Application of RF-DETR and YOLOv12 Model on a Novel Solar Panel Dataset for Defect Detection in Sustainable Energy System

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Abstract: Solar panels are essential for sustainable energy as they convert sunlight into clean, renewable electricity with minimal environmental impact. However, defects such as cracks and hot spots can diminish performance by causing power loss and accelerating solar cell degradation. Therefore, precise defect detection is critical for effective maintenance and sustainability. This study assesses two innovative models, RF-DETR and YOLOv12, using a novel dataset to compare precision, recall, and mean Average Precision (mAP) with the aim of enhancing defect detection accuracy and efficiency. A four-stage methodology is employed, wherein high-resolution drone images from thermal and high-definition cameras are processed to improve quality. Noise reduction and contrast enhancement are applied prior to model implementation to ensure precise and reliable defect detection under various conditions, thereby evaluating model effectiveness and accuracy. RF-DETR demonstrated superior performance over YOLOv12 across all metrics, achieving a precision of 0.83, recall of 0.78, and F1-score of 0.81 in single-class detection, compared to YOLOv12x's precision of 0.66 and F1-score of 0.72 versus 0.57 in multi-class tasks.

Keywords: Solar Panel Defect Detection, RF-DETR, YOLOv12, Deep Learning Method, Image Processing.

Introduction

Solar panels play a crucial role in sustainable energy systems by converting sunlight into electricity via photovoltaic technology, thereby promoting energy independence through the use of an abundant resource [1]. Advances in energy storage and grid integration enhance the capacity of solar energy to meet energy demands while minimizing environmental impact [2]. However, defects in solar panels, such as hot spots, cracks, and snail trails, can diminish performance, leading to power loss and accelerated cell degradation. Furthermore, extreme weather conditions and environmental stressors exacerbate damage, necessitating regular system inspections [3].

Over the past decade, defect detection has undergone significant transformation through the application of deep learning, advancing from basic pattern recognition to systems capable of image comprehension. These methodologies are categorized into three distinct approaches (Figure 1), each demonstrating strengths across various domains. This advancement addresses recognition challenges in sectors such as autonomous driving, healthcare, security surveillance, and solar panel defect detection [4]. Accurate defect detection is essential for the maintenance of solar panels, facilitating automated monitoring and defect identification. However, challenges remain in distinguishing defects from complex backgrounds and managing multi-scale defects. Traditional image processing methods encounter limitations in feature extraction, which impacts accuracy [5]. In contrast, deep learning techniques, particularly convolutional neural networks, exhibit potential for automating defect detection and classification in solar panels [6].

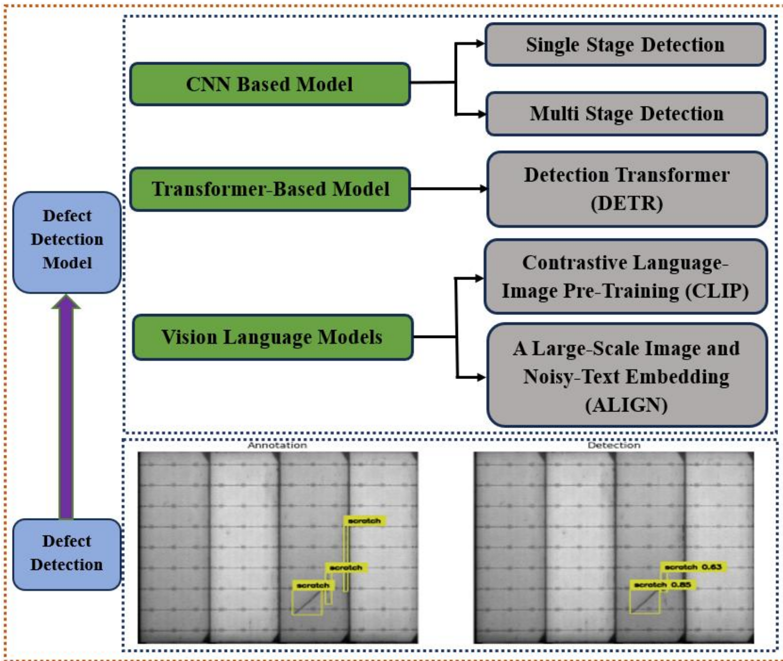

Figure 1. Classification of defect detection model.

Convolutional Neural Networks (CNNs), such as YOLO and R-CNN, are employed to process spatial hierarchies. In contrast, Transformer-based models like DETR utilize self-attention mechanisms to capture global context and facilitate post-processing [7]. Vision Language Models, exemplified by CLIP, achieve integration of textual and visual data through multimodal learning. Hybrid models, including RetinaMask and EfficientDet, amalgamate different architectures to enhance performance. Deep learning models, particularly CNNs, are predominant due to their superior accuracy, robustness, and generalization capabilities across various applications, such as the detection of defects in solar panels [8]. As hybrid, sparse coding, and traditional feature-based methods, like Histogram of Oriented Gradients (HOG), become obsolete, the emphasis shifts towards precise and efficient processing. Manual inspection is inadequate for meeting production standards, particularly in identifying small defects [9]. CNN and Transformer-based models represent the state-of-the-art, with automation contributing to reduced error rates [10].

Among the six primary methodologies for defect detection, models based on Convolutional Neural Networks (CNN) and Transformers have become prominent in the last five years due to their scalability, accuracy, and adaptability [11]. The RF-DETR model integrates innovations from Deformable DETR, LW-DETR, and a DINOv2 backbone to enhance global context modeling and domain adaptability. This model eliminates the need for anchor boxes and Non-Maximum Suppression, facilitating end-to-end training, real-time inference, and scalability through its Base (29M) and Large (128M) variants [12]. Although RF-DETR has outperformed YOLOv11, a formal benchmark comparison with YOLOv12 is still necessary. Therefore, a comparative analysis between RF-DETR and YOLOv12 is crucial, focusing on the following research components:

1. Novel Dataset Application: Implement RF-DETR and YOLOv12 on a novel, high-resolution dataset specifically curated for the detection of defects in solar panels, which includes a variety of environmental conditions and defect types such as broken panels, hot spots, black borders, scratches, and lack of electricity. This approach aims to evaluate the models' robustness and generalizability in practical scenarios.
2. Comparative Performance Analysis: Undertake a comprehensive, quantitative comparison of RF-DETR and YOLOv12 by assessing metrics such as precision, recall, F1-score, and mAP for each defect category. This analysis will elucidate the strengths and limitations of each model in accurately identifying specific defect types.

Research Method

Defect detection in solar panels involves four distinct stages: image collection, image processing, model implementation, and performance evaluation. During the image collection phase, drones and thermal cameras are employed to capture images under various conditions, including those with defective panels, to construct a comprehensive dataset. The image processing stage involves preparing these images by reducing noise and enhancing contrast. In the model implementation phase, a machine learning model is selected and trained. Finally, performance evaluation assesses the model's accuracy and efficiency using specific metrics, as illustrated in Figure 2.

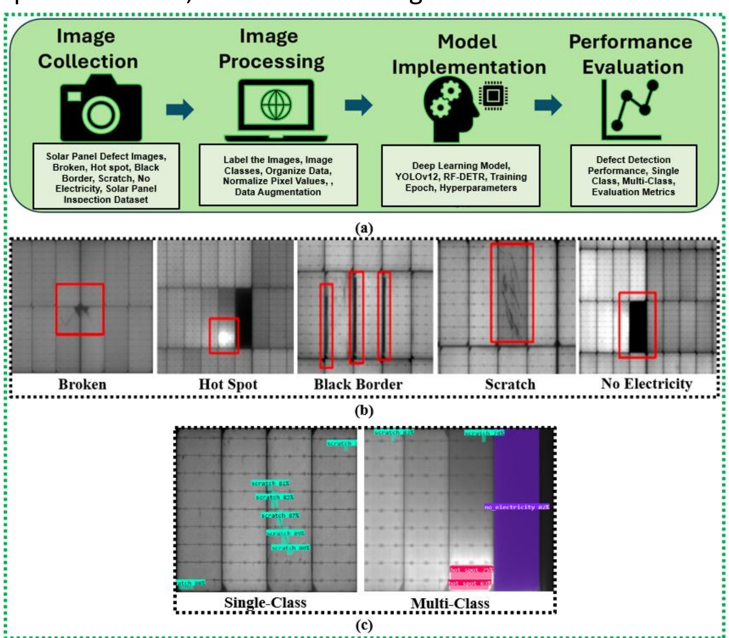

Figure2. Outline of the experimental setup: (a) Flowchart comparing RF-DETR and YOLOv12, (b) Classification of defects in solar panels, (c) Classification of single-class and multi-class images.

Results and Discussions

In a comparative analysis of solar panel defect detection models, RF-DETR and various YOLOv12 variants (YOLOv12s, YOLOv12n, YOLOv12x) were assessed using Precision, Recall, and F1-Score metrics for both single-class and multi-class scenarios, as presented in Table 1. For single-class detection, RF-DETR demonstrated superior performance, achieving a Precision of 0.83, Recall of 0.78, and an F1-Score of 0.81.

Among the YOLOv12 models, YOLOv12x exhibited the highest performance, with a Precision of 0.71, Recall of 0.62, and an F1-Score of 0.66, although it remained inferior to RF-DETR. The YOLOv12n and YOLOv12s models recorded lower F1-Scores of 0.61 and 0.59, respectively. RF-DETR employs a DINOv2 backbone and deformable attention mechanisms to effectively model global context and detect partially occluded instances.

Table 1. Comparative analysis of Precision, Recall, and F1 Score for single-class and multi-class defect detection for solar panel.

Models	Single Class			Multi Class		
	Precision	Recall	F1-Score	Precision	Recall	F1-Score
RF-DETR	0.83	0.78	0.81	0.74	0.71	0.72
YOLOv12s	0.58	0.60	0.59	0.47	0.45	0.52
YOLOv12n	0.66	0.57	0.61	0.47	0.59	0.46
YOLOv12x	0.71	0.62	0.66	0.49	0.68	0.57

RF-DETR exhibited robust performance in multi-class defect detection, achieving a Precision of 0.74, a Recall of 0.71, and an F1-Score of 0.72, thereby demonstrating effective detection and classification across various categories. In comparison, among the YOLOv12 models, YOLOv12x achieved the highest Recall at 0.68, although it recorded lower Precision and F1-Score values of 0.49 and 0.57, respectively, compared to RF-DETR. The YOLOv12n and YOLOv12s models were less effective, with F1-Scores of 0.46 and 0.52. The DINOv2 backbone and deformable attention mechanisms of RF-DETR facilitate context modeling and differentiation between defect types.

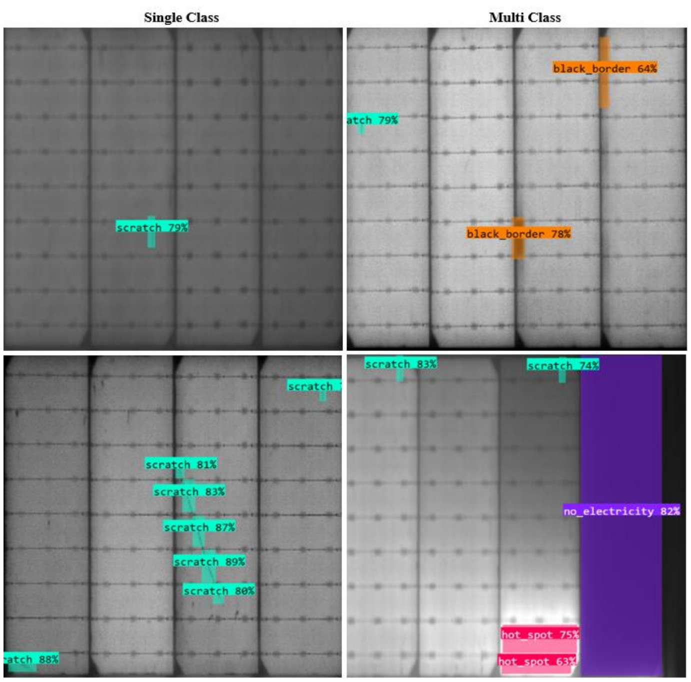

Figure 5. Visual analysis of defect detection for solar panel employing RF-DETR.

RF-DETR demonstrates superior performance compared to all YOLOv12 variants in both single-class and multi-class panel defect detection, achieving higher precision, recall, and F1-Scores. While YOLOv12x approaches RF-DETR in terms of multi-class recall, it remains inferior in precision and F1-Score. The smaller YOLOv12 models exhibit reduced accuracy, thereby rendering RF-DETR more suitable for defect detection in solar panels. These results are consistent with existing studies on requirements and precision-recall trade-offs. Additionally, YOLOv8 and YOLOv9 were assessed for solar panel applications.

Figure 5 illustrates that RF-DETR demonstrates superior performance in localizing defects within panel images. The model's bounding boxes effectively capture defects, reducing false positives and accurately distinguishing between defect types, thereby enhancing precision and recall. It delineates boundaries and identifies defect classes. Conversely, as depicted in Figure 6, YOLOv12 models exhibit difficulties in localization and differentiation. This discrepancy is likely attributable to RF-DETR's DINOv2 backbone and deformable attention mechanism.

While YOLOv12 models exhibit increased speed, they generate less accurate bounding boxes in the detection of solar panel defects. The smaller versions of YOLOv12, specifically the 's' and 'n' variants, frequently fail to identify subtle defects or incorrectly classify regions, resulting in reduced recall and F1-Scores. Although YOLOv12x enhances sensitivity, it continues to face challenges in precise localization, particularly in multi-class scenarios. Conversely, RF-DETR offers more precise localization in areas with complex or clustered defects, thereby enhancing its reliability for real-world solar panel inspections and automated photovoltaic defect detection.

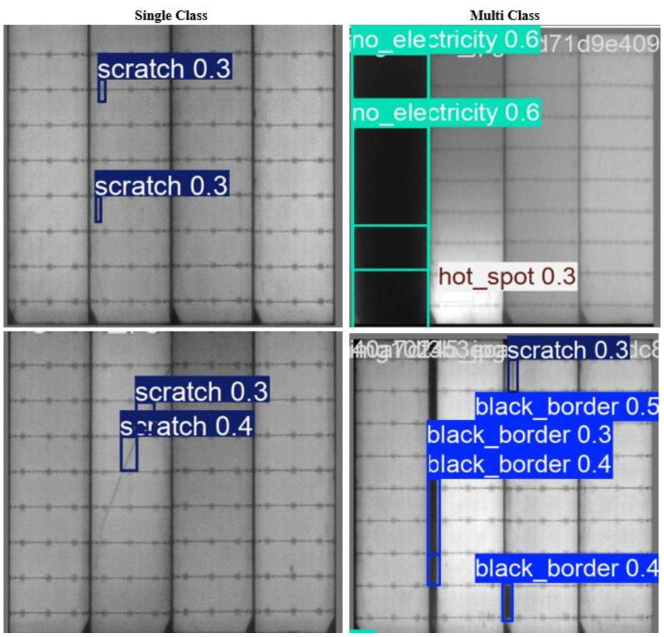

Figure 6. Visual inspection of defect detection for solar panel employing YOLOv12.

The analysis indicates that RF-DETR exhibits a superior baseline mean Average Precision (mAP) compared to YOLOv12, suggesting enhanced initial detection capabilities, potentially due to more effective initialization or training, as illustrated in Figures 7 and 8. RF-DETR demonstrates rapid improvement during the initial epochs, achieving a mAP of approximately 0.6 by epoch 9, whereas YOLOv12 remains below 0.1 for numerous epochs. RF-DETR reaches a peak mAP@0.5 of approximately 0.85, which is about 30 percentage points higher than YOLOv12's peak of 0.55. Although both models eventually plateau, RF-DETR maintains greater consistency and is preferred for high-precision defect detection, consistent with transformer-based methodologies.

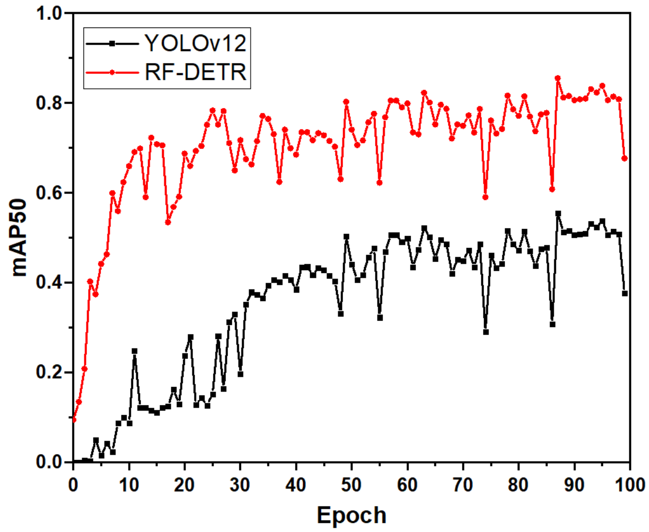

Figure 7. Compirative analysis of RF-DETR and YOLOv12 based on mAP@50.

RF-DETR and YOLOv12 were compared using mAP@0.5:0.95, which measures detection precision across Intersection over Union thresholds. RF-DETR started higher at approximately 0.0566 mAP, while YOLOv12 began near zero. RF-DETR consistently surpassed 0.3 by epoch 9, peaked around 0.52 versus YOLOv12's approximately 0.32, and remained more stable throughout training overall, suggesting better suitability for applications requiring precision across multiple IoU thresholds.

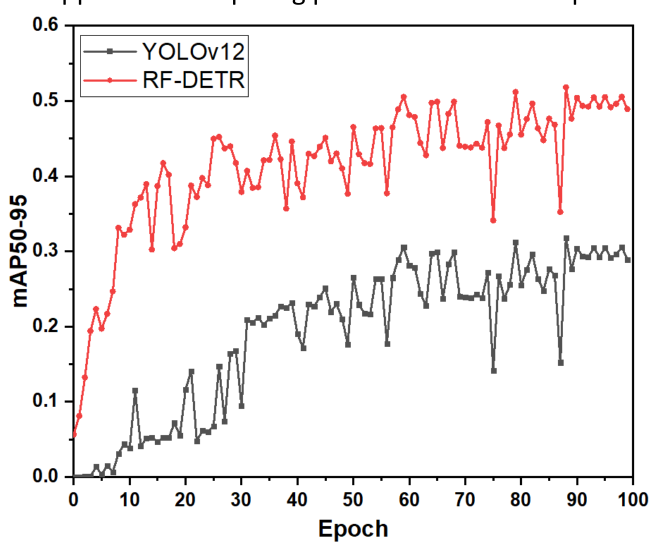

Figure 8. Compirative analysis of RF-DETR and YOLOv12 based on mAP@50:95.

Conclusion

This research investigates the application of RF-DETR and YOLOv12 models, utilizing a novel solar panel dataset, to enhance defect detection in sustainable energy systems. Solar panels are integral to renewable energy; however, defects can substantially reduce their efficiency. Traditional defect detection methods often suffer from limitations, such as subjectivity and inefficiency. This study seeks to evaluate and compare the performance of RF-DETR, which incorporates a DINOv2 backbone and deformable attention mechanisms for enhanced global context modeling, with YOLOv12, which employs CNN-based attention for local feature extraction. By assessing these models on a novel dataset, the research aims to identify the most effective approach for high-precision, fine localization, and multi-class detection of defects. Ultimately, the objective is to improve solar panel inspection and maintenance practices.

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