Satellite Image Object Detection of Pools

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Problem: Identifying Pools using Satellite Imagery

- Build a model capable of detecting multiple pools in one image
- Make it generally fast, able to identify pools without taking excessive time to process a single input
- Compare performance of both multispectral and visible imagery

Applications and Motivation

- Local governments who require permitting or extra tax for pool owners
  - This would give them a simple way to check residents and make sure their data is correct.
- Insurance companies
  - Many home insurance policies will charge more if you have a pool and this could stop people from hiding pools.
- Potential business owners trying to assess how much of the local population owns pools.
  - This would allow businesses to assess how much of the market they have in services like pool cleaning and maintenance.
- Additional motivation of gaining understanding of industry tools and real world applications of computer vision.

Initial Ideas & Research Areas

For this project, we sought to use the following ML concepts in our greater implementation of an object detection (CNN) model:

- Dataset Sourcing
- Transfer Learning
- Multi-Box Implementation

For each one of these, we had to conduct research to decide which industry standard implementations would be the best. We used the following criteria to decide:

a. What solutions exist
b. Which ones are the most efficient
c. Which ones are the most compatible, scalable, etc

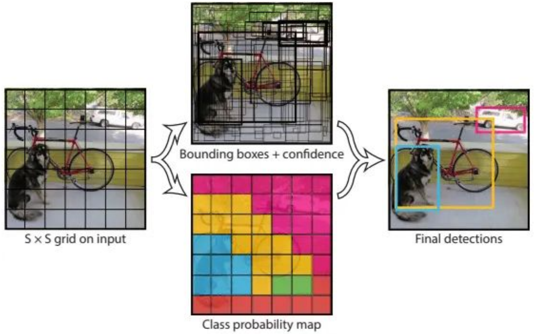
YOLO

Basic Idea:

Residual Block (Gridding)

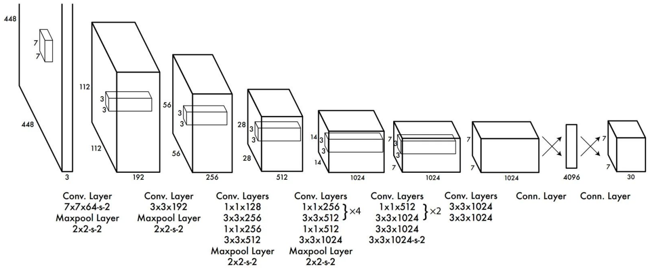
Bounding-Box Regression

IoU (Intersection over Union)



Model:

- YOLO makes training, freezing and manipulating a model very simple.
  - We are supplied with a large library that contains functions and files for easily defining training and using models
  - Because it has a large community backing, there is plenty of online support documentation



Transfer Learning

Transfer learning involves freezing a ‘backbone’ of important image processing layers after a general training and then changing the weights of the last few layers on a smaller set of data.

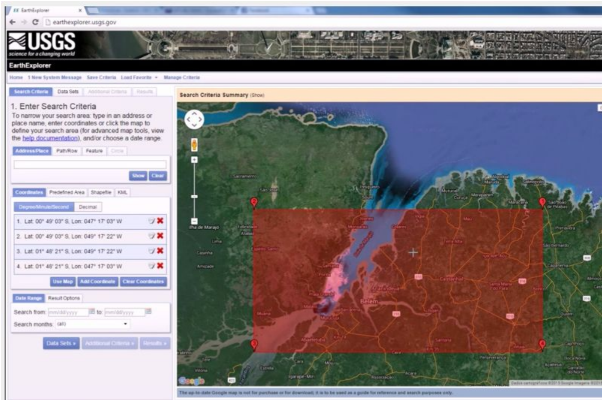
- With YOLO, this can be done by running a training script with a given parameter –-freeze x
  - Where x is the number of layers to freeze
- Backbone, Neck, Head
  - Extract features
  - Further refining
  - Bounding box, prediction → part to freeze?

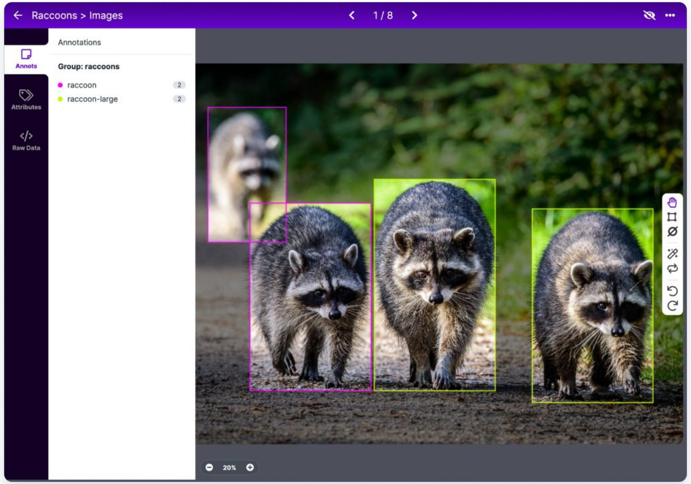
https://kikaben.com/yolov5-transfer-learning-dogs-cats/

Dataset Creation and Image Sourcing

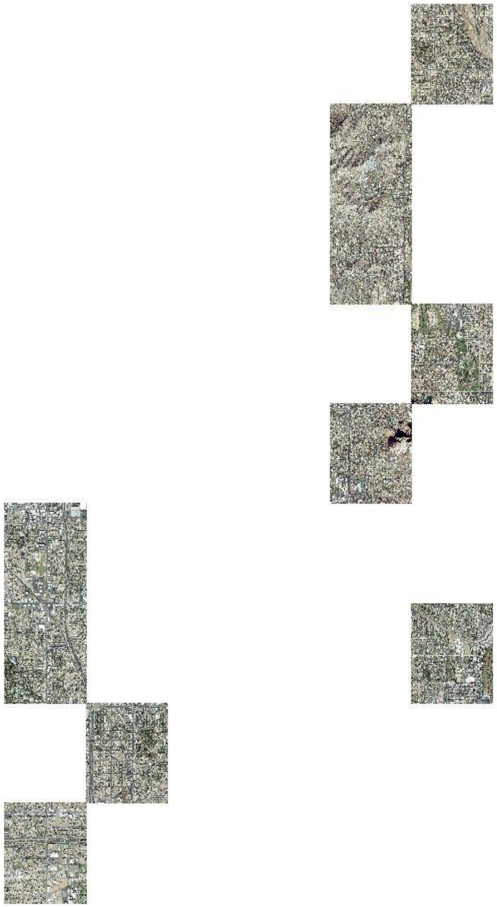
Tools Used:

- USGS Earth Explorer: sourcing satellite imagery files
- QGIS: free software used to view the satellite imagery files and convert to .jpeg
- Roboflow: data management and labeling software used to add bounding boxes and export in format expected by YOLOv8





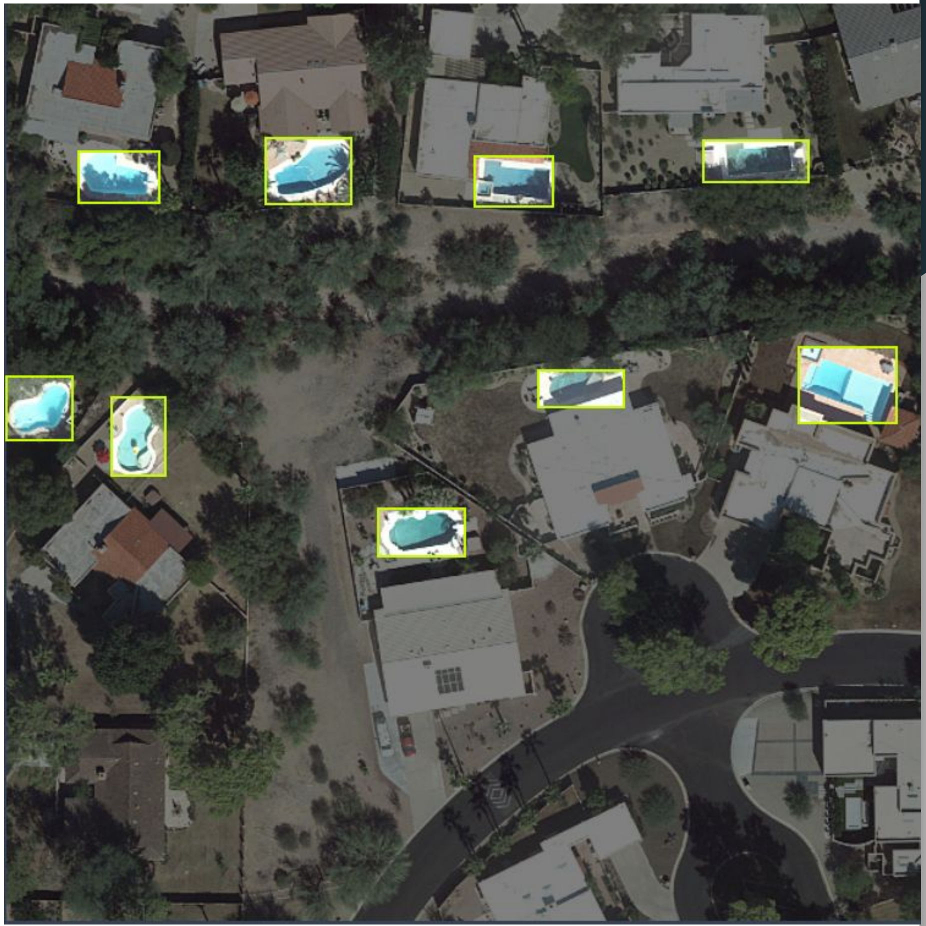
Selected sections from Earth Explorer loaded in to QGIS for conversion from .tif to .jpeg



Each .tif file gets converted into image files with dimensions 6250x6250

Larger sections split into smaller image chips of dimensions 625x625

Final images with bounding boxes added with Roboflow

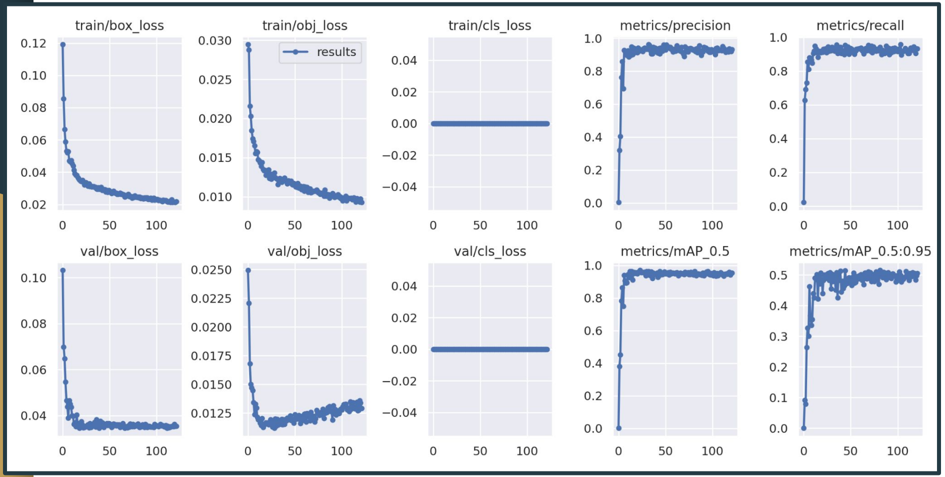


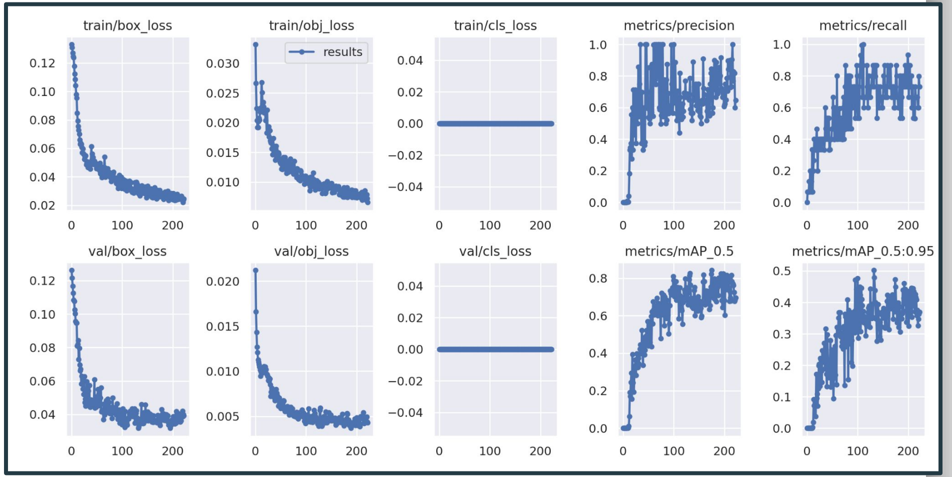
Is Multispectral Imagery Better?

Arizona Dataset vs New York Dataset

97.1% mAP | 93.3% precision | 93.2% recall

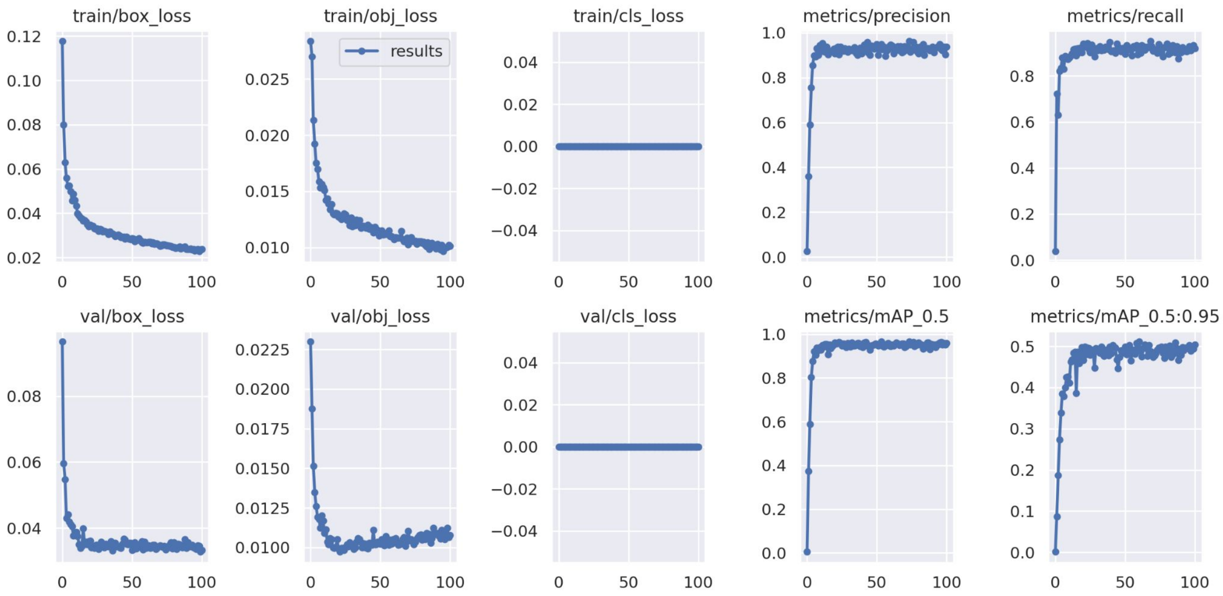
84.3% mAP | 84.4% precision | 73.3% recall





Combined Dataset

96.6% mAP 95.0% precision 91.9% recall



- Smooth curves
- Slightly less accurate than AZ only model
- Far more Accurate than NY Model
- Overall, provides us a more versatile model which can accurately handle NY and AZ

Model Error

Ground Truth

Predicted

Model better than human!

Ground Truth

Predicted

Model Mistake

Ground Truth

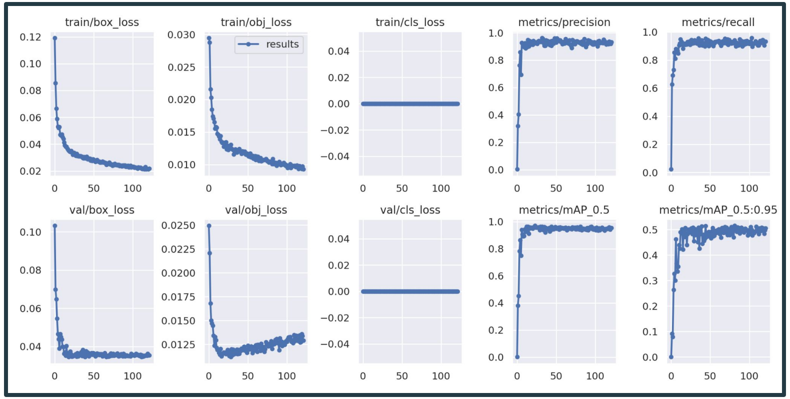
Predicted

Roboflow Model vs Transfer Learning Model

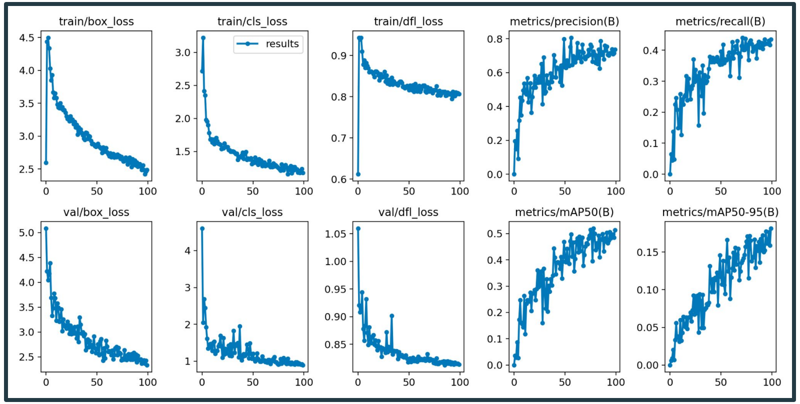
97.1%	93.3%	93.2%
mAP	precision	recall

Box(P	R	mAP50
0.732	0.433	0.51

Roboflow



Transfer Learning



Conclusions

- Dataset Quality, Diversity and Quantity
- Computer Vision Implementation
- Industry Standard Tools

Questions?