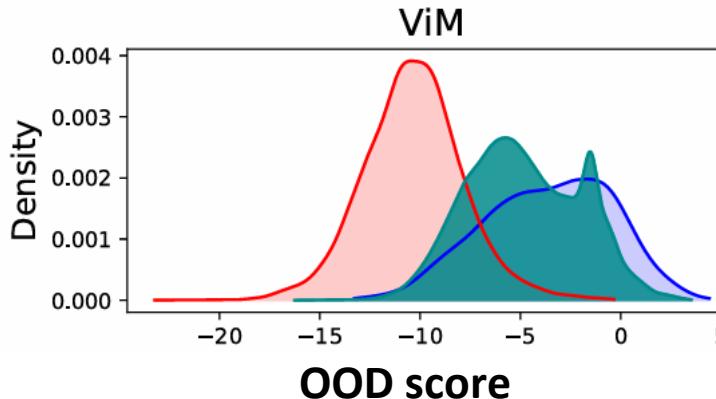


- What is the best OOD definition?
- Semantics-centric framework
  - Most widely used.
  - Any samples not included in the class definition of training domain => OOD
  - Treating C-OOD (Covariate shifted data, e.g. *ImageNet-ES*) as OOD or ID in entirety.
  - SOTA OOD detection techniques (ViM, ODIN, etc.) developed to work well under this framework.

# Experiments: Out-of-Distribution (OOD) detection



- Semantics-centric framework
  - Test on three OOD detection techniques: ViM, MSP, ODIN
  - Model: EfficientNet-B0
  - Three datasets
    - In-Distribution (ID): Tiny-ImageNet
    - Semantics OOD (S-OOD): Texture-O
    - Covariate shifted OOD (C-OOD): *ImageNet-ES*

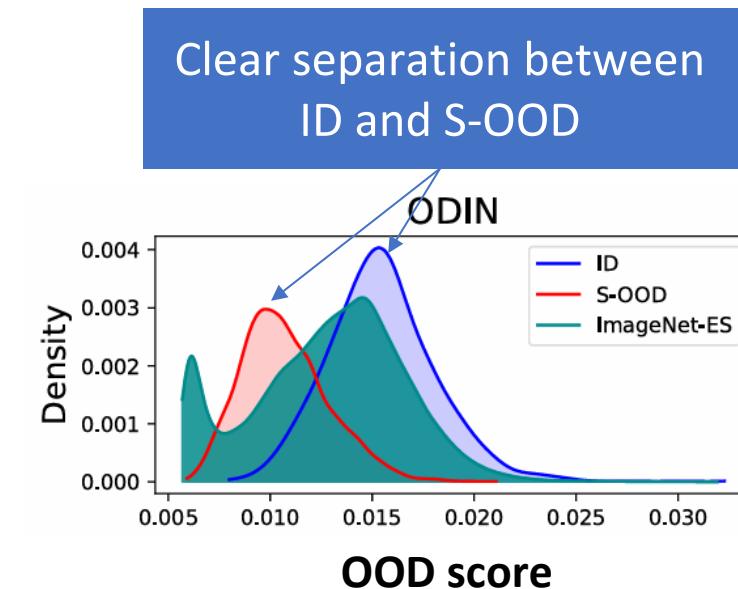
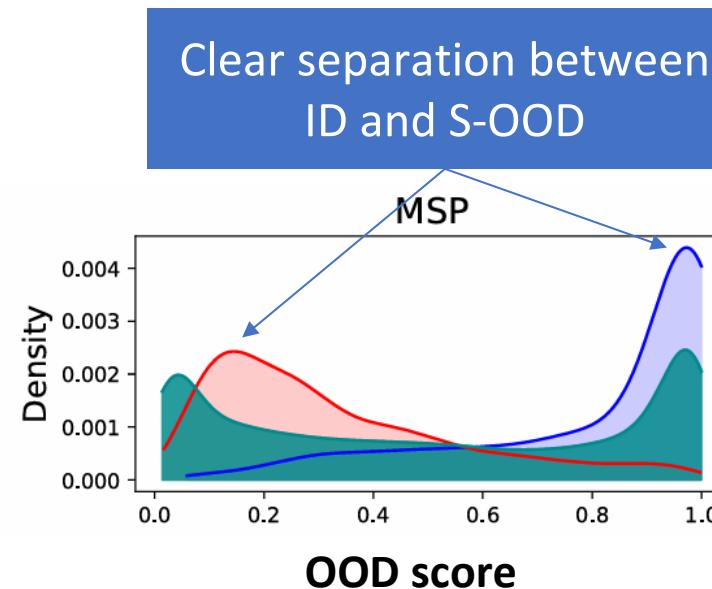
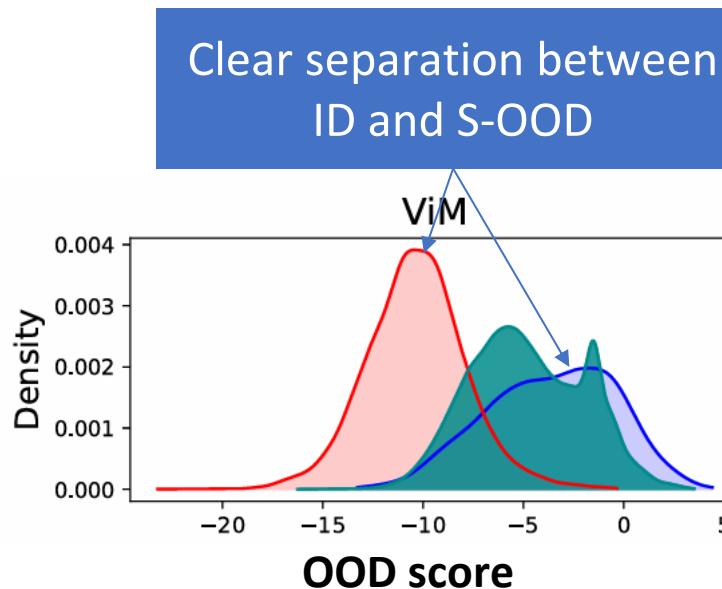


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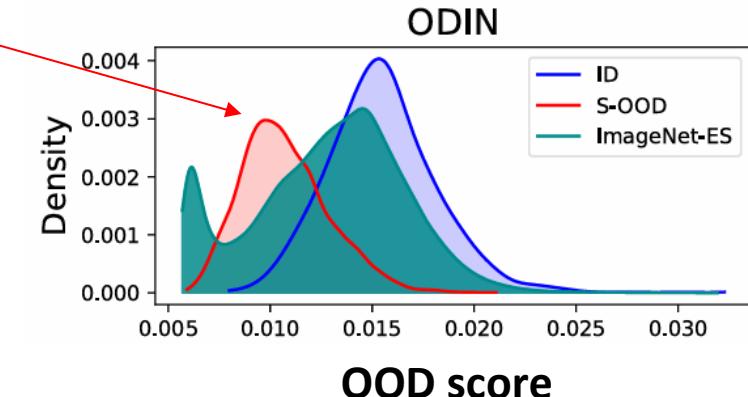
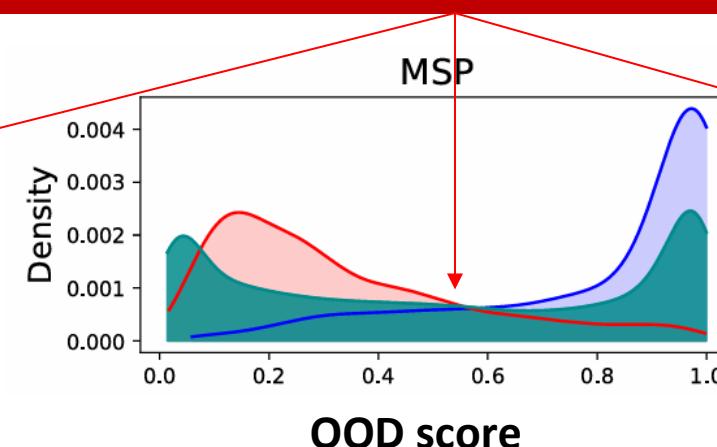
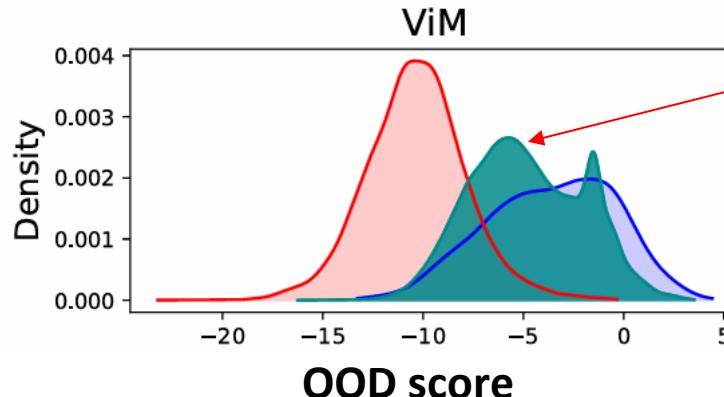
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No clear distinction on *ImageNet-ES*!



# Experiments: Out-of-Distribution (OOD) detection

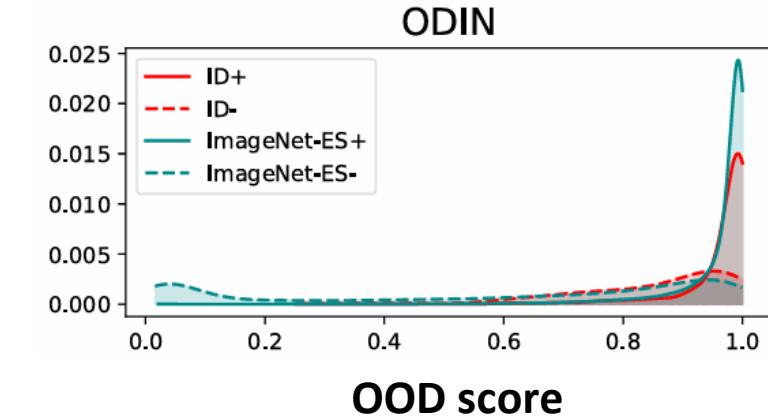
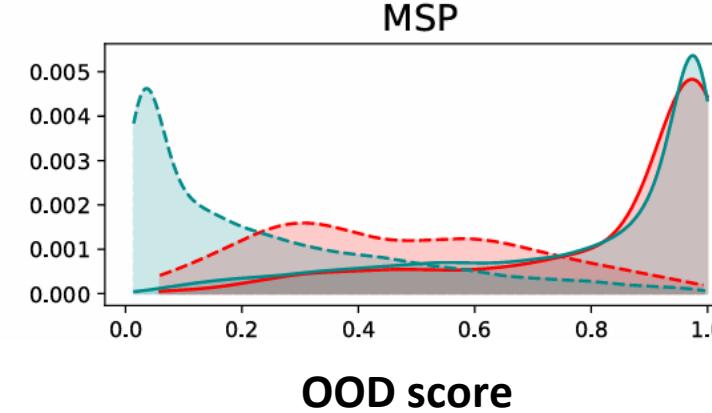
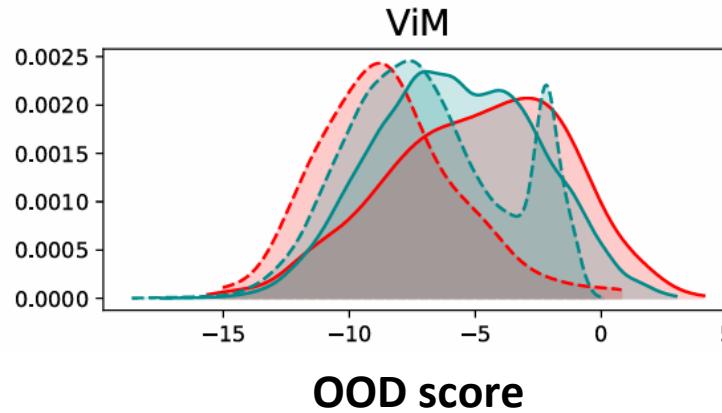


- Alternative framework: Model-Specific OOD framework
  - Model specific acceptance or rejection (MS-A or MS-R)
  - MS-A: correctly classified by model (ID+, C-OOD-)
  - MS-R: misclassified by model (S-OOD, ID-, C-OOD-)

# Experiments: Out-of-Distribution (OOD) detection



- Alternative framework: Model-Specific OOD framework
  - Test on three OOD detection techniques: ViM, MSP, ODIN
  - Model: EfficientNet-B0
  - Two datasets
    - In-Distribution (ID): Tiny-ImageNet
    - Covariate shifted OOD (C-OOD): *ImageNet-ES*

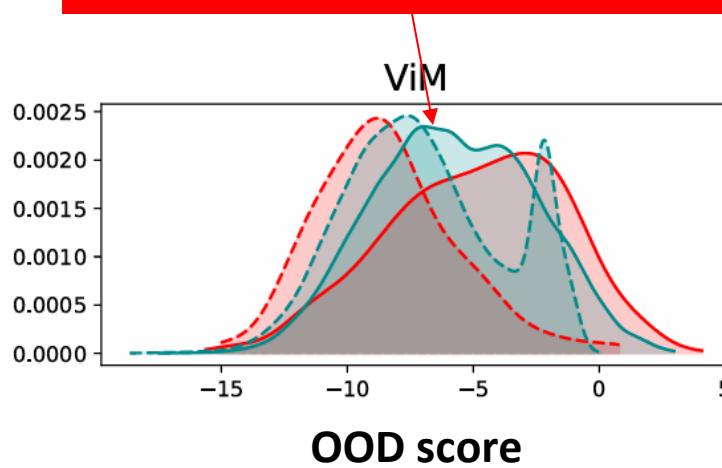


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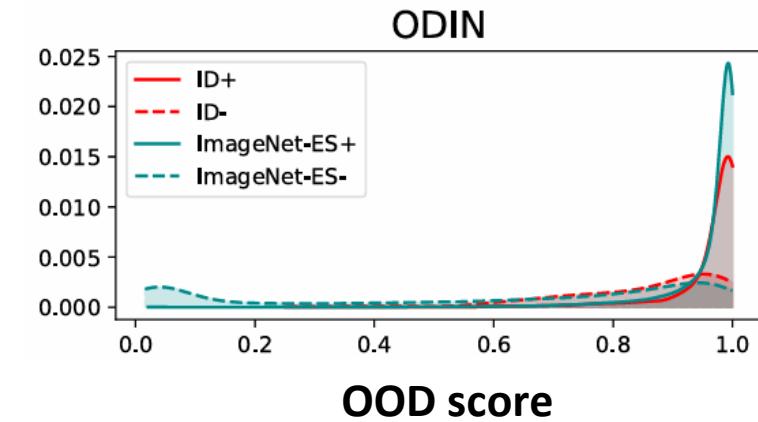
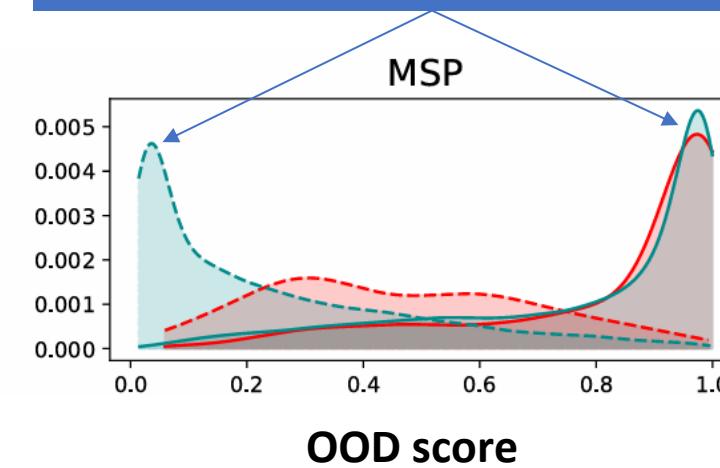


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    - Covariate shifted OOD (C-OOD): *ImageNet-ES*

Still, no clear distinction between *ImageNet-ES+* and *ImageNet-ES-*



Clear separation between *ImageNet-ES+* and *ImageNet-ES-*



# Experiments: Out-of-Distribution (OOD) detection



- Evaluation of OOD detection methods
  - Do current OOD methods work consistently on real covariate shift samples?

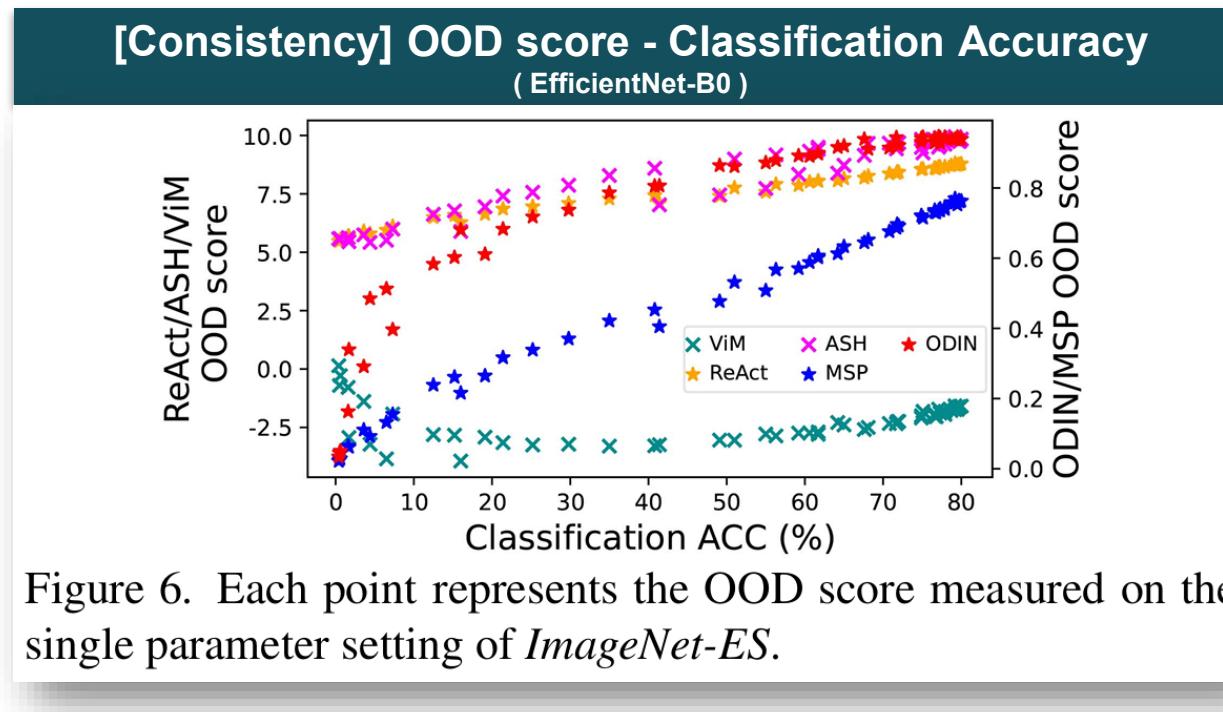


Figure 6. Each point represents the OOD score measured on the single parameter setting of *ImageNet-ES*.

Classical methods (MSP or ODIN) show more desirable correlation

SOTA method (ViM) accepts numerous samples as ID which are misclassified by the model

# Experiments: Out-of-Distribution (OOD) detection



- Evaluation of OOD detection methods
  - Do current OOD methods work consistently on real covariate shift samples?

[Consistency] OOD score - Classification Accuracy  
( EfficientNet-B0 )

***With ImageNet-ES, we found that no single method is superior in both C-OOD and S-OOD detection.***



Figure 6. Each point represents the OOD score measured on the single parameter setting of *ImageNet-ES*.

samples as ID which are misclassified by the model

# Experiments: Domain generalization



- How to enhance the robustness in the environmental and sensor domain (*ImageNet-ES*)?
  - **Basic** digital augmentation: color-jitter, solarize and posterize
  - **Advanced** digital augmentation: DeepAugment and AugMix
  - Include **real-world perturbed data** (*ImageNet-ES*) for finetuning

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Table 2. Evaluation with different robustness enhancing strategies.  
The result is based on ResNet-50. (IN: ImageNet)

ID	Comp.aug	Basic digital aug	Advanced digital aug	Incl. <i>ImageNet-ES</i>	Eval dataset		
					IN	IN-C	<i>ImageNet-ES</i>
1	✓				85.8	51.0	49.6
2	✓		✓		85.8	51.7	50.4
3	✓	✓	✓		85.5	57.4	49.1
4	✓				86.9	51.9	55.8
5							
6							

Digital augmentation improves the robustness on digitally corrupted images(*ImageNet-C*),

But NOT on real-world perturbed images.

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3	✓	✓	✓		85.5	57.4	49.1
4	✓			✓	<b>86.0</b>	51.8	<b>55.8</b>
5	✓	✓		✓	85.8	51.4	54.5
6	✓	✓	✓	✓	84.0	<b>57.9</b>	53.7

Including *ImageNet-ES* data for finetuning improves the robustness on both digitally or real-world corrupted images.

# Experiments: Sensor parameter control



- In practice, sensor parameter control is as important as obtaining smart model.

Table 3. Evaluation of various models on *ImageNet-ES*. (IN: ImageNet, AE: Auto exposure)

Model	Num. Params	Pretraining Dataset	DG method	<i>ImageNet-ES</i>			Best
				IN	AE	All params	
ResNet-50 [8]	26M	IN-1K	-	86.3	32.2	50.2	80.1
		IN-21K	DeepAugment [13] +AugMix [12]	87.0	53.3	61.4	84.0
ResNet-152 [8]	60M	IN-1K	-	87.6	41.1	54.3	83.3
Efficientnet-B0 [32]	5M	IN-1K	-	88.1	51.4	58.1	83.8
Efficientnet-B3 [32]	12M	IN-1K	-	88.3	62.0	66.2	86.8
SwinV2-T [23]	28M	IN-1K	-	90.7	54.2	63.1	86.8
SwinV2-B [23]	88M	IN-1K	-	92.0	60.1	65.6	89.0
OpenCLIP-b [17]	87M	LAION-2B	Text-guided pretrain	94.3	66.3	71.0	92.7
OpenCLIP-h [17]	632M	LAION-2B	Text-guided pretrain	94.7	79.1	77.6	94.7
DINOv2-b [26]	90M	LVD-142M	Dataset curation	93.6	74.5	73.9	92.2
DINOv2-g [26]	1.1B	LVD-142M	Dataset curation	94.7	84.3	79.6	94.2

Well-tuned parameter setting (Best)  
improves the prediction accuracy  
by 9.9 ~ 47.9 (vs Auto Exposure)  
by 14.6 ~ 29.9 (vs All params)

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SwinV2-T [23]	20M	IN-1K	-	88.2	62.0	67.0	86.8
SwinV2-B [23]	80M	IN-1K	-	88.1	53.6	63.6	89.0
OpenCLIP-b [17]	8.7M	LAION-2B	-	88.3	71.0	71.0	92.7
OpenCLIP-h [17]	632M	LAION-2B	Text-guided pretrain	94.7	79.1	77.6	94.7
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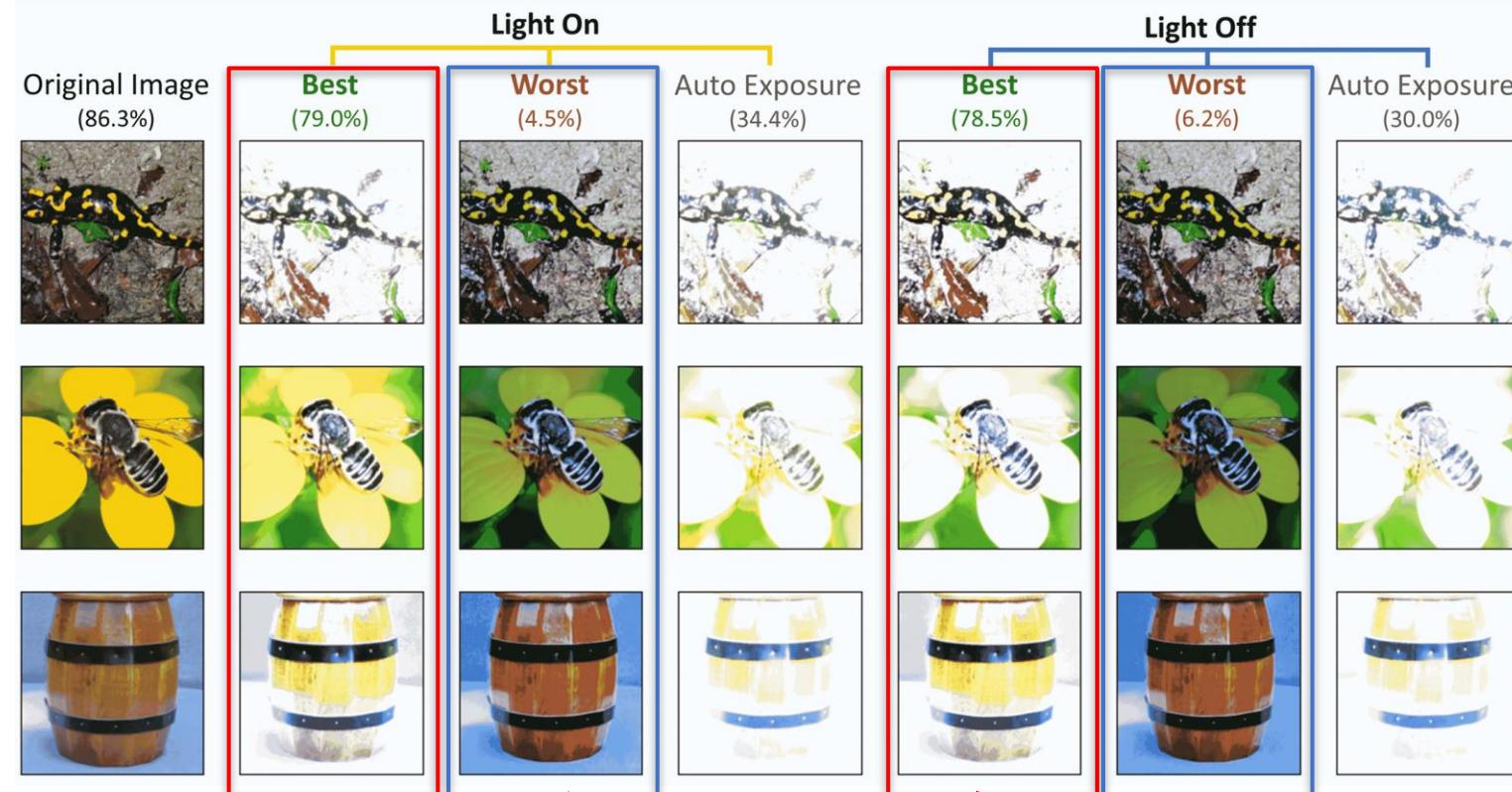
120x larger model size  
400x more training data

Even Efficientnet-B0 with the best  
outperforms OpenCLIP-h with auto  
exposure setting!

# Experiments: Sensor parameter control



- Qualitative analysis on *ImageNet-ES*



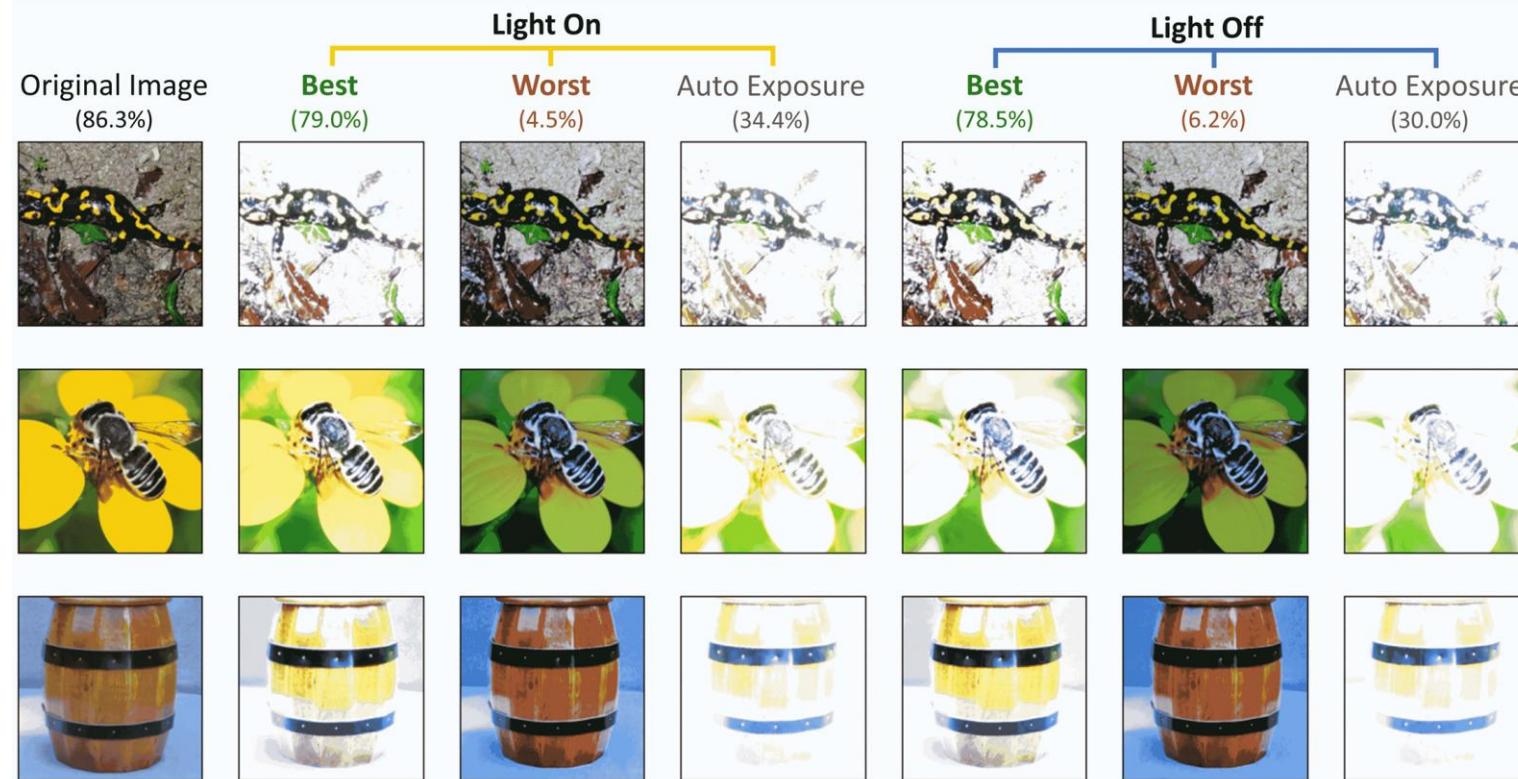
Looks too bright on human eyes  
But model prefers them

Looks okay to human eyes,  
Not to the model

# Experiments: Sensor parameter control



- Qualitative analysis on *ImageNet-ES*



Sensor control should prioritize features based on **model's perspective**,  
rather than human intuition

# Conclusion & Future work



- Investigated distribution shifts resulting from perturbations in Environmental and Sensor domains.
- ***ES-Studio***: controllable testbed for environmental and sensor domains
- ***ImageNet-ES***: A novel covariate shifted dataset from the environment & sensor domain
- **OOD detection**: Limitation of semantics-centric framework => Need for new OOD detection method to incorporate both S-OOD and C-OOD
- **Domain generalization**: ES-augmentation improves the robustness in both conventional and ImageNet-ES benchmarks.
- **Sensor parameter control**
  - With well-tuned sensor parameters, light model could perform comparably to heavier and advanced model.
  - Need of model-centric design instead of relying solely on human aesthetics.
- Future work: Improve ES-Studio to take photos of real objects or printed photos, rather than capturing display.



Thank you:)