POI Geometries Retrieval with Image Segmentation from Satellite Imagery

One of the tasks I worked on during my time at Locatium.AI

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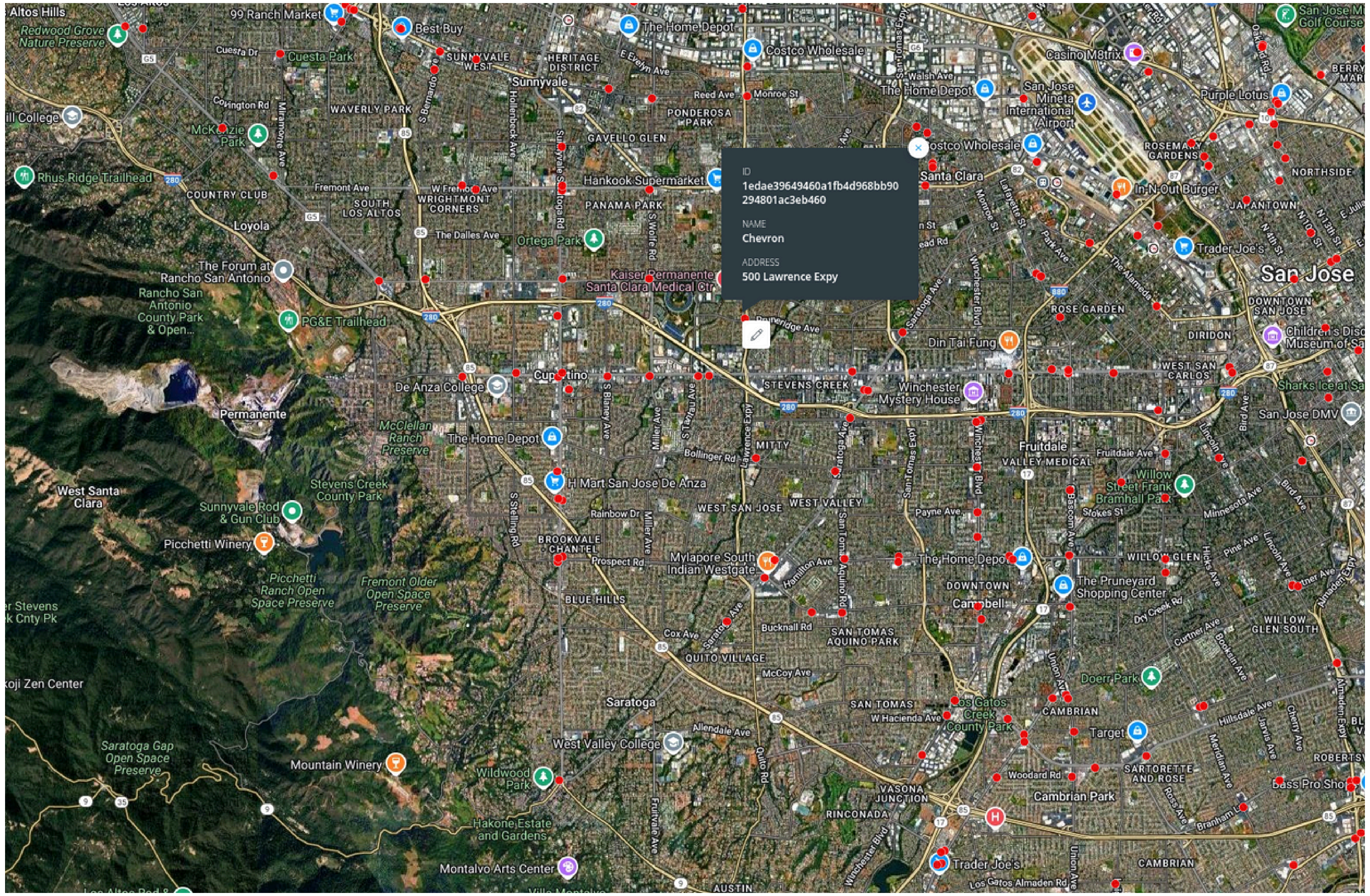
Due to internal confidentiality constraints, this represents only a limited subset of the company's full internal dataset, and the mobility data provider cannot be disclosed.

Segmentation vs Detection

Object detection identifies and localizes individual objects in an image by assigning them a class label and a bounding box.

Image segmentation classifies every pixel in an image, partitioning it into regions that correspond to different objects or semantic categories.

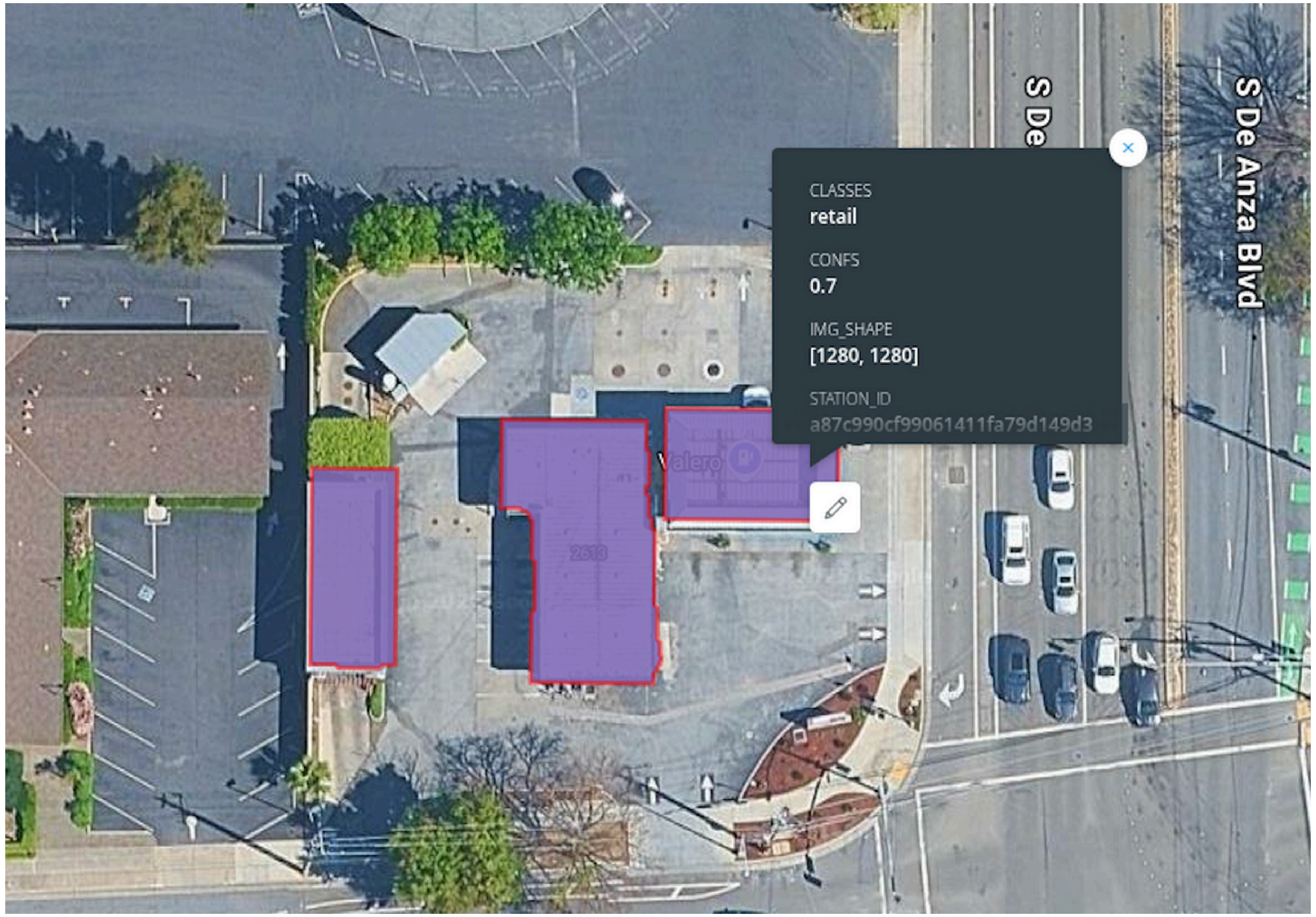
Input



The framework needs to associate a satellite image with each ground site; therefore, the input consists of:

- High-resolution satellite images centered on POI locations.
- Predefined geographic coordinates for each site (lon/lat)

Output



The output consists of a structured table where each row represents a geometry extracted for a specific site, accompanied by the confidence score assigned by the model to that output.

Obtain Site Parcels

Foundational Literature and Methodological Starting Point

While numerous papers apply deep learning to satellite imagery, *Gao et al. (2021)* [1] is particularly relevant for its YOLOv3-based detection of gas-station footprints.

The authors developed an improved YOLO architecture capable of reliably identifying gas-station buildings in remote-sensing images.

Extending this line of work, YOLOv11 is used here to perform precise segmentation of gas-station parcels.

Satellite Imagery

The YOLOv11 model was fine-tuned on a diverse dataset of over 12,000 gas-station images, primarily from California and supplemented with stations from southern and midwestern states.

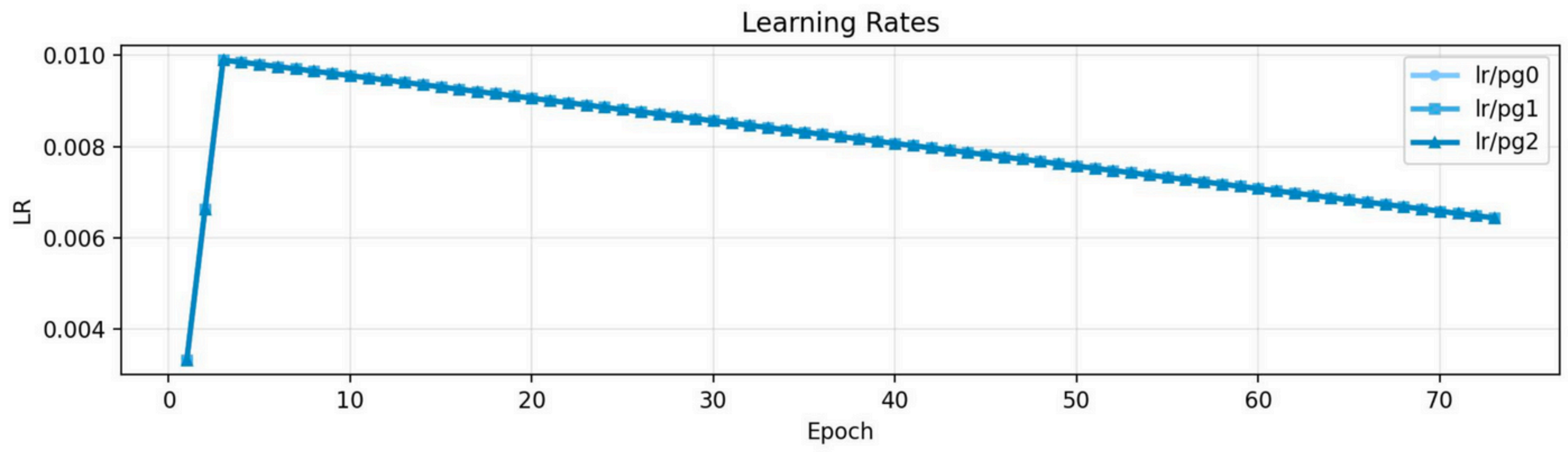
Images were obtained from the company's internal provider, whose identity cannot be disclosed, and pre-centered on the station parcels to facilitate segmentation while retaining contextual features.

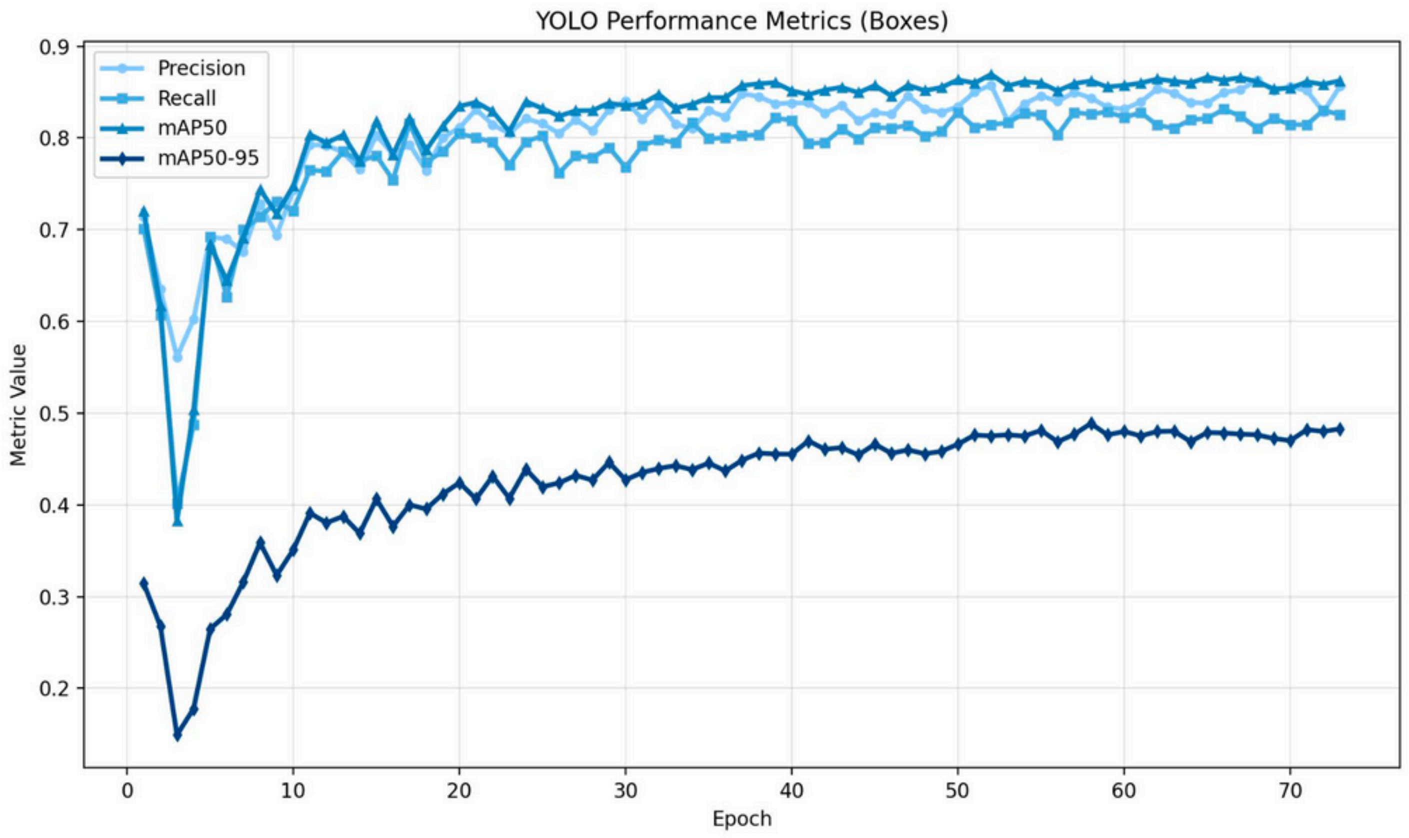
[1] Jinfeng Gao, Yu Chen, Yongming Wei, and Jiannan Li. Detection of specific building in remote sensing images using a novel yolo-s-ciou model. case: Gas station identification. Sensors, 21(4):1375, 2021.

Obtain Site Parcels

Training Set Up

The dataset was partitioned into training (70%), validation (15%), and test (15%) sets to ensure robust model development and reliable performance evaluation.





Training ran for just over 70 epochs with batch size 16 and a learning rate scheduler that ramped up in the first 5 epochs then decayed linearly. Metrics improved rapidly during the first 15 epochs before plateauing. Data augmentation, including rotations and geometric transformations, was applied to enhance robustness.

Obtain Site Parcels

Results

The YOLOv11 model achieved high precision, recall, and mAP in detecting and segmenting gas station parcels. This strong performance is partly due to images being pre-centered on each station, which simplified the task for the model.

Any missed or poorly segmented stations were manually corrected using QGIS, ensuring complete and accurate polygon coverage.

Metric	Precision	Recall	mAP@50	mAP@50:95
Bounding Boxes	0.973	0.964	0.983	0.609
Segmentation Masks	0.960	0.951	0.965	0.574

Deployment

Remote GPU Model Serving via Dockerized Microservices

Designed and deployed a remote, GPU-enabled inference infrastructure using Docker to serve multiple point-of-interest (POI) category models. The system is organized as a containerized microservice architecture, where an Nginx reverse proxy routes incoming requests to a Flask-based API. The API orchestrates request handling, dispatches inputs to the appropriate model container within the Docker network, and returns only the processed outputs (GeoDataFrames) to the client.

This setup enables efficient remote execution of compute-intensive models from a local environment, minimizing data transfer while fully leveraging centralized GPU resources for scalable and maintainable inference.