

Objective

- Lack of precise data on behind the meter photovoltaic (PV) system capacity and output.
- Develop a **machine learning model** that, given a certain geographical location, can **detect the amount of solar panel arrays** and then estimate the **yearly solar power generation**.
- Meet the needs of urban planning and renewable energy sectors, and efficient electrical supply allocation and overall grid stability management.

System Design and Requirements

System Design

- Satellite Image and Solar Information Retrieval
- Solar Panel Detection
- Solar Energy Estimation
- Roboflow for annotation
- Segment Anything Model for pseudo label generation

System Requirements

- Collection and annotation of over 2000 images
- Achieve 85% mAP50 for bounding boxes and 80% mAP50 for masks.
- Fully automated end-to-end process.
- Scalable address processing.
- Generalizable to U.S. addresses.

Conclusion and Future Work

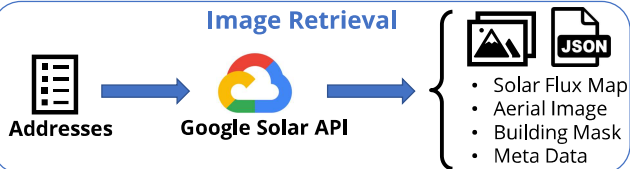
Conclusion

- Our system demonstrates the feasibility of using a vision-based algorithm to analyze residential solar panels on a large scale.
- System implementation follows intended design with some caveats.

Limitations and Future Work

- Limited training image dataset
- Lack of fined-grained ground truth data to validate our estimation
- Could analyze feeder data and account for other factors such as precipitation or soiling to improve PV energy estimation.
- Could utilize different APIs (pvlib, pvgis, pvwatts)

Image Retrieval



Solar Panel Detection



Monthly PV Energy Estimation

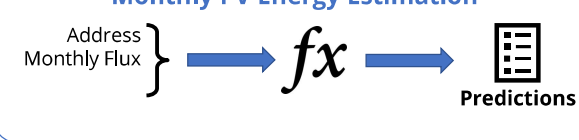


Image Collection, Processing, and Annotation



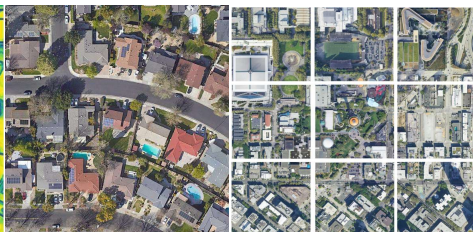
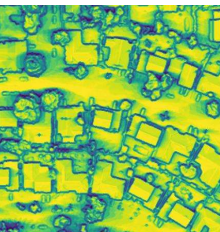
Four, 640x640 patches of one 1280x1280 pixels image.

- Learned on 1656 train + 414 validation, 640x615 pixel images [3].
- Sampled addresses from many urban counties across USA to generate training and validation set.



Left: unannotated image with solar panels.
Right: annotated image with solar panels using square bounding boxes [3].

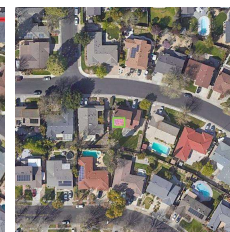
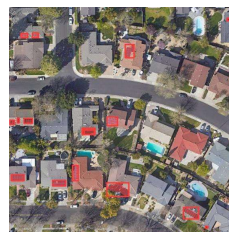
- Used Roboflow to host the dataset, train, run inferences, and annotate images.
- First set of custom dataset images were annotated using square bounding boxes.
- Collects **solar flux** (incident sunlight) map (left), **RGB image** (center), and can automatically do this for a **grid of images** (right).



Solar Panel Detection

	Train Epoch	Box mAP 50	Box mAP 50-95	Recall	Mask mAP 50	Mask mAP 50-95
YOLOv8+ BBox	100	0.86	0.65	0.75	-	-
YOLOv8-seg+ Polygon	100	0.86	0.67	0.77	0.84	0.47

- Detector: Ultralytics YOLOv8-seg [1].
- Instance mask pseudo label generator: Segment Anything Model (SAM) [2].
- Post process detection results by filtering instances with building mask and calculate instance mask area.



Left: visualized detection results.
Right: detection results filtered by center building mask.

Monthly PV Energy Estimation

$$\text{System Size} = \text{Array Area} \times 1 \frac{\text{kW}}{\text{m}^2} \times \text{module efficiency}$$

$$E = P_s \times r_p \times H_{s,d}$$

Where:

E: is the monthly potential in kWh

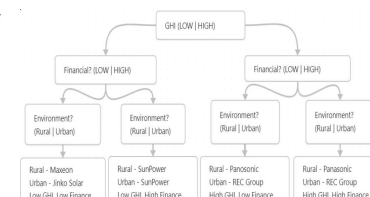
P_s : Peak power of the system in kW

r_p : System losses

$H_{s,d}$: Monthly total radiation in kWh/kW/month

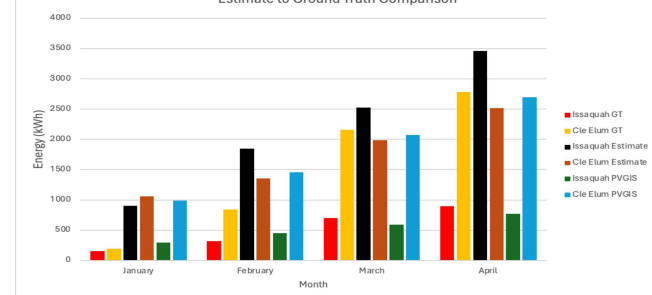
Algorithm from similar study done [4].

- Array area is generated from our detection model.
- Peak power is the system size.
- We keep system losses constant at 14% for each ROI.
- Monthly total radiation is taken from flux map layers generated from Google Solar.



Flow chart to inference solar panel for each address. Module efficiency taken from selected module dataset at Standard Test Conditions.

Estimate to Ground Truth Comparison



PVGIS specifications chosen as crystalline-silicon technology, optimal azimuth, optimal array tilt, 14% system losses [5].