

## Introduction

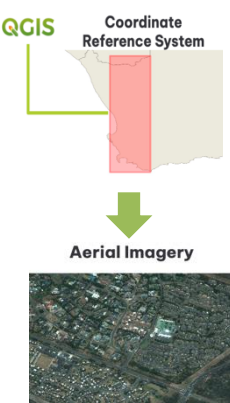
Cape Town faces persistent **load shedding**, the scheduled disconnection of electricity power in certain areas to prevent a complete power outage when electricity demand exceeds supply. As a result, wealthier households install rooftop **solar energy systems** to stay powered, while low-income communities are unable to access a stable energy source.

Unequal access to energy deepens economic inequality and limits opportunities for growth. By determining the **location** and **quantity** of solar energy systems, we can identify areas with low energy capacity. Collecting such data is critical for implementing policy changes in Cape Town that aim to alleviate the impacts of load shedding.

## Objectives

- **Detect and classify solar energy systems** (solar panels, water heaters, and pool heaters) from aerial imagery
- **Estimate solar energy capacity** across Cape Town based on the predicted locations of **solar panels**
- **Build an end-to-end data pipeline**: dataset processing → model training → post-processing → output evaluation

## Data



- **Cape Town, South Africa aerial imagery**
  - Coordinate Reference System: ESRI 102562
  - Coordinates in (x, y), measured in meters from (0°, 0°) origin
  - Annotated in QGIS, preserving metadata
  - Total 2,802 images (12,500x12,500, 8cm/pixel)
- To ensure annotation quality, **top images by annotation count were manually refined.**

Dataset Group	Number of Images	Number of Annotations by Class				
		Solar Panels	Water Heater	Pool Heater	Uncertain	Total
Initial	268	10,787	5,216	2,503	1,920	19,735
Refined	15	2,033	1,983	1,146	0	5,162

Figure 1. Summary of Annotation Counts by Class

## Model Selection

YOLO + U-Net and U-Net were evaluated on unseen images (889 annotations). U-Net showed higher precision for solar panels, while YOLO + U-Net yielded higher recall. Final selection should consider **actual prediction accuracy.**

Model	Class	IoU	Precision	Recall
YOLO + U-Net	Solar Panel	0.762	0.778	0.974
	Water Heater	0.525	0.765	0.626
	Pool Heater	0.698	0.798	0.846
U-Net	Solar Panel	0.793	0.832	0.943
	Water Heater	0.501	0.769	0.589
	Pool Heater	0.694	0.819	0.819

Figure 2. Performance comparison of YOLO+U-Net vs. U-Net

## Data Pipeline

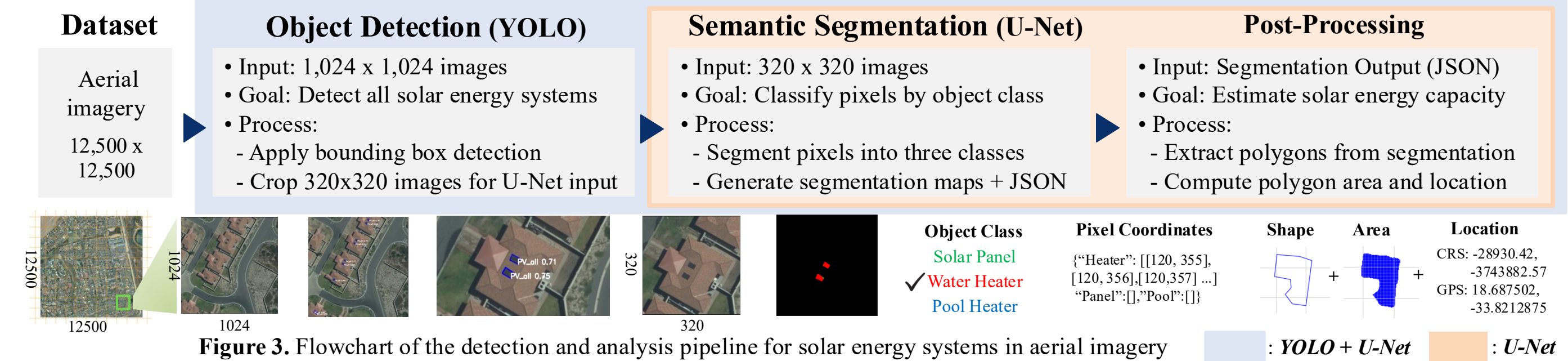


Figure 3. Flowchart of the detection and analysis pipeline for solar energy systems in aerial imagery

## Object Detection (YOLO)

- YOLOv11\_OBB is an object detection model that supports oriented bounding boxes, enabling localization of tilted or rotated solar energy systems in aerial imagery.
- The input is 1,024 x 1,024 images and all solar types were grouped into a single class for binary detection. The detected object was cropped into a 320 × 320 patch for subsequent semantic segmentation.
- Model performance was evaluated using mean Average Precision(mAP).

Metric	Value
mAP@0.5	82.5%
mAP@0.5:0.95	70.3%

\* @.5 = IoU ≥ .5, @.5:.95 = mean over range

Figure 4. YOLO mAP performance



Figure 5. (Left) 1,024x1,024 detection patch (Right) 320x320 crop centered on the object

## Semantic Segmentation (U-Net)

- U-Net is an image segmentation model to predicts a class label (solar panel, water heater, pool heater) for each pixel in an image to create a segmentation map.
- The input is 320 x 320 images and their corresponding one-hot encoded masks. The output is a segmentation mask. (**Black**: background, **green**: solar panel, **red**: water heater, **blue**: pool heater).
- Model performance was evaluated using Intersection over Union (IoU).

Metric ( IoU)	Value
Solar Panel	68.7%
Water Heater	60.4%
Pool Heater	74.5%

Figure 6. U-Net IoU performance



Figure 7. (Left) 320x320 input image (Right) 320x320 segmentation mask

**Model Training Summary:** Both YOLO and U-Net were trained on 15 12,500 x 12,500 aerial images (5,162 solar objects) with a learning rate of 1e-4. YOLO performed binary object detection by learning all solar energy systems as a single class, whereas U-Net performed multi-class segmentation for solar panels, water heaters, and pool heaters.

## Post-Processing

**Polygonization:** Predicted pixels coordinates are grouped into polygon shapes for solar objects

**Area Calculation:** The area of each solar object is computed using polygon geometry and geospatial data

**Georeferencing:** The vertices of each polygon are converted into latitude/longitude

**Rooftop Grouping:** In the future, solar objects will be grouped by rooftop for household-level solar energy estimates

## Results

### Regional Accuracy in Solar Panel Area Estimation

Model	Region (Image ID)	Ground Truth Area (m²)	Predicted Area(m²)	Absolute Error (m²)	Relative Error	Accuracy
Yolo + U-Net	W57B_8	2833.9	2819.6	-14.3	-0.5%	99.5%
	W24A_17	1193.4	2399.2	1205.8	101.0%	1.0%
	W25C_16	413.1	501.2	88.0	21.3%	78.7%
	<b>Total</b>	<b>4440.5</b>	<b>5720.0</b>	<b>1279.5</b>	<b>28.8%</b>	<b>71.2%</b>
U-Net	W57B_8	2833.9	2750.3	-83.6	-2.9%	97.1%
	W24A_17	1193.4	1249.7	56.3	4.7%	95.3%
	W25C_16	413.1	427.8	14.7	3.6%	96.4%
	<b>Total</b>	<b>4440.5</b>	<b>4427.8</b>	<b>-12.6</b>	<b>-0.3%</b>	<b>99.7%</b>

Figure 8. Accuracy of solar panel area estimation by model

## Limitations & Future Research

- The model used 5,162 annotations from 15 of 2,802 aerial images for training and pipeline setup.
- Prediction may improve with refined post-processing and evaluation at the individual panel-level.

- A comparative evaluation was conducted on 337 solar panels across three regions in Cape Town to assess the accuracy of the U-Net and YOLO + U-Net models in estimating solar panel area.
- **U-Net demonstrated higher and more consistent accuracy** in solar panel prediction, making it suitable for region-wise estimation of solar panel area.