Model Card: Solar Panel Detection (YOLOv8m)

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Abstract

This document provides a detailed overview of the Solar Panel Detection model (v1.0). The model utilizes the YOLOv8-Medium architecture to identify and localize solar PV panels in aerial imagery. It was trained on a composite dataset aggregated from Roboflow archives. The model achieves a mean Average Precision (mAP) of 91.5% at IoU 0.5, demonstrating high reliability for automated infrastructure auditing and renewable energy capacity estimation.

MODEL DETAILS

- **Model Name:** Solar Panel Detection v1.0
- **Architecture:** Ultralytics YOLOv8-Medium (25.8M parameters).
- **Framework:** PyTorch 2.9.0 / Ultralytics 8.3.234.
- **Input Resolution:** 640×640 pixels.
- **License:** MIT License (Codebase), Dataset licenses vary by source.
- **Model Date:** December 4, 2025.
- **Hardware:** Trained on NVIDIA Tesla T4 (15GB VRAM).

INTENDED USE

Primary Use Cases

- **Automated Asset Monitoring:** Detecting solar installations in satellite or drone imagery to update geospatial databases.
- **Capacity Estimation:** Counting panels to estimate power generation potential for residential or commercial zones.
- **Maintenance Auditing:** Identifying physical damage or debris accumulation (when coupled with higher-resolution zoom).

Out-of-Scope Use Cases

- **Ground-Level Detection:** The model is specialized for aerial/nadir perspectives; performance on street-view imagery is not guaranteed.
- **Thermal Defect Analysis:** This model detects the presence of panels (RGB), not thermal hotspots or internal electrical faults.

DATA OVERVIEW

The training data was constructed by merging three distinct open-source datasets to ensure diversity in resolution, lighting, and background environments.

Dataset Composition

Source Dataset	Contribution
`solar_panels_rf100`	Roboflow 100 Benchmark subset
`solar_pv_detection`	High-density residential installations
`ww_solar_panel`	Varied industrial/commercial setups

Data Split Statistics

- **Training Set:** 3,050 images (containing 16,174 instances).
- **Validation Set:** 568 images (containing 3,708 instances).
- **Preprocessing:** Auto-orientation, resizing to 640px.
- **Augmentation:** Mosaic (1.0), Mixup (0.1), HSV-Hue (0.015), HSV-Saturation (0.7), HSV-Value (0.4), Translation (0.1), Scale (0.5).

TRAINING PROCEDURE

The model was trained using a standard Stochastic Gradient Descent approach with the AdamW optimizer.

Hyperparameters

Parameter	Value	Parameter	Value
Epochs	100	Initial LR (lr_0)	0.001
Batch Size	8	Final LR (lrf)	0.01
Optimizer	AdamW	Momentum	0.937
Weight Decay	0.0005	Patience	20 epochs

Training Dynamics

Training spanned 3.26 hours. The loss functions (Box, Cls, DFL) showed steady convergence.

- **Box Loss:** Reduced from 1.63 (Epoch 1) to 0.76 (Epoch 100).
- **Classification Loss:** Reduced from 2.08 (Epoch 1) to 0.53 (Epoch 100).
- **Precision Improvement:** Started at 0.409, stabilized ≈ 0.88 by Epoch 85.

EVALUATION RESULTS

The following metrics were calculated on the validation set (568 images) using the weights from the best-performing epoch.

Quantitative Metrics

Class	Precision	Recall	F1 Score	mAP@50	mAP@50-95
Solar Panel	**0.877**	**0.837**	**0.857**	**0.915**	**0.685**

Table 1: Final validation metrics. The high F1 Score (0.857) indicates an optimal balance between precision and recall.

Interpretation

- **mAP@50 (91.5%):** The model is highly effective at detecting panels with a standard intersection-over-union overlap of 50%.
- **mAP@50-95 (68.5%):** The high score in this strict metric indicates excellent bounding box localization accuracy (the predicted boxes fit the panels very tightly).
- **Precision vs. Recall:** The balance (0.877 vs 0.837) suggests the model is slightly conservative; it prioritizes being correct when it claims a detection over finding every single obscure panel.

ASSUMPTIONS, LIMITATIONS, AND BIAS

Assumptions

- The model assumes a "bird's eye" or high-angle oblique view.
- Images are assumed to be RGB (Visual Spectrum).
- Solar panels are assumed to be rectangular or semi-rectangular geometries.

Known Limitations

1. **Occlusion:** Heavily occluded panels (e.g., covered by tree branches) may be missed due to the objectness threshold.
2. **Glare/Reflection:** Extreme specular reflection (sun glint) on panels can occasionally cause false negatives by washing out feature details.
3. **Resolution Dependency:** Performance degrades on low-resolution satellite imagery where panels occupy fewer than 15×15 pixels.

Failure Modes

- **False Positives:** Skylights, swimming pools, and greenhouses may occasionally be misclassified as solar arrays due to similar blue rectangular features.
- **False Negatives:** Dark-colored rooftops (black shingles) with flush-mounted black panels may result in missed detections due to low contrast.

RETRAINING AND MAINTENANCE GUIDANCE

To maintain model performance or adapt to new environments:

1. **Threshold Tuning:** For production use, a Confidence Threshold of 0.45 is recommended to balance precision and recall.

2. **Data Drift:** If the deployment involves a different geographical region (e.g., changing from suburban US to desert environments), collect 200-500 new sample images and perform fine-tuning (freeze the backbone, retrain the head).

3. **Hard Negative Mining:** If the model consistently misidentifies skylights, add a dataset of skylights labeled as "background" (empty) to penalize false positives during retraining.

ETHICAL CONSIDERATIONS

- **Privacy:** While the model detects infrastructure, it is applied to aerial imagery which may incidentally capture private property. Users must adhere to local geospatial data privacy regulations.

- **Bias:** The training data predominantly features Western-style residential and commercial architecture. The model may underperform on informal settlements or unique panel configurations found in developing regions.