

# Developing Elevator Recognition Software for Indoor Autonomous Driving Robot

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### The need for research





- Elevator state-awareness model for boarding sequences of indoor autonomous robots
  - To be able to react flexibly to special situations
  - + door closes in the process of boarding after seeing the door open
  - + button not pressed properly after entering the elevator normally , etc.
  - to recognize the status of elevators
  - recognition of various indicators (elevator switches, signs, license plates, etc.),
  - Need for a detector that is robust to motion blur caused by robot movement is required.

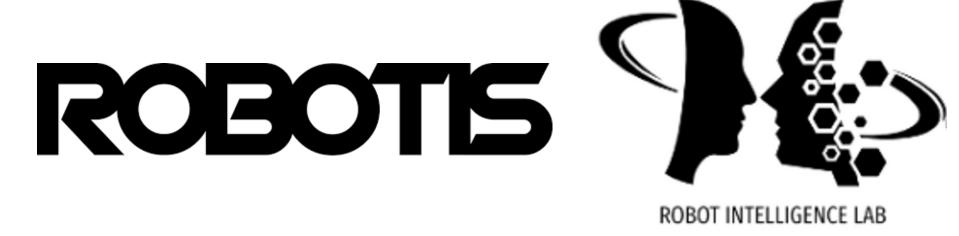


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# 1. Assignment Background and Development Environment

## 1.1 Assignment Goals











Different elevator indicator configurations, shapes, and looks in different buildings

- Developing a robust detector that can effectively detect different indicator shapes
  - Domain Adaptation: models motion blur due to robot movement and image changes due to different light conditions
  - Data Augmentation: Since we cannot consider all possible camera angles when training the detector, we will research/use data augmentation techniques utilizing Camera Perspective Can we be flexible enough to handle various situations?
- Design a response protocol for occlusions, which are relatively common inside elevators.

### 1.2 Assignment Requirements

# ROEDIS



### Recognize elevator entries and exits

#### Recognize elevator exterior state

- 1. Elevator current floor
- 2. Direction of elevator travel
- 3. Elevator doors open/arrival

#### Recognize elevator interior state

- 1. Elevator current floor
- 2. Direction of elevator travel
- 3. Elevator doors open/arrival

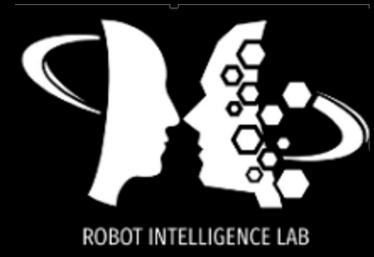


#### Recognize elevator load status

- Door is fully closed/open
- 2. Door opening or closing



# ROEDIS



### 1.3 Challenge Environment and Constraints



### **Development Environment**

**Powered by Orin AGX** 

Jetpack 4.6: The latest version currently released

**ROS2 Foxy** 

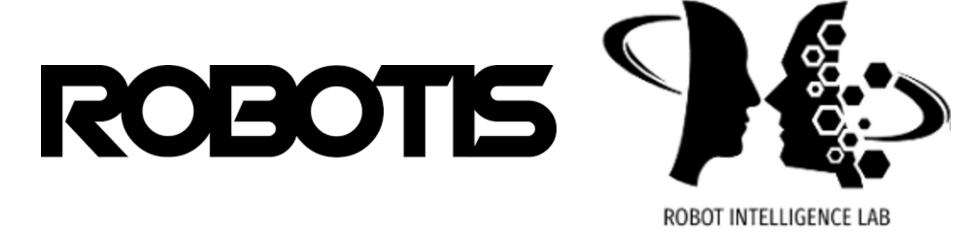


#### Camera

The CSI camera you want to use

**Resolution: FHD** 

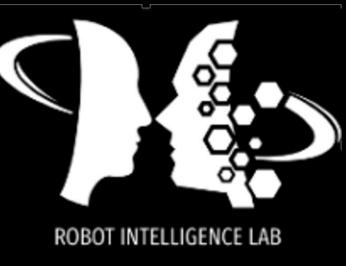
Viewing angle: wide angle greater than 120 degrees

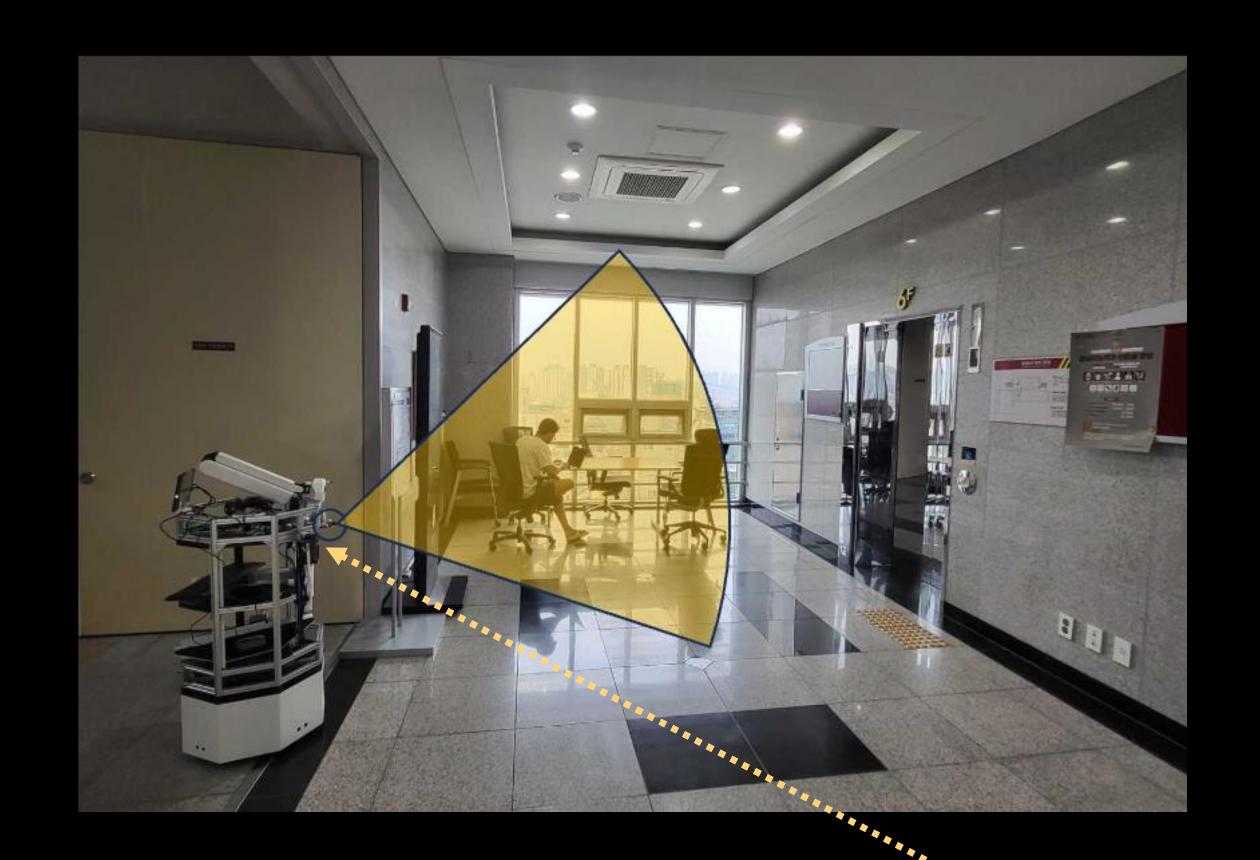


### 2. Setting up environment at Korea University

# 2.1 Angle of view issues ROBOTS







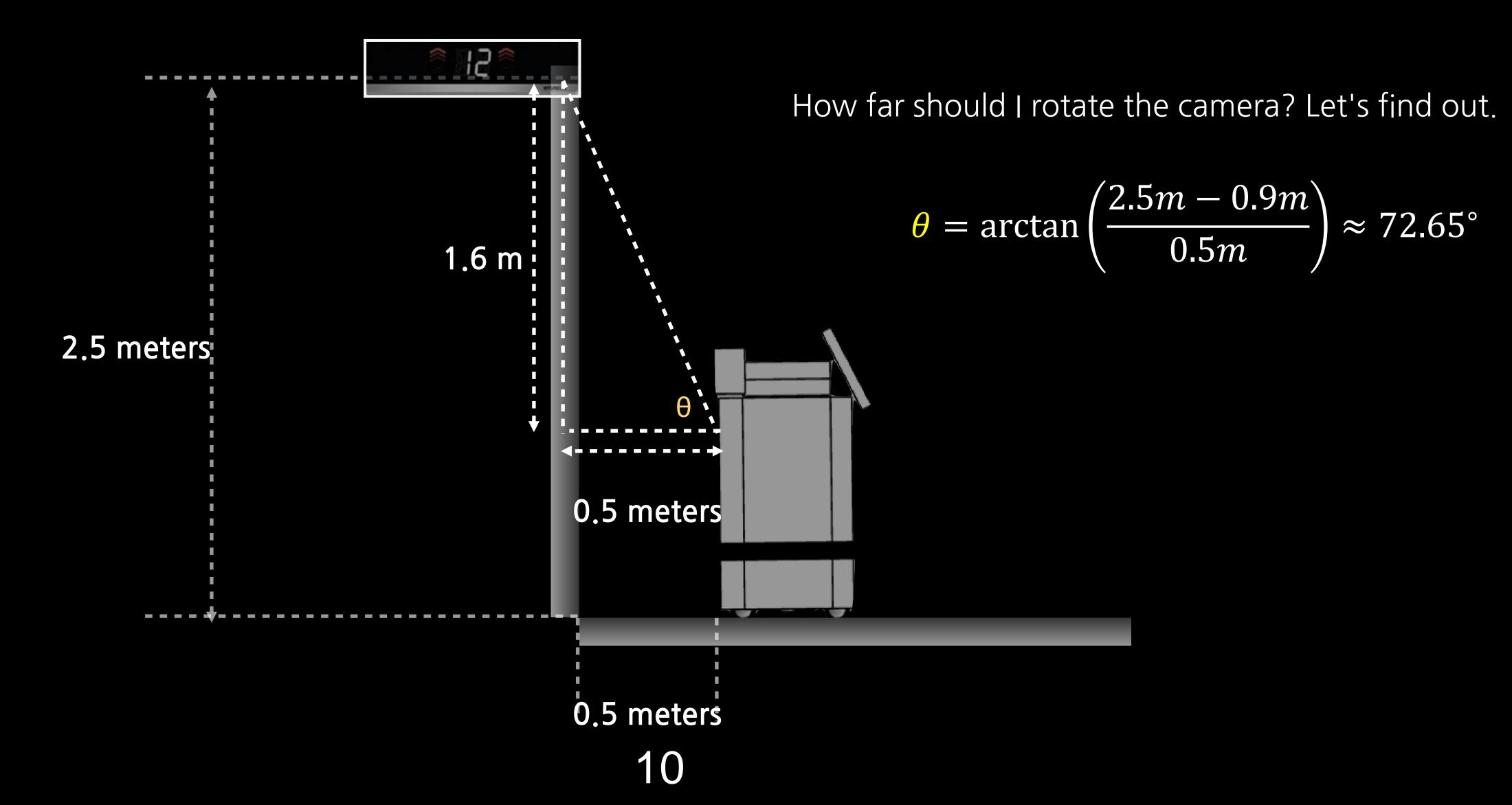


Initially, the robot's camera was located at the front of the robot, In this case, you'll need to move away from the boarding location to get to the I could barely see all the indicators. 9

## 2.1 Angle of view issues



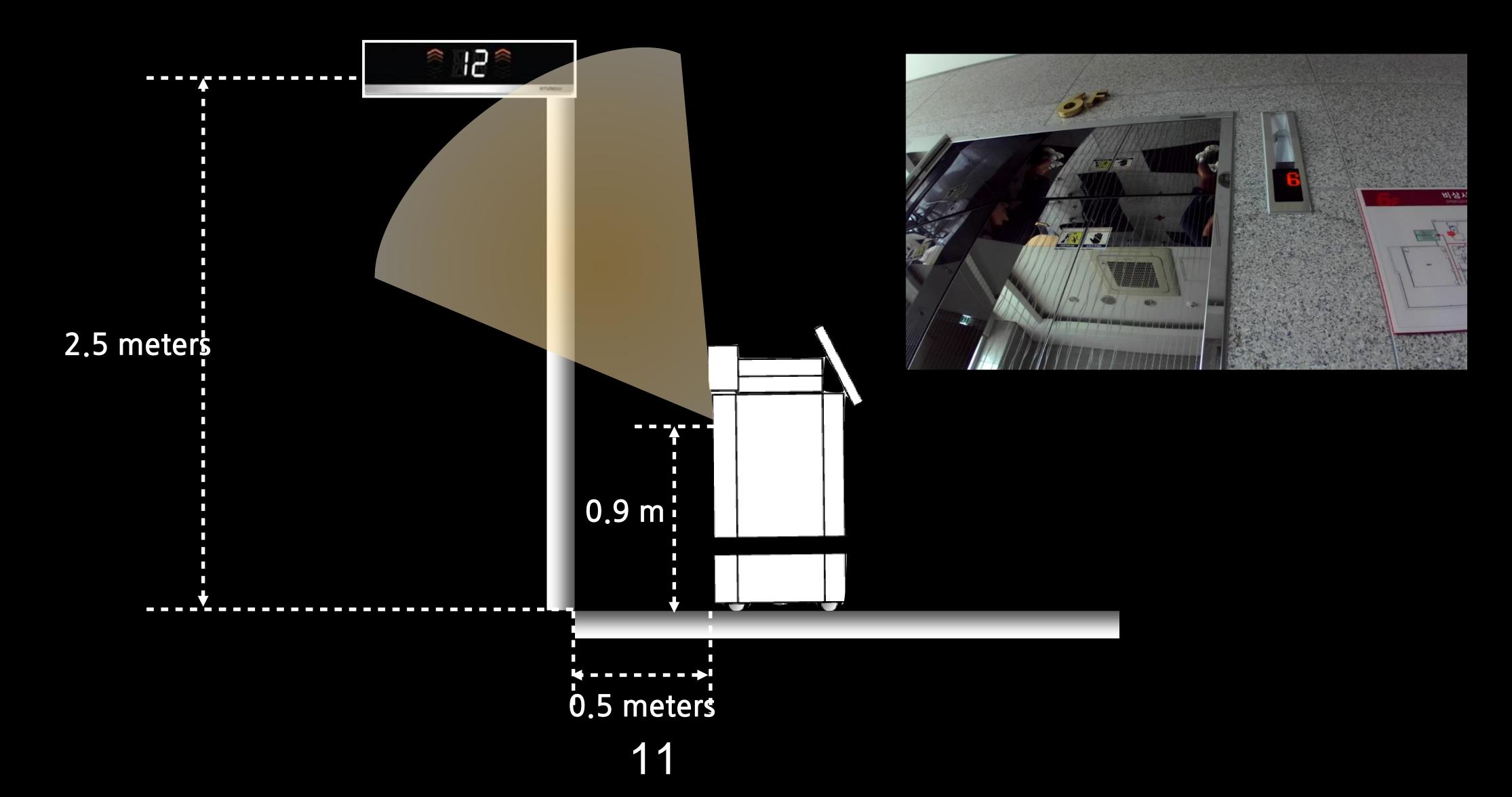




# 2.1 Angle of view issues ROBOTS











### 3. Hierarchical two Step Approach

# 3.1 Hierarchical Approach ROBOTS (September-November 22)



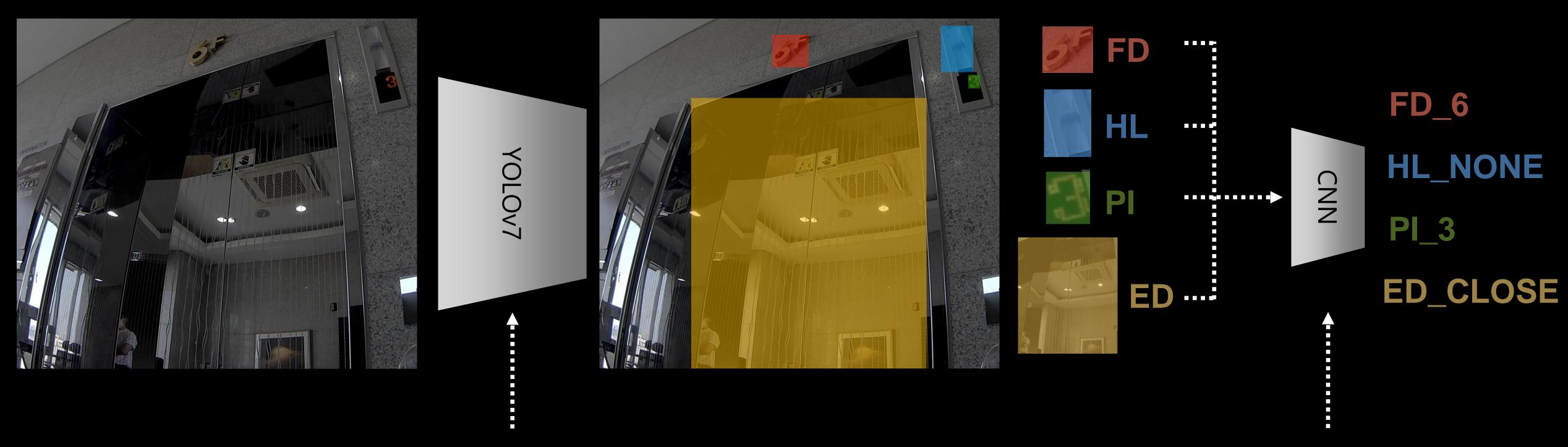


	Abbreviations	Templates	Definition	
Elevator Door		ED (Status)	Whether the door is	ED_OPEN
	ED	ED_{Status}	open or closed	ED_CLOSE
Floor Designator	FD	FD_{Floor Count}	Display the current number of floors	FD_B2
				:
				FD_7
Hall Lantern	HL	HL_{Direction}	Current direction of travel	HL_UP
				HL_DOWN
				HL_NONE
Landing Operator Pannel	LOP	LOP_{Direction}		LOP_UP
			Elevator button	LOP_DOWN
				LOP_NONE
Position Indicator	PI	PI_{Number of layers}	Current elevator location	PI_B2
				:
		idycisj		PI_7





YOLOv7 (Single Stage) + CNN (Second Stage)



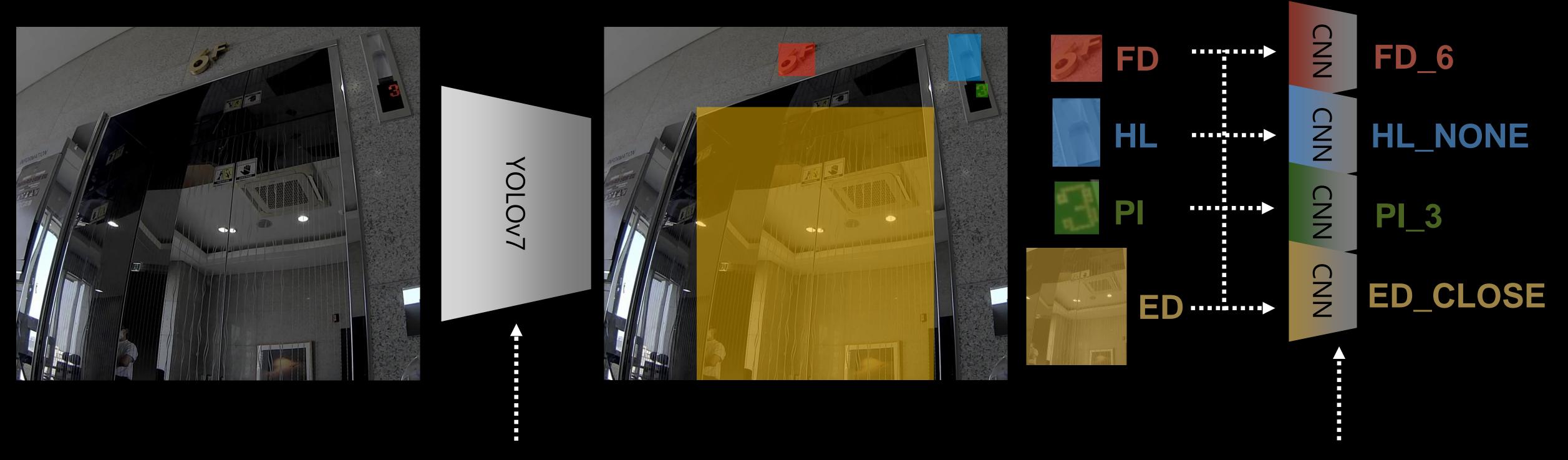
Detect large classes like ED,FD,PI,HL,LOP first

Detecting state from large classes





YOLOv7 (Single Stage) + 6xCNN (Second Stage)



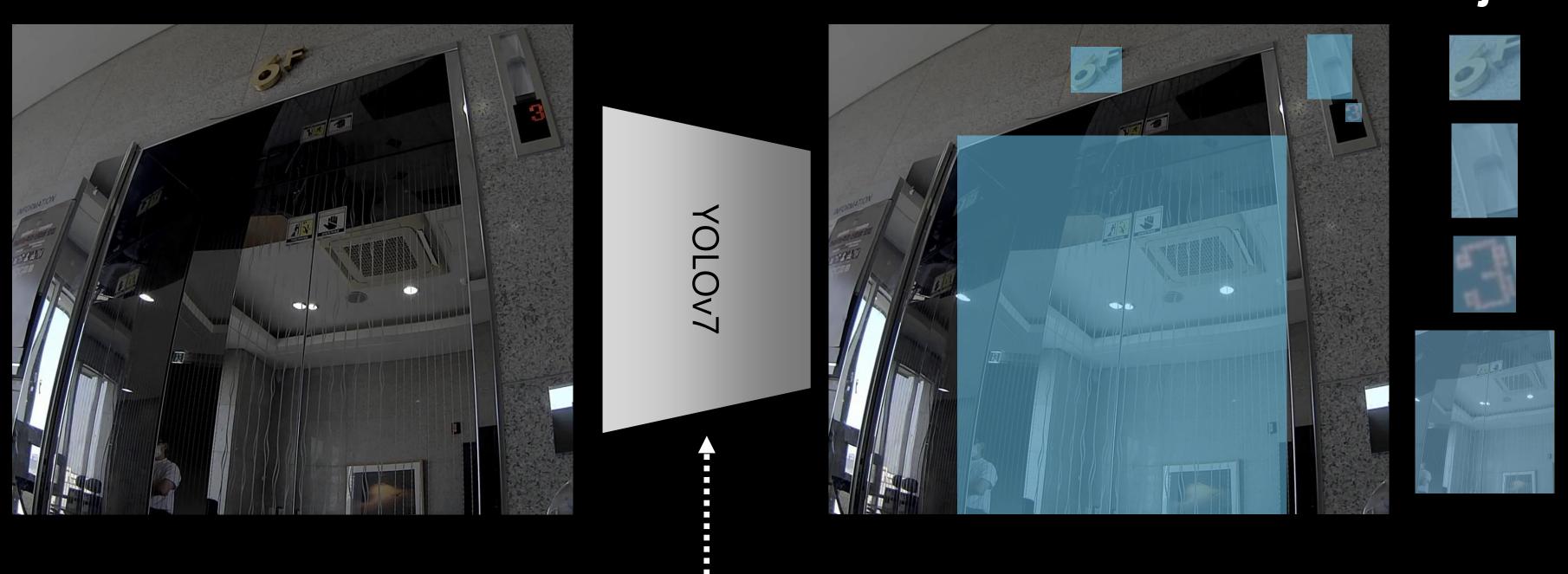
Detect large classes like ED,FD,PI,HL,LOP first

Train different CNNs on different clas





YOLOv7 (Objectness) + CNN (Second Stage)



Object

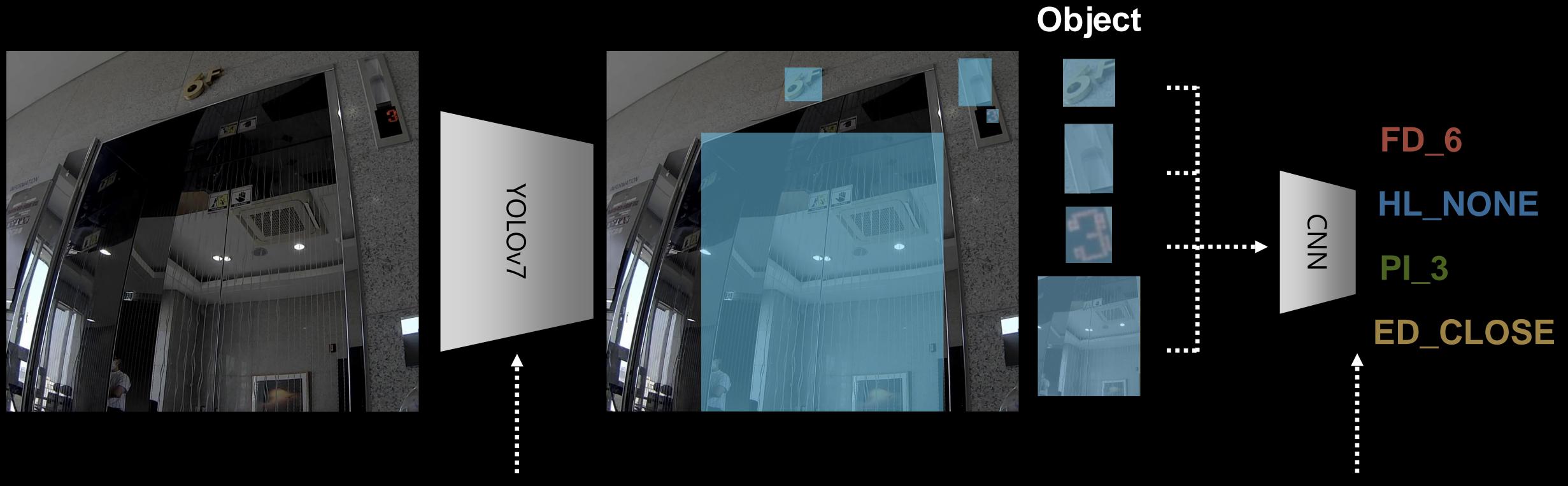


Detect ED,FD,PI,HL,LOP by viewing them all as Object





YOLOv7 (Objectness) + CNN (Second Stage)



Detect ED,FD,PI,HL,LOP by viewing them all as Object

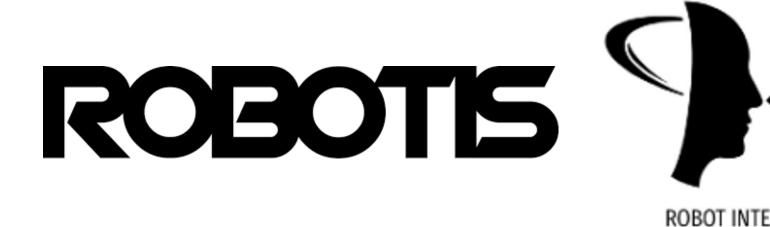
If CNN is a large class and Detect all states

# 3.3 Methodology Comparison ROBOTS





	mAP(0.5)	mAP(0.95)
Single-Stage	0.2993	0.1414
YOLOv7 (SingleStage) + CNN (Second Stage)	0.1081	0.048
YOLOv7 (SingleStage) + 6xCNN (Second Stage)	0.1264	0.0557
YOLOv7 (Objectness) + CNN(Second Stage)	-	-



**ROBOT INTELLIGENCE LAB** 

### 4. Patch Augmentation

# 4.1 Small Object Detection ROBOTS





#### Resize that label to make it smaller

1920 pixels

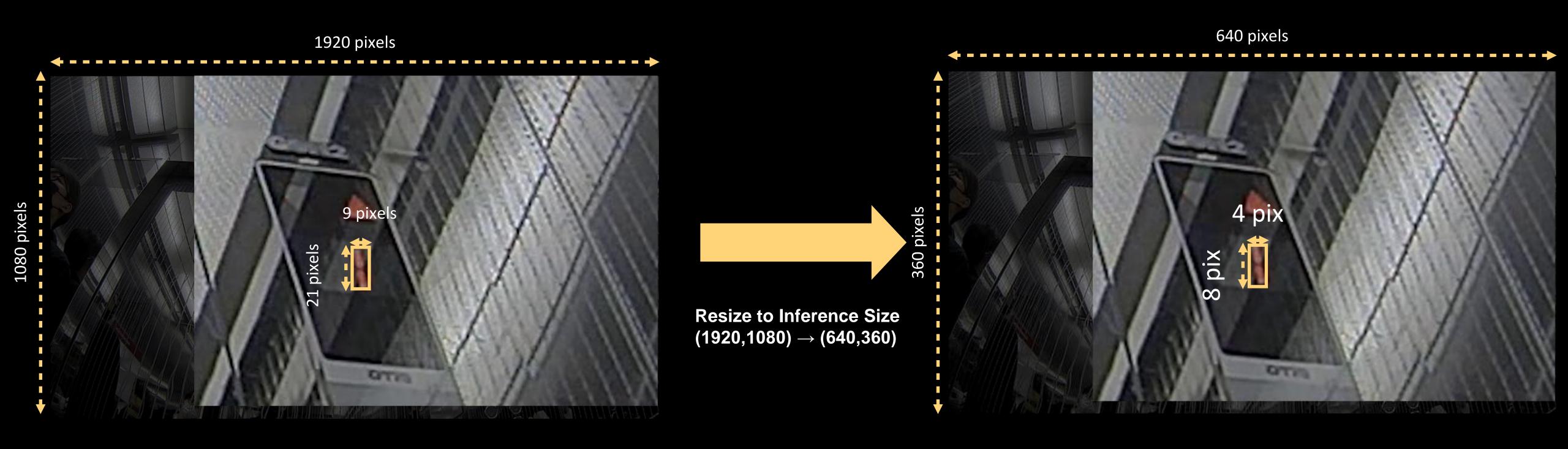


# 4.1 Small Object Detection ROBOTS



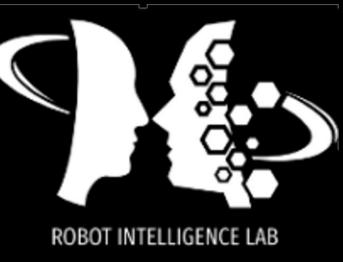


### Lots of very small labels, especially numbers and letters



# 4.2 Patch Augmentation ROBOTS





Resize also breaks the resolution.





Patch at 1920x1080

Patch at 640x360

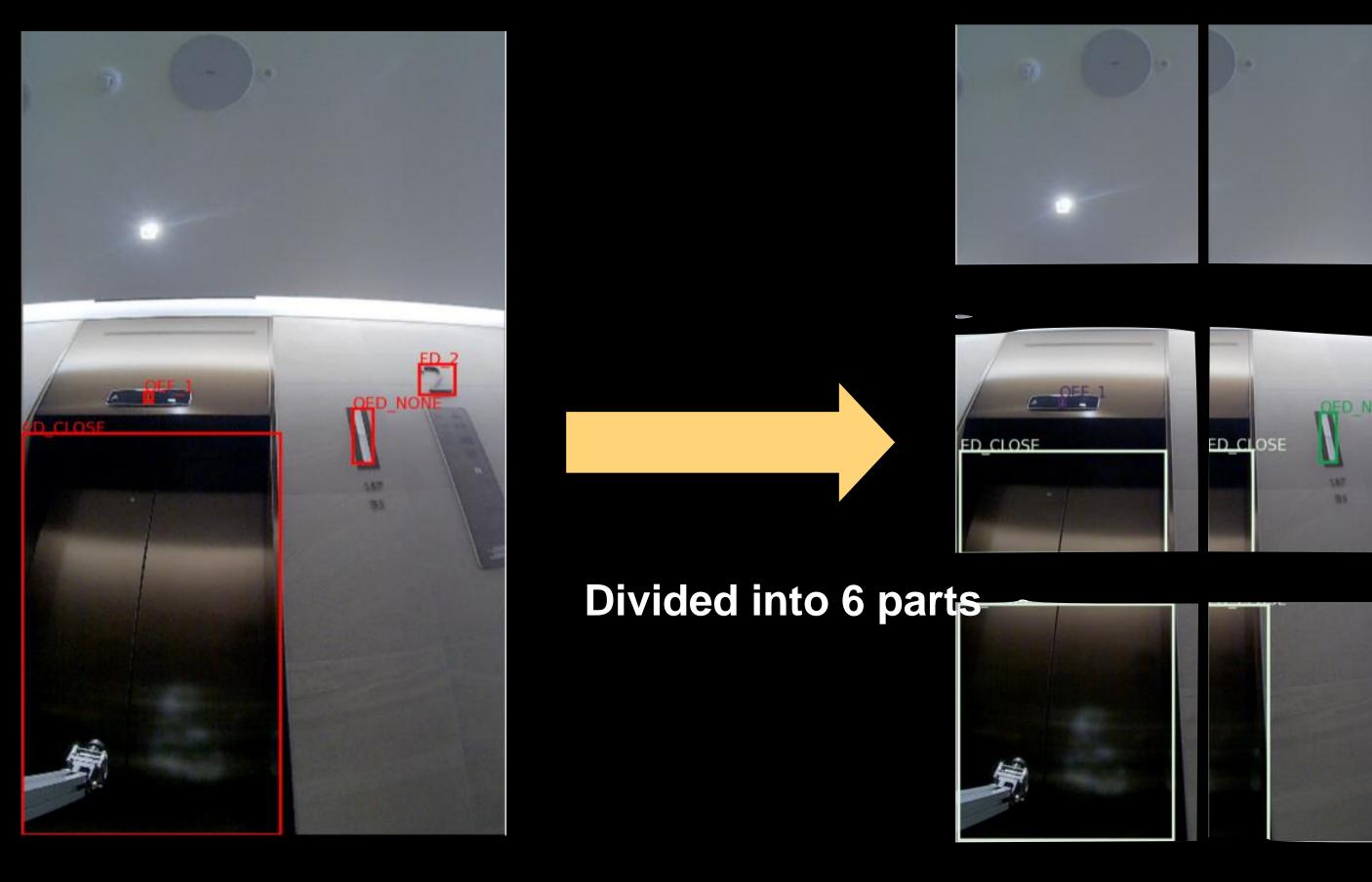
Increase your resolution when you train to train

# 4.2 Patch Augmentation (Feb-Mar 23)





Let's start by cropping the patch to 640x640



(1920 x 1080)

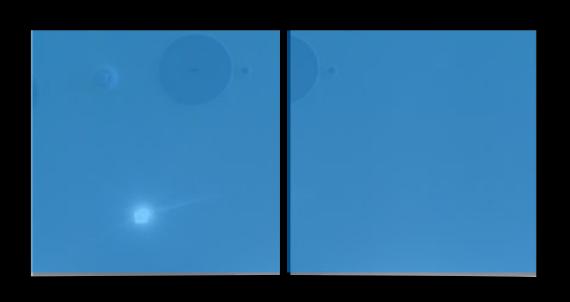
6 x (640 x 640)

## 4.2 Patch Augmentation









that does not include a **Patches** 

(Remove from Dataset)



containing a label **Patches** 

Divided into 6 parts

(1920 x 1080)

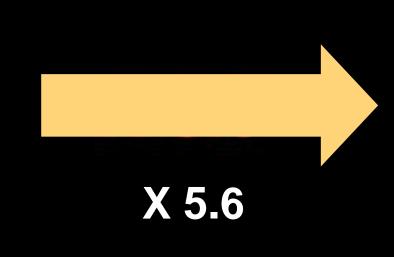
6 x (640 x 640)

# 4.2 Patch Augmentation ROBOTS











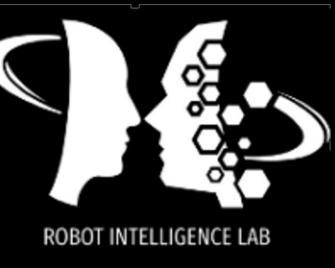


Existing data: 5,000 photos

Existing data + Patch Augmentation: 28,000 sheets

# 4.4 Patch Augmentation ROBOTS





### Improve performance by simply augmenting patches

Metric		Status Metric		
Test Time Augmentation	mAP@0.5		Test Time Augmentation + Patches + Full Image	
Details		Precision/Recall/F1		
YOLOv7	0.730	0.813/0.881/0.843	0.602/0.934/0.736	
YOLOv7 (+Patch Aug.)	0.784	0.878/0.792/0.833	0.767/0.961/0.853	

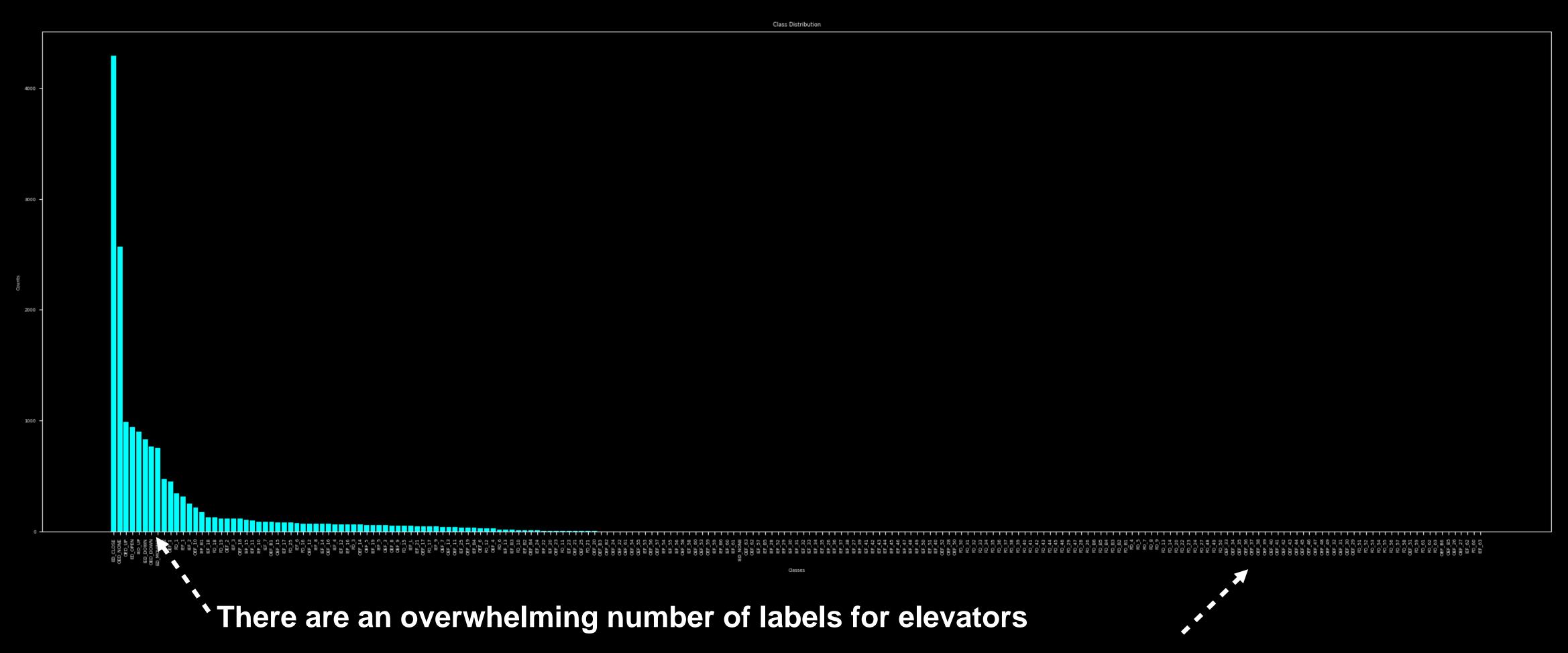


### 5. Diffusion Augmentation





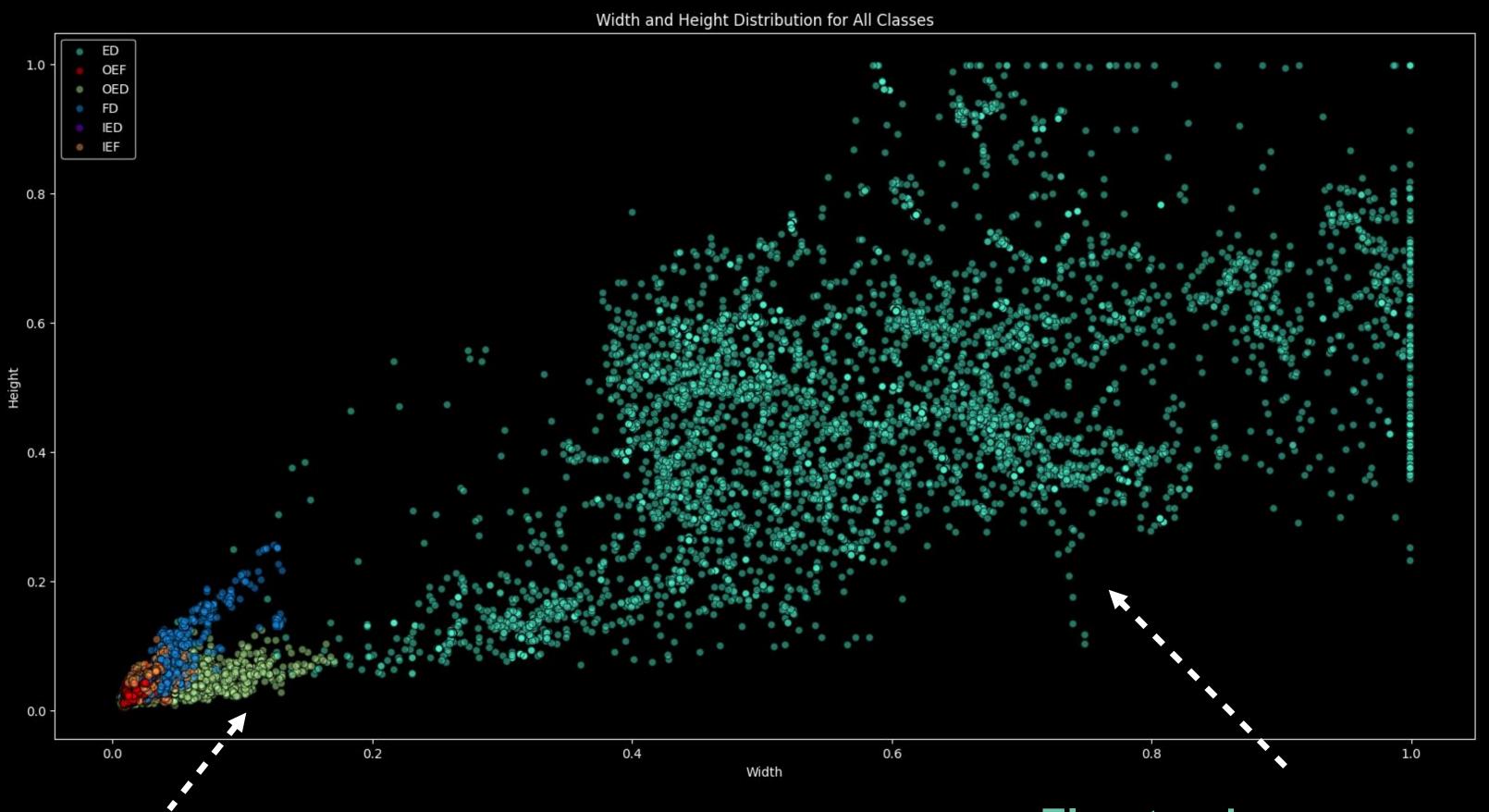
Basic statistics for a dataset of seven locations







Basic statistics for a dataset of 7 places :: Label size and count.



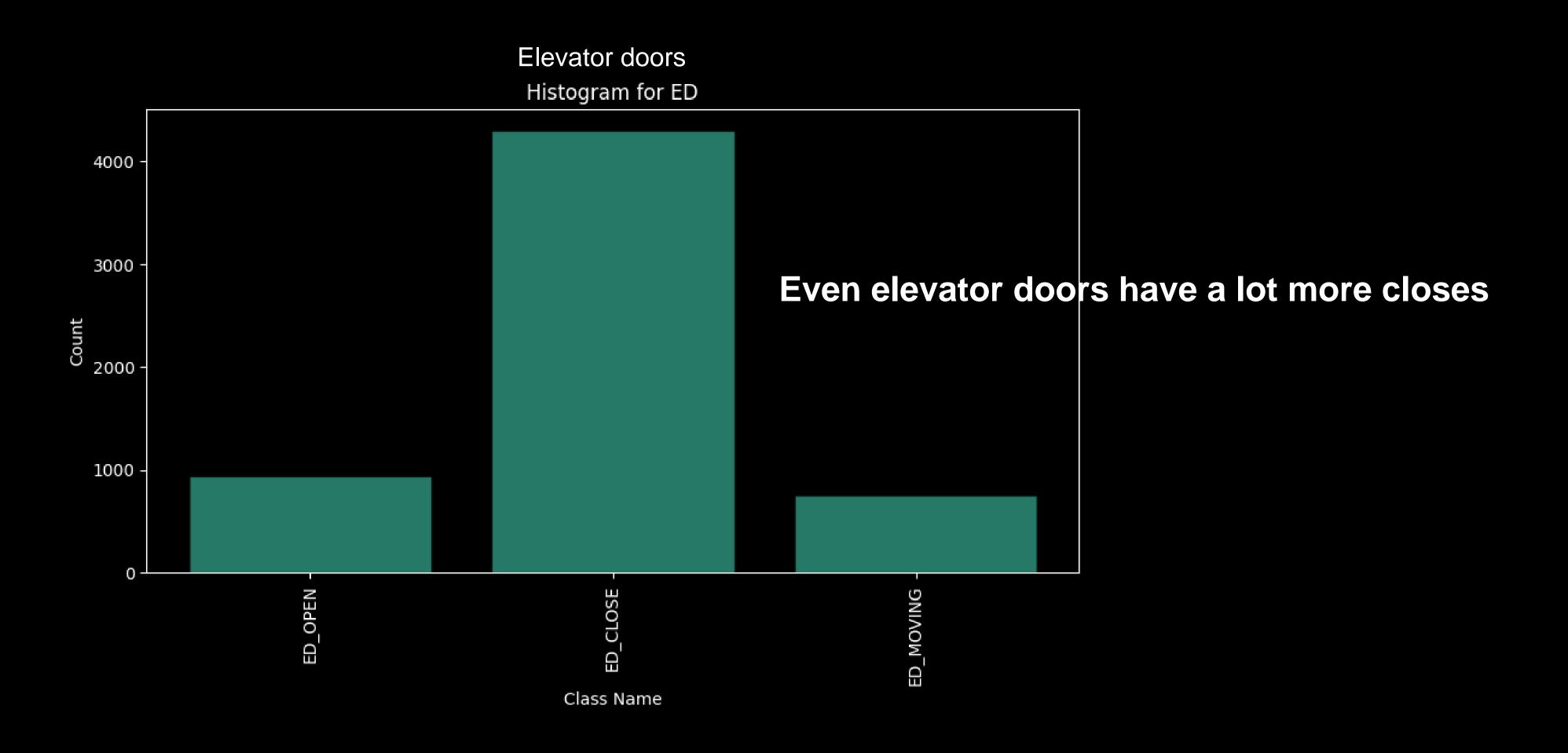
In comparison, other labels are overwhelmingly few and far between. It takes up fewer pixels in the image.

Elevator doors are overwhelming and It takes up an large amount of pixels.





Basic statistics for a dataset of 7 places :: Highly unbalanced, even among the few classes.

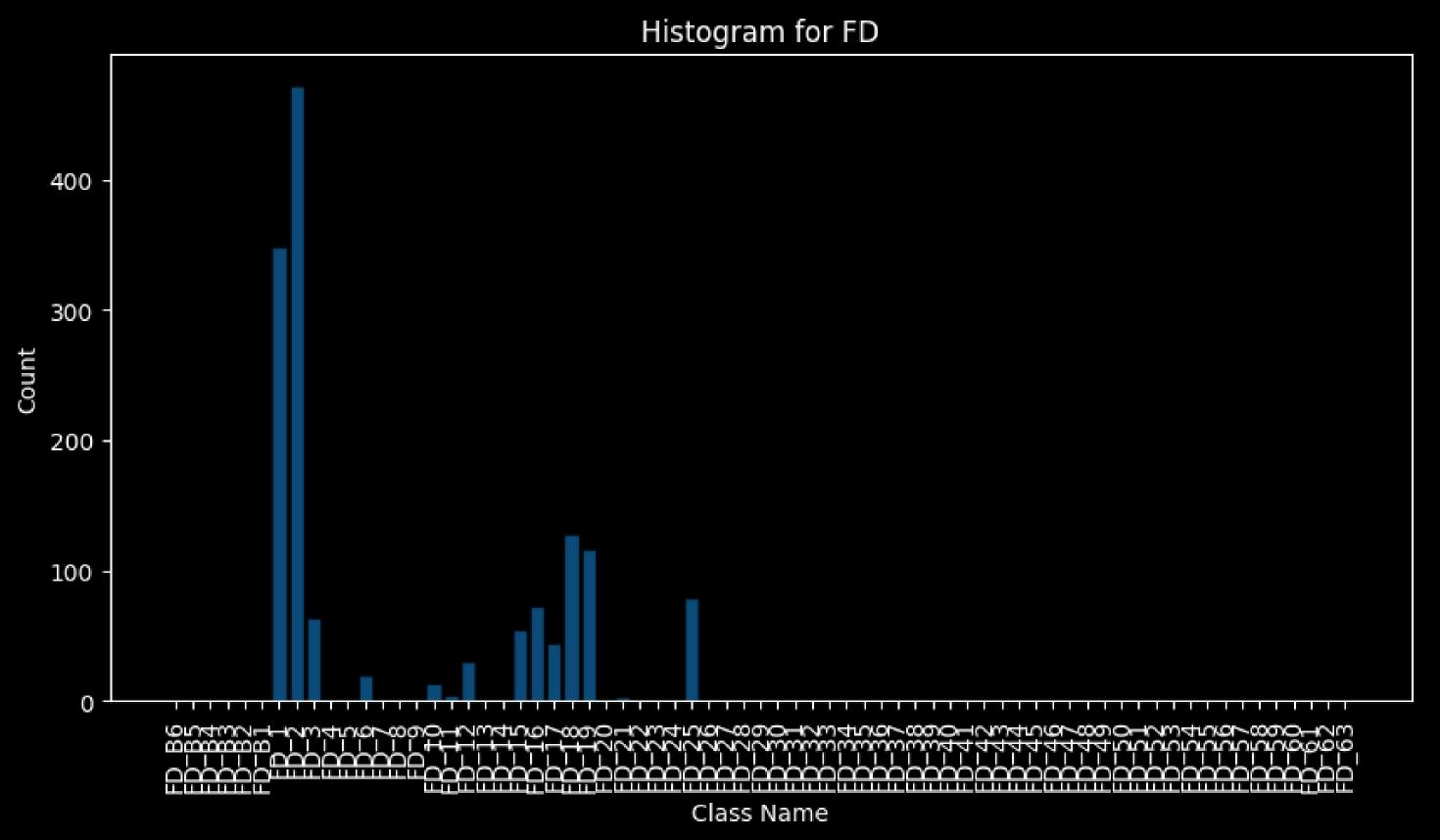






Basic statistics for a dataset of 7 places :: Highly unbalanced, even among the few class

The current floor of the house ant (Floor Designer)



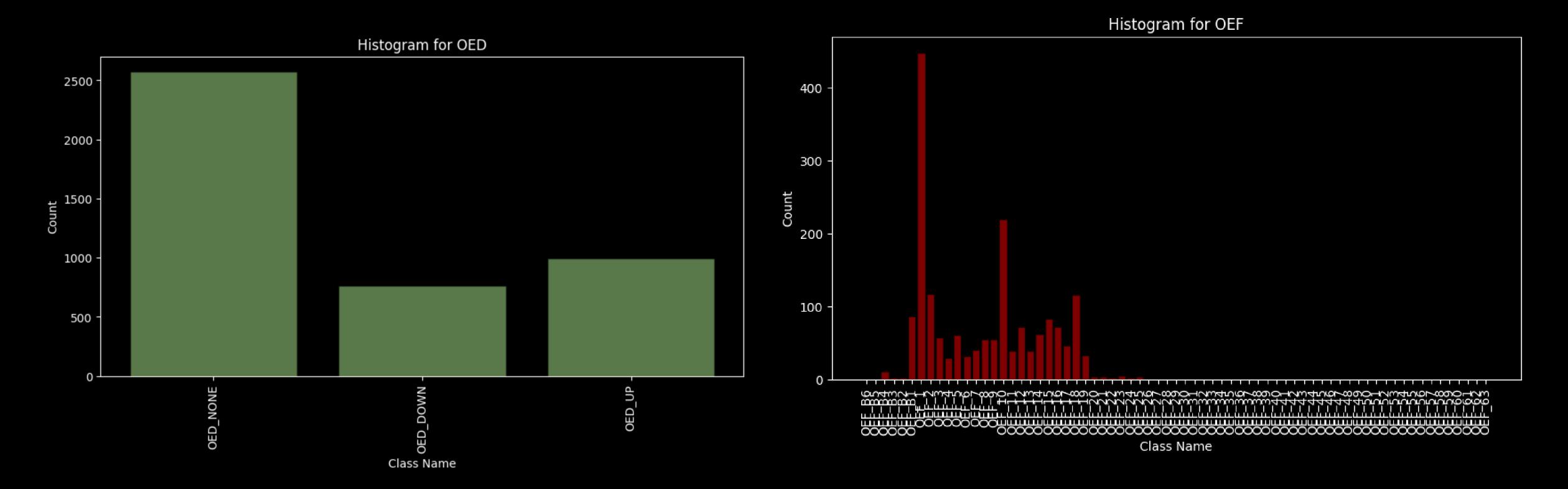
For external floor counts, they tend to cluster around a certain number of floors. Significant impact on dataset unbalanced experience.





Basic statistics for a dataset of 7 places :: Highly unbalanced, even among the few classes.

Outdoor Elevator Direction/Floor



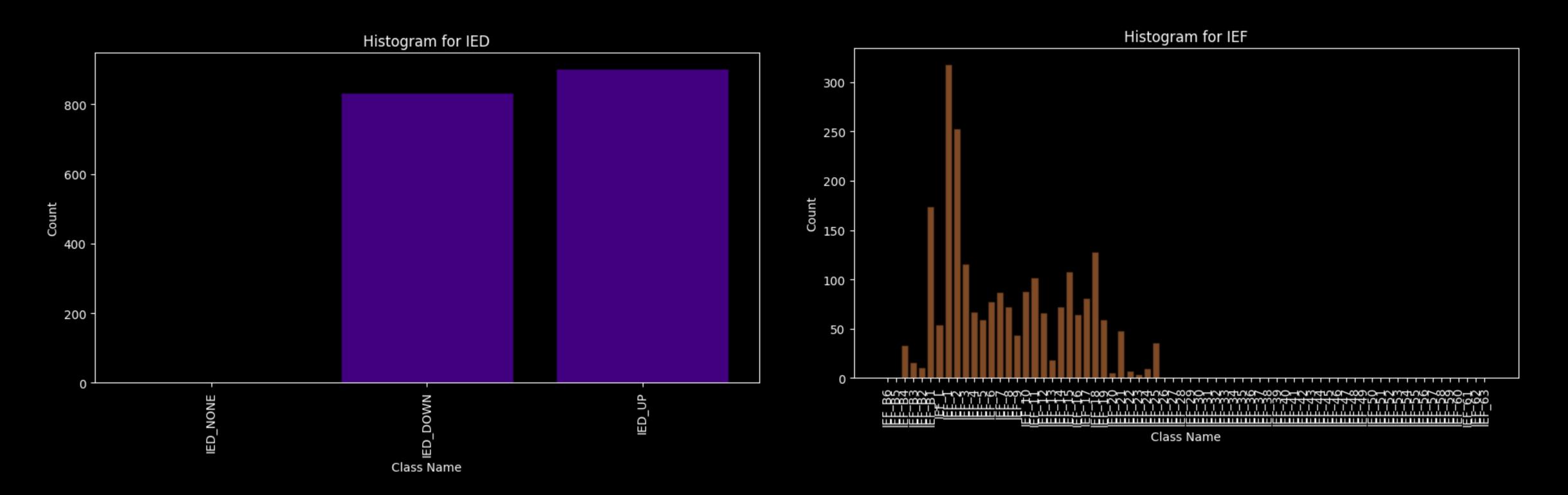
Outside the elevator, the indicator for the floor and direction of the elevator also has a severe label imbalance.





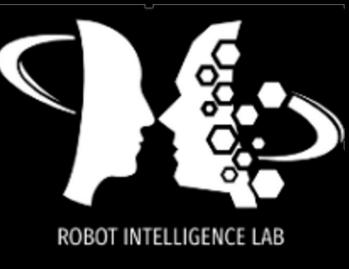
Basic statistics for a dataset of 7 places :: Highly unbalanced, even among the few classes.

Indoor Elevator Direction/Floor



In an elevator, the indicator for the floor and direction of the elevator also has a severe label imbalance.







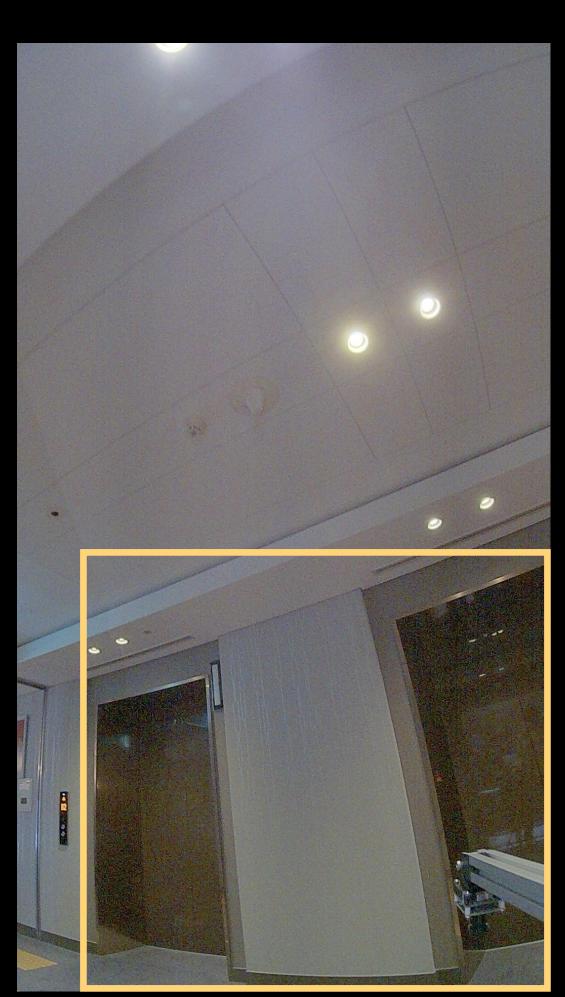
What about inpainting the class with a diffusion model?

Select a target class and click Get the Crop Image for that class

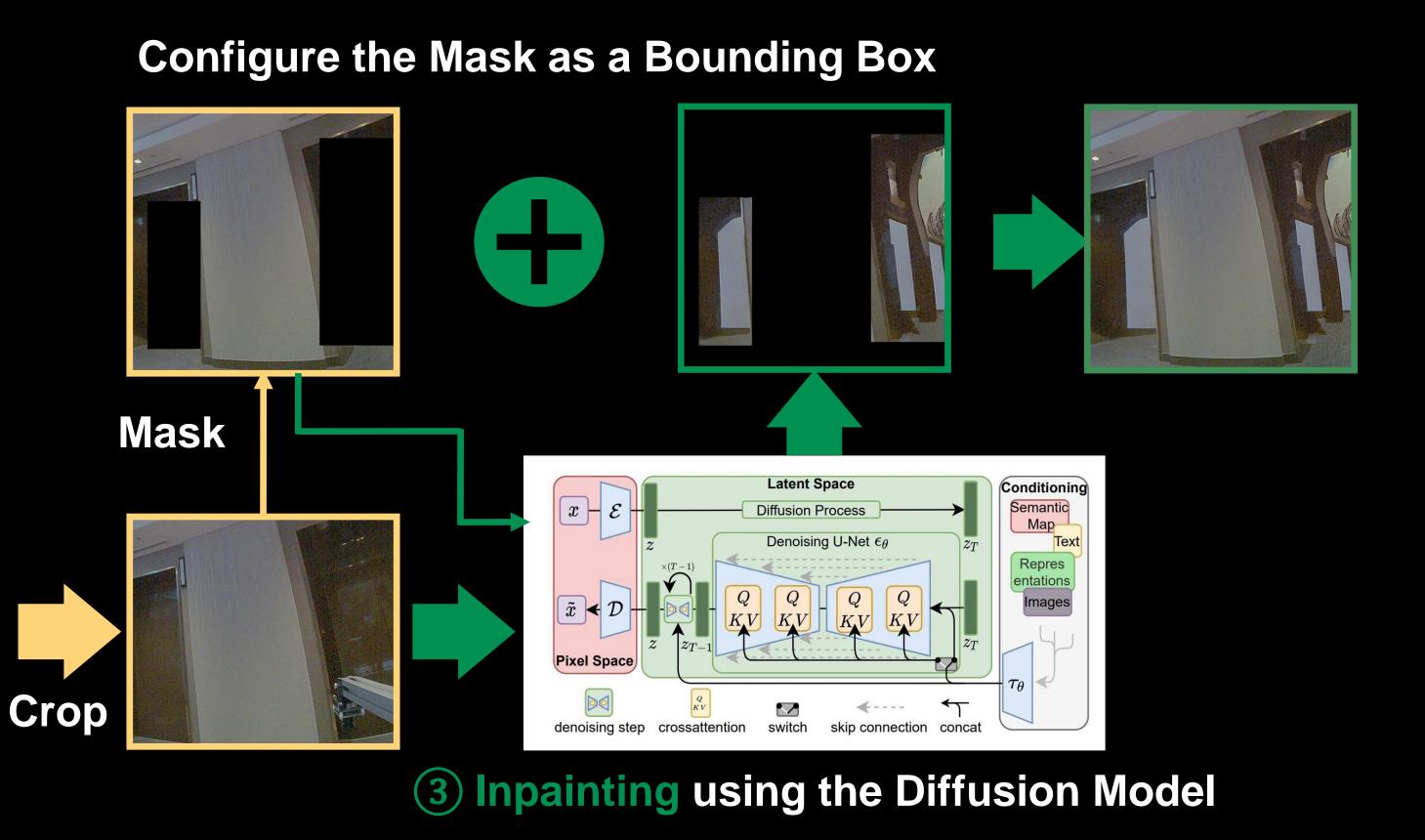




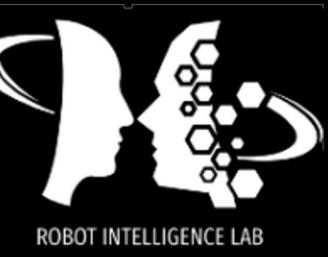




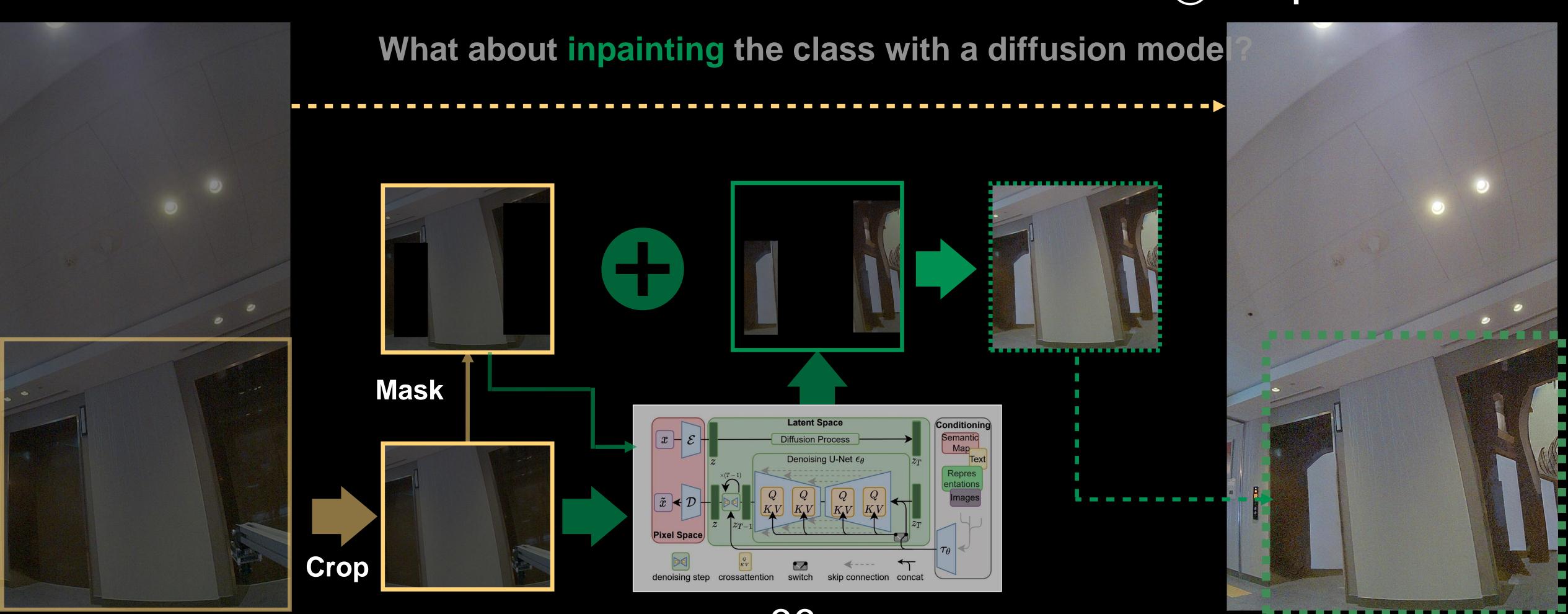
What about inpainting the class with a diffusion model?



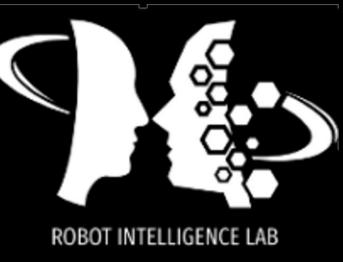




4 Complete the new imag

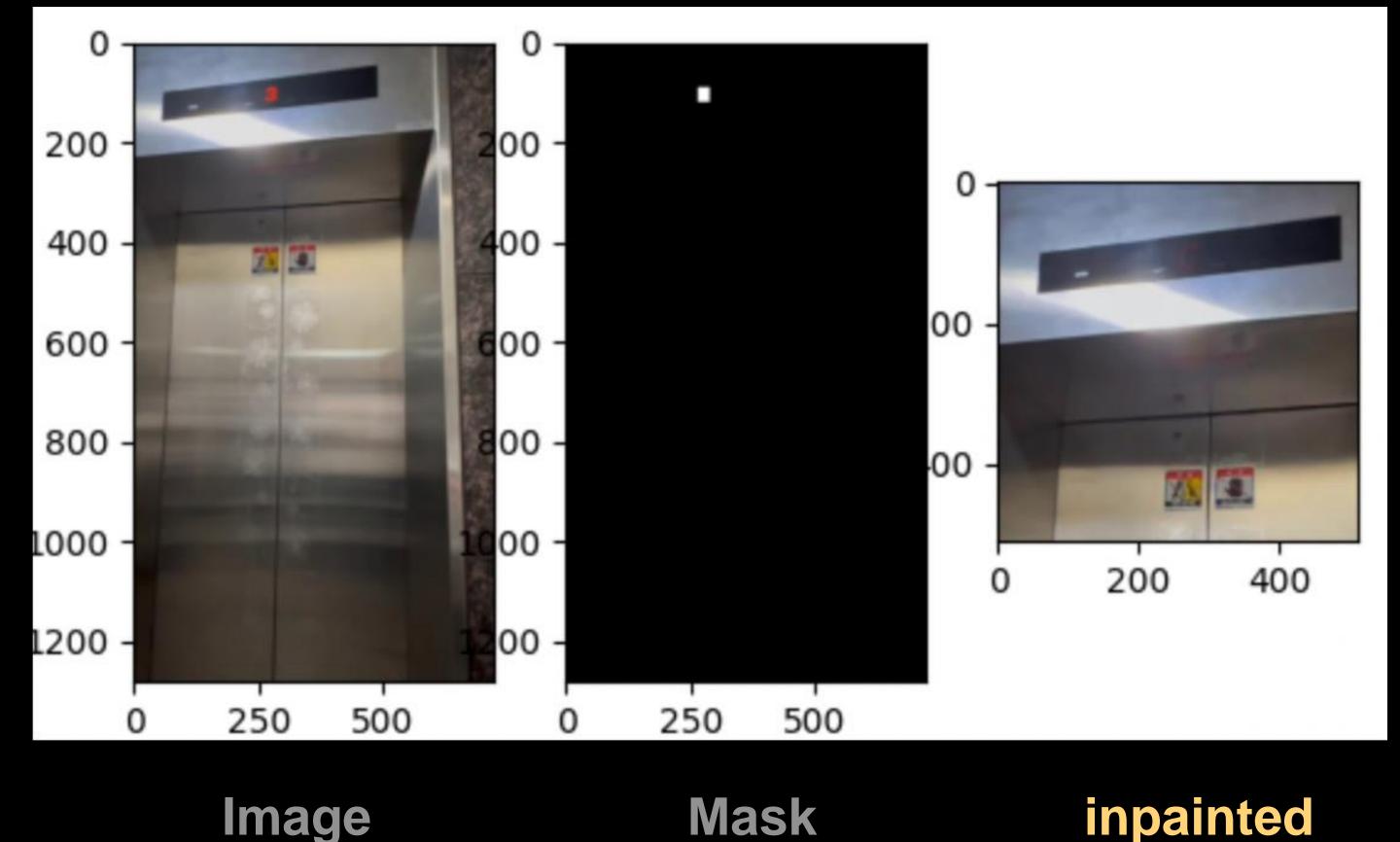




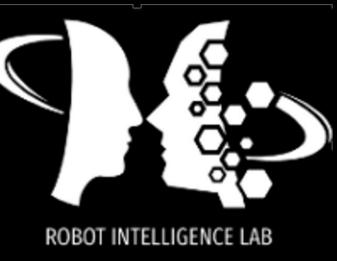


#### Can the floor plan generation model do a good job?

Prompt: "The photo of elevator floor the display indicating the elevator floor of 6 floor"







Can the floor plan generation model do a good job?

Prompt: "elevator display digit with 3 floor"

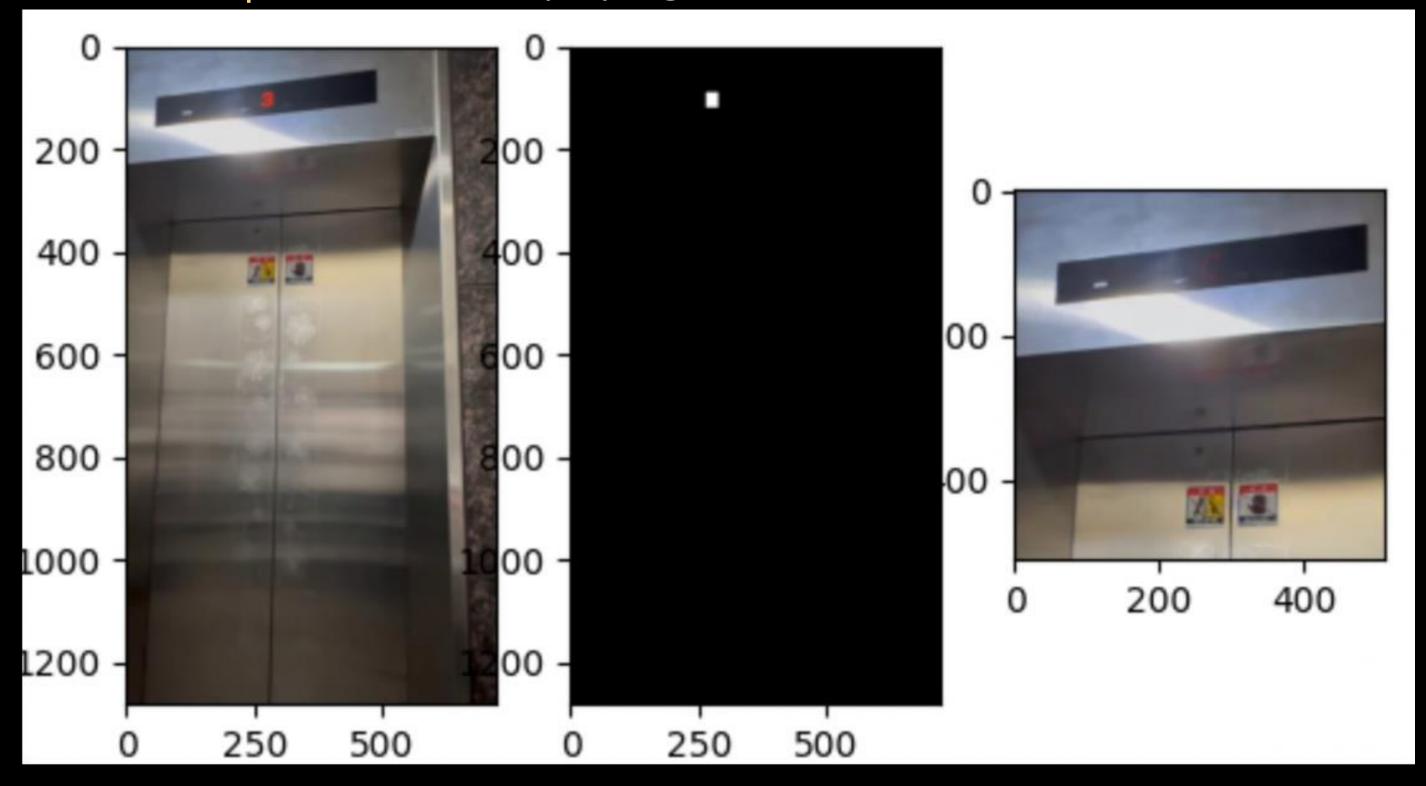


Image Mask inpainted
Generating letters and numbers is still a bit lacking





### Additional performance gains with Diffusion inpainting

Metric		Status Metric		
Test Time Augmentation	mAP@0.5	X	+Test Time Augmentation + Original Image	
Details		Precision/Recall/F1		
YOLOv7	0.730	0.813/0.881/0.843	0.602/0.934/0.736	
YOLOv7 (+Patch Aug.)	0.784	0.878/0.792/0.833	0.767/0.961/0.853	
YOLOv7 (+Patch Aug. + Diffusion Inpainting)	0.779	0.898/0.771/0.827	0.792/0.956/0.867	





### 6. Finetuning

## 6.1 Fine-tuning





### Can a model trained on seven locations be effectively applied to other locations?

Pretraining	7 Place Model	7 Place Model	COCO	7 Place Model	7 Place Model	COCO
Fine-tuning		(Ananti, Henna, Mayfield)	(Ananti, Henna, Mayfield)		(Ananti, Henna, Mayfield)	(Ananti, Henna, Mayfield)
		Precision			Recall	
Ananti	0.531	0.534	0.123	0.509	0.887	0.156
Henna	0.581	0.626	0.146	0.749	0.922	0.276
Mayfield	0.438	0.515	0.208	0.670	0.877	0.366

## 6.1 Fine-tuning





Can a model trained on seven locations be effectively applied to other locations?

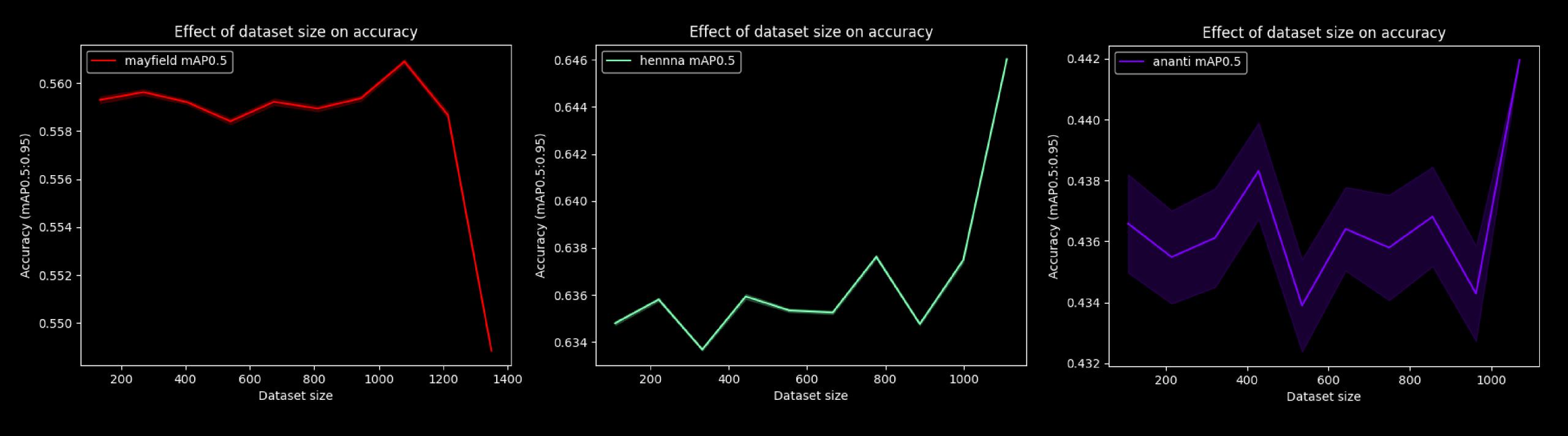
- 1. The model trained with 7 locations performs significantly better than COCO and
- 2. With 7 locations, training data performs better with new locations
- 3. Fine-tuning for new places improves performance. (1000 or so)
  - 3.1 Consistently better performance for all venues (Ananti, Henna, Mayfield)

## 6.1 Fine-tuning



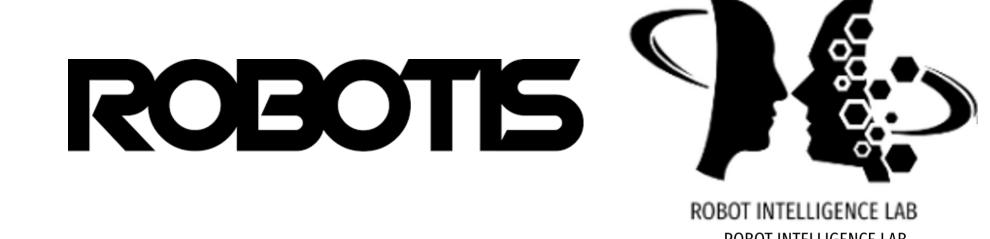


### How much data should you use for fine-tuning?



There is no dramatic performance improvement from 200 to 1000 photos. Overall, there is a small increase in performance as more data is added.

### Conclusion



- 1. Develop a recognition package for elevator status recognition
- 2. Developing to return to 80FPS to 100FPS in Orin
- 3. Suggestions for how data can be effectively augmented during training for state recognition in different locations
- 4. Shows that pretraining is essential for domain adaptation.
- 5. Developed a "Pretraining Model for Elevator Condition Recognition" that outperformed finetuning on public datasets such as COCO by an average of 4x on public datasets.
- 6. (1-4) Provide a codebase to configure a system that performs better as more data is added