



EcoVision: Automated Solar Panel Cleanliness Detection

Improving Energy Output Through Automated Soiling Detection

Solar panels lose efficiency when dirty, and manual inspections are slow and expensive. EcoVision uses advanced computer vision to automate soiling detection, ensuring optimal energy production.

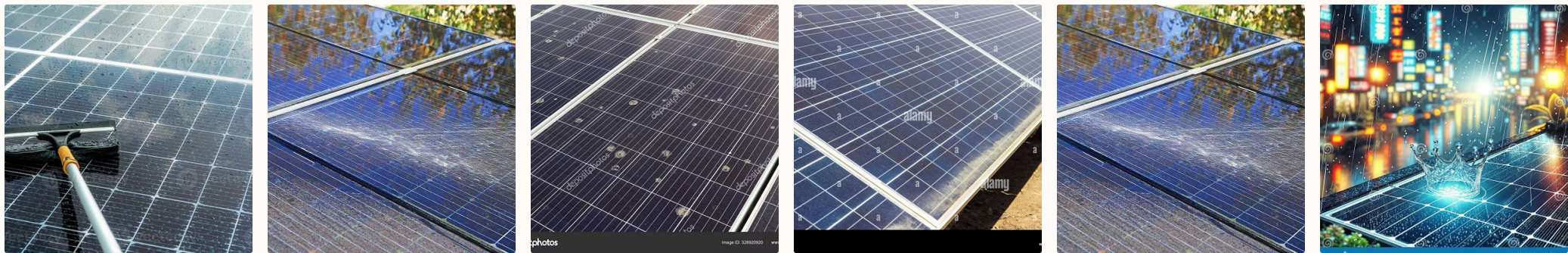
By: David A. Suarez

EcoVision Data: What We Detect

Our system processes diverse image sources to classify panels as "clean" or "dirty," handling varied conditions with robust algorithms.

1	2
Binary Labels Clean vs. Dirty (clear classification)	Image Sources Fixed cameras and drone imagery
3	4
Real-World Variability Adapts to lighting, angles, shadows, and glare	Noise Handling Manages ambiguous cases like wet vs. dirty

Visual examples of our detection capabilities:



The Real-World Problem: Soiling Reduces Efficiency



Efficiency Loss

Soiling (dust, bird droppings, pollen, ash) reduces PV efficiency by 5-30% depending on region.



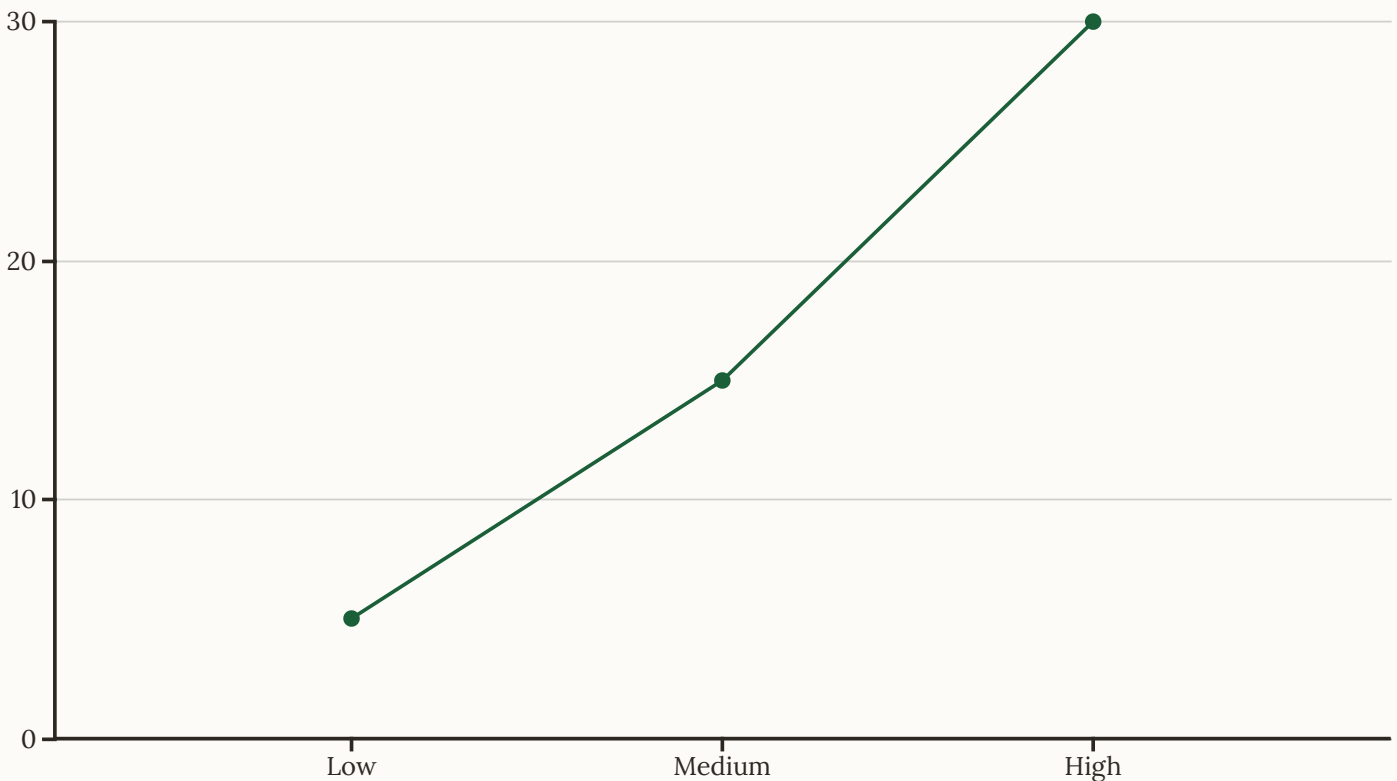
Decreased Yield

This directly impacts energy yield and revenue, accelerating degradation and creating hotspots.



Monitoring Gaps

Remote sites often lack reliable and consistent monitoring, exacerbating the problem.



Energy loss significantly increases with higher soiling levels, impacting overall plant performance.

Why This Matters: Stakeholders & Costs

Operators

Need accurate detection to guide cleaning schedules and optimize operations.



O&M Teams

Avoid wasting labor and water on unnecessary cleaning, maximizing efficiency.

Environmental

Minimizes unnecessary water use, especially critical in arid regions.



Grid/Utility

Dirty panels lead to reduced generation stability, affecting grid reliability.

Example Dataset & Detection Capabilities

Our system detects soiling through binary classification and optional segmentation.

1

Data Input

Images from fixed cameras and drones are analyzed for clean vs. dirty labels.

2

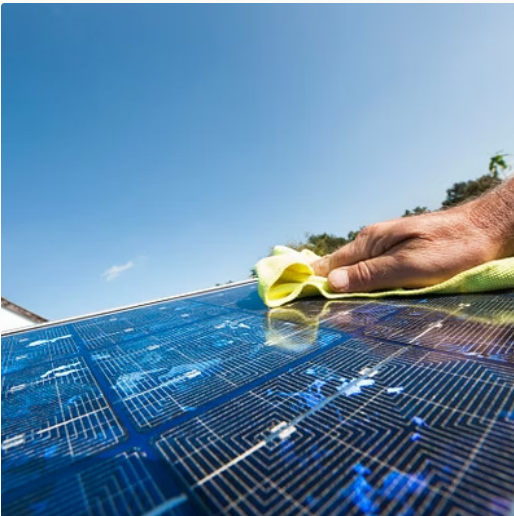
Variability Handled

The system accounts for lighting, angles, shadows, and glare for robust detection.

3

Noise Reduction

Sophisticated algorithms minimize noise and handle ambiguous cases like wet surfaces vs. actual dirt.



System Outputs & Smart Usage



Primary Output

"Clean/Dirty" classification with confidence score.



Optional Segmentation

Detailed segmentation mask highlighting dirty regions.

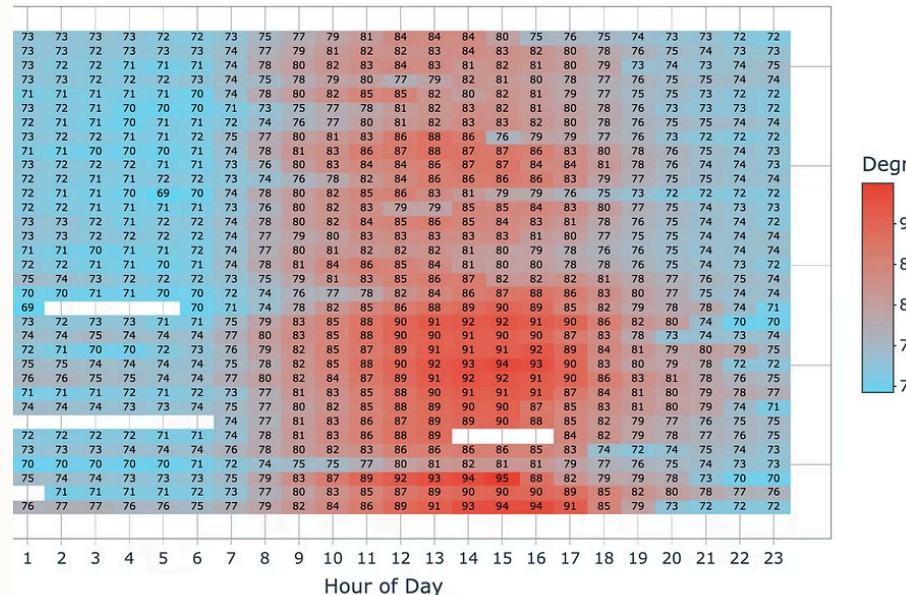


Targeted Cleaning

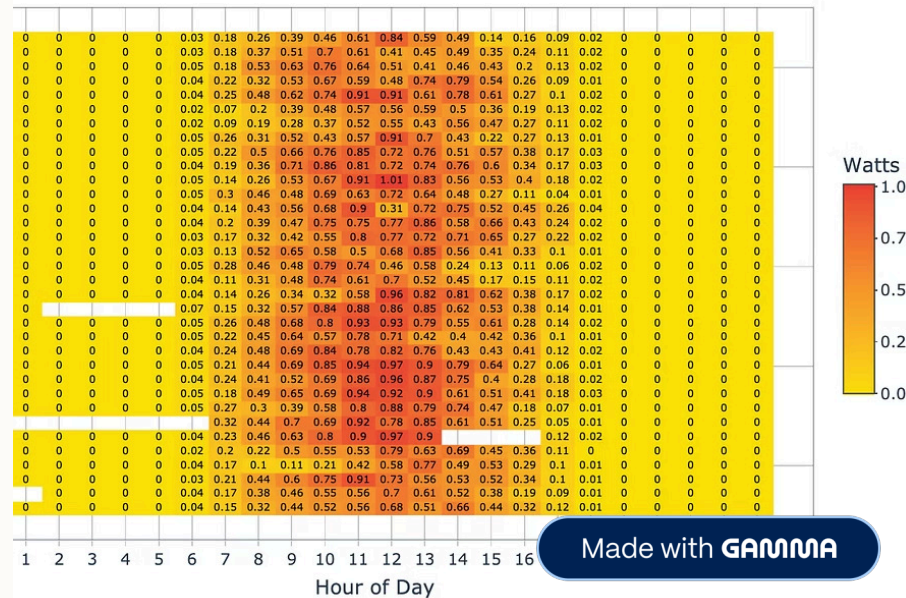
Enables precise and efficient cleaning schedules.

Visualize overall panel health with a severity heatmap and track dirty panel percentages over time.

Ambient Temperature Heatmap



Irradiation Heatmap



Challenges & Success Criteria

Overcoming Challenges

- Class imbalance and seasonal drift
- Glare and occlusions impact image quality
- Requires consistent retraining with new field data

Defining Success

- >90% classification accuracy
- Low false negatives to ensure proper cleaning
- Month-long pilot and cross-season field validation

Accuracy	90%+	88%	High
Recall	95%+	92%	High
F1 Score	90%+	89%	High

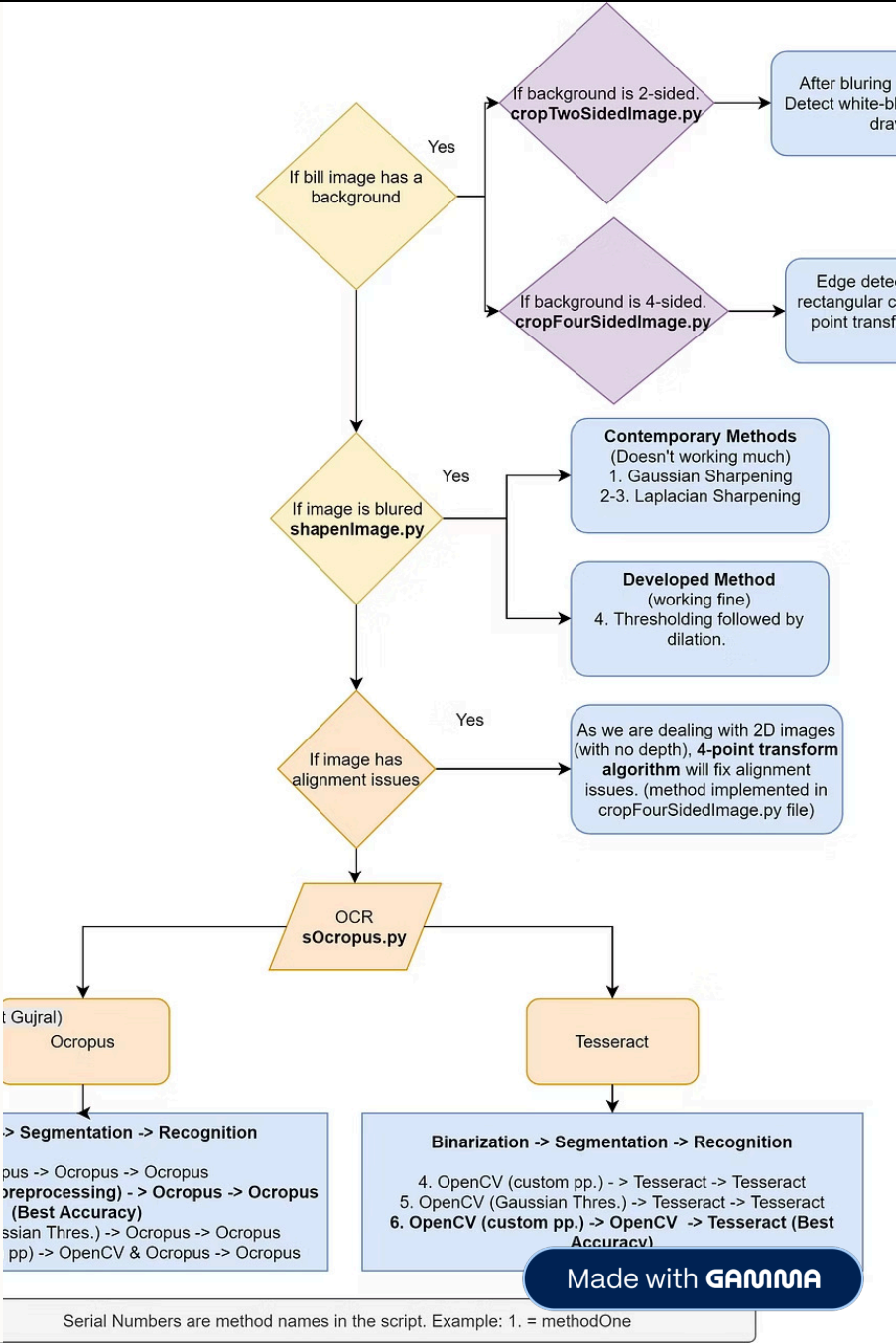
Our focus is on achieving high accuracy and recall for reliable operational impact.

Technical Pipeline Overview

A modular and robust system from data acquisition to cleaning recommendations.



The pipeline can be deployed on edge devices or in the cloud, offering flexible scalability.



Why AlexNet? High-Level Architecture

A proven CNN for image classification tasks.

Proven Performance

AlexNet is a classic CNN with strong performance for image classification.

Baseline Model

An excellent starting point for small to medium-sized datasets.

Core Structure

Combines convolutional, ReLU, pooling, and dense layers for robust feature extraction.



The diagram illustrates the sequential flow of the AlexNet architecture using four horizontal green arrows of increasing length, stacked vertically. Each arrow contains a label for a specific stage of the process: 'Input', 'Convolutions', 'Pooling', and 'FC & Softmax'. The arrows point from left to right, indicating the direction of data flow through the network.

Input

Convolutions

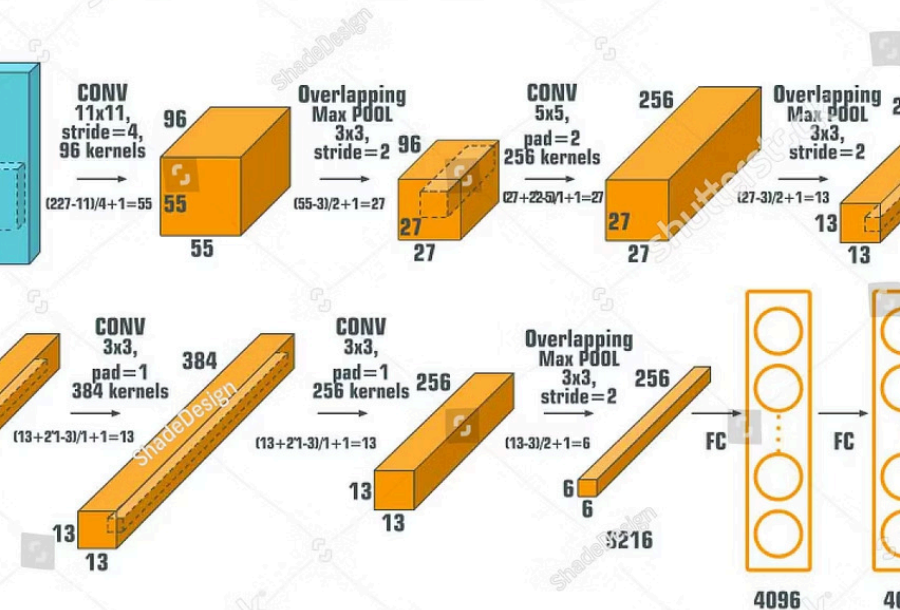
Pooling

FC & Softmax

Input size is standardized to 227x227x3 RGB for optimal processing.

AlexNet

CONVOLUTIONAL NEURAL NETWORK



AlexNet Layer Breakdown

Key Layers

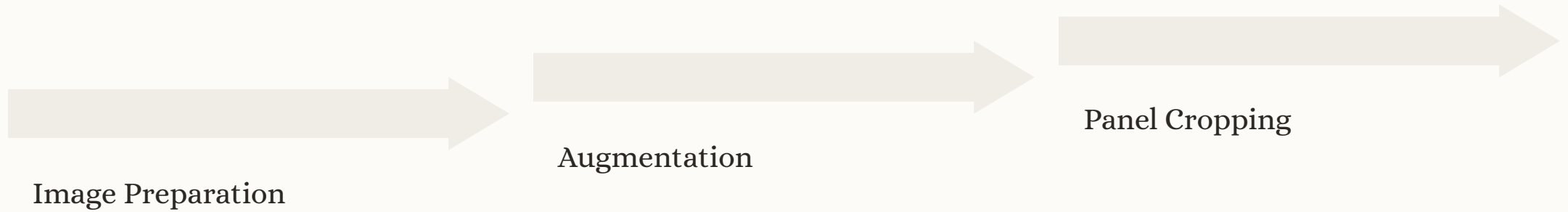
- **Conv1:** 11×11 filters, 96 channels, followed by pooling.
- **Conv2:** 5×5 filters, 256 channels, followed by pooling.
- **Conv3, Conv4:** 3×3 filters, 384 channels.
- **Conv5:** 3×3 filters, 256 channels, followed by pooling.

Output & Classification

- **FC Layers:** Three fully connected layers (4096 neurons each) for high-level feature combination.
- **Output:** Softmax layer for binary classification (Clean vs. Dirty).

This architecture efficiently extracts hierarchical features for accurate soiling detection.

Preprocessing & Data Integration



Robust preprocessing is crucial for model generalization and performance in varied field conditions.

Preprocessing & Data Augmentation

Transforming raw images into optimal inputs for AlexNet, enhancing model robustness and accuracy.

Data Preparation

- Resize/Crop to 227x227 pixels
- Normalize using ImageNet means (for pretrained weights)
- Crop individual panels from wide images

Augmentation Techniques

- Flip (horizontal/vertical)
- Brightness/Contrast Jitter
- Slight Rotation
- Synthetic Dirt Overlays
- Shadow Augmentation



These steps ensure our model learns from a diverse and representative dataset.