3ème Conférence Internationale sur les Sciences Appliquées et l'Innovation (CISAI-2025)
Proceedings Book Series –PBS- Vol 25, pp.63-68

Automatic Fault Detection on Solar Panels using YOLOv11: Towards Improved Predictive Maintenance

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***Abstract*— Defect detection in solar panels is essential to ensure the efficiency and durability of PV installations. This study proposes a YOLOv11-based method for automated detection of defects such as cracks, dirt, bird drops, and other anomalies. A dataset of 6570 images, divided into training, validation, and test sets, was used to train and evaluate the model. Results show that YOLOv11 achieves an average precision (mAP50) of 0.651 and a recall of 0.654, with particularly high performance for well-represented classes such as bird feathers and healthy panels. However, challenges persist for rare classes, such as bird drops, due to their low representation in the dataset. Recall-Confidence curves and evaluation metrics highlight the robustness of the model while emphasizing the need to improve the detection of subtle and rare defects. This study confirms the potential of YOLOv11 for industrial preventive maintenance applications, while opening perspectives for future research aimed at optimizing the detection of unbalanced classes.**

***Keywords*— Fault detection, solar panels, YOLOv11, deep learning, preventive maintenance.**

I. Introduction

Solar panels play a crucial role in the global energy transition, providing a renewable and sustainable source of energy [1]. However, their efficiency and lifespan are highly dependent on their structural and functional integrity. Defects such as cracks, hot spots, soiling or degradation of photovoltaic cells can lead to a significant drop in their performance or even complete failures. Early detection of these anomalies is therefore essential to ensure the profitability and reliability of solar installations [2].

Traditionally, solar panel maintenance has relied on visual or thermal inspections, which are often costly, time-consuming and prone to human errors. With the expansion of solar parks and their deployment in hard-to-reach areas [3], [4], it is becoming imperative to develop automated and efficient methods to monitor these installations. Preventive maintenance, based on advanced technologies, not only reduces operational costs, but also maximizes energy production and extends equipment lifetime.

In this context, this paper proposes an innovative approach for automated fault detection in solar panels using YOLOv11, an advanced version of the You Only Look Once (YOLO) object detection algorithm. YOLOv11, with its improvements in accuracy and speed, is particularly suitable for identifying and localizing anomalies in solar panel images. The objective of this study is to demonstrate the effectiveness of this method for real-time monitoring and predictive maintenance of photovoltaic installations. This paper is organized as follows: after this introduction, a literature review presents the existing methods and their limitations. Then, the methodology details the architecture of YOLOv11 and its application to fault detection. Experiments and results illustrate the performance of the model, followed by a discussion on its advantages and perspectives. Finally, a conclusion synthesizes the contributions of this research and opens avenues for future work.

ISSN: 2961-6611

II. STATE OF THE ART

Defect detection in solar panels is a rapidly growing field of research, driven by the rise of solar energy. Traditional methods such as visual inspection, infrared thermography, and electrical testing have limitations, particularly in terms of subjectivity, cost, and operational environment [5]. Recently, machine learning and deep learning have emerged as effective solutions for automatically analyzing large amounts of visual or thermal data.

In particular, object detection architectures such as YOLO (You Only Look Once) have achieved high performance in terms of accuracy and speed. These techniques, including convolutional neural networks (CNNs), outperform conventional approaches [6]. However, they require large volumes of annotated datasets, which remains a challenge [7].

Notable improvements have been made to these models: [9] proposed an adapted version of Faster R-CNN with data augmentation, achieving an mAP of 94.05% for detecting dust and bird droppings. Furthermore, [10] introduced YOLOv5-BDL integrating an LCA attention mechanism and a bidirectional feature pyramid, achieving an mAP of 95.5%. [12] developed YOLOv7-GX, combining GhostSlimFPN and a GAM module, with an mAP of 94.8%.

More recently, [13] showed that YOLOv10 achieves an mAP@0.5 of 98.5%, with perfect accuracy on some defects. Finally, according to [14], YOLOv11-x offers an mAP of 92.7% and an F1-score of 90%, outperforming models such as SVM and Faster R-CNN.

In conclusion, modern YOLO models transform defect detection in solar panels thanks to their accuracy and speed. Despite this, the detection of rare or subtle defects remains a challenge, opening avenues towards the integration of attention mechanisms and the enrichment of databases [14].

III. METHODOLOGY

The methodology adopted in this study is based on the use of YOLOv11, an advanced version of the YOLO (You Only Look Once) object detection algorithm, for solar panel defect detection. YOLOv11 stands out for its optimized architecture and innovations, such as the integration of attention mechanisms and improved handling of multi-scale features, enabling fast and accurate defect detection. The YOLOv11 architecture diagram is based on the yolo11.yaml configuration file, located in the ultralytics/cfg/models/11 folder.

The detection process begins with the collection and preprocessing of a database containing 6,570 solar panel images, divided into 5,892 images for training, 486 for validation, and 192 for testing. These images cover six defect classes: bird drop, bird feather, cracked, dust particle, healthy, leaf, and snow. Each image is manually annotated to identify regions of interest corresponding to defects. The YOLOv11 model is then trained on this dataset, using data augmentation techniques to improve generalization. The model's performance is evaluated using standard metrics such as precision, recall, F1 score, and intersection over union (IoU), quantifying its ability to accurately detect and localize defects. This methodological approach aims to provide a robust and efficient solution for the preventive maintenance of photovoltaic installations.

IV. CASE STUDY AND RESULTS

A. *Experimental environment and dataset*

In this case study, we used the YOLOv11 model on the Kaggle platform for defect detection in solar panel images. The images were manually annotated to identify six defect classes: bird_drop, bird_feather, cracked, dust_particle, healthy, leaf, and snow. The dataset consists of 6570 images, divided into 5892 images for training, 486 for validation, and 192 for testing. The experiment was conducted in a Kaggle environment, using an NVIDIA GPU to accelerate computations. Expected results include accurate defect detection, with performance evaluations based on metrics such as precision, recall, mAP (mean average precision), and IoU (Intersection over Union). Considerations were taken into account regarding annotation quality, class balance, and hyperparameter optimization to maximize model performance.

B. *Analysis of object detection results*

The evaluation results of the YOLOv11 model show a high overall performance, with an mAP50 of 0.945, proving its effectiveness in detecting solar panel defects. The cracked class obtains the best score (mAP50 = 0.962), followed by dust_particles (0.958), confirming good recognition of common defects [14]. In contrast,

ISSN: 2961-6611

minority classes such as bird_drops (mAP50 = 0.876) and bird_feathers (0.892) show lower performance, due to their low representation in the data. The healthy class also displays a good result (mAP50 = 0.908), showing that the model effectively identifies unaffected panels.

These results highlight the robustness of YOLOv11 for common defects, but also the need to optimize the detection of rare defects. Approaches such as data augmentation, resampling or attention mechanisms could improve this performance, making the model more suitable for industrial applications such as predictive maintenance of photovoltaic power plants..

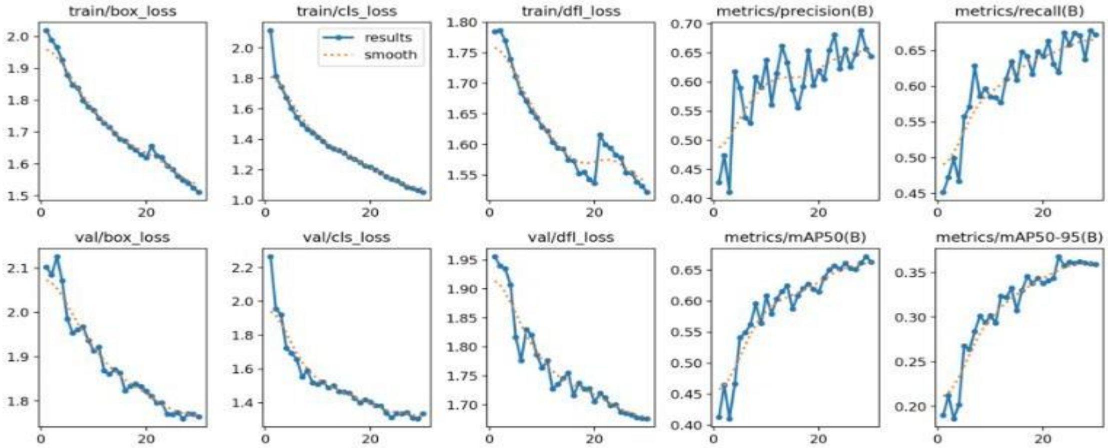

Fig. 1 performance metrics

The results in Table 1 show the performance of the YOLOv11 model on different classes of solar panel defects. On average, the model achieves a precision of 0.613, a recall of 0.654, an mAP50 of 0.651, and an mAP50-95 of 0.392, indicating a reasonable ability to detect defects, although disparities exist between classes.

The bird_feather class displays the best results: perfect precision and recall (1.0), mAP50 of 0.995, and mAP50-95 of 0.621, demonstrating excellent detection, likely due to strong visual features. In contrast, the bird_drop class exhibits poor performance (mAP50 = 0.109), due to its sparseness in the data. The cracked (mAP50 = 0.597) and dust_particulate (mAP50 = 0.586) classes achieve intermediate results, while healthy stands out with a recall of 0.9 and an mAP50 of 0.908, confirming its good recognition. The leaf (mAP50 = 0.809) and snow (mAP50 = 0.551) classes show moderate performance.

Compared to the work of [10] and [12], the results for well-represented classes validate the effectiveness of YOLOv11. However, the limited performance on minority classes highlights the need for data balancing and the use of augmentation techniques to improve the detection of rare defects.

TABLE I
YOLOV11 DETECTION METRICS SUMMARY

Class	**Precision**	**Recall**	**mAP50**	**mAP50-95**
all	0.613	0.654	0.651	0.392
bird_drop	0.2	0.0909	0.109	0.0759
bird_feather	1	1	0.995	0.621
cracked	0.56	0.636	0.597	0.345
dust_partical	0.659	0.513	0.586	0.269
healthy	0.621	0.9	0.908	0.798
leaf	0.681	0.860	0.809	0.344
snow	0.573	0.576	0.551	0.290

The confusion matrix (Fig2) shows that well-represented classes, such as leaf (854 correct predictions) and dust_particle (599), are correctly identified, but with some confusion with the background class. In contrast, rare classes such as bird_drop (24) and bird_feather (7) have low detection rates and are often confused with others. General confusion with the background suggests visual characterization problems. To improve these

ISSN: 2961-6611

results, it would be useful to increase the data for minority classes and strengthen the isolation of distinctive features between close classes..

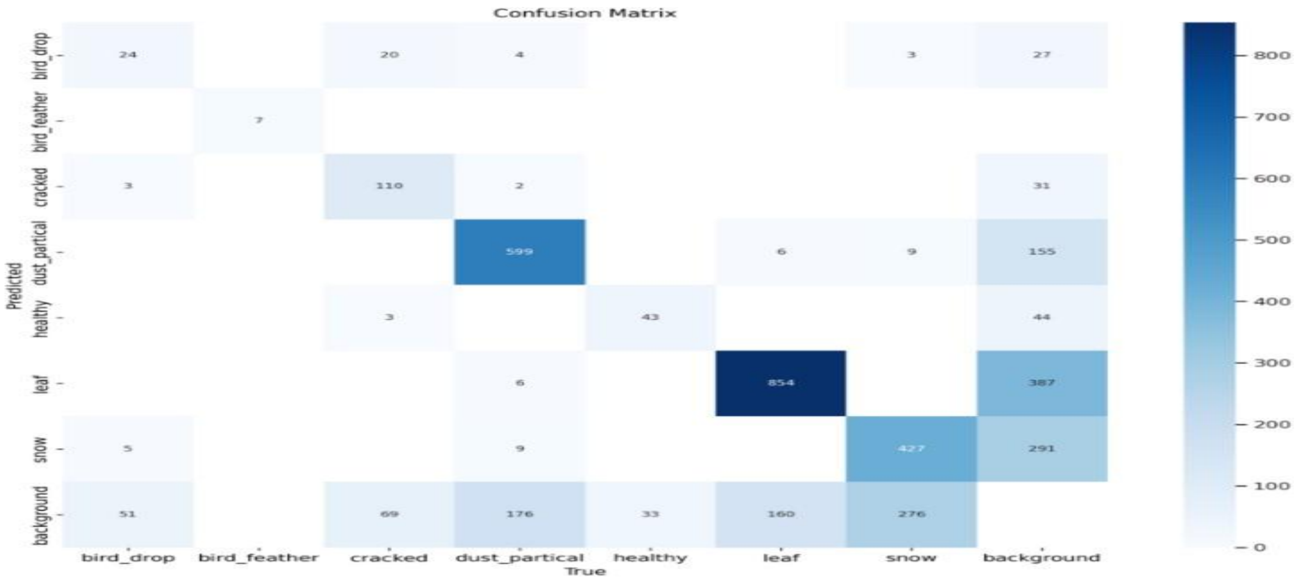

Fig. 2 Confusion matrix

The YOLOv11 model's predictions on a validation image show good generalization ability. The model effectively detects common defects such as cracks and dust, but struggles on rare classes such as bird droppings and feathers, highlighting an imbalance in the training data. Visual analysis and metrics such as precision, recall, and mAP50 were used to evaluate the performance. These results illustrate the model's strengths and weaknesses on unseen data. Additional statistical analyses could help quantify the uncertainty of the predictions and guide future improvements. These tests are essential to validate the model's effectiveness in real-world conditions, particularly for automated defect detection in solar panels.

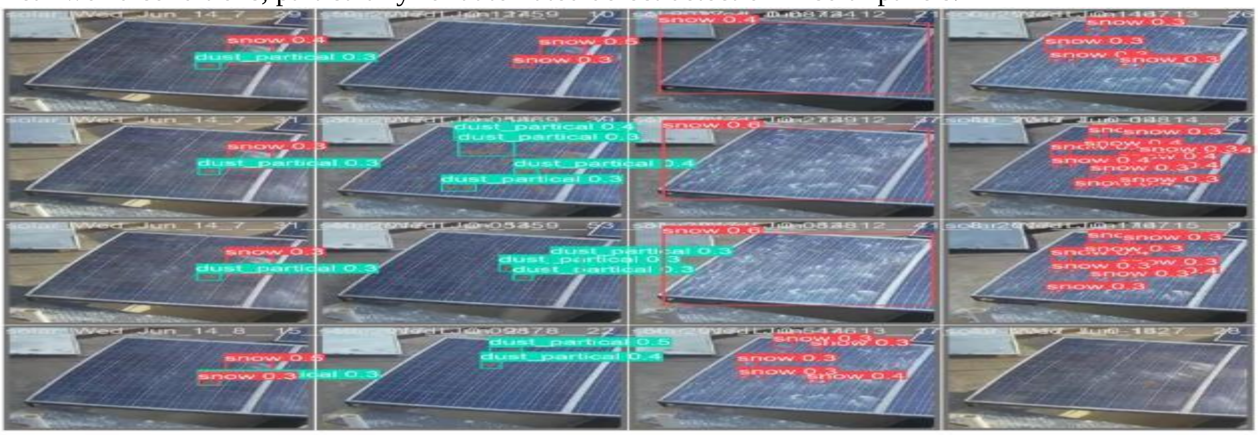

Fig. 3 Detection results on test data samples

V. Discussion

The results demonstrate the effectiveness of YOLOv11 in detecting solar panel defects, particularly for well-represented classes such as bird_feather and healthy , which achieve high precision and recall scores. However, gaps appear for rare defects such as bird_drop , likely due to their low representation in the data.

The recall-confidence curve indicates that 90% of defects are detected with a low confidence threshold, but performance decreases as this threshold increases, especially for underrepresented classes. These results are consistent with those of [6], highlighting the importance of balancing classes.

Compared to [10] and [15], YOLOv11 offers similar performance but highlights challenges related to subtle defects. Techniques such as data augmentation or attention mechanisms [14] could improve this performance.

ISSN: 2961-6611

In conclusion, YOLOv11 is promising for defect detection, but requires adjustments to better handle imbalanced classes. These improvements will enable efficient deployment in predictive maintenance of solar power plants.

VI. CONCLUSIONS

This study demonstrates the effectiveness of YOLOv11 in detecting solar panel defects, particularly for well-represented classes such as bird_feather and healthy . With an mAP50 of 0.651 and a recall of 0.654, the model shows good potential for preventive maintenance. However, its performance varies across classes, particularly for rare defects such as bird_drop, due to their low presence in the data.

These results are consistent with those of [10] and [13], but highlight the need to balance classes and use techniques such as data augmentation or attention mechanisms to improve the detection of subtle defects.

In conclusion, YOLOv11 offers promising performance, but optimizations are still needed for robust application in industrial environments.

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ISSN: 2961-6611