MODEL CARD: SūryaNetra

1. Model Details

- **Architecture:** YOLOv8 (You Only Look Once), fine-tuned for small object detection in aerial imagery.
- **Task:** Object Detection (Bounding Box) & Semantic Segmentation approximation.
- **Input:** High-resolution RGB satellite imagery (Google Maps Static API, ESRI).
- **Output:** Bounding boxes for solar_panel, Confidence Score (0-1), and Estimated Area (m^2).
- **Frameworks:** PyTorch, Ultralytics, OpenCV.

2. Intended Use

Primary Use Case: This model is designed specifically for the **PM Surya Ghar: Muft Bijli Yojana** audit pipeline. It is intended to:

1. Verify the *presence* of rooftop solar installations at specific GPS coordinates.
2. Estimate the effective solar area to validate subsidy capacity claims (up to 3kW).
3. Flag non-compliant or empty sites for fraud prevention.

Out-of-Scope Use Cases:

- This model is not designed for *thermal* defect detection (hotspots).
- It is not intended to count individual photovoltaic cells (micro-detection).
- It should not be used as the sole decision-maker for legal prosecution without human review (hence the "Citizen Appeal" workflow).

3. Training Data & Sources

The model was trained on a diverse dataset of Indian and international rooftop imagery to ensure robustness across urban and semi-urban environments.

- **Primary Datasets:**
    - *Alfred Weber Institute of Economics (Roboflow)*: High-contrast urban roofs.

- *LSG1547 Project (Roboflow)*: Semi-urban and cluttered roof environments.
- *Piscinas Y Tenistable (Roboflow)*: Used for negative sample training (distinguishing pools/tennis courts from panels).

- **Augmentation Strategy:**
  - To handle India's diverse atmospheric conditions, we applied: *Random Brightness (±25%)*, *Gaussian Blur* (simulating smog/haze), and *Mosaic Augmentation* (to handle scale variations).

4. Model Logic & Innovations

Standard object detection fails in governance audits due to **GPS Drift** (satellite coordinates rarely align perfectly with the roof center). SūryaNetra mitigates this via:

A. Swarm-Overlap Logic

Instead of requiring "Containment" (Panel inside Coordinate), we utilize **Geometric Intersection**.

- **Buffer Zone 1:** 1200 sq. ft. (Immediate Audit Zone)[4].
- **Buffer Zone 2:** 2400 sq. ft. (Extended Search Zone)[5].
- **Decision Rule:** If Intersection_Over_Union (IoU) > 0 between a high-confidence detection and the Buffer Zone, the site is marked **VERIFIABLE**.

B. Latitude-Dynamic Quantification

Pixel area is not constant on Mercator maps. We implemented a dynamic scaler:

$$Area_{m^2} = Area_{pixels} \times C \times \cos(Latitude)$$

This ensures a house in Kashmir (North) and Kerala (South) receive accurate area estimates despite map projection distortion.

5. Performance Metrics

Metrics extracted from best training epoch (See Model Training Logs/results.csv):

- **mAP@50 (Mean Average Precision): 0.856 (85.6%)** - *High reliability in identifying panel boundaries.*
- **Precision: 0.884** - *Low False Positive rate (few non-solar roofs flagged as solar).*

- **Recall: 0.796** - *Moderate False Negative rate (mitigated by Citizen Appeal loop).*
- **F1 Score: 0.838** - *Balanced harmonic mean of Precision and Recall.*
- **Inference Speed:** ~140ms per site (Edge-ready on CPU).

6. Limitations & Bias

- **Urban Bias:** The model performs best on flat concrete roofs common in Tier-1 cities. Confidence drops on sloping tiled roofs (Mangalore tiles) found in rural coastal areas.
- **Occlusion:** Heavy tree cover (Canopy Density > 60%) significantly lowers recall.
- **Mitigation:** These limitations are addressed by the **Citizen Appeal Workflow**, allowing beneficiaries to upload ground-truth evidence when the model fails.

7. Retraining Guidance

- **Trigger:** Retrain when "Citizen Appeal" data exceeds 500 verified images.
- **Process:** Add verified citizen uploads to the training set (labeled solar_ground) to improve robustness against occlusion.