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Comparative Analysis of YOLO Models for Real-Time Solar Panel Defect Detection

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Introduction to the Solar Energy Industry

In 2024, the solar energy industry experienced unprecedented growth. Global renewable energy capacity increased by 15.1% to reach 4,448 GW, with solar energy contributing a record 452 GW in new capacity—more than three-quarters of all new renewable additions. China, the United States, India, Germany, and Brazil together accounted for approximately 75% of these global solar additions. Investment in solar PV worldwide exceeded USD 480 billion in 2023, setting a new industry record [1].

The United States saw its largest ever annual increase in solar capacity, installing nearly 50 GW in 2024—a 21% rise from the previous year [2]. Solar power accounted for about 66% of all new electricity generation capacity added to the U.S. grid. California led the nation with over 48 GW of installed solar, followed by Texas with 32 GW [3].

Texas solidified its position as a national leader in solar energy in 2024. The state added around 9.7 GW of new solar capacity, the highest of any state that year. Notably, in March 2024, solar generation in Texas surpassed coal for the first time, highlighting the state's rapid energy transition. The economic impact of solar in Texas is significant, with billions invested and substantial revenue generated for landowners and local governments. Solar energy's rapid expansion in 2024 set new records globally and in the United States, with Texas at the forefront of this growth. The state's leadership in new capacity additions and its milestone of surpassing coal generation underscore the transformative impact of solar power on the energy landscape [4-9].

Solar Panel Manufacturing and Fault Detection

Solar panel manufacturing is a multi-stage process, primarily using crystalline silicon. The process begins with high-purity silicon, typically derived from quartz sand, hydrogen, and chlorine. Typically, the Czochralski method is used to grow monocrystalline silicon ingots, which are then sliced into wafers using diamond-coated wire saws [10]. These wafers are assembled into solar cells, interconnected with metal ribbons, and encapsulated with ethylene-vinyl acetate (EVA) and laminated glass to form durable, waterproof modules [11].

Defects in solar panels can reduce their performance. Typical types of defects include:

- Cracks: Cracks in the silicon cells can disrupt current flow and lead to reduced production, potentially causing faster degradation.
- Hotspots: Localized areas of overheating, often caused by defects like cracks or poor solder joints, which can accelerate degradation and even lead to fires.
- Delamination: Separation of the layers in the panel, allowing moisture and air to enter, which can lead to corrosion and electrical shorts.

- Potential Induced Degradation (PID): Performance degradation caused by voltage stress, leading to a drop in energy production.
- Snail trails: Dark streaks that can indicate microcracks or moisture penetration.

Solar panel defects can cause power losses in individual panels of 10% or more, impacting on the overall efficiency of the solar system. Studies show that 15% of PV panels exhibit defects, leading to a 16% performance decrease. This results in a substantial annual energy loss of 0.35 GWh. Underperformance due to equipment issues has surged, leading to an estimated $10 billion in lost revenue globally in 2024 [12].

Solar Panel Fault Detection Methods

Detecting underperforming photovoltaic panels can be done using monitoring software. However, detecting types of failures often requires examining of individual panels. Some methods require direct connection to the panels while others can use photographs to detect flaws. Some methods of detecting faults in panels are described below.

Thermal Imaging

Infrared thermography is a rapid, non-destructive method for identifying overheated panels and hotspots. Drone-based thermal imaging enables large-scale, efficient inspections, even in challenging locations [13].

Electroluminescence (EL) Imaging

EL imaging provides high-resolution, non-destructive detection of micro-cracks and defects invisible to the naked eye. It involves applying DC current to the panel and capturing emitted light with specialized cameras. Up to 30% of underperformance can be attributed to defects detectable only by EL imaging [14].

Electrical Parameter Analysis

Traditional methods include I-V curve analysis and impedance testing, providing quantitative performance but requiring physical access and specialized equipment [15].

Recent Study with Advanced AI and Machine Learning Approaches

Deep Learning (CNNs):

A recent study evaluated 24 CNN architectures for automated solar cell defect detection using a dataset of 3,102 images. MobileNetV2 and Xception achieved the highest accuracy rates of 99.95% and 99.29% respectively. The results demonstrate that lightweight models like MobileNetV2 can effectively enhance solar panel quality control systems [16].

YOLO-Based Detection:

Another recent study presented a comprehensive evaluation of YOLO algorithms (v9, v10, v11) for solar panel defect detection, demonstrating both significant strengths and notable limitations. The research's primary strengths include its systematic multi-algorithm comparison across latest YOLO versions with baseline comparisons to v5, SVM, and Faster R-CNN, diverse dataset coverage spanning thermal and optical imaging modalities, and comprehensive defect categorization addressing both physical (dust, snow, bird droppings, damage) and electrical (cell, multi-cell, shadow) defects with practical relevance to grid stability concerns. However, the study suffers from critical weaknesses including limited dataset scale (191-792 images) insufficient for robust deep learning validation, inconsistent image resolutions that may introduce bias, and moderate performance metrics where YOLO v11-X achieved only 89.7% precision and 87.7% recall—falling below industry requirements for critical infrastructure applications. Additionally, the research lacks sufficient dataset details regarding data splits and cross-validation methodology, provides limited baseline comparisons ignoring other state-of-the-art frameworks, and offers no real-world validation or computational efficiency analysis for practical deployment. While the study represents a meaningful contribution to automated solar panel inspection technology, the moderate performance results and methodological limitations suggest that larger-scale validation and improved accuracy metrics are essential before industrial deployment can be considered viable. [17].

Introduction of Yolo Family and the Solar Panel Fault Detection

The You Only Look Once (YOLO) family of algorithms represents a paradigm shift in real-time object detection, fundamentally changing how machines perceive and analyze visual data. Originally introduced by Joseph Redmon et al. in 2015, YOLO revolutionized object detection by framing it as a single regression problem, where a unified neural network predicts bounding boxes and class probabilities directly from full images in one evaluation [28]. The name "You Only Look Once" refers to the algorithm's ability to require only one forward propagation pass through the neural network to make predictions, unlike previous region proposal-based techniques like R-CNN that require thousands for a single image. Since its inception, the YOLO family has evolved through numerous iterations including YOLOv2, YOLOv3 [18, 19], and subsequent versions developed by different research teams after Joseph Redmon stepped away from computer vision research in 2020. Each successive version has introduced architectural improvements and optimization techniques: YOLOv2 incorporated batch normalization and anchor boxes, YOLOv3 introduced the Darknet-53 backbone with multi-scale predictions, YOLOv4 implemented CSPNet architecture with advanced training strategies, YOLOv5 focused on PyTorch implementation and ease of use, YOLOv8 (20 enhanced performance with anchor-free detection and improved backbone architectures, YOLOv9 introduced Programmable Gradient Information (PGI) and Generalized Efficient Layer Aggregation Network (GELAN), YOLOv10 eliminated non-maximum suppression for end-to-end detection, YOLO11 (2024) provided enhanced feature extraction with optimized efficiency, and YOLO12 pioneered attention-centric architecture departing from traditional CNN approaches. This continuous evolution has established YOLO as one of the most widely adopted frameworks for real-time object detection applications, spanning from autonomous vehicles and surveillance systems to industrial automation and medical imaging [20-25].

A key challenge for applying YOLO models to solar panel fault detection is the limited availability of public datasets, which hinders the full potential of AI techniques. For example, a recent paper in solar panel fault detection [17] does not explicitly state the exact size (number of images) of the solar panel image dataset used for training and evaluation. The methodology section describes the use of high-resolution thermal and visual images, and mentions data augmentation and transfer learning, but does not provide a specific count of images or dataset size. It does not provide a systematic comparison with other YOLO versions (such as YOLOv5, YOLOv8, etc.) or alternative object detection frameworks. This is a common limitation in the current academic literature: most studies focus on a single YOLO version and do not benchmark across multiple models or datasets. As a result, there is little guidance on which YOLO version or model size is best suited for different deployment scenarios in solar panel fault detection.

Our Comprehensive Comparative Study for Solar Panel Fault Detection

A Large Solar Panel Image dataset

Recently, a large solar panel image dataset became available on https://universe.roboflow.com/class-dataset/new2_panel/dataset/3 [26]. The dataset contains 13337 solar panel images, including 11924 for training, 688 for validation, and 725 for testing, with five categories: 'crack', 'hotspot', 'clean', 'dirt', and 'snow_panel'. Figure 1, below shows some solar panel image examples.

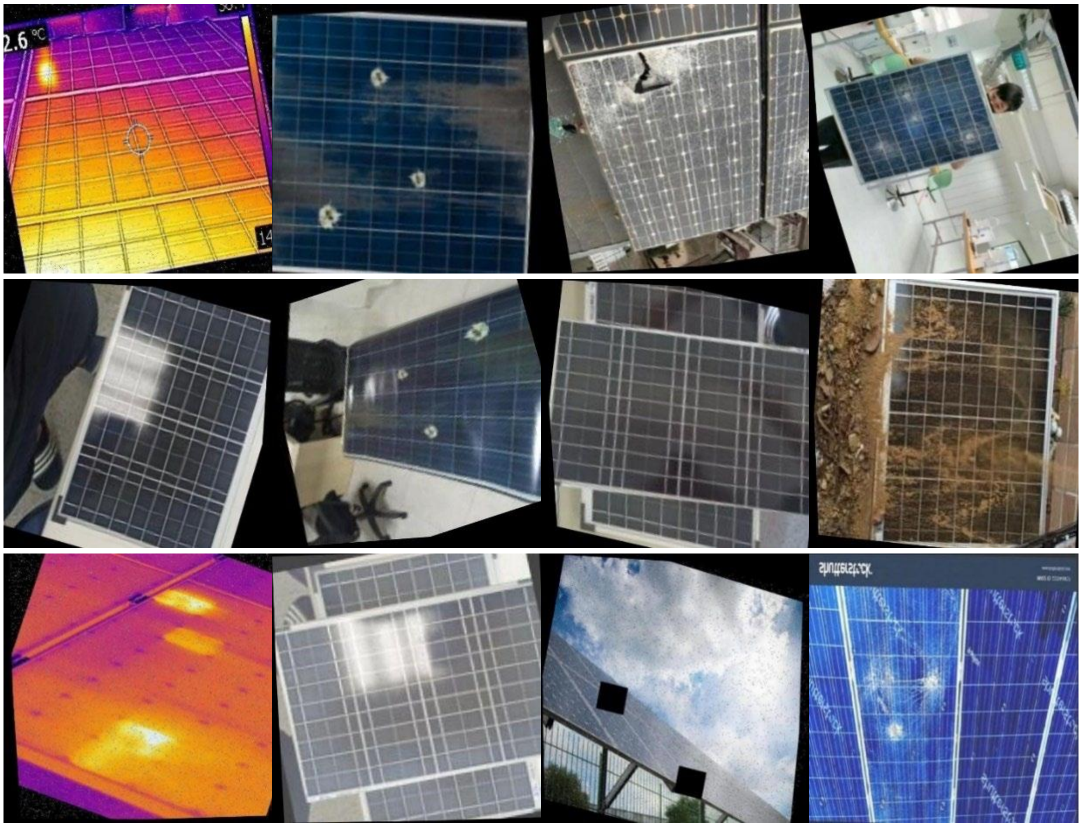

Figure 1. Solar panel image examples in our experiments.

YOLO Models in our comparative study

The reason to choose these YOLO models for solar panel fault detection is rooted in their proven ability to deliver high accuracy and efficiency in object detection tasks, including the identification and localization of defects in photovoltaic modules. YOLO's architecture allows for rapid, end-to-end analysis of images from thermal, electroluminescence, or visible-light sources, making it highly compatible with drone-based and automated inspection systems. Academic studies confirm that YOLO-based systems are particularly effective for real-time monitoring, automated maintenance, and large-scale solar farm inspections. Their adaptability, scalability, and consistent performance across multiple model sizes and versions make YOLO models a leading choice for both research and industrial applications in solar panel fault detection. We selected YOLO v5, YOLO v8, YOLO v9, YOLO v10, YOLO v11, and YOLO v12.

Based on YOLO v3, YOLOv5 further improved the model's performance and added new features such as hyperparameter optimization, integrated experiment tracking, and automatic export to popular export formats.

Released in 2023 by Ultralytics, YOLOv8 provides new features and improvements for enhanced performance, flexibility, and efficiency, supporting a full range of vision AI tasks.

YOLOv9 introduces innovative methods like Programmable Gradient Information (PGI) and the Generalized Efficient Layer Aggregation Network (GELAN).

YOLOv10 created by researchers from Tsinghua University using the Ultralytics Python package, provides real-time object detection advancements by introducing an End-to-End head that eliminates Non-Maximum Suppression (NMS) requirements.

Representing the Ultralytics' latest YOLO models, YOLO v11 delivers state-of-the-art (SOTA) performance across multiple tasks, including object detection, segmentation, pose estimation, tracking, and classification, leveraging capabilities across diverse AI applications and domains.

Building on Residual Efficient Layer Aggregation Networks (R-ELAN), YOLO v12 introduces an attention-centric architecture that departs from the traditional CNN-based approaches used in previous YOLO models yet retains the real-time inference speed essential for many applications. This model achieves state-of-the-art object detection accuracy through novel methodological innovations in attention mechanisms and overall network architecture, while maintaining real-time performance.

Our comparative study adopts all these models and examines the detection performance on the large solar panel fault image dataset. First, we train the models on the training image dataset, and compare the detection performance on the validation images, and the testing images.

Detection Results and Analysis

A systematic evaluation was conducted on YOLO versions 5 through 12, encompassing all available model sizes (nano, small, medium, large, and extra-large) to assess their effectiveness in solar panel fault detection. The primary metric for comparison was Mean Average Precision (maP) mAP50, as it directly reflects the models' ability to accurately localize and classify faults, with mAP50-95 providing a more stringent assessment across varying IoU thresholds.

Our detection results on the validation image data set and the testing image data set are given by Tables 1 and 2.

Table 1. Detection results on the validation dataset with the trained Yolo models.

model	precision	recall	mAP50	mAP50-95	fitness	f1_score	total_time (ms)
yolov10b	0.9048	0.8765	0.9216	0.7355	0.7541	0.890425	6.4556
yolov10l	0.8877	0.8735	0.9193	0.7346	0.7531	0.880543	7.9337
yolov10m	0.8827	0.8412	0.9067	0.7254	0.7435	0.86145	5.3415
yolov10n	0.8486	0.8189	0.8915	0.6906	0.7107	0.833486	2.5012
yolov10s	0.8839	0.8817	0.9237	0.7335	0.7526	0.882799	3.1611
yolov10x	0.9297	0.8581	0.9245	0.7467	0.7645	0.892466	11.1231
yolov11l	0.9095	0.8551	0.9302	0.7295	0.7496	0.881461	7.6129

yolov11m	0.9077	0.8643	0.929	0.7288	0.7488	0.885469	6.2726
yolov11n	0.9288	0.8219	0.9136	0.7087	0.7292	0.872086	3.1402
yolov11s	0.8868	0.8736	0.9243	0.7268	0.7466	0.880151	3.7593
yolov11x	0.8728	0.8534	0.9174	0.7136	0.734	0.862991	12.233
yolov12l	0.9308	0.8352	0.9229	0.727	0.7466	0.880412	11.7906
yolov12m	0.8982	0.8523	0.919	0.7053	0.7267	0.874648	8.1022
yolov12n	0.9251	0.8339	0.9159	0.7011	0.7226	0.877136	3.6102
yolov12s	0.921	0.8467	0.9199	0.7117	0.7325	0.882289	4.9517
yolov12x	0.9024	0.8331	0.9145	0.7075	0.7282	0.866366	18.1766
yolov5l	0.909	0.8399	0.9174	0.7233	0.7427	0.873085	7.749
yolov5m	0.9009	0.8507	0.9263	0.7322	0.7516	0.875081	5.3156
yolov5n	0.8573	0.8611	0.9035	0.687	0.7087	0.859196	3.0528
yolov5s	0.9164	0.8479	0.9257	0.7201	0.7406	0.88082	3.6205
yolov5x	0.9338	0.8113	0.9194	0.7221	0.7418	0.86825	12.2857
yolov8l	0.9179	0.8803	0.9289	0.7436	0.7622	0.898707	8.4032
yolov8m	0.9197	0.8773	0.939	0.7579	0.776	0.898	5.995
yolov8n	0.9092	0.8446	0.9085	0.7023	0.723	0.87571	3.3036
yolov8s	0.9068	0.8746	0.9302	0.7388	0.7579	0.890409	4.4007
yolov8x	0.9085	0.875	0.9271	0.7392	0.758	0.891435	12.1817
yolov9c	0.9084	0.8753	0.9379	0.75	0.7687	0.891543	8.0121
yolov9e	0.8921	0.8301	0.923	0.716	0.7367	0.859984	16.2932
yolov9m	0.9064	0.8865	0.935	0.7446	0.7637	0.89634	6.7559
yolov9s	0.9234	0.8536	0.9261	0.7364	0.7554	0.887129	5.1337

Table 2. Detection results on the testing dataset with the trained Yolo models

model	precision	recall	mAP50	mAP50-95	fitness	f1_score	total_time (ms)
yolov10b	0.8666	0.8366	0.8892	0.6963	0.7156	0.851336	6.3936
yolov10l	0.8588	0.8414	0.8969	0.6914	0.7119	0.850011	7.8629
yolov10m	0.8394	0.8347	0.876	0.6794	0.699	0.837043	5.1317
yolov10n	0.8097	0.8037	0.8545	0.63	0.6525	0.806689	3.2674
yolov10s	0.8684	0.8225	0.8958	0.6741	0.6963	0.844827	3.3675
yolov10x	0.8821	0.8513	0.901	0.7058	0.7254	0.866426	11.0197
yolov11l	0.8781	0.8062	0.8886	0.6775	0.6986	0.840615	7.5011
yolov11m	0.852	0.8479	0.8932	0.6809	0.7021	0.849945	6.1808
yolov11n	0.8793	0.8134	0.8891	0.6481	0.6722	0.845067	3.7126
yolov11s	0.8819	0.8202	0.8941	0.6779	0.6995	0.849932	5.0847
yolov11x	0.8696	0.8196	0.8932	0.6763	0.698	0.84386	12.1303
yolov12l	0.8574	0.8301	0.8934	0.6773	0.6989	0.843529	11.7998
yolov12m	0.8695	0.8219	0.8866	0.6605	0.6831	0.84503	7.9914

yolov12n	0.8777	0.7998	0.8827	0.6508	0.674	0.836941	3.983
yolov12s	0.8578	0.8165	0.8861	0.652	0.6754	0.836641	5.2366
yolov12x	0.8652	0.8196	0.8882	0.6693	0.6912	0.841783	18.2651
yolov5l	0.8704	0.84	0.8938	0.6735	0.6956	0.85493	7.6515
yolov5m	0.8861	0.835	0.8983	0.681	0.7027	0.859791	5.2408
yolov5n	0.8418	0.8162	0.8717	0.6349	0.6585	0.828802	3.876
yolov5s	0.8652	0.818	0.8902	0.663	0.6857	0.840938	5.014
yolov5x	0.8556	0.8319	0.8918	0.673	0.6949	0.843584	12.1745
yolov8l	0.9011	0.8577	0.9121	0.7055	0.7262	0.878865	8.3836
yolov8m	0.885	0.846	0.9014	0.7014	0.7214	0.865061	5.8001
yolov8n	0.8515	0.8046	0.8807	0.6473	0.6706	0.827386	4.0136
yolov8s	0.8813	0.8344	0.9044	0.69	0.7114	0.857209	4.8176
yolov8x	0.8786	0.854	0.9133	0.7023	0.7234	0.866125	12.0938
yolov9c	0.8924	0.8444	0.9102	0.7033	0.724	0.867737	7.9925
yolov9e	0.861	0.8109	0.89	0.6804	0.7014	0.835199	16.2807
yolov9m	0.8725	0.8633	0.9082	0.6921	0.7137	0.867876	6.9042
yolov9s	0.8762	0.8391	0.9004	0.686	0.7075	0.857249	4.1129

The detection results on the validation solar panel image dataset, shown in Table 1, the highest mAP50 scores were achieved by the medium and large models of the latest YOLO versions. Specifically, YOLOv8m (0.939), YOLOv9c (0.9379), and YOLOv9m (0.935) emerged as the top performers, closely followed by YOLOv8l (0.9289) and YOLOv11l (0.9302). The YOLOv12 family also demonstrated strong performance, with YOLOv12l (0.9229) and YOLOv12n (0.9159) outperforming the earlier YOLO versions in their respective size categories. Below is our summary of analysis on the validation dataset.

Top Performing Models

- **YOLOv8m** achieved the **highest mAP@0.5 (0.939)** and **mAP@0.5:0.95 (0.7579)**, with strong precision (0.9197) and recall (0.8773), making it the most balanced and accurate model in terms of both localization and classification performance.
- **YOLOv9c** followed closely with an mAP@0.5 of 0.9379 and mAP@0.5:0.95 of 0.750, while maintaining high precision (0.9084) and recall (0.8753).
- **YOLOv10x** attained the **highest precision (0.9297)** and the **best fitness score (0.7645)**, indicating superior object detection with minimal false positives.
- **YOLOv8l** also showed strong overall performance, with an mAP@0.5:0.95 of 0.7436 and the **highest F1-score (0.8987)**, indicating optimal balance between precision and recall.

Lightweight Model Analysis (Speed vs Accuracy Tradeoff)

- **YOLOv10n** and **YOLOv5n** exhibited the **lowest inference times (2.5 milliseconds and 3.05 milliseconds respectively)**, but at the cost of reduced mAP@0.5:0.95 values (0.6906 and 0.687 respectively). These models are better suited for resource-constrained or real-time edge applications where speed is prioritized over precision.
- **YOLOv8n** and **YOLOv12n** achieved a more favorable balance between detection accuracy and speed compared to other "nano" models, with mAP@0.5:0.95 values of 0.7023 and 0.7011, respectively.

Large Model Comparison

- Larger models such as **YOLOv12x**, **YOLOv5x**, and **YOLOv11x** showed relatively **longer inference times (12–18 milliseconds)**, with only marginal improvements in detection accuracy over their medium or small counterparts. This makes them less efficient for real-time deployment, despite slightly better raw metrics.
- Notably, **YOLOv12l** displayed high precision (0.9308) but lower recall (0.8352), suggesting it may be more prone to missing detections despite high confidence in those it makes.

Based on the detection results on the testing dataset across various YOLO models (v5, v8, v9, v10, v11, v12), the top performers by metric is YOLOv8l on precision metric (0.9011), YOLOv9m on recall (0.8633), YOLOv8x on mAP50 (0.9133), YOLOv10x on mAPp50-95 (0.7058), YOLOv8l on F1 score (0.8788865), YOLOv8l on Fitness (0.7262), and YOLOvn on speed (3.2674 milliseconds). Overall, the best performer is YOLOv8l with the highest precision, fitness, F1 score, near top mAP50, mAP50-95 and a reasonable inference time (8.38 milliseconds).

A clear pattern emerges when we examine the validation and testing results: models that perform well during validation generally maintain strong performance on the testing set. This is especially true for the YOLOv8 and YOLOv9 series, indicating that these models not only learn well during training but also generalize effectively to unseen data. For example, YOLOv8l and YOLOv8x demonstrate top-tier results on both validation and testing, suggesting stable learning dynamics and robustness. YOLOv9m also shows high recall and F1 scores in both sets, supporting its reliability.

This consistency reinforces the generalization power of the later YOLO models, especially version 8 and 9, in both controlled (validation) and real-world (testing) conditions.

Considering both the outcomes on validation dataset and the testing dataset, the overall ranking of models remained consistent, indicating strong generalization from validation to unseen data. YOLOv8x (0.9133), YOLOv8l (0.9121), and YOLOv9c (0.9102) led in mAP50, with YOLOv11l (0.8886) and YOLOv12l (0.8934) maintaining competitive scores. The drop in mAP50 from validation to test was generally modest for the top models, suggesting minimal overfitting and robust real-world applicability. Precision and recall values were also highest among these top performers, with YOLOv8l (precision: 0.9011, recall: 0.8577) and YOLOv9m (recall: 0.8633) standing out.

Inference time is a critical consideration for practical deployment. The nano and small models (e.g., YOLOv5n, YOLOv10n, YOLOv11n, YOLOv12n) consistently offered the fastest inference (as low as ~2 ms), making them suitable for edge or real-time applications, albeit with a trade-off in mAP50 (typically in the range of 0.85–0.91). In contrast, extra-large models (e.g., YOLOv12x, YOLOv8x) achieved the highest detection accuracy but at the cost of significantly increased inference times (up to ~18 ms for YOLOv12x).

Conclusion

In summary, for solar panel fault detection tasks demanding state-of-the-art accuracy, YOLOv8m/l/x and YOLOv9c/m are the most effective choices, balancing high mAP50, robust generalization, and reasonable inference speed. YOLOv11 and YOLOv12 offer strong alternatives, particularly where model family diversity or specific deployment constraints are required. For edge or real-time applications, the nano and small variants of all families—most notably YOLOv5n, YOLOv10n, YOLOv11n, and YOLOv12n—provide the best trade-off between speed and accuracy. The results underscore the importance of aligning model selection with deployment requirements, considering both detection performance and computational constraints.

Acknowledgements

The support for this study from the SHSU Institute of Homeland Security is highly appreciated. We are also very grateful to Mr. Scott Lynn at the SHSU IHS for his insightful comments and professional editorial help.

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Liu, Q. (2025). Comparative Analysis of YOLO Models for Real-Time Solar Panel Defect Detection (Institute for Homeland Security Report No. 2025-1024). Institute for Homeland Security.
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