# Re-surveilling surveillance

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# Background

- Police surveillance cameras in Baltimore form one of many layers of state surveillance imposed upon residents.
- Little documentation, control, or oversight of surveillance landscape
- What role do tech vendors play in surveillance? How can open source tech be used for accountability?

## Tasks

- Identify cameras in images (object detection)
- Categorize camera types once detected (classification)

## Goals

- Improve upon / expand on models I built before—**DONE!**
- Map locations of cameras for spatial analysis—**NOT DONE**

# About the data

| | Google Street View | Objects365 | Mapillary Vistas |
|---|---|---|---|
| Size (train, val, test) | 473 / 119 / 79 | 393 / 107 / 54 | 3,202 / 929 / 484 |
| Setting | Street | Outdoors & indoors | Street |
| Used for | Detection & classification | Detection | Detection |
| Release | Maybe a TOS violation? | Released for research | Released for research |
| Source | Sheng, Yao, and Goel (2021) | Shao et al. (2019) | Neuhold et al. (2017) |

# Tools

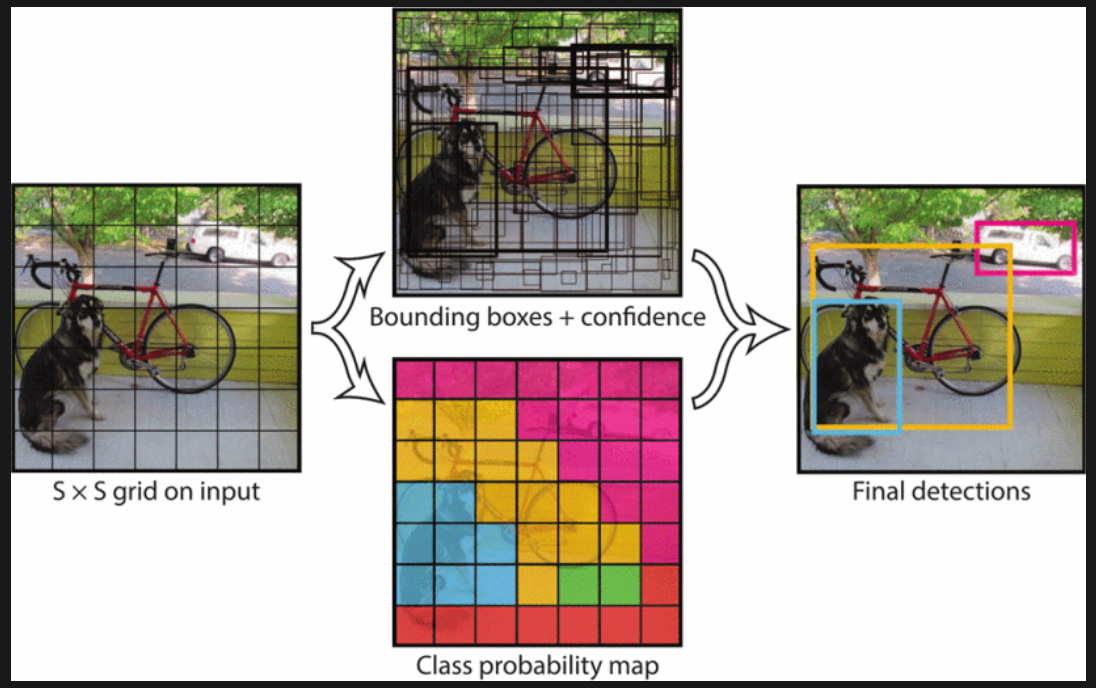
| | |
|---|---|
| Ultralytics YOLOv8 | Models with built-in modules for training, tuning, & validation |
| Pytorch | Underlies Ultralytics models |
| Roboflow | Dataset creation & management |
| Weights & Biases | Experiment tracking |
| Paperspace | Virtual machine (8 CPUs, 16GB GPU) |

# Models

| YOLO | RT-DETR |
| --- | --- |
| Latest generation YOLO model | Transformer-based model from Baidu |
| Detection & classification (& others) | Detection only |
| Smaller architecture (medium has 26M params) | Larger architecture (large has 33M params) |
| Trains very quickly & can train small models on laptop | Trains slowly & needs more GPU RAM |
| Doesn’t perform as well | Performs better |
| Well-documented & integrated | New, not fully integrated to ecosystem (e.g. no `tune` method) |

# YOLO family

- Ultralytics released YOLOv8 this year (Jocher, Chaurasia, and Qiu (2023))
- Avoids anchor box calculations and comparisons of other detection models




YOLOv1 diagram. Redmon et al. (2016)

# Model variations

## Detection

- Freezing all but last few layers—increased speed, maybe increased accuracy
- Tiling images—better detection of small objects

## Classification

- No RT-DETR classifier, so just trying different sizes of YOLO

# Model variations

After lots of trial & error, best bets for detection:

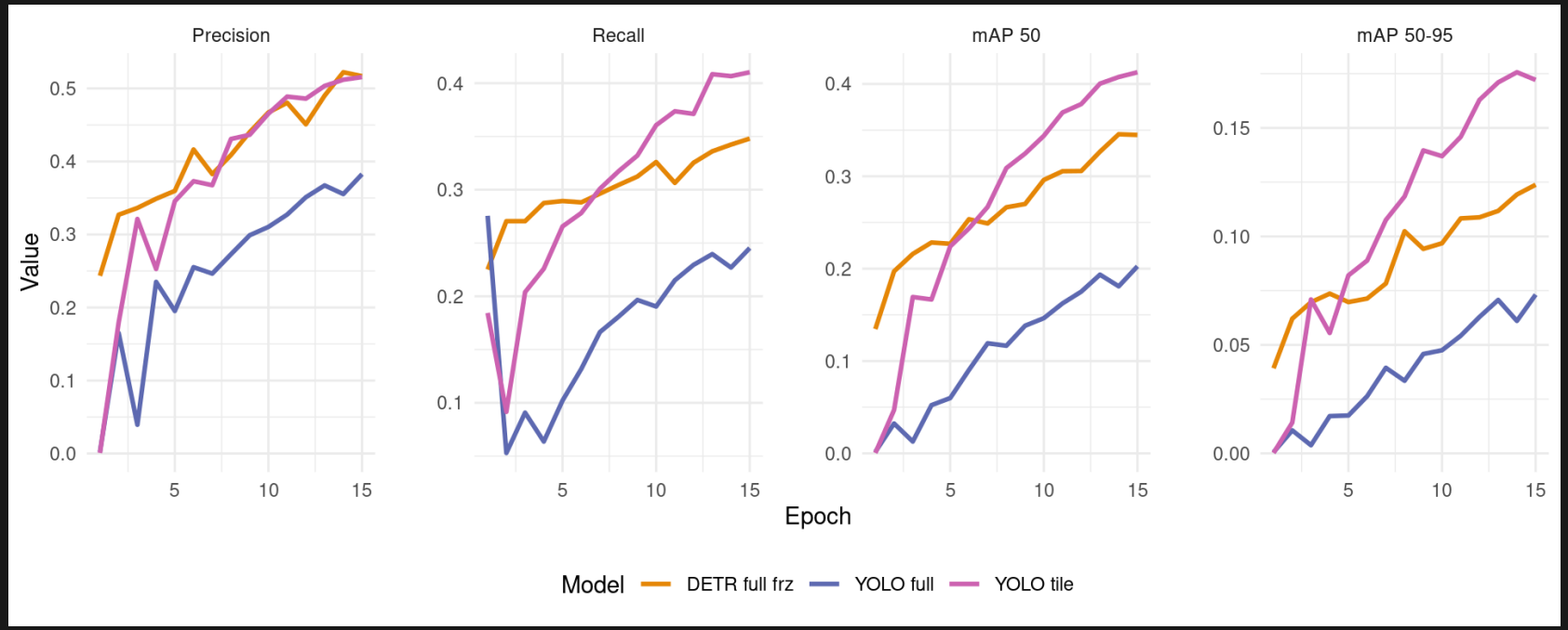
- YOLO trained on full-sized images
- YOLO trained on tiled images
- RT-DETR trained on full-sized images with freezing

Example tiled image

# Results

## Training & first round of validation

YOLO works well on tiled images, but it will need to transfer to full-sized images to be useful




Training results - YOLO & DETR models

# Results

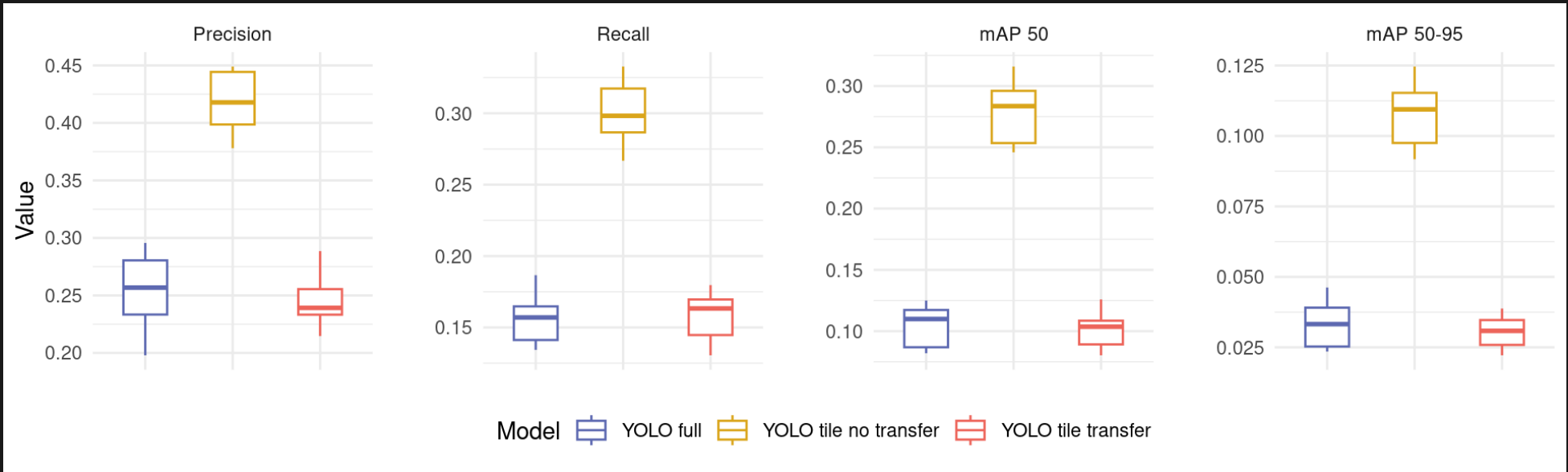
## Validation examples, DETR model


Validation labels


Validation predictions

# Results

## Tuning




Tuning results - YOLO variations only

# Results

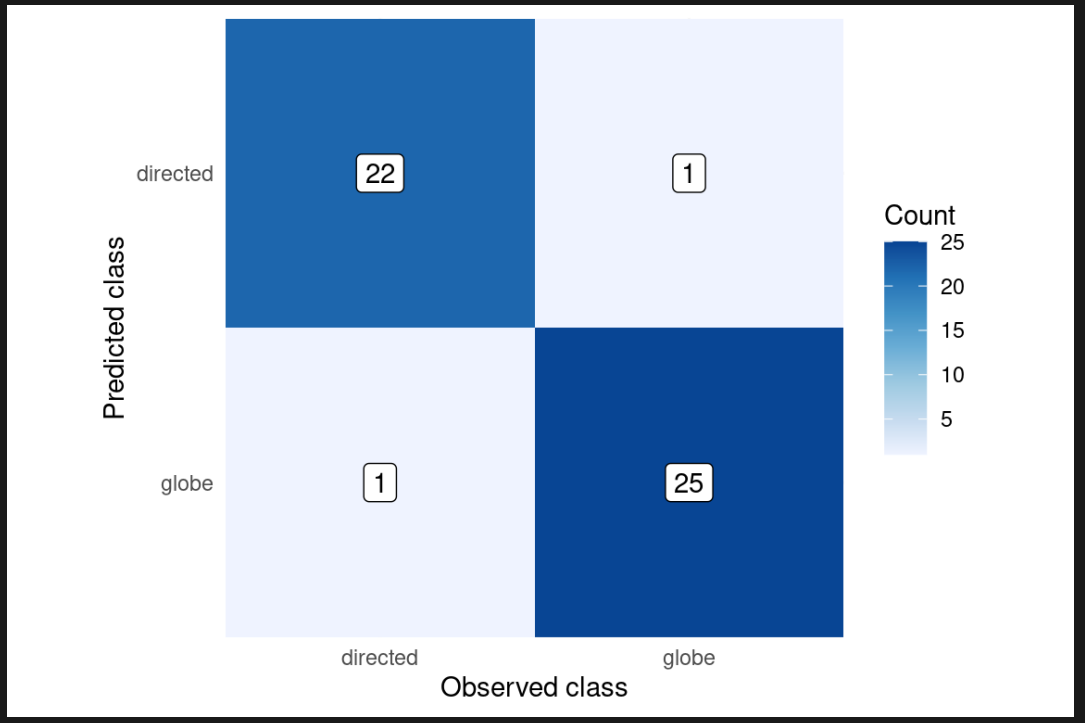
## Tuning—what went wrong?

- Clearly needs more tuning—these metrics are *worse* than untuned models!
- Pick a model & tune extensively & methodically—probably YOLO tiled
  - However, that model runs the risk of not transferring well

# Results

## Classification

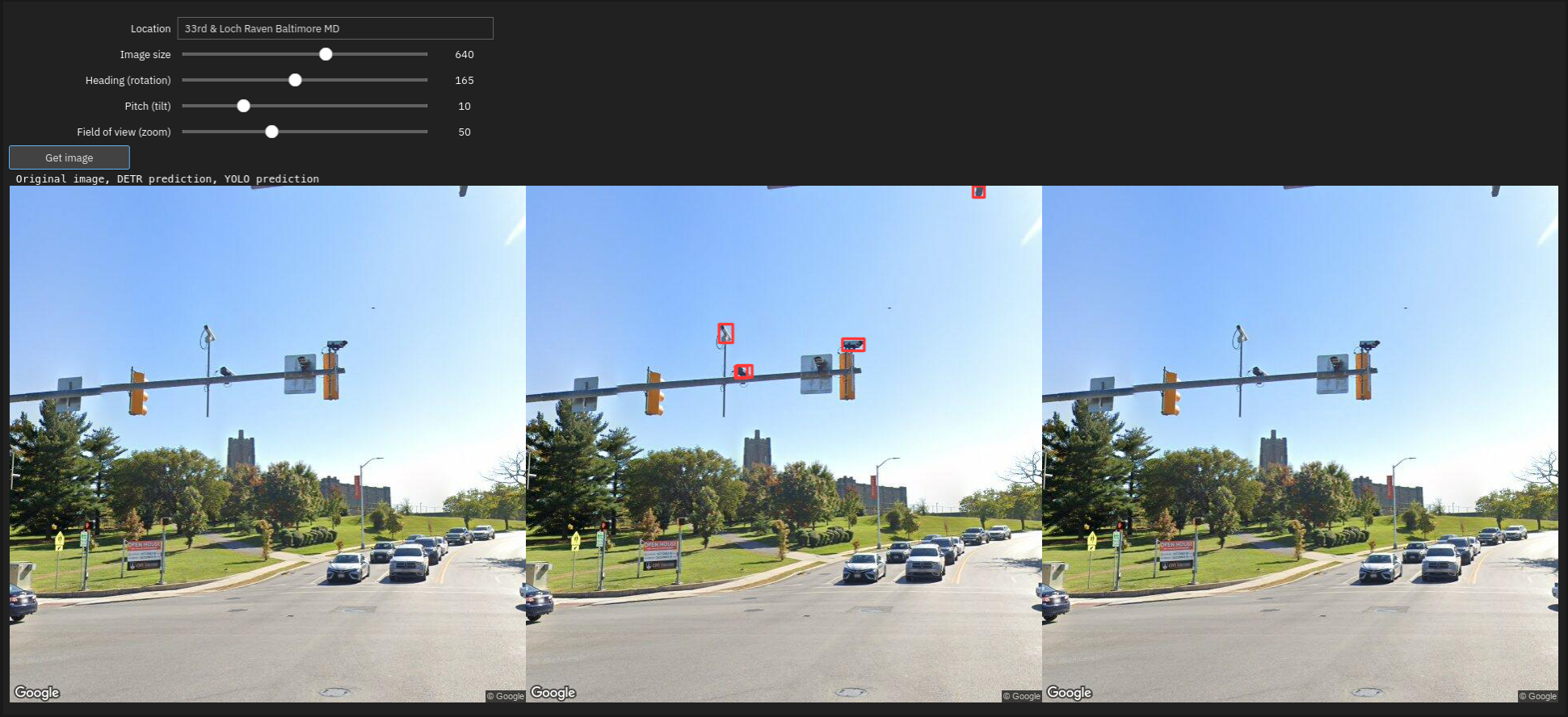
- Works very well
- However, this was only a very small dataset




Confusion matrix, YOLO medium, validation set

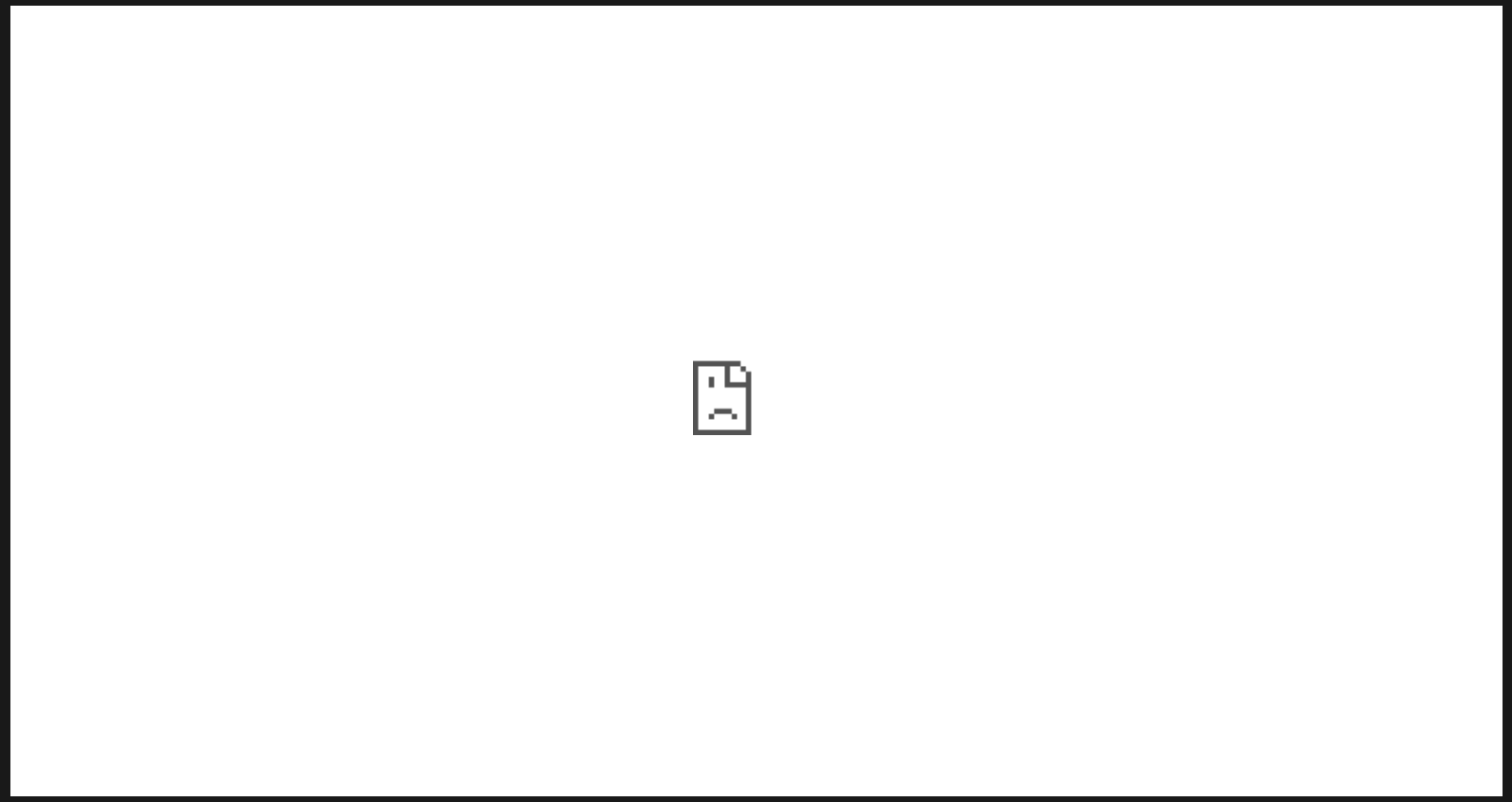
# Results

## Inference




Screenshot of an earlier demo

# Demo



Working interactive demo: https://camilleseab-surveillance.hf.space

# Challenges

- Many moving parts to work together
- Some components are very new & incomplete
- Hard to find lots of high-quality data
- Google Street View images aren’t permanent
- Formatting images & annotations to be compatible
- Reliable, sustained compute power
- A lot to learn!

# Potential improvements

- Need a better tuning methodology—switch to W&B
- Longer training—common benchmarks use 300 epochs
- Add slicing to inference step (SAHI, Akyon, Onur Altinuc, and Temizel (2022))
- Label more images for a larger dataset
  - Can use AI labelling assistants

# Next steps?

- Use the classification model to add classes back to detection images
- Infer on Mapillary images with location data for spatial analysis
  - Mapillary already has so many objects annotated, might only need to do this to fill in gaps

# Conclusions & implications

- This is a potentially useful start but needs more work still
- Surveillance studies, movements for police accountability seem to be tech-averse (with good reason), but there is a role for the technologies deployed against communities to be used by them as well
- Inherently reactionary to be chasing surveillance state after its infrastructure is built

# References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