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Solar Panel Health Monitoring System using Deep Learning Approach

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ABSTRACT: In recent years, solar energy has emerged as a pillar of sustainable development. However, maintaining panel efficiency under extreme environmental conditions remains a persistent hurdle. This study introduces an automated defect detection pipeline that leverages deep learning and computer vision to identify five standard anomaly classes: Non-Defective, Dust, Defective, Physical Damage, and Snow on photovoltaic surfaces. To build a robust foundation, a heterogeneous dataset of 8973 images was sourced from public repositories and standardized into a uniform labeling scheme. This dataset was then expanded through an aggressive augmentation strategy, including flips, rotations, zooms, and noise injections. A YOLOv11-based model was trained and fine-tuned using both fixed and adaptive learning rate schedules, achieving a mAP@0.5 of 85% and accuracy, recall, and F1-score above 95% when evaluated across diverse lighting and dust scenarios. The optimized model is integrated into an interactive dashboard that processes live camera streams, issues real-time alerts upon defect detection, and supports proactive maintenance scheduling. Comparative evaluations highlight the superiority of this approach over manual inspections and earlier YOLO versions in both precision and inference speed, making it well suited for deployment on edge devices. Automating visual inspection not only reduces labor costs and operational downtime but also enhances the longevity of solar installations. By offering a scalable solution for continuous monitoring, this work contributes to improving the reliability and cost-effectiveness of large-scale solar energy systems.

KEYWORDS: solar panel defect detection; computer vision; YOLOv11; deep learning; real-time monitoring; renewable energy; proactive maintenance; Saudi Vision 2030

I. INTRODUCTION

Solar energy has recently gained significant attention as a potential sustainable and renewable energy source. Solar panels, also known as photovoltaic panels, harvest solar energy from the sun to provide the energy we use every day. Using renewable energy is commonly viewed as contingent upon developing sustainable energy sources, decreasing reliance on fossil fuels, and mitigating climate change. It is crucial for decreasing global warming and reducing greenhouse gas emissions. Furthermore, it can significantly help minimize the amount of water needed to produce energy and improve air quality. However, solar panel installation on land may have adverse effects on nearby species, habitats, soil, and water supplies. When sunlight falls on the solar cells in the panels, the solar energy is absorbed, producing electrical charges. The energy makes the electrons shift within the semiconductor material (usually silicon), creating direct current (DC) electricity. The generated electricity can either be consumed directly or stored in batteries to be used later. Generally, solar panels represent a clean and renewable power source that does not produce greenhouse gases. Consequently, this power may be fetched to DC to Alternating Current (AC) converter (DC2AC) to produce electricity, which can be used to generate power. Although devices and home appliances are available on the market that operate directly on DC, such as lights, fans, and burners, most existing and new devices operate on AC. Solar panels are typically placed in areas with maximum sun exposure, such as rooftops or large solar farms, to provide



sustainable energy and reduce reliance on fossil fuels. These panels can either expand the electrical supply of a building or provide electricity in remote or off-grid locations.

Dusty solar panels are unable to produce the desired output. Through several investigations at varying dust levels on the solar panels, Chen et al. observed that a dust density of 10 g per square meter decreased the output power of solar panels by 34%. Moreover, photoelectric conversion efficiency and filling factor (FF) also decline with the increase in dust density. They concluded that for every 10 g per square meter rise in dust mass density, the conversion efficiency reduces by 3.4% on average. Solar energy is a significant part of the world's transition to cleaner power, and Saudi Arabia is investing heavily in solar farms as part of a potential shift away from its reliance on oil-based power. However, harsh weather conditions, such as dust storms, scorching heat, and sudden rain, make panel care particularly challenging. Manual checks are slow and may miss early warning signs. If minor defects are identified promptly, they can be addressed before they impact on the farm's overall performance. Automating the process means less time walking the fields, fewer missed defects, and more consistent energy production, helping to meet clean energy goals with better reliability and lower costs.

Manual inspection, which involves walking among thousands of solar panels or scanning them one by one with thermal cameras, is time-consuming and requires a lot of effort; thus, it is humanly impossible. On large solar farms, defects such as dust covers, small cracks from hail, physical damage from tools or animals, and snow buildup can go unnoticed until the energy output drops sharply. Fixing issues after panels have already lost efficiency leads to wasted electricity and increased costs. A better approach is needed to quickly and reliably spot surface-level problems using regular camera images so that repair teams know exactly where to focus before a minor flaw becomes a significant loss.

Deep learning object detection models, such as YOLOv11, can process images in real time. By training on thousands of panel images labeled with dust spots, cracks, dents, and snow areas, the model learns to spot these issues under varied lighting and angles. Data augmentation, such as flipping images, rotating them, or adjusting brightness before training makes the detector more resilient against real-world conditions. Once trained, the model runs on small, inexpensive computers right at the site. Clear labels for each defect type enable technicians to identify what requires urgent repair and what can wait for routine cleaning.

II. RELATED WORK

2.1. Computer Vision Approaches for Solar Panel Defect Detection

Recent advances in computer vision and deep learning have enabled significant progress in automated solar panel defect detection. This section reviews key studies that have contributed to this rapidly evolving field.

Zhang and Yin developed an improved YOLOv5 algorithm for identifying solar cell surface defects. Their model incorporates deformable convolution and attention mechanisms to adaptively scale defect detection based on feature size. Through enhancements in data augmentation and feature extraction techniques, their approach achieved a mean average precision (mAP) of 89.64%. Resultantly outperforming earlier versions in both precision and speed, making it particularly suitable for photovoltaic monitoring applications. Advancements in attention-based mechanisms have further improved detection accuracy. Dwivedi et al.

2.2. Specialized Deep Learning Models for Defect Classification

Researchers have developed increasingly specialized models to address the unique challenges of solar panel defect detection. Prabhakaran et al. created a Multi-Variant Deep Learning Model (RMVDM) that employs advanced preprocessing techniques, including Region-Based Histogram Approximation (RHA) and Gray Scale Quantization Algorithm (GSQA). These methods significantly enhance image processing workflows, facilitating more accurate and efficient defect detection on solar panel surfaces.

Al-Otun developed a sophisticated deep learning system for defect detection using electroluminescence (EL) images. The Independent Light-Depth Convolutional Neural Network (CNN-ILD) model features multiple branches, each analyzing different image aspects to capture important details. This approach achieved accuracy between 88.41% and 98.05% in identifying defects on solar panels, demonstrating considerable effectiveness compared to similar models.

2.3. YOLO-Based Approaches for Real-Time Applications

YOLO (You Only Look Once) algorithms have proven remarkably successful in real-time defect detection applications. Haeruman et al. utilized YOLOv7 to detect defects in PV panels by analyzing infrared images captured by drones. Their model achieved a paramount average precision of 85.9%, making it well suited for real-time deployment in solar farm environments. Building on this foundation, Cao et al. developed an advanced YOLOv8-GD model for detecting defects in solar panels using electroluminescence images. By enhancing feature extraction procedures and integrating DW-Conv (DepthWise Convolution) into the YOLOv8 backbone, they achieved a mean average precision (mAP) of 92.8% at an IoU threshold of 0.5 and 63.1% from 0.5 to 0.95. This significant improvement in accuracy, coupled with a 16.7% reduction in model size, demonstrates YOLOv8-GD's potential for efficient real-time PV panel inspection. Özer and Türkmen proposed a deep learning approach for detecting the condition of solar panels in solar plants. In this regard, they have investigated various members of the YOLO family, including YOLOv5, YOLOv7, and YOLOv8 for varying numbers of epochs. Consequently, they found that YOLOv5 exhibited the highest F1-score value at 150 epochs, which was 97%. They aimed to deploy the model using a drone for periodic inspection of solar panels at the power plant. It is commonly observed that the YOLO family has been most widely used in solar panel defect detection, especially YOLOv5 and YOLOv8.

Like solar panel defect detection, the YOLO family has various applications in related areas, such as printed circuit board (PCB) defect detection proposed by Mo et al. [16]. The authors investigated a YOLOv5s-based improved model, coined as SE-ENv2 GC-Neck TSCODE (SGT-YOLO), to provide a better trade-off between model complexity and accuracy. The proposed approach improved the mAP and mAP0.5 by 2.7% and 6.4% on a state-of-the-art PCB defect detection dataset. Similarly, the YOLO family has been successfully employed for insulator defect detection in transmission lines and Unmanned Aerial Vehicles (UAV) imagery-based fire detection.

2.4. Fully Automated Systems and Alternative Approaches

Bartler et al. designed a fully automated system for detecting defects in solar cells using electroluminescence images. Their process begins with image cleaning and distortion correction before isolating areas of interest. A deep CNN then classifies various defect types, including cracks, dislocations, and discolorations. To address limited training data, they employed data augmentation techniques to create additional examples and improve model reliability. Zhang and Duranay explored an alternative approach using infrared solar module images for defect classification. Their EfficientNetB0 model combined with a support vector machine (SVM) classifier achieved 93.93% accuracy in classifying defects across 12 different classes, demonstrating the effectiveness of hybrid deep learning approaches in enhancing solar energy system performance.

As far as the defect detection is concerned, it usually covers burns, hotspots, and solar cell damage as depicted in **Figure 1a**. In terms of dust detection, it mainly covers the sand and dust covering the solar panels that may hinder the energy conversion process as illustrated in **Figure 1b** which is a major case in Saudi Arabia due to heavy and frequent sandstorms. Likewise, physical damage is depicted in **Figure 1c**.



Figure 1. (a) Defective, (b) dusty panel, (c) physical damage.

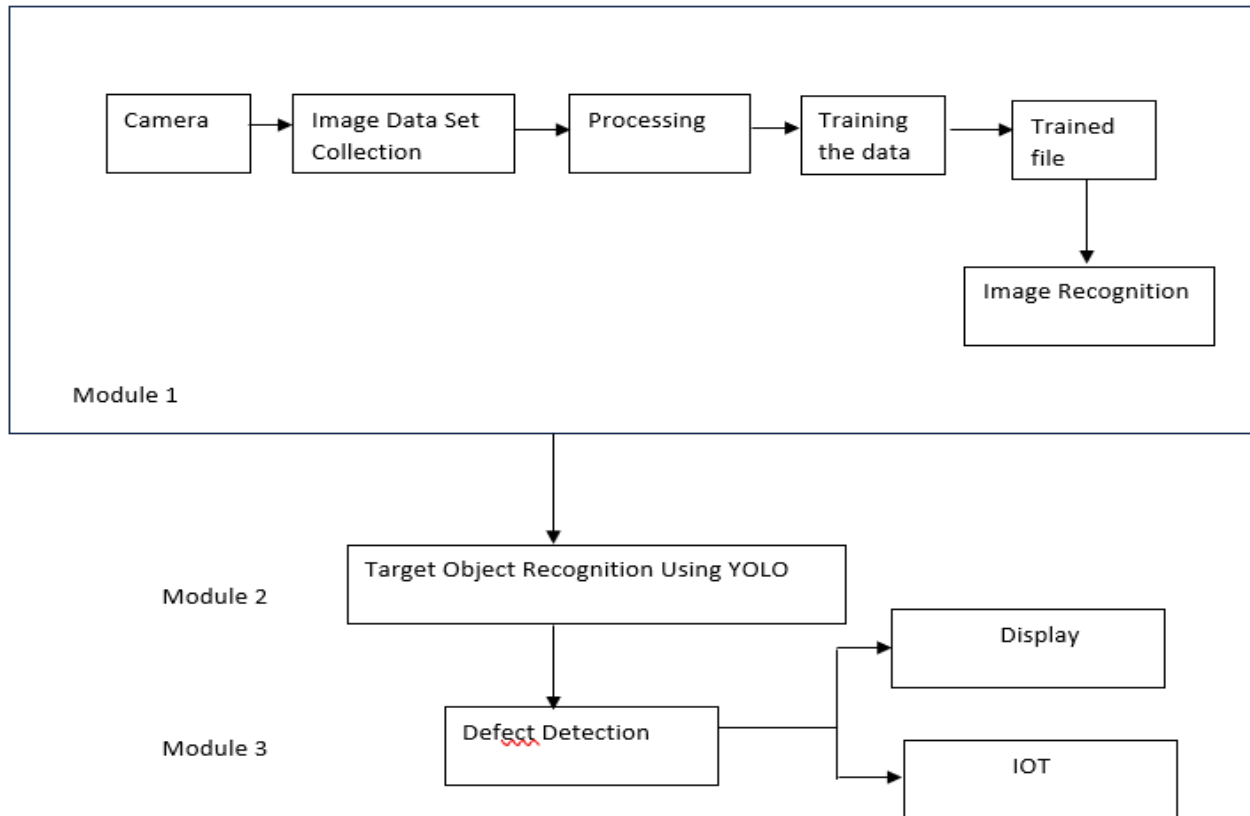


Figure 2. Block Diagram of Solar Panel Defect Deduction

To address this aforementioned gap, the proposed study presents a comprehensive model for detection of solar panel defects, dust, and snow at the same time. This results in a multi-class classification problem with five classes including Non-Defective, Dust, Defective, Physical Damage, and Snow on photovoltaic surfaces. In this regard, various datasets from open sources have been integrated and augmented for the development of a proposed YOLOv11-m model.

The rest of the paper is organized as follows: **Section 2** presents the proposed methodology; **Section 3** presents the experimental results; **Section 4** is dedicated for discussion, while **Section 5** concludes the study.

III. BLOCK DIAGRAM

The provided block diagram outlines the sequential architecture of an Image-Based Defect Detection System leveraging deep learning, specifically the YOLO (You Only Look Once) algorithm, and integrating it with an IoT (Internet of Things) framework for real-time monitoring and reporting. The system is functionally divided into three main modules. Module 1: Training and Model Generation focuses on preparing the intelligence for the system. This process begins with the Camera acquiring raw visual data, which is stored in the Image Data Set Collection block.

Decision and Reporting utilize the results from YOLO for the primary function of the system, which is Defect Detection. In this block, logic is applied to the YOLO output to classify whether the detected object is acceptable or defective, based on the learned features. For example, if YOLO identifies a crack or a misplaced component, the system flags it as a defect. The decision from the defect detection block is then channelled into two parallel output streams for communication. The first output is routed to a Display, which provides local visual feedback to operators, showing the camera feed, the detected bounding boxes, and the final defect classification (e.g., "PASS" or "FAIL"). The second, and crucial, output is routed to the IOT block. This integration means the system uses a communication



protocol (like MQTT, HTTP, or CoAP) and a network interface (Wi-Fi, Ethernet, or cellular) to transmit the defect status, potentially along with timestamps and image metadata, to a remote server or cloud platform. This IoT connection enables remote monitoring, historical data logging, automated alerts, and integration with manufacturing execution systems (MES), allowing for comprehensive quality control management and traceability across a distributed industrial environment, thereby completing the full cycle from raw image acquisition and model training to automated, networked decision-making.

IV. PROPOSED YOLOV11-BASED APPROACH

Data Pre-Processing and Augmentation

To build a robust model capable of fine detection across various environmental and angular conditions, the following augmentations have been employed. The range of each type of augmentation has also been provided. The selection of augmentation types and their values is based on the literature review and the most widely targeted weather and environmental conditions.

- Flips: horizontal and vertical.
- 90° rotations (CW and CCW).
- Random zoom-crop (0–20%).
- Free rotations $\pm 15^\circ$.
- Shear $\pm 10\%$ (H and V).
- Grayscale on 15% of images.
- Saturation $\pm 20\%$, exposure $\pm 10\%$.
- Gaussian noise $\leq 0.3\%$ pixels.
- Auto-orient $\rightarrow$ resize to 640×640 (letter-boxed).

4.1. Dataset Cleaning, Normalization, and Scaling

Pixel values are normalized to improve convergence during training. Whereas scaling ensures consistency in object size representation across the dataset. Annotation was performed using a combination of Grounding DINO and manual labeling (refined via Roboflow), ensuring proper bounding box placement and consistent labeling across all images. Additionally, the following operations were performed on the dataset: removing irrelevant or unusable images; the images that do not match the intended use case or are of poor quality were discarded.

4.2. Model Training Environments

For model building, training, testing, and validation, two state-of-the-art environments have been considered as follows:

1. Google Colab: YOLOv11-m backbone, 150 epochs, batch size 32.
2. Roboflow Train: The same dataset, with Roboflow's hyperparameter sweeps and early stopping. Highest-accuracy Roboflow weights integrated into our existing dashboard for live inference and alerting.

4.3. Model Deployment

Finally, the trained model was deployed and validated through real-time webcam integration tests, ensuring robustness before deployment in an industrial setting. For the final model training phase, Google Colab was utilized, leveraging its powerful computing resources. Technical details of the final model include: Ultralytics Version: 8.3.40, Python: 3.11.11, Torch: 2.6.0+cu124, CUDA:0 (NVIDIA L4, 22693MiB), and YOLOv11s summary (fused): 238 layers, 9,416,283 parameters, 0 gradients, and 21.3 giga floating point operations per section (GFLOPs).

4.4. Proposed YOLOv11-Based Approach

For the research, the YOLOv11-m architecture is implemented, chosen based on a balance of accuracy and edge-device latency suitable for complex environments [27]. To optimize model performance, meticulous hyperparameter tuning was performed, accompanied by strategic pre-processing and augmentation methods. Data pre-processing involved automatically orienting images and resizing them to a consistent resolution of 640×640 pixels.

Augmentation strategies significantly enriched the dataset variability as mentioned above. This structured augmentation protocol substantially increased the robustness and generalizability of the detection model, addressing potential

variability within real-world environmental conditions. **Figure 3** presents the architecture of YOLOv11-m exploited in the study.

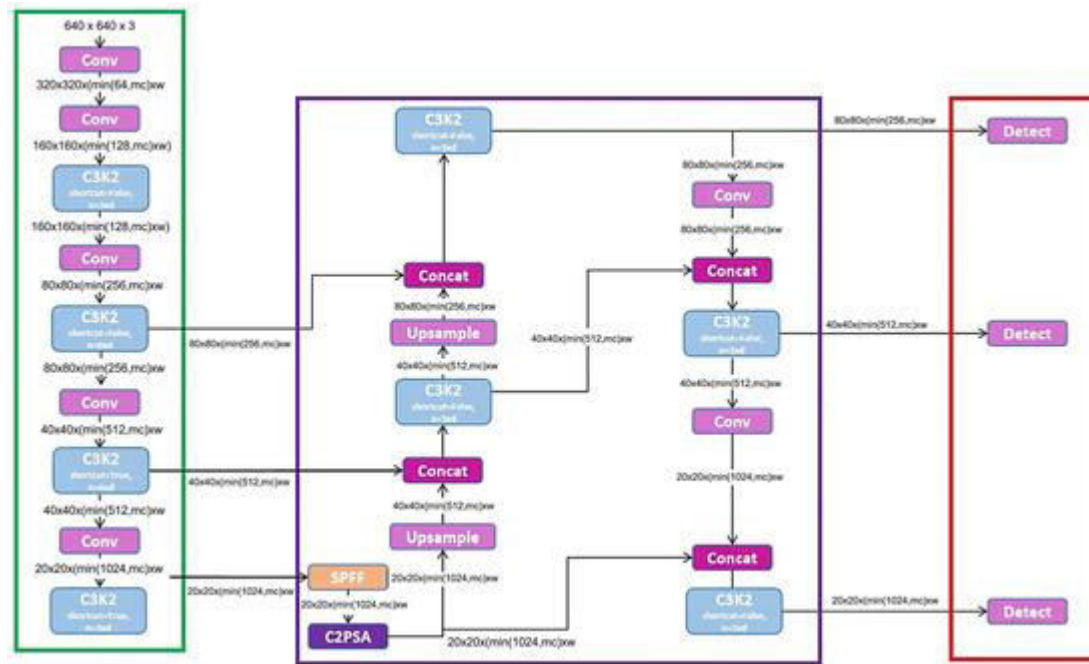


Figure 3. YOLOv11-m default model architecture.

4.5. Performance Evaluation

The primary metric for evaluating the model's performance was mean average precision (mAP). Specifically, we focused on the commonly used threshold of $mAP@0.5$ to align with industry standards and benchmark comparisons. The dataset was strategically split into training, testing, and validation subsets to ensure a balanced evaluation framework. Throughout model training, performance metrics were systematically monitored and logged, allowing iterative refinements via further hyperparameter adjustments and dataset balancing as required. The following formula shows how to calculate the mean average precision:

$$mAP = \frac{1}{N} \sum_{i=1}^N AP_i \quad (1)$$

where N is the total number of queries and AP_i is the average precision at i th query found by averaging realized precision at each relevant point at the ordered list of outcomes.

Other than that, the accuracy, precision, recall, and F1-score are the most common metrics used for evaluating machine learning and deep learning models as given in Equations (1)–(5), respectively. Here the values correspond to true positive (TP), true negative (TN), false positive (FP), and false negative (FN).

V. DISCUSSION

Figure 4 illustrates the training dynamics of the YOLOv11 model over 300 epochs. The top row tracks training loss components—bounding-box regression (train/box_loss), classification (train/cls_loss), and distribution-focal loss (train/dfl_loss)—all of which fall steeply within the first 50 epochs and continue a smooth, monotonic decline, signaling stable convergence. The corresponding validation losses (bottom row) mirror this trajectory and level off at comparable magnitudes, indicating minimal over-fitting and good generalization to unseen data.

Performance metrics on the same graph confirm this aforementioned trend. Precision climbs rapidly to ≈ 0.88 and plateaus after epoch 120, while recall stabilizes near 0.80, reflecting a balanced detector that captures most defects without an excessive false-positive rate. The overall $mAP@0.50$ reaches 0.85 by epoch 150 and remains steady,

matching the Roboflow evaluation reported earlier. A gradual rise in $mAP@0.50-0.95$ to ~ 0.70 demonstrates the model's competence across stricter IoU thresholds, crucial for pinpointing small cracks or dust patches on panel surfaces.

Collectively, these curves verify that the augmentation regimen and automated hyperparameter tuning achieved consistent optimization without divergence between training and validation sets. The final checkpoint, therefore, meets the stated deployment criterion ($\geq 85\%$ $mAP@0.50$) and is suitable for real-time solar panel health monitoring.

By replacing routine manual checks on the mounted solar panels, the proposed system aims to free technicians to work on more complex tasks while ensuring panels stay clean and undamaged. Technicians will need training to trust and use AI alerts correctly. Using camera streams raises questions about privacy—images must be stored and handled following local laws. It is also important to explain what the system can and cannot do so users understand that hidden faults still need human inspection. With clear rules and open communication, automated inspection can improve solar energy output safely, and effectively while keeping human expertise at the center of decision-making.

Figure 5 provides the proposed model's output for various classes. It is apparent that in most cases, the detection accuracy is above 90% which demonstrates the promising nature of the proposed approach for solar panel dust and defect detection for diverse environmental conditions.

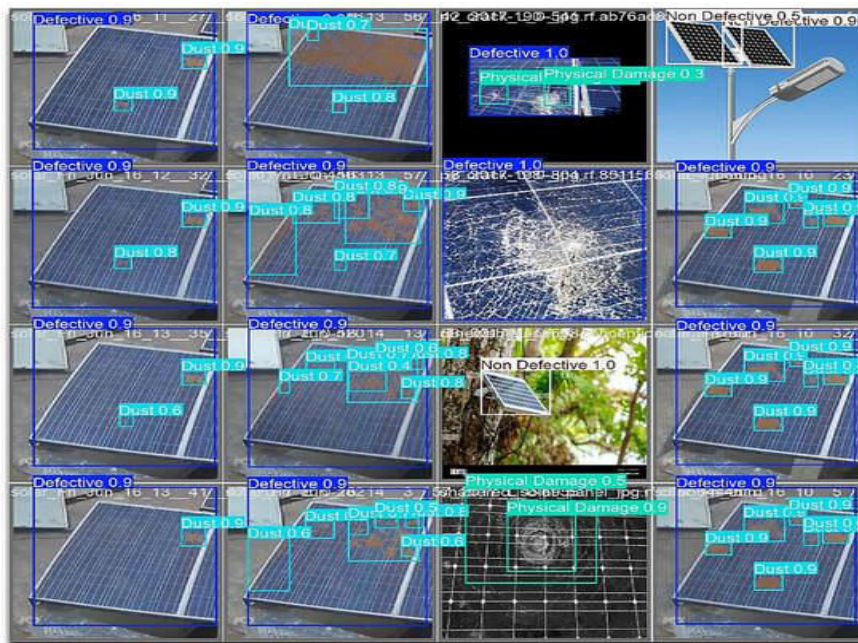


Figure 5. Model's detection output.

VI. CONCLUSION

The final solar panel corpus was built by cherry-picking the highest-quality images from three public collections—Kaggle's Solar-Panel Dust Detection (for dust-laden surfaces), RoboFlow's Solar-Panel Detection project (providing clean modules, physical damage shots, and snow scenes), and the Roboflow 6Rainstorm Final Project (adding additional defective and snow instances). All raw annotations were remapped into a unified five-class scheme—Non-Defective, Dust, Defective, Physical Damage, Snow—and duplicate or low-resolution frames were discarded. The merger produced 8973 RGB images covering a wide range of illumination, camera angles, and environmental conditions typical of large-scale photovoltaic farms. Before training, every image was auto-oriented and letter-boxed to a fixed 640×640 resolution, then partitioned into 8212 training, 440 test, and 321 validation images. Labels were exported in YOLO-txt format to ensure compatibility with the Ultralytics pipeline, and the aggressive augmentation policy (flips, multi-angle rotations, zoom-crops, shear, grayscale injection, color jitter, and pixel noise) generated three



synthetic variants per original, enriching minority classes and improving robustness to dust haze, lens glare, and seasonal artifacts.

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