YOLOv8n-Based End-to-End Solar Panel Inspection: Detection and Multi-Class Classification with SVM Comparison

Yakoub NETTARI
Department of Electrical and Electronics Engineering
Istanbul Sabahattin Zaim University
Istanbul, Türkiye
email: yakup.cezayirli@izu.edu.tr
ORCID: 0000-0002-6426-0632

Fella Berrimi
Sciences Faculty, Ferhat Abbas University, Setif 1
Setif, Algeria
email: berrimifella@gmail.com
ORCID:0000-0002-5415-3470

***Abstract*—Accurate detection and classification of solar panel conditions are critical for enabling preventive maintenance and ensuring optimal photovoltaic (PV) energy production. This paper presents an automated inspection system based on the YOLOv8n object detection architecture for the detection of photovoltaic panels and their classification into six distinct condition categories. These categories include clean surfaces, common environmental contaminants (e.g., dust, bird droppings, and snow), as well as complex defect patterns such as electrical and physical damage. The proposed YOLOv8n-based system demonstrates strong performance, achieving an overall classification accuracy of 0.98 for clean or lightly affected panels (Clean, Dust, Bird, and Snow) and 0.96 for panels exhibiting complex defects or mixed condition states. To robustly validate this deep learning approach, results are benchmarked against a classical Support Vector Machine (SVM) classifier, which was trained on extracted handcrafted visual features and achieved an accuracy of 0.956 across the tested classes. Experimental results confirm that the YOLOv8n model significantly surpasses the SVM baseline in terms of robustness, scalability, and detection performance, particularly under challenging and visually ambiguous panel conditions.**

***Index Terms*—Solar panel inspection, YOLOv8n, object detection, classification, support vector machine, photovoltaic diagnostics**

I. Introduction

The rapid global expansion of photovoltaic (PV) installations has intensified the demand for automated, reliable, and real-time inspection systems capable of identifying production-compromising defects. Traditional manual inspection methods are inherently labor-intensive, subjective, and operationally infeasible for large-scale deployments. Recent advancements in computer vision and deep learning have profoundly improved the automation of PV diagnostics, notably through the development of high-performance object detection architectures like the You Only Look Once (YOLO) family [1]–[3].

YOLO-based detectors have proven effective across a wide spectrum of industrial and environmental applications due to their capacity for simultaneous object localization and classification in real-time. Subsequent iterations, including the highly optimized YOLOv8 [3], offer enhanced feature representation, accelerated convergence, and superior performance on challenging datasets. These characteristics make them exceptionally well-suited for solar panel inspection, where defects often manifest as irregular shapes, variable contrast, and overlapping physical conditions.

In parallel, deep convolutional neural networks (CNNs) have established robust capabilities in solar panel defect detection, achieving accurate identification of anomalies such as cracks, hotspots, soiling, and structural degradation [4], [5]. More specialized studies have focused on the detection of intricate cell-level cracking patterns and heterogeneous damage types [6]–[8]. Despite these strides, many photovoltaic diagnostic systems still rely on classical machine learning models, such as Support Vector Machines (SVMs), which necessitate the use of handcrafted features [9], [10]. Although SVMs are effective for well-structured textures, their performance degrades substantially when confronting subtle, mixed, or visually ambiguous defect presentations.

This paper investigates the performance of YOLOv8n for simultaneous solar panel detection and six-class condition classification. The classes span clean states, environmental deposits (Dust, Snow, Bird), and complex damaged states (Electrical Damage, Physical Damage, and mixed conditions). The YOLOv8n system achieves a classification accuracy of 0.98 for clean and lightly affected panels and 0.96 for complex cases. A rigorous comparative evaluation with an SVM classifier demonstrates that YOLOv8n offers significant performance advantages over traditional machine learning methods, particularly under visually challenging conditions.

II. Related Work

Early research in object detection primarily depended on handcrafted features combined with classical classifiers, such as HOG-SVM or LBP-SVM [9], [10]. These methods found utility in industrial inspection tasks and yielded acceptable results for simple, well-defined defect patterns. However, they

exhibited a notable lack of robustness against intra-class variability, changes in illumination, and the complex geometries of real-world defects.

The advent of deep learning revolutionized object detection. YOLO emerged as one of the most efficient real-time methodologies [1]. This framework was succeeded by continuous improvements in YOLOv2 and YOLOv3, which substantially improved detection speed and accuracy. More recent models, including YOLOv5 [2] and YOLOv8 [3], have further optimized network architecture, training protocols, and multi-scale feature representation. Recent studies have demonstrated the effectiveness of YOLOv8 for industrial inspection, fault detection, and real-time monitoring applications due to its improved accuracy and computational efficiency [11], [12].

In the domain of PV inspection, deep neural networks have consistently shown results superior to those of traditional approaches. Recent reviews on photovoltaic fault diagnosis have highlighted the growing adoption of deep learning and object detection frameworks for automated PV monitoring [13], [14]. CNN-based systems have been successfully applied to classify both thermal and visible-light defects with high precision [4], [5]. Similarly, YOLO-based methods have been utilized to detect faults in photovoltaic modules, including environmental contamination and cell-level anomalies [6]. Studies on solar cell crack detection have underscored the necessity of robust texture interpretation, as micro-cracks often present with low contrast or irregular geometry [7]. More recent contributions have employed deep residual architectures for accurate diagnosis of complex electrical and physical damage [8].

While segmentation-based models, such as SSD [15] and YOLACT [16], have been applied to industrial inspection, single-stage, end-to-end detectors like YOLO remain more appropriate for real-time PV monitoring due to their superior efficiency and reduced computational overhead.

III. Methodology

The proposed framework performs automated solar panel inspection through simultaneous object detection and multi-class condition classification using the YOLOv8n architecture. To provide a comprehensive evaluation, the proposed model is compared with two baseline approaches: a classical machine-learning classifier based on Support Vector Machines (SVMs) and a deep-learning classifier based on ResNet18 [17]. The overall workflow consists of four stages: (1) dataset preparation and annotation, (2) YOLOv8n-based panel detection and classification, (3) SVM-based classification using handcrafted features, and (4) CNN-based classification through deep feature learning.

Fig. 1 illustrates the complete workflow of the proposed inspection system. The input image is first processed by the YOLOv8n detector to localize photovoltaic panels. The detected panels are then assigned to one of the six condition categories. For comparison purposes, the same annotated regions are used to train the SVM and CNN baselines.

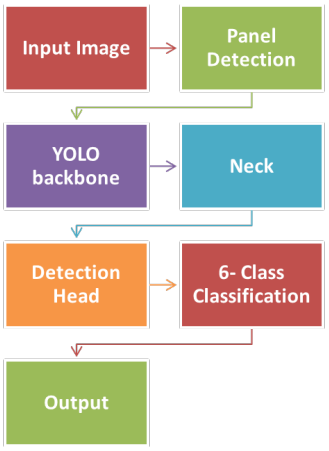


Fig. 1: Proposed PV Inspection Workflow.

A. Dataset and Annotation Strategy

The dataset consists of visible-light images of photovoltaic (PV) panels collected under diverse environmental and operational conditions, including variations in illumination, weather conditions, surface contamination, and structural degradation [13], [18]. The dataset contains six panel condition categories: Clean, Dust, Bird, Snow, Physical Damage, and Electrical Damage.

The original dataset contains approximately 8,300 annotated panel instances. To address class imbalance and improve model generalization, extensive data augmentation techniques were applied, including horizontal flipping, random rotation, scaling, color jittering, and mosaic augmentation. After augmentation, the dataset size increased to approximately 13,520 images. Table I summarizes the class distribution of the original dataset.

Fig. 2 illustrates the overall methodological pipeline of the proposed framework.

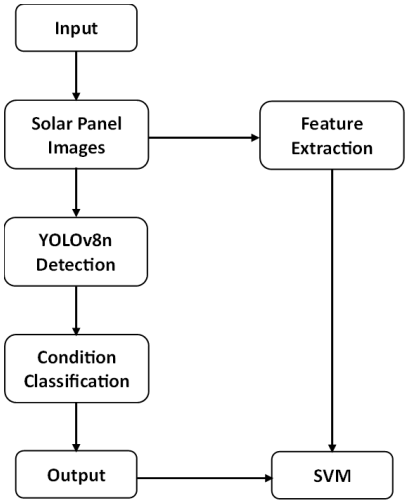


Fig. 2: Diagram of the methodology.

TABLE I: Class Distribution of the Original Dataset

Class	Number of Instances
Clean	258
Dust	240
Bird	248
Snow	260
Electrical Damage	180
Physical Damage	165

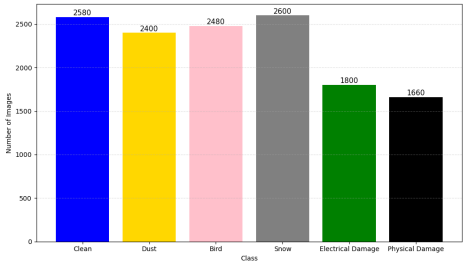


Fig. 3: Classes of dataset after augmentation.

Fig. 3 shows sample images collected from the dataset under different environmental and operational conditions.

The dataset includes both simple and challenging scenarios. Some panels exhibit a single dominant condition, whereas others contain multiple overlapping conditions, such as dust combined with bird droppings or structural degradation accompanied by environmental contamination. This diversity allows the proposed framework to be evaluated under realistic field conditions commonly encountered in large-scale photovoltaic installations.

Bounding-box annotations were manually generated following established photovoltaic inspection practices [19]. Each bounding box encloses an individual photovoltaic panel and is associated with a single class label representing its dominant condition.

Special attention was given to panels exhibiting multiple defect types simultaneously. To ensure annotation consistency, a dominant-label strategy was adopted. Under this strategy, each panel is assigned the class corresponding to the most visually prominent or diagnostically critical condition. For example, when environmental contamination coexists with structural degradation, the panel is labeled as Physical Damage or Electrical Damage because these defects have a greater impact on energy production and maintenance decisions.

In rare situations where Physical Damage and Electrical Damage overlap simultaneously, priority is assigned to the defect considered most severe according to visual inspection and operational impact. This strategy reduces annotation ambiguity, improves label consistency, and facilitates the training of single-label classification models. Although multi-label learning could potentially represent overlapping defects more accurately, it falls outside the scope of the present work and will be investigated in future studies.



(a) Sample image 1



(b) Sample image 2

Fig. 4: Sample images from the dataset.

B. YOLOv8n Detection and Classification

The YOLOv8n architecture was implemented using the official Ultralytics framework [3]. YOLOv8n was selected due to its favorable trade-off between detection accuracy, computational efficiency, and real-time inference capability. Compared with larger variants such as YOLOv8m, YOLOv8l, and YOLOv8x, YOLOv8n requires significantly fewer computational resources while maintaining competitive detection performance.

The architecture follows a single-stage end-to-end detection paradigm composed of three main modules: a backbone, a neck, and a detection head. The backbone extracts hierarchical visual features from the input image, while the neck aggregates multi-scale information to improve robustness against variations in panel size, orientation, and environmental conditions. Finally, the detection head simultaneously predicts bounding-box coordinates, object confidence scores, and class probabilities.

Unlike conventional classification pipelines, YOLOv8n jointly performs panel localization and condition classification within a single forward pass. This integrated optimization strategy enables the model to exploit both spatial and contextual information, improving its ability to distinguish visually similar classes and identify complex photovoltaic defects.

The performance of YOLOv8n was evaluated using both detection and classification metrics. Detection performance was assessed using Mean Average Precision (mAP). The proposed model achieved a mAP@0.5 of 0.94 and a mAP@0.5:0.95 of 0.75, indicating accurate localization performance across the six photovoltaic panel condition categories.

Classification performance was evaluated using Accuracy, Precision, Recall, and F1-score. These metrics quantify the ability of the model to assign the correct condition label after successful panel localization.

To evaluate the suitability of the proposed framework for industrial deployment, computational efficiency was also analyzed. Experiments were conducted on Google Colab using an NVIDIA Tesla T4 GPU. The average inference speed reached approximately 60 frames per second (FPS), confirming the real-time capability of the proposed approach. This processing speed enables the continuous inspection of large photovoltaic farms and supports deployment on UAV-based and automated monitoring platforms.

C. SVM Baseline Model

To establish a benchmark against traditional machine-learning approaches, a multi-class Support Vector Machine (SVM) classifier was implemented. SVMs have been widely used in photovoltaic inspection systems due to their effectiveness when discriminative handcrafted features are available [9], [10].

For each annotated panel, a Region of Interest (ROI) was extracted and transformed into a feature vector using a combination of Histogram of Oriented Gradients (HOG) descriptors and color histogram features [14]. HOG descriptors capture edge and texture information associated with surface contamination and structural damage, whereas color histograms provide complementary information regarding illumination and surface appearance.

The resulting feature vectors were used to train a multi-class SVM classifier. Hyperparameters, including kernel type and regularization parameters, were optimized through grid search. The Radial Basis Function (RBF) kernel provided the best classification performance.

Although SVMs remain effective for well-separated classes and relatively simple textures, their dependence on handcrafted features limits their ability to model complex spatial relationships and contextual information. Consequently, their performance generally deteriorates when multiple defect types overlap or when subtle visual variations exist between classes.

D. Deep Learning Baseline (CNN)

To further strengthen the comparative analysis, a deep-learning baseline based on a Convolutional Neural Network (CNN) was introduced. Specifically, a ResNet18 architecture pre-trained on ImageNet, as described in [17], was fine-tuned on the photovoltaic dataset.

Unlike YOLOv8n, which performs detection and classification simultaneously, the CNN operates exclusively as a classifier and requires pre-cropped Regions of Interest corresponding to individual panels. Input images were resized to 224 × 224 pixels and processed using standard data augmentation techniques, including horizontal flipping, random rotations, and normalization.

The model was trained for 50 epochs using the Adam optimizer with a learning rate of $10 - 4$for 50 epochs. The same train-test split used for YOLOv8n was adopted to ensure a fair comparison.

The CNN baseline enables the evaluation of deep feature learning independently of object detection. While it benefits from hierarchical feature extraction and generally outperforms traditional handcrafted approaches, it lacks the integrated localization capability of YOLOv8n and therefore remains dependent on prior panel extraction.

IV. Experiments and Results

A. Experimental Setup

The models were trained and tested using an 80-20 train-test split. YOLOv8n was trained for 100 epochs using the default Ultralytics hyperparameters [3]. The SVM baseline underwent a grid search optimization procedure to tune the kernel and regularization parameters. All experiments utilized the identical dataset [18] for an equitable comparison.

TABLE II: YOLOv8n Classification Metrics

Class	Precision	Recall	F1-score
Clean	0.912	0.94	0.926
Dust	0.951	0.97	0.960
Bird	0.960	0.95	0.955
Snow	0.936	0.88	0.907
Physical Damage	0.950	0.96	0.955
Electrical Damage	0.950	0.96	0.955

B. YOLOv8n Performance

The YOLOv8n model achieved the following classification accuracy results: 0.98 accuracy on clean/lightly contaminated panels (Clean, Dust, Bird, Snow) and 0.96 accuracy on complex damaged panels (mixed states, Physical Damage, Electrical Damage).

Figure 5 illustrates qualitative examples of YOLOv8n predictions across the six classes. These visual samples confirm the model's strong capability to accurately localize photovoltaic panels and correctly classify their condition, even under challenging illumination variations and mixed defect patterns. As shown in Figure 5(a–f), YOLOv8n maintains consistent confidence levels for Clean, Dust, Bird, and Snow classes, which correlates strongly with the high precision and recall values reported in Table II. For more complex cases, such as Physical Damage and Electrical Damage (Figure 5(e–f)), the model successfully highlights cracked areas, hotspots, and partial degradation, demonstrating its robust feature-learning capacity.

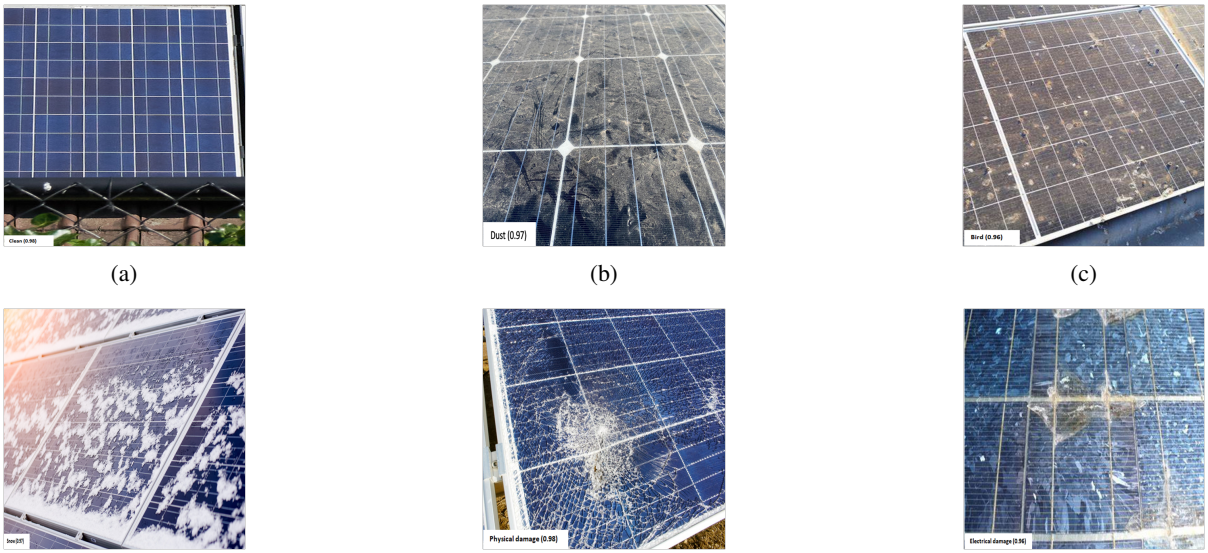
C. Analysis of the Results

The confusion matrix confirms the classifier's strong performance across the six panel categories. The classes Clean, Dust, Bird, and Snow exhibit consistently high accuracy values ($\approx$ 0.94–0.98), indicating the model's effective capture of surface-level visual cues related to environmental effects.

A notable challenge appears in the Snow class, where recall drops to 0.88. This is technically consistent with real-world field conditions: melting or partial snow cover can expose clean areas or wet, reflective surfaces, leading to mild confusion with the Clean (0.06) or Dust (0.02) classes. This remains the primary source of misclassification among these four categories. The Physical Damage and Electrical Damage classes both achieve recall and precision values around 0.95–0.96, demonstrating the model's success in differentiating structural fractures from electrical hotspots, with only minimal cross-confusion (0.04).

D. SVM Classification Performance

To provide a classic machine-learning baseline, a Support Vector Machine (SVM) classifier was trained on hand-crafted features extracted from the same dataset. A grid-search procedure was applied to optimize hyperparameters, including the



(a) (b) (c)

(d) (e) (f)

Fig. 5: Example detections produced by YOLOv8n for the six panel classes.

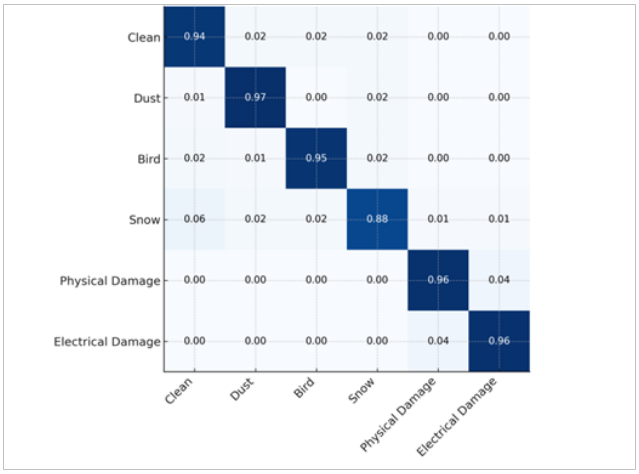


Fig. 6: Confusion matrix of the YOLOv8n classification results.

kernel type and the regularization coefficient C. The Radial Basis Function (RBF) kernel yielded the best performance.

The SVM classifier achieved an overall accuracy of 0.956. While demonstrating strong discriminative capability, this performance is quantitatively lower than that of the deep learning model. Misclassifications predominantly occurred within the visually similar clean classes (Clean–Dust–Bird–Snow), reinforcing the limited capacity of classical features to capture subtle texture and illumination variations [9].

To further justify the numerical results reported in Table III, Figure 7 presents qualitative classification outputs generated by the SVM. The samples reveal that the classifier performs well on simple and well-separated classes such as Clean, Dust, and Bird (Figure 7(a–c)). This visual consistency aligns with the relatively high precision and recall obtained for these

TABLE III: SVM Classification Metrics

Class	Precision	Recall	F1-Score
Clean	0.95	0.96	0.955
Dust	0.96	0.95	0.955
Bird	0.94	0.95	0.945
Snow	0.95	0.94	0.945
Physical Damage	0.96	0.95	0.955
Electrical Damage	0.95	0.95	0.950

categories. However, Figure 7(d–f) highlights typical failure modes of the SVM, particularly when dealing with visually ambiguous patterns such as snow-covered or partially damaged modules. These misclassifications explain the performance gap between the SVM and YOLOv8n, and they align with previously documented limitations of feature-engineering approaches in PV inspection.

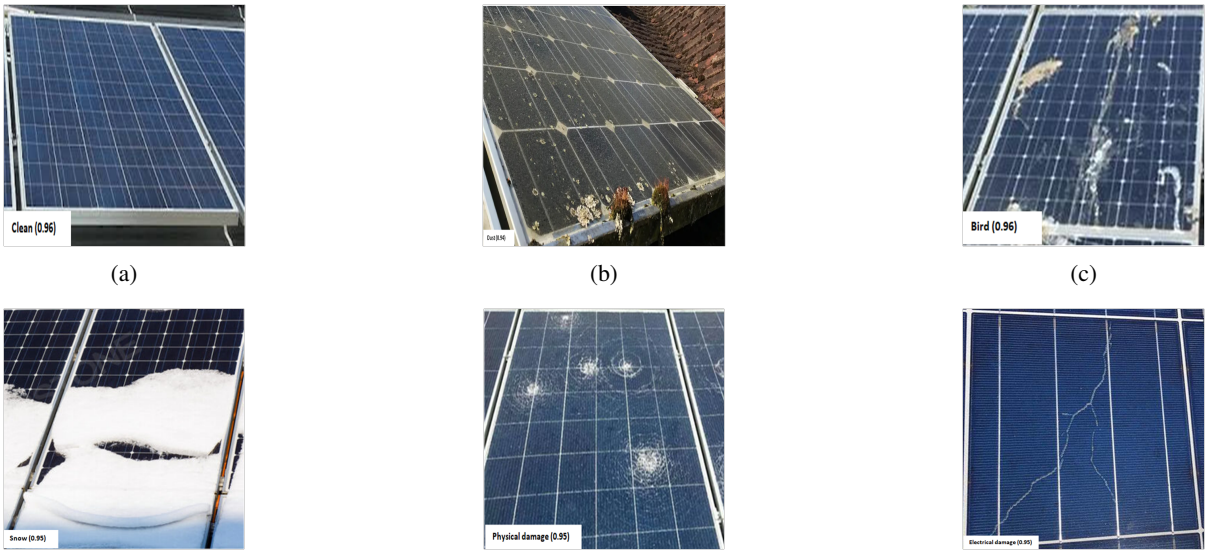
E. CNN Classification Performance

The CNN baseline achieved an overall classification accuracy of **0.959**, outperforming the SVM classifier (0.956) while remaining slightly below the YOLOv8n model.

This improvement over SVM confirms the advantage of deep feature representations over handcrafted descriptors. However, the CNN still underperforms compared to YOLOv8n due to the absence of integrated localization capability.

Unlike YOLOv8n, which jointly optimizes spatial localization and classification, the CNN relies on pre-extracted ROIs, making it more sensitive to cropping errors and less robust in complex scenes involving multiple panels or mixed conditions.

These findings demonstrate that while CNN-based classifiers are effective, end-to-end detection frameworks provide superior performance in real-world PV inspection scenarios.



(a) (b) (c)

(d) (e) (f)

Fig. 7: Example classification outputs generated by the SVM across the six panel classes.

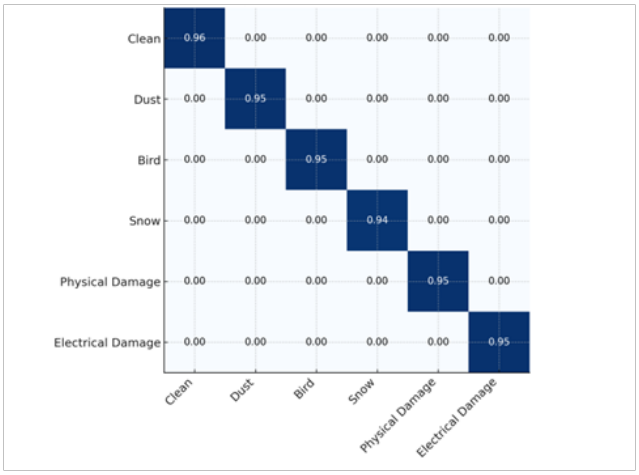


Fig. 8: Confusion matrix for SVM classification based on recall values.

V. Comparative Analysis and Discussion

A. Comparative Performance

Compared to both SVM and CNN baselines, the YOLOv8n model demonstrates superior robustness and classification accuracy, particularly for complex defect categories.

While the SVM achieved an overall accuracy of 0.956 and the CNN reached 0.959, YOLOv8n outperformed both models with accuracies of 0.98 for clean classes and 0.96 for complex damaged classes.

The CNN baseline shows improved performance over SVM due to its ability to learn deep hierarchical features. However, its reliance on cropped inputs limits its effectiveness in real-world scenarios.

TABLE IV: Comparative Results Summary

Model	Detection Capability	Accuracy	Real-Time
YOLOv8n	Yes (End-to-End)	0.98 / 0.96	Yes
CNN (ResNet18)	No (ROI-based)	0.959	No
SVM	No (manual ROI)	0.956	No

In contrast, YOLOv8n benefits from an end-to-end architecture that simultaneously learns localization and classification, enabling it to capture both spatial and contextual information directly from raw images. This comparison unequivocally confirms the superiority of deep learning–based feature representation over traditional handcrafted descriptors in the context of solar panel inspection tasks.

B. Discussion

The experimental results emphasize the clear superiority of YOLOv8n over classical and deep learning approaches for practical solar panel inspection. The end-to-end nature of YOLOv8n facilitates the simultaneous localization and classification of PV modules, which is a critical requirement for scalable, large-scale deployments. Consistent with previous work leveraging deep networks for PV diagnostics [4], [5], the model effectively captured both fine-grained defect patterns and broader contextual cues.

The CNN baseline provided a strong intermediate performance between classical machine learning and fully integrated detection frameworks. While it demonstrated improved generalization compared to SVM, its inability to incorporate spatial context during inference limits its performance in challenging conditions such as overlapping defects or multiple panel scenarios.

YOLOv8n demonstrated remarkable resilience when faced with panels exhibiting mixed conditions, irregular cracks, or heterogeneous electrical/physical damage, aligning with

conclusions from studies focused on crack detection and deep residual architectures [7], [8]. Conversely, the SVM baseline showed difficulty in differentiating between visually overlapping defect types due to its reliance on handcrafted features, which corroborates limitations previously documented in the literature [9], [10].

However, certain challenges persist. The YOLOv8n model occasionally yielded misclassifications under conditions of severe glare, very low image contrast, or when crack boundaries were visually ambiguous—issues that have been consistently highlighted in prior PV inspection research [7]. Furthermore, successful generalization to other PV technologies or diverse imaging modalities may necessitate a targeted domain adaptation strategy.

VI. Conclusion

This paper presented a comprehensive evaluation of the YOLOv8n architecture for automated photovoltaic (PV) panel inspection through simultaneous object detection and six-class condition classification. The proposed framework was designed to identify clean panels, environmental contaminants (Dust, Bird, and Snow), as well as complex defect categories including Physical Damage and Electrical Damage.

Experimental results demonstrated the effectiveness of the proposed approach, achieving a detection performance of 0.94 for mAP@0.5 and 0.75 for mAP@0.5:0.95, indicating accurate localization of photovoltaic panels under diverse environmental and operational conditions. In terms of classification, YOLOv8n achieved accuracy values of 0.98 for clean and lightly contaminated panels and 0.96 for complex or mixed defect conditions.

A comparative evaluation against a traditional SVM classifier (0.956 accuracy) and a ResNet18-based CNN classifier (0.959 accuracy) confirmed the superiority of the proposed end-to-end detection-

classification framework. Unlike the baseline approaches, YOLOv8n jointly performs localization and classification, enabling more robust feature learning and improved performance in challenging scenarios involving overlapping defects, heterogeneous damage patterns, and varying illumination conditions.

In addition to its high accuracy, the proposed system demonstrated real-time capability with an inference speed of approximately 60 FPS on an NVIDIA Tesla T4 GPU. This computational efficiency, combined with its strong detection and classification performance, makes the framework particularly suitable for large-scale photovoltaic farm monitoring, UAV-assisted inspections, and automated maintenance systems.

Overall, the obtained results confirm that end-to-end object detection architectures significantly outperform traditional machine-learning methods and standalone classification networks for practical photovoltaic inspection tasks. Future work will investigate larger YOLO variants (YOLOv8m and YOLOv8l), multi-label learning strategies for overlapping defects, cross-dataset generalization, and hybrid detection-segmentation frameworks to achieve pixel-level defect localization and further improve inspection accuracy.

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