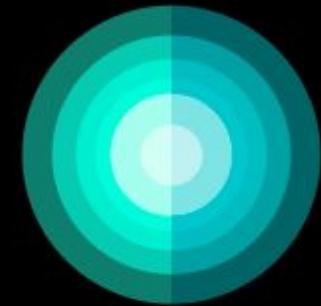


# EPRI-CV: Computer Vision as Inventory Tool

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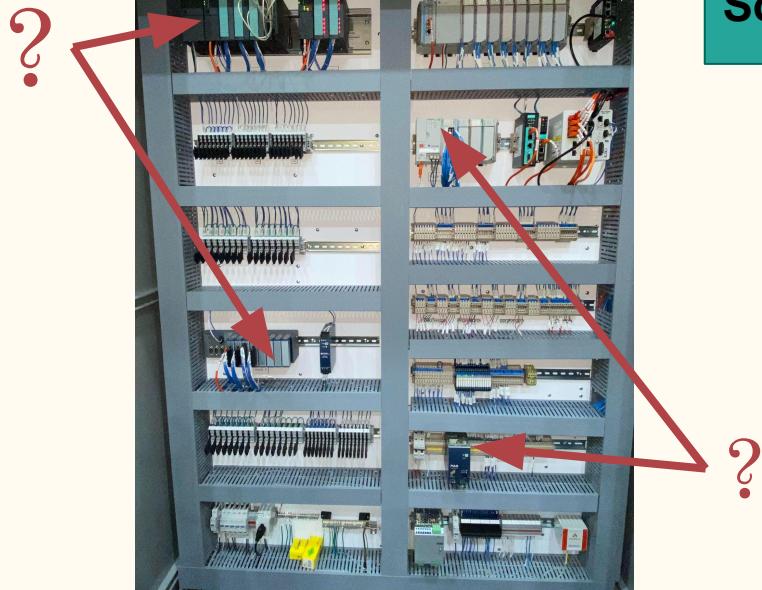
Agnieszka Czeszumska, Frederic Colomer, Jenny Shih,  
Lennart Schmidt, Sergey Komarov



sea VISIONARIES

# Problem Statement

Control panels in power plants are not well-inventoried; in-person inspections time consuming



Develop a computer vision model to identify specific cyber-security modules



Inspector takes a photo of the cabinet...



... runs photo through inference with the model



... inventory!

# Computer Vision Basics

**Classification**



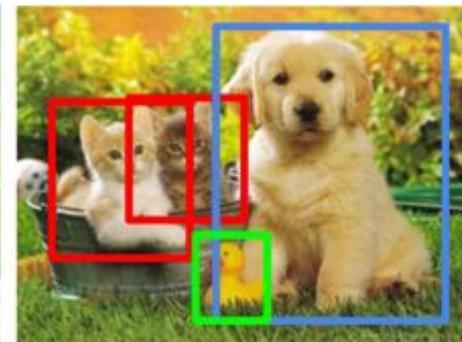
CAT

**Classification + Localization**



CAT

**Object Detection**



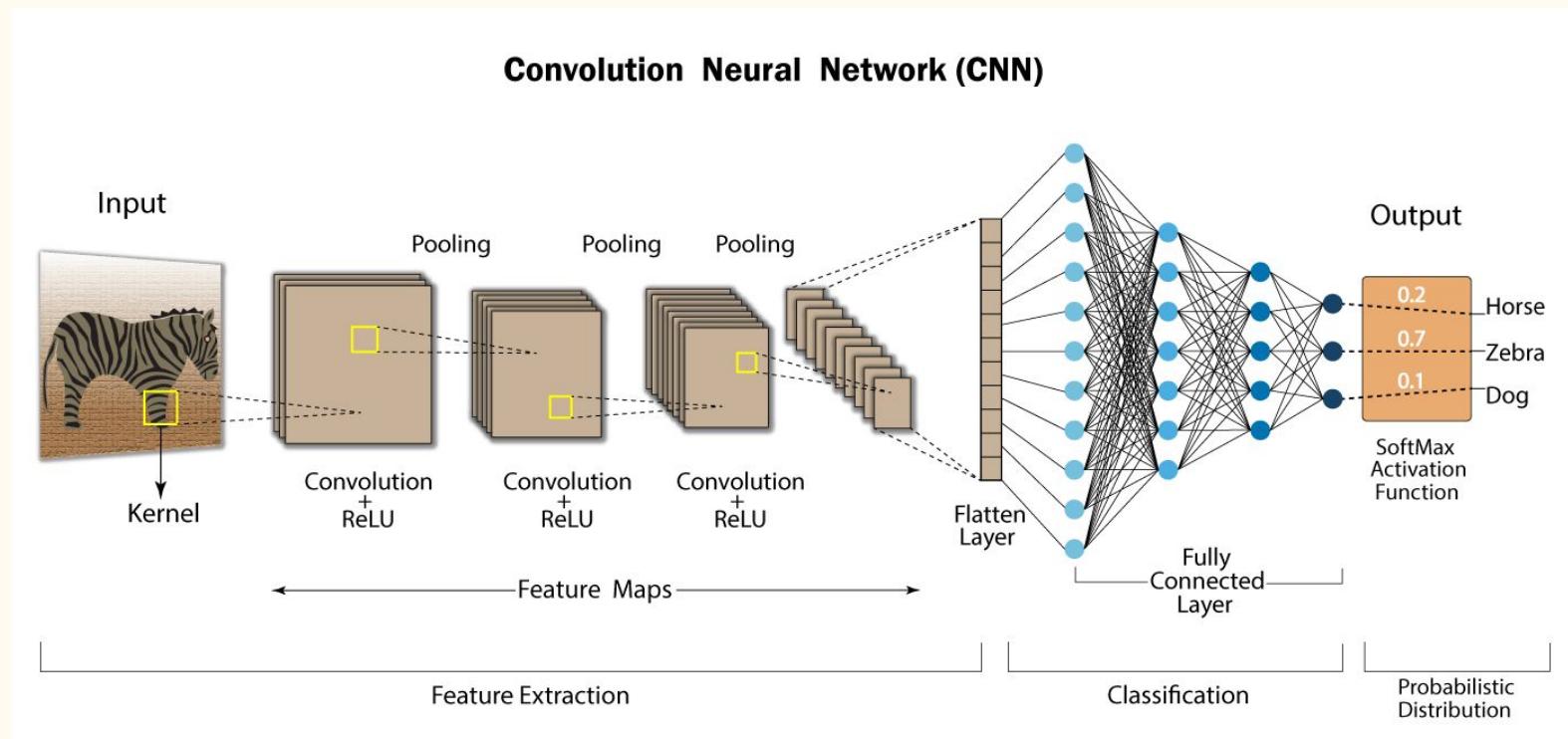
CAT, DOG, DUCK

Multiple objects of several classes in our problem



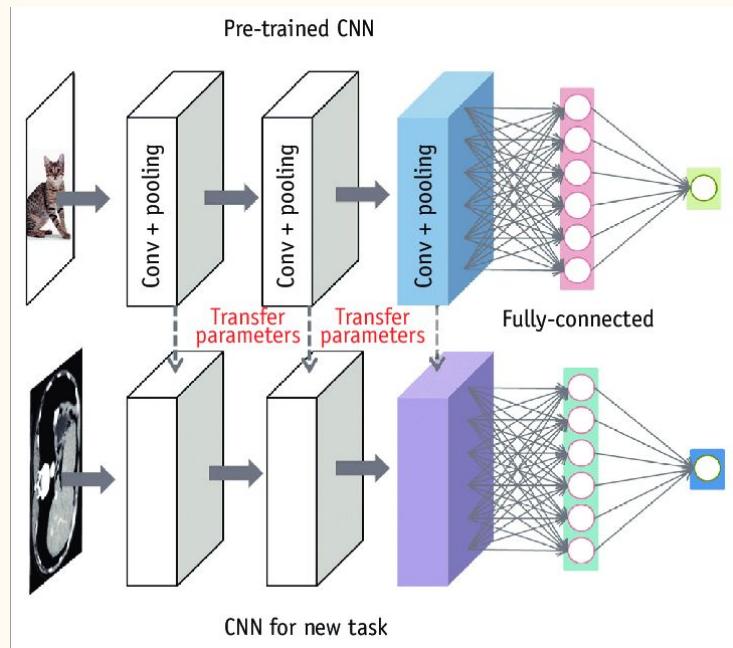
Object Detection

# CV and Deep Learning: Convolutional Neural Networks (CNN)



# Basics Of Our Approach:

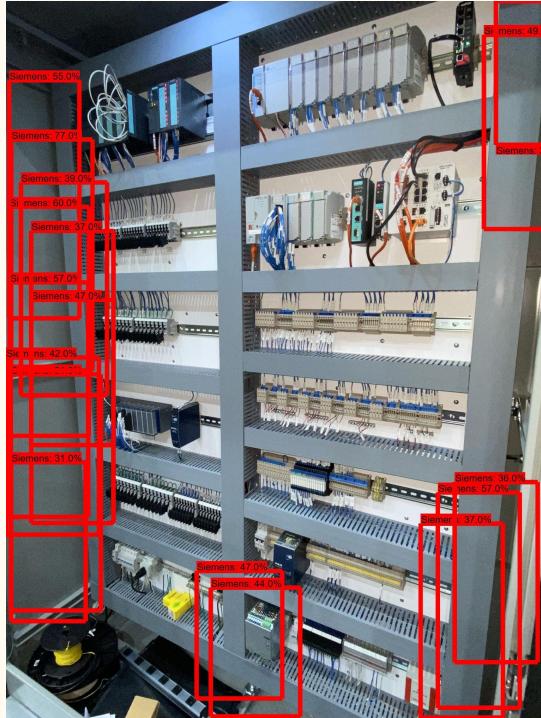
- No time to train the model from scratch  
→ choose a pre-trained CNN model and use **transfer learning**:
  - Keep the structure
  - Start from pre-trained weights/parameters
  - Additional classes of objects can be added



[https://www.researchgate.net/figure/Transfer-learning-Transfer-learning-is-process-of-taking-pretrained-model-usually\\_fig1\\_338540456](https://www.researchgate.net/figure/Transfer-learning-Transfer-learning-is-process-of-taking-pretrained-model-usually_fig1_338540456) [accessed 27 Aug, 2021]

# A First Model

Out of the box performance:



Oh.  
That is clearly quite bad.

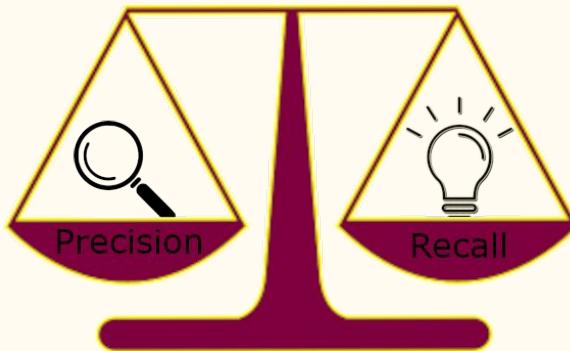
But **how** bad?

# Recall vs. Precision

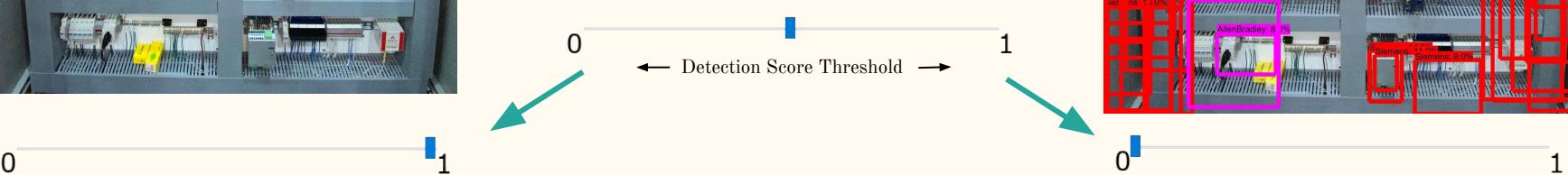
Perfect Precision:



Do we make mistakes?



Do we miss things?

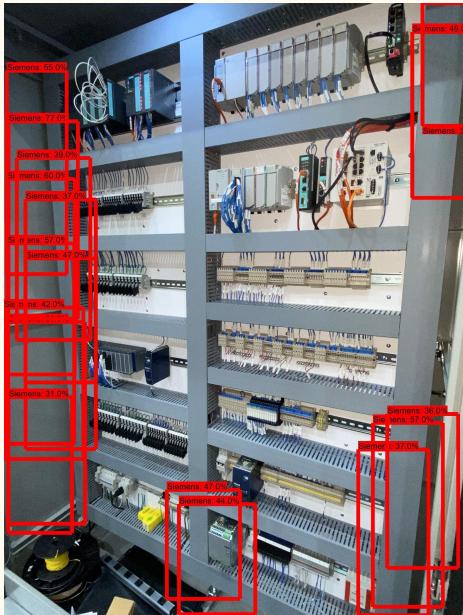


Total Recall:



# A First Model - Evaluated

Visually:

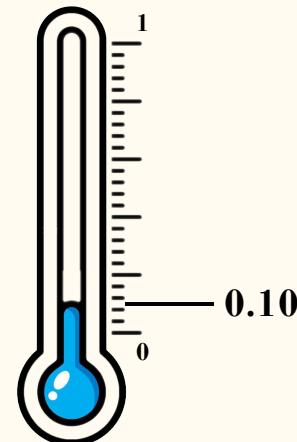


Confusion Matrix:

|              |              | A First Model predicted Siemens |      |
|--------------|--------------|---------------------------------|------|
|              |              | AllenBradley                    | None |
| ground truth | AllenBradley | 3                               | 0    |
|              | Siemens      | 0                               | 53   |
| None         | AllenBradley | 7                               | 25   |

Precision: 0.125  
Recall: 0.035

mAP Score:



# Available Data

Original EPRI images were photographs of the same cabinet as training and test data  
(if used for training, leads to data leakage)

## TRAINING DATA

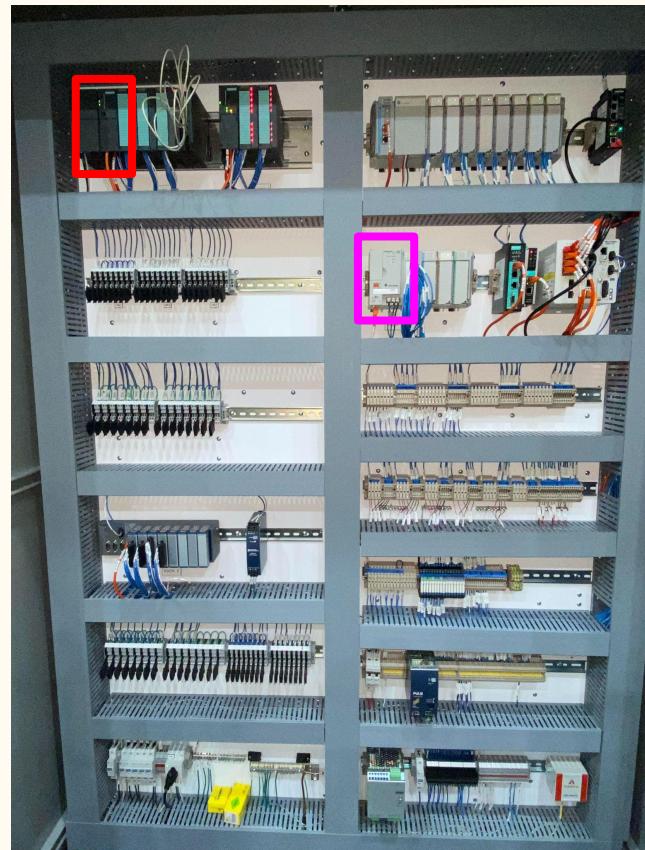


Siemens S7-300



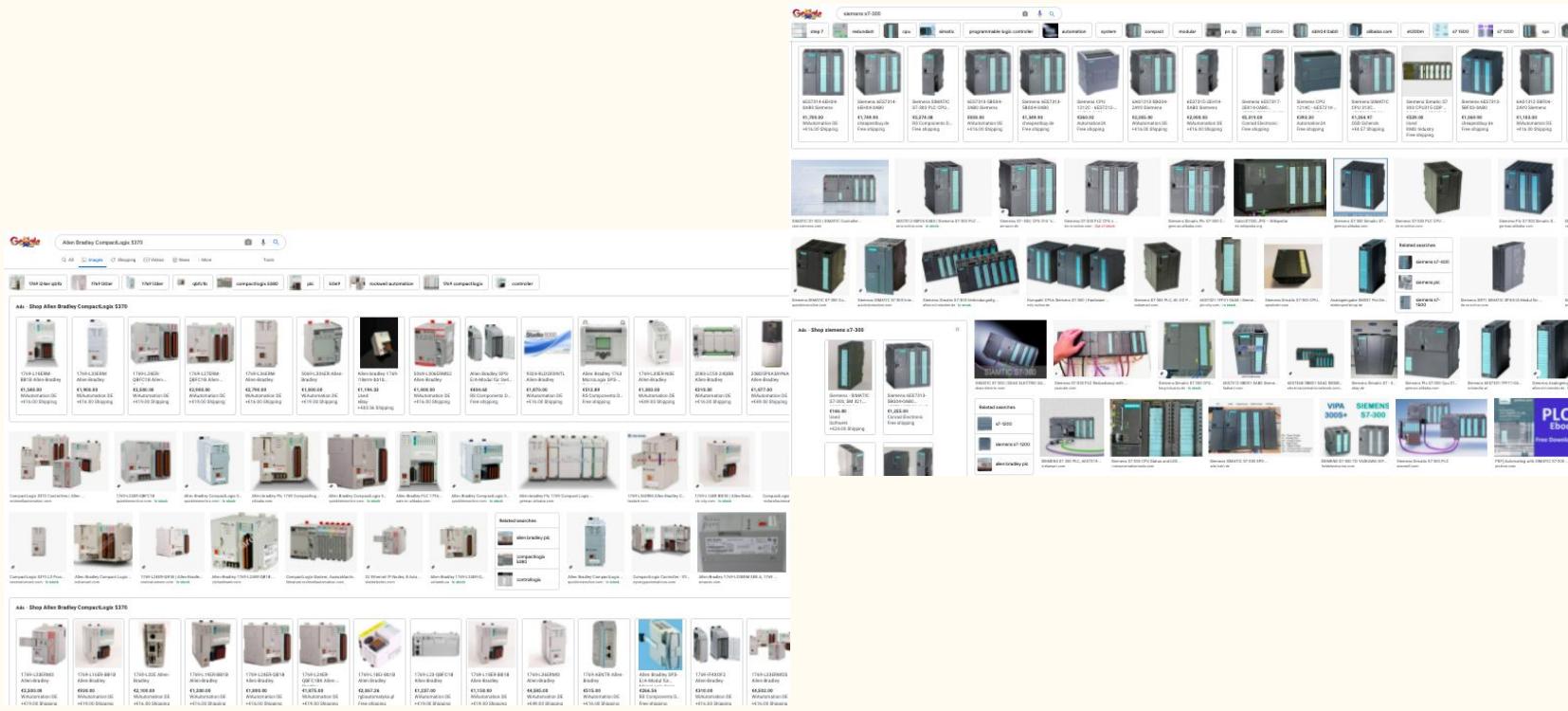
Allen Bradley CompactLogix 5370

## TEST DATA



# Image Synthesis

## Scraping and labeling controller images from using Google search

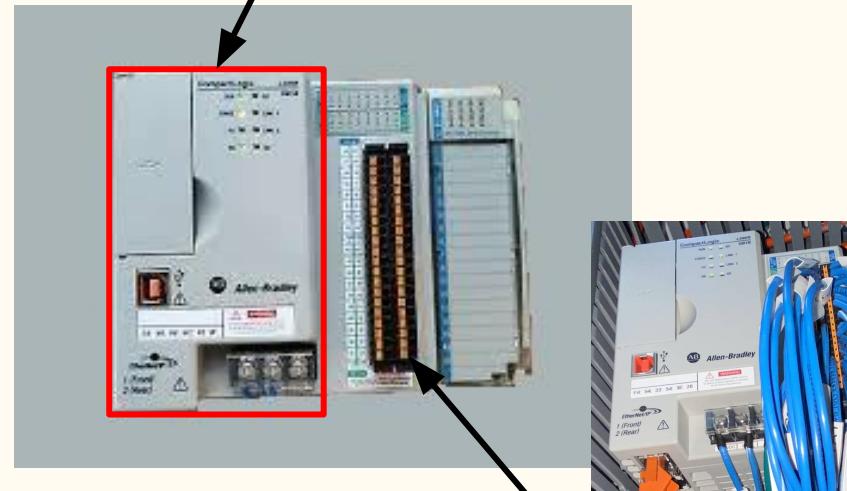


# Image Synthesis

Which part of the object to include?



Mask →



**Bounding box -**  
the part that the model is  
trained to “pick out”

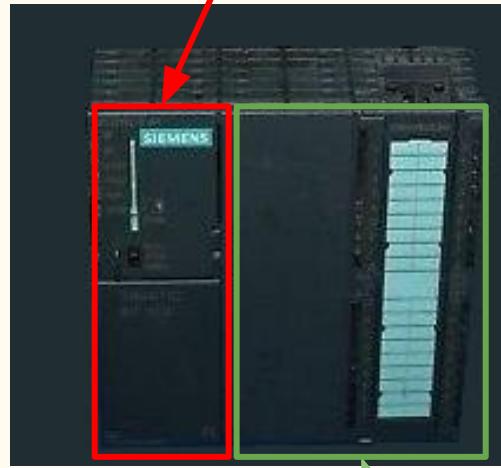
Cables usually plugged in here

# Image Synthesis

Which part of the object to include?



Mask →

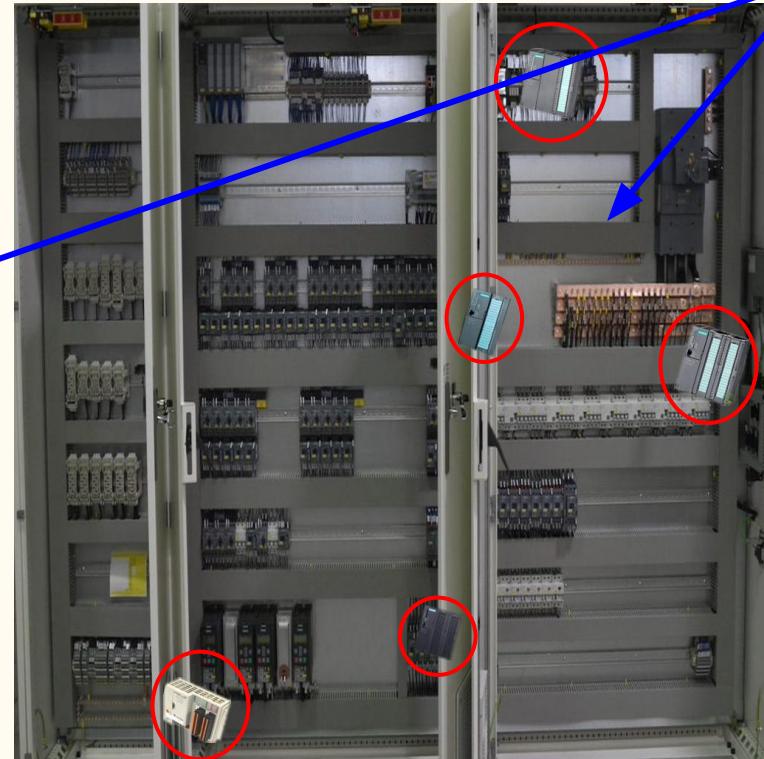
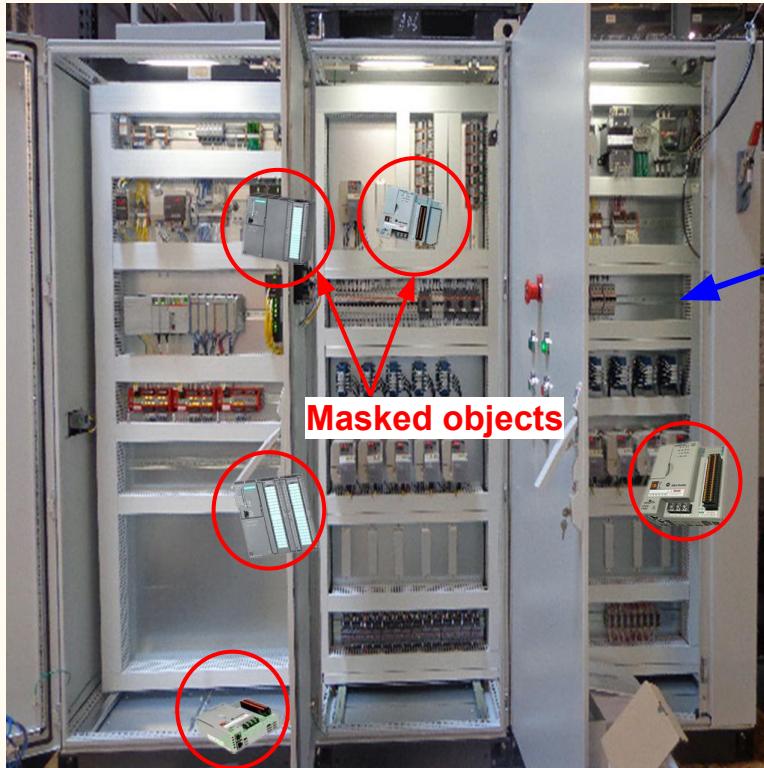


**Bounding box -**  
the part that the model is  
trained to “pick out”

Does not always appear with the controller

# Image Synthesis

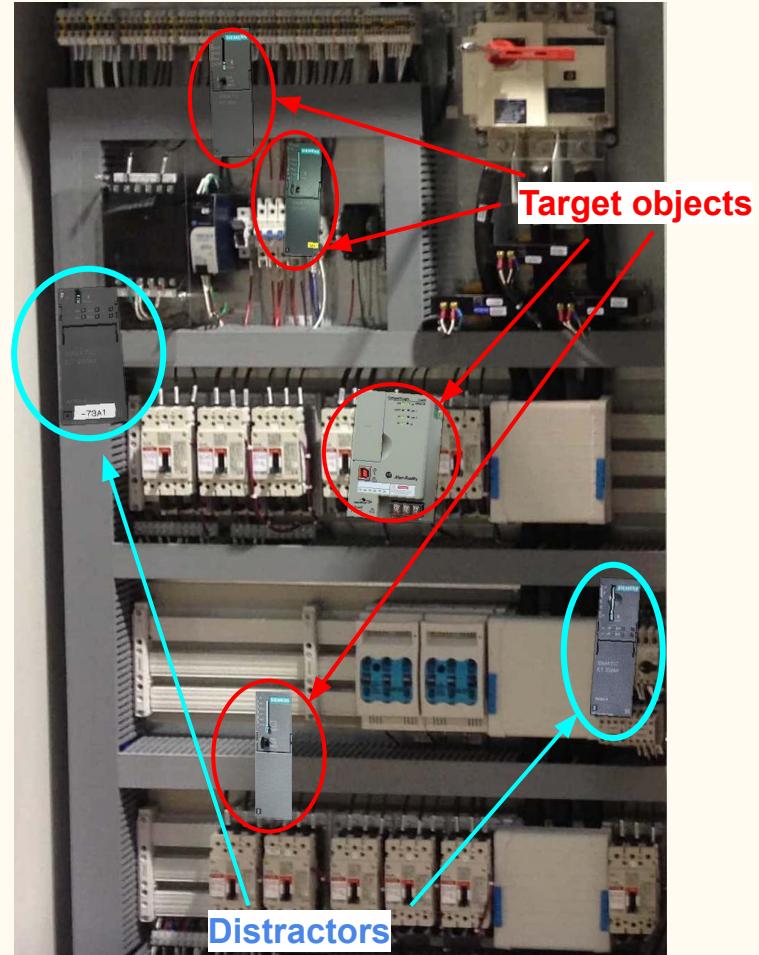
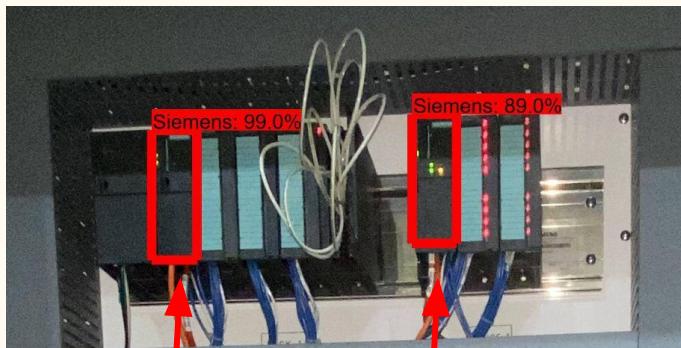
Pasting controller images onto random electrical cabinet backgrounds



Electrical cabinet  
backgrounds

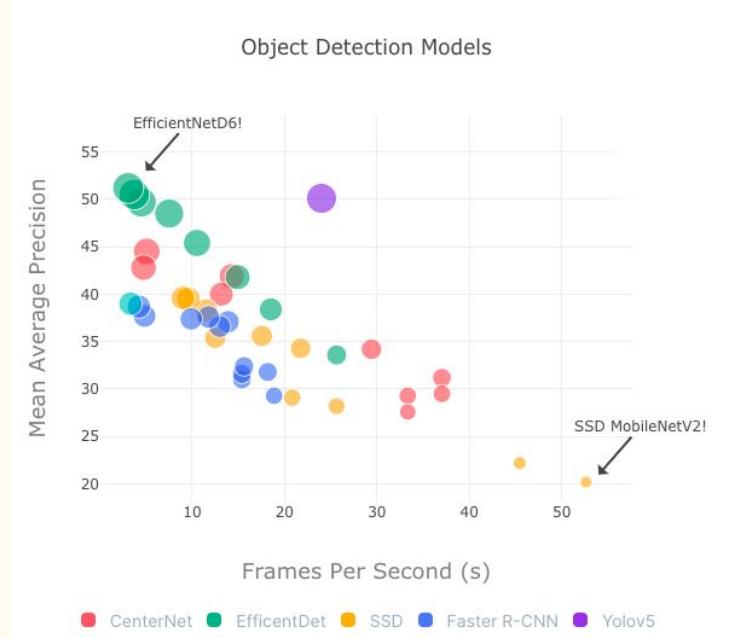
# Image Synthesis

Adding distractors - Helping model better identify the correct targets



# Comparison Between Various Models

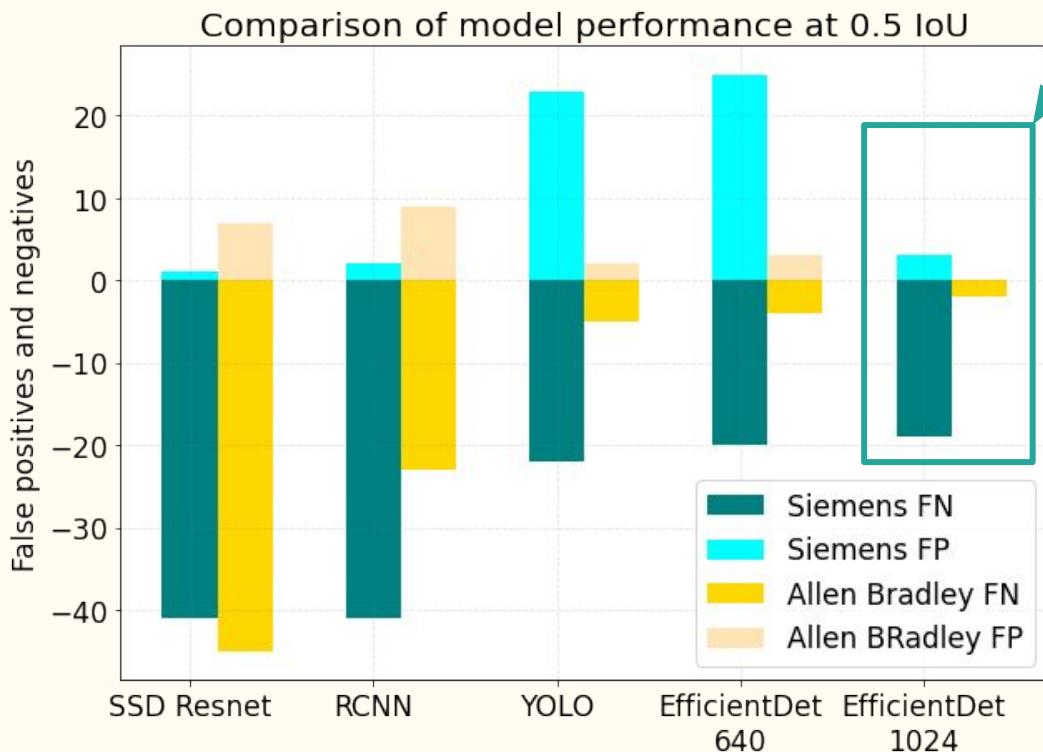
Tradeoff between computing power and performance



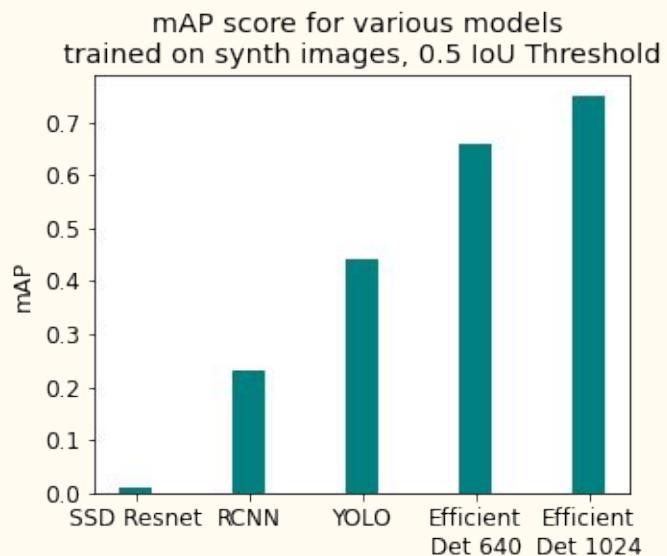
Models that we trained and tested included:

- YOLO4
- SSD ResNet152 V1 FPN 640x640
- Faster R-CNN ResNet50 V1 640x640
- EfficientDet D1 640x640
- EfficientDet D4 1024x1024

# Models trained on synthetic images and evaluated on test images from EPRI

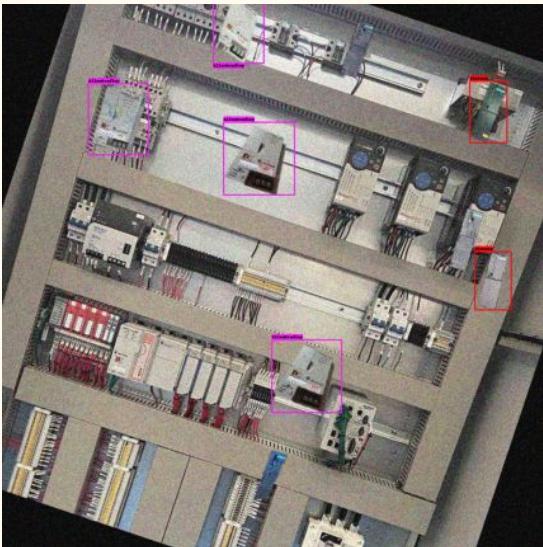


EfficientDet at 1024 resolution has overall least FP and FN for both modules, and relatively good mAP

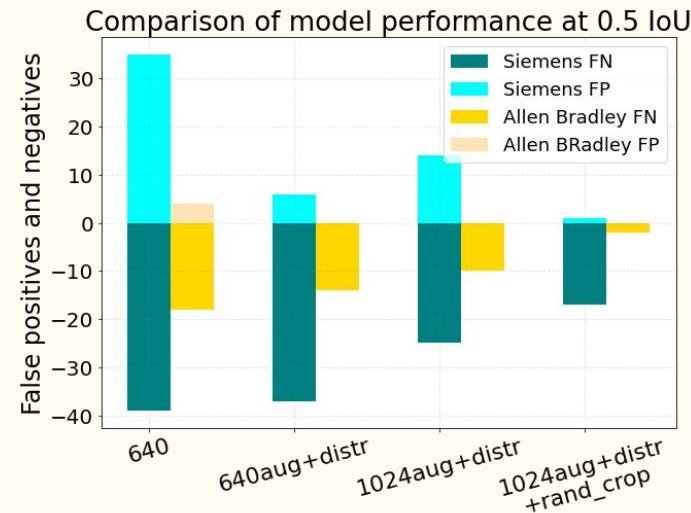
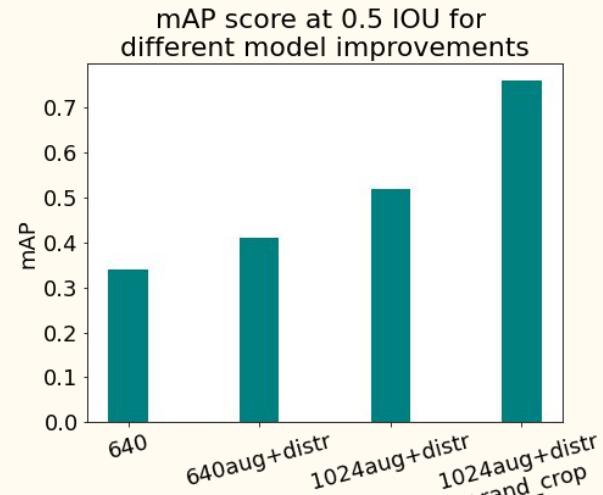


# EfficientDet: Modeling

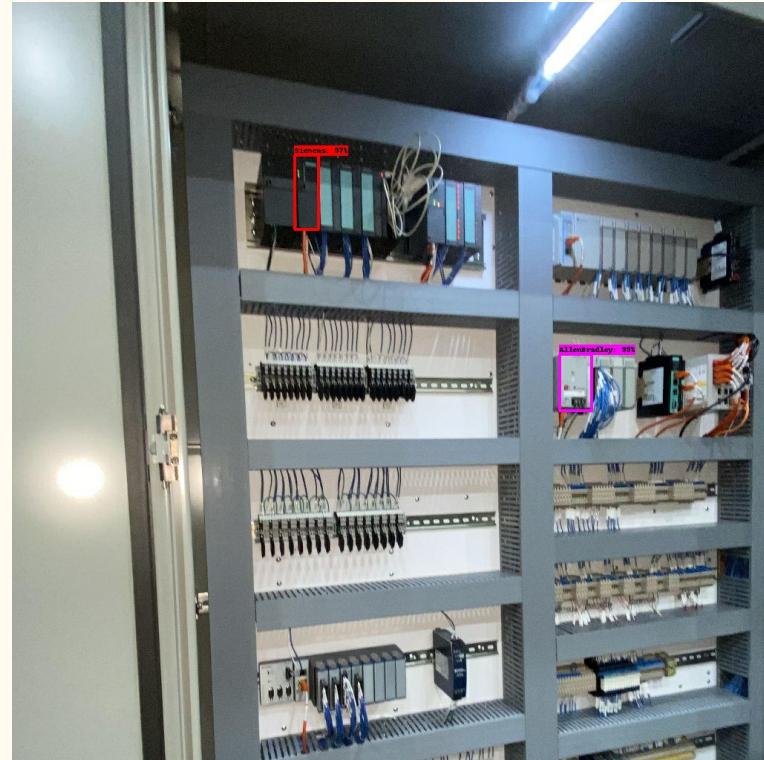
- Higher input image resolution
- Image augmentation
- Distractor objects
- Model-specific parameters:  
learning rate, anchor boxes, ...



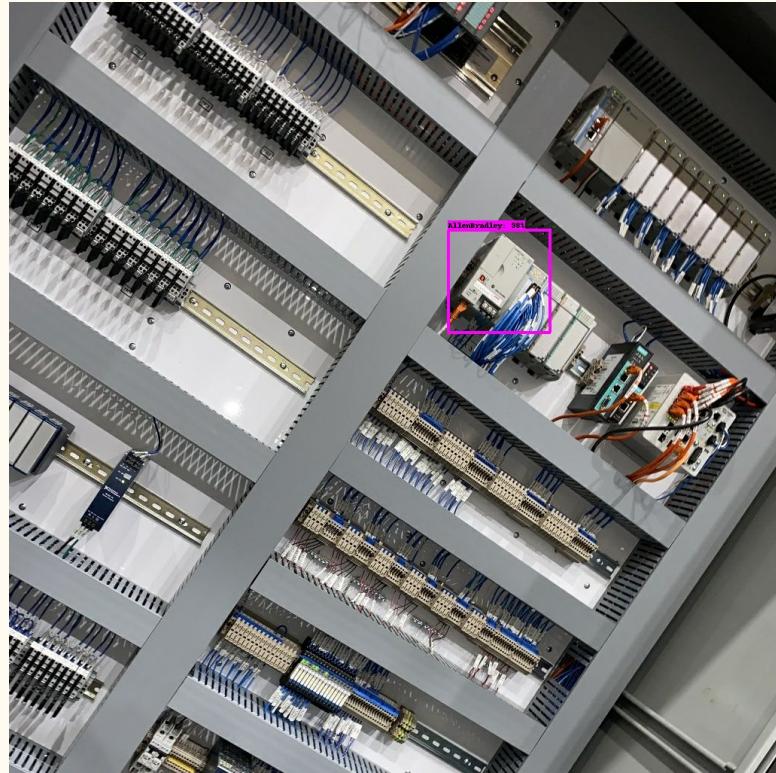
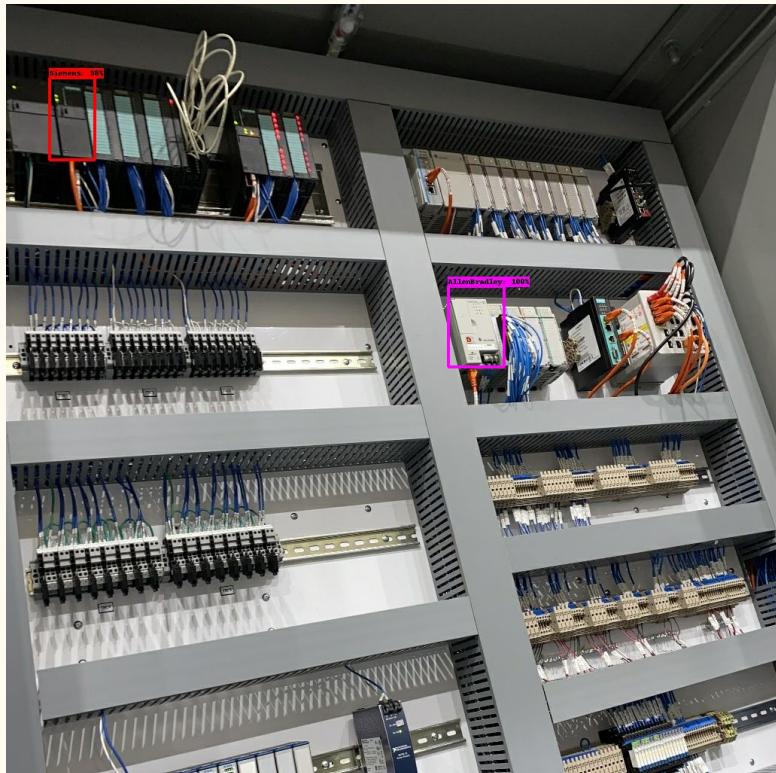
example of an augmented training image



# EfficientDet: Results



# EfficientDet: Results



# EfficientDet: Results



# EfficientDet: Results

a single false detection + non-detections due to obliqueness



# EfficientDet: Results

all images

|              |              | predicted    |         |      |
|--------------|--------------|--------------|---------|------|
|              |              | AllenBradley | Siemens | None |
| ground truth | AllenBradley | 42           | 0       | 3    |
|              | Siemens      | 0            | 23      | 18   |
|              | None         | 0            | 1       |      |



only face-on images

|              |              | predicted    |         |      |
|--------------|--------------|--------------|---------|------|
|              |              | AllenBradley | Siemens | None |
| ground truth | AllenBradley | 18           | 0       | 0    |
|              | Siemens      | 0            | 15      | 1    |
|              | None         | 0            | 0       |      |



# How The Model Could Be Improved

- More diverse training and testing data; data from real control cabinets would be ideal
- Include more controllers as new classes
- Tweaking model hyperparameters - a more exhaustive search

# Conclusion

Fake it till you make it!

Proof-of-concept completed successfully - demonstrable feasibility of using computer vision as an inventory tool

