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Photovoltaic Panel Defect Detection System

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***Abstract*— Detecting defects in photovoltaic (PV) panels is important for maintaining their performance, especially in large-scale solar farms where manual inspection is time-consuming and inefficient. This work presents a simple and practical deep learning solution that makes this process easier and more accessible by using images captured through UAVs (drones), enabling efficient monitoring of large areas. A customized YOLOv8m-based model is designed to automatically detect and classify defects, even with a relatively small dataset of around 700–800 images across five categories. To handle the lack of data, class-based GAN augmentation is used to increase data variety and improve balance between classes. The model is further improved with additions like a C2f-PSA module for better attention and a custom Multi-Scale Feature Fusion (MCFF) block to help detect small and hard-to-spot defects. While these improvements enhance the model's ability to learn features, they also make it more sensitive to dataset size and design choices, sometimes affecting accuracy. To make the system useful in real-world situations, a user-friendly web application and dashboard are developed using Streamlit, allowing users to upload images, see detected defects with their severity levels, and easily understand the results. The system also enables users to generate and download detailed reports with annotated images, making it a complete and practical solution for efficient PV panel monitoring and maintenance in large solar installations.**

Keywords—Photovoltaic Defect Detection, YOLOv8, GAN, PSA, MCFF, Deep Learning, Object Detection.

I. Introduction

The global surge in demand for sustainable and renewable energy has driven the rapid proliferation of photovoltaic (PV) systems worldwide. While solar panels transform sunlight into electrical energy, their efficiency is significantly compromised by physical defects that can occur during manufacturing, transit, or extended use. Even minor defects can result in substantial power losses and, if not identified early, may ultimately lead to system failure.

Typical defects found in photovoltaic panels encompass micro-cracks, hotspots, fractured cells, and surface impediments like dirt or bird droppings [5]. These defects not only diminish efficiency but also compromise the system's reliability and longevity. Consequently, ongoing surveillance and prompt identification are crucial.

Conventional inspection methods depend primarily on manual observation and standard image processing techniques [4]. Although these methods may suffice for small-scale installations, they prove inefficient for large solar farms because of their time-intensive nature and restricted accuracy. Recent breakthroughs in deep learning, especially within object detection models, have facilitated the development of automated inspection systems with high accuracy [3].Among these models, the YOLO (You Only Look Once) family [6] has become popular because it can achieve high-accuracy real-time detection [7]. However, standard YOLO models struggle with detecting small defects [13], managing imbalanced datasets, and ensuring precise localization [14].

To address these limitations, this paper introduces an improved YOLOv8 framework that incorporates attention mechanisms [8], multi-scale feature fusion, and GAN-based data augmentation.

II. Literature Survey

There has been a significant evolution in the field of photovoltaic (PV) defect detection in which deep learning is widely used due to its superior accuracy and automation capability. In initial studies, traditional machine learning approaches like neural networks and support vector machines were utilized for detecting micro-cracks and hot spots in PV modules based on electrical properties [20]. Later on, CNN-based methods, along with segmentation approaches like Deeplabv3+, have shown promising results in terms of defect localization accuracy [8]. Recently, YOLO based object detection algorithms have become prevalent due to their potential to perform real-time and accurate detection [1]. Research works like PV-YOLO [1], ESD-YOLOv8 [17], and CWE-YOLOv8 [6] have introduced lightweight designs and feature extraction schemes to boost the detection performance. In addition, there have been efforts for transformer-based approaches for exploiting long-range dependences among features [2], [19]. Furthermore, other issues like class imbalance [4], [16] and deployment schemes

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using UAV and IoT platforms have also gained attention recently [9], [12], [13].

TABLE I. SUMMARY OF EXISTING WORKS

Reference	Method	Key Contribution	Limitation
Winston et al. [20]	NN + SVM	High classification accuracy	Requires handcrafted features
Xu et al. [8]	Deeplabv3+	Improved segmentation accuracy	High computational cost
Yin et al. [1]	PV-YOLO	Lightweight real-time detection	Limited small defect detection
Lang and Lv [2]	Transformer + Attention	Better feature representation	Computationall y intensive
Rao et al. [4]	Imbalance-aware learning	Improved minority class detection	Limited deployment focus
Zhang et al. [17]	ESD-YOLOv8	Enhanced feature fusion	Sensitive to dataset quality
Chen et al. [14]	RT-DETR-Pro	Accurate localization	Slower inference speed

III. PROBLEM STATEMENT AND OBJECTIVES

Although deep learning has significantly improved photovoltaic (PV) defect detection, several challenges still remain. Detecting small and subtle defects, such as micro-cracks and minor physical damages, is particularly difficult because these defects occupy only a few pixels and are hard to localize accurately [6], [17]. Traditional object detection models often fail to retain the fine-grained spatial details needed for such defects.

Another issue is class imbalance in PV defect datasets. Some defect categories occur much less frequently than others, leading to biased training and reduced performance on minority classes [4], [16]. Overcoming this imbalance is important for building reliable detection systems.

In addition, defect-related information can be lost during deep feature extraction, especially when defects appear at different scales. Improved feature fusion techniques are therefore needed to strengthen multi-scale representation and detection performance [7], [17]. Accurate localization is also challenging, as imprecise bounding boxes can affect both defect classification and severity assessment [14].

Hence, there is a need for an efficient PV defect detection framework that can improve small defect recognition, handle class imbalance, enhance multi-scale feature extraction, and provide accurate localization for real-world photovoltaic inspection applications.

The main objectives of this work are:

i. To develop an automated photovoltaic defect detection system using an enhanced YOLOv8m framework.
ii. To address class imbalance in photovoltaic datasets using GAN-based data augmentation.
iii. To improve the detection of small and complex defects through attention mechanisms and multi-scale feature fusion.
iv. To enhance localization accuracy for reliable defect identification and severity assessment.
v. To develop a user-friendly dashboard for visualization, analysis, and reporting of detected defects.
vi. To provide an efficient and scalable solution for large-scale photovoltaic monitoring and maintenance.

IV. PROPOSED METHODOLOGY

A. System Overview

The proposed system adopts a structured pipeline that combines data preparation, augmentation, model enhancement, and evaluation [17]. The comprehensive workflow guarantees efficient learning and precise defect detection [1].
The main stages of the system include:

i. Data collection and preprocessing.
ii. GAN-based data augmentation
iii. Model enhancement using advanced modules
iv. Training and evaluation

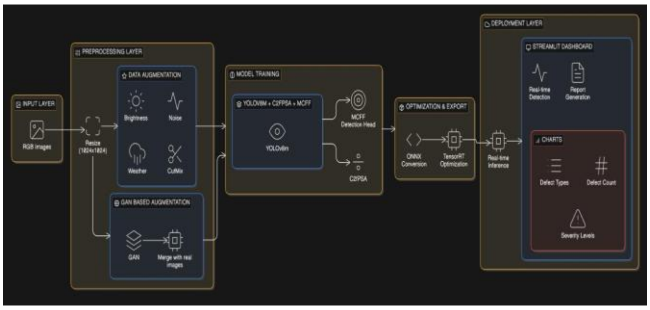

Fig. 1. Overall architecture of the proposed photovoltaic defect detection system

Fig. 1 illustrates the complete architecture of the proposed photovoltaic defect detection framework. The system starts with RGB image acquisition, followed by preprocessing steps such as resizing and data augmentation techniques including brightness adjustment, weather simulation, noise injection, and CutMix. To tackle class imbalance, synthetic samples generated by GANs are integrated into the dataset.

The improved dataset is subsequently employed to train the adapted YOLOv8m model, which incorporates the C2fPSA attention mechanism and the MCFF detection head. Finally, the trained model is optimized for deployment and integrated into a Streamlit-based dashboard to enable real-time defect detection, visualization, and report generation.

B. Dataset Preparation

The dataset employed in this study comprises annotated images of photovoltaic panels [11], with each image featuring labeled defect regions. The dataset encompasses a diverse range of defect types, including Bird Drops, Dusty, Electrical Damage, Physical Damage and Snow.

To ensure proper training and evaluation, the dataset is split into three subsets:

i. Training set for model learning
ii. Validation set for hyperparameter tuning
iii. Testing set for final performance evaluation

To enhance data quality and consistency, preprocessing steps including resizing, normalization, and annotation verification are implemented.

Fig. 2. Common Defects in Photovoltaic Panels

Fig. 2 depicts the five defect categories examined in this study. These defects display considerable differences in appearance, size, and texture, which renders automated detection a difficult endeavor. While bird droppings and dust buildup usually cover the panel surface, physical and electrical damage typically manifest as localized anomalies. Snow cover creates extensive occlusions that can significantly diminish energy production. The variety of these defect patterns requires robust feature extraction and multi-scale detection capabilities.

C. *GAN-Based Data Augmentation and Class Imbalance Handling*

To achieve optimal performance, deep learning models necessitate vast quantities of data. However, gathering labeled photovoltaic defect data is difficult and frequently leads to imbalanced datasets. To tackle this issue, Generative Adversarial Networks (GANs) are utilized for data augmentation [15].

GAN consists of two networks:

i. Generator: Produces synthetic images.
ii. Discriminator: Evaluates image authenticity

By employing adversarial training, GANs learn to produce realistic defect images that closely mimic actual data. These synthetic samples are incorporated into the training dataset to enhance its diversity.

The dataset displayed an imbalanced distribution across defect categories, with some classes containing significantly fewer samples than others. To tackle this problem, a class-wise GAN augmentation approach was utilized. Synthetic images were generated for minority classes until a more balanced class distribution was achieved. These augmented samples were added to the training dataset to better represent underrepresented defects, which helps reduce model bias and improve generalization. Comparable research has highlighted the necessity of tackling class imbalance to enhance defect detection within photovoltaic datasets [4], [16]. The use of GAN provides several advantages:

iii. Enhances representation of minority classes
iv. Improves model generalization
v. Reduces overfitting

D. *Selection of YOLOv8m*

Various object detection models, such as Faster R-CNN, SSD, YOLOv5, transformer-based detectors, and RT-DETR [3], [14], [19], have been investigated for photovoltaic defect detection. Although Faster R-CNN offers high detection accuracy, its slower inference speed restricts its use in real-time inspection applications. While SSDs provide efficient inference, they exhibit diminished performance in detecting small defects. While transformer-based methods offer robust contextual comprehension, they demand extensive datasets and substantial computational power [2], [19]. YOLOv8 was chosen for this study due to its effective balance between detection accuracy and inference efficiency. Its anchor-free architecture, enhanced feature extraction, and lightweight design make it ideal for UAV-assisted photovoltaic inspections and real-time deployment. Moreover, YOLOv8's modular architecture allows for the incorporation of custom components like C2fPSA and MCFF, which significantly improves the detection of small and multi-scale defects [6], [17].

E. *Enhanced YOLOv8m Architecture*

The baseline YOLOv8m architecture is improved by incorporating attention and feature fusion mechanisms to enhance defect detection, especially for small and multi-scale defects. The suggested changes involve integrating C2fPSA modules into the backbone and adding a lightweight Multi-Scale Cross Feature Fusion (MCFF) module to the neck [17].

1) C2fPSA (C2f-based Spatial Attention): In the deeper stages of the backbone, specifically at the P4 (1/16) and P5 (1/32) feature levels, the standard C2f blocks are replaced with C2fPSA modules. This module embeds a spatial attention mechanism into the Cross Stage Partial (C2f) architecture, allowing the network to concentrate on defect-relevant areas while preserving efficient feature propagation. Consequently, the model enhances its capacity to identify subtle, small-scale defects without substantially increasing computational complexity.

2) Multi-Scale Cross Feature Fusion (MCFF): The MCFF (Multi-Scale/Context Feature Fusion) module is integrated into the network's neck, positioned immediately after each concatenation operation within the multi-scale feature fusion process. It is applied across all three detection scales: P3 for small objects, P4 for medium objects, and P5 for large objects. In the YAML configuration, MCFF is positioned immediately after the feature maps are combined (e. g., after merging backbone P4 and upsampled features, or backbone P3 and upsampled features, and similarly in the downsampling path for P4 and P5). By refining these fused features before they are passed to the subsequent C2f blocks, MCFF enhances cross-scale feature interaction, resulting in improved detection performance for objects of varying sizes.

By integrating attention-enhanced feature extraction in the backbone with efficient multi-scale feature fusion in the neck, the proposed architecture delivers superior localization and classification performance while preserving a lightweight design.

F. *Training Strategy*

The model is trained with optimized hyperparameters to guarantee stable and efficient learning. Training consists of iterative updates designed to minimize loss and enhance detection accuracy.
Key training configurations include:

vi. Number of epochs: 200
vii. Batch size: 16
viii. Image resolution: 1024 × 1024
ix. Learning rate scheduling using cosine decay
x. Optimizer: SGD

V. EXPERIMENTAL SETUP

The photovoltaic defect detection system was developed using Python, with PyTorch as the deep learning framework and Ultralytics YOLOv8 for object detection. All experiments were performed on GPU-enabled hardware, which helped speed up training and improve overall efficiency [12].

A. *Hardware and Software Environment*

GPU-supported environment (NVIDIA RTX 4060 (8 GB VRAM), Intel Core i7 processor, 16 GB RAM) was used for training and evaluation. The implementation relied mainly on Python, PyTorch, and YOLOv8, along with supporting libraries for data preprocessing, visualization, and performance analysis.

B. *Experimental Workflow*

The process began by loading the photovoltaic dataset and its annotations. Data preprocessing and augmentation techniques were then applied, including GAN-based augmentation to generate additional samples for underrepresented defect classes. After preparing the dataset, the enhanced YOLOv8m model was trained, while validation performance was monitored throughout the process to reduce the risk of overfitting. Finally, the trained model was tested on unseen data to evaluate its ability to perform effectively in real-world conditions. GPU support enabled faster experimentation and efficient optimization of the proposed approach [12].

VI. RESULTS AND DISCUSSION

A. *Evaluation Metrics*

To assess the performance of the proposed model, several standard metrics are employed. These metrics offer a thorough insight into both detection accuracy and reliability. The evaluation metrics include:

i. Precision: Measures correctness of predictions.
ii. Recall: Measures ability to detect all defects
iii. Mean Average Precision (mAP50): Overall detection performance
iv. F1-score: Balance between precision and recall

B. *Results and Analysis*

The improved YOLOv8m model shows substantial gains compared to baseline models [9]. Combining attention mechanisms with feature fusion enhances the detection of small and complex defects [8].

Incorporating GAN-based augmentation enhances performance for underrepresented classes.
Overall observations include:

i. Improved detection accuracy across all defect types.
ii. Better performance in detecting small defects
iii. Enhanced robustness against dataset imbalance
iv. Stable real-time performance

TABLE 2. Performance Comparison of Baseline and Proposed Models

Model	**Precision**	**Recall**	**mAP @0.5**
YOLOv8s	0.533	0.449	0.452
YOLOv8m	0.592	0.483	0.482
YOLOv8m+GAN	0.670	0.586	0.608
YOLOv8m+C2fPSA	0.593	0.567	0.523
Proposed Model (C2fPSA + MCFF + YOLOv8m)	0.893	0.825	0.836

To further validate the effectiveness of the proposed model, qualitative results are presented through detection outputs. The model accurately detects various defect types, providing precise bounding boxes and confidence scores.

Fig.3 illustrates the defect detection interface of the developed system. Users are able to upload images or videos of photovoltaic modules for analysis. The system produces annotated detection results by identifying defect regions through bounding boxes and class labels. Furthermore, the system displays defect details including severity, confidence scores, and location coordinates to facilitate a quick evaluation of module status.

Detection Visualization Panel: Shows input images with predicted bounding boxes that highlight defect areas. Each detection includes class labels, severity and confidence scores, enabling users to readily interpret the model's outputs.

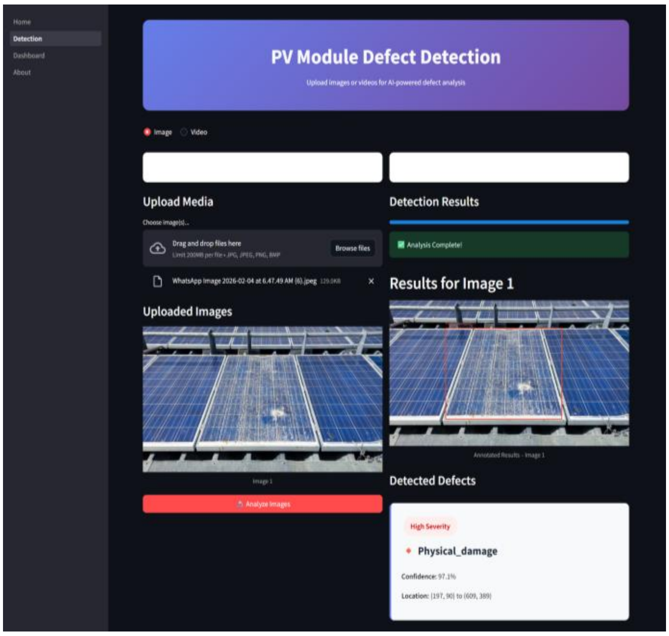

Fig. 3. Detection results showing identified defects

Class-wise Analysis displays the distribution of detected defect types, facilitating the identification of common defects and the assessment of performance across each class.

Confidence Score Analysis visualizes prediction confidence levels to enhance understanding of model reliability and pinpoint uncertain predictions.

VII. DASHBOARD-BASED RESULT ANALYSIS

To improve the interpretability and real-world applicability of the proposed photovoltaic defect detection system, a visual dashboard has been developed to analyze model predictions and performance metrics. The dashboard offers an intuitive interface for monitoring detection results, facilitating efficient evaluation and decision-making.

Fig.4 depicts the analytics dashboard employed to monitor the health of photovoltaic systems. The dashboard displays key performance indicators such as the total number of defects detected, average confidence scores, and the distribution of severity levels. Visual tools like bar and pie charts allow users to pinpoint dominant defect categories and evaluate overall defect trends in the monitored photovoltaic system.

Fig.5 illustrates the dashboard's ability to monitor defect occurrences over time. The defect trend graph visualizes temporal variations in detected defects, whereas the detection history table maintains detailed inspection records that include timestamps, defect types, severity levels, confidence scores, and associated images. This feature facilitates maintenance planning and long-term performance analysis.

The dashboard is essential for connecting model outputs to real-world deployment. By offering real-time visualization and analytical insights [18], it enables more effective monitoring of photovoltaic systems and aids in maintenance decision-making.

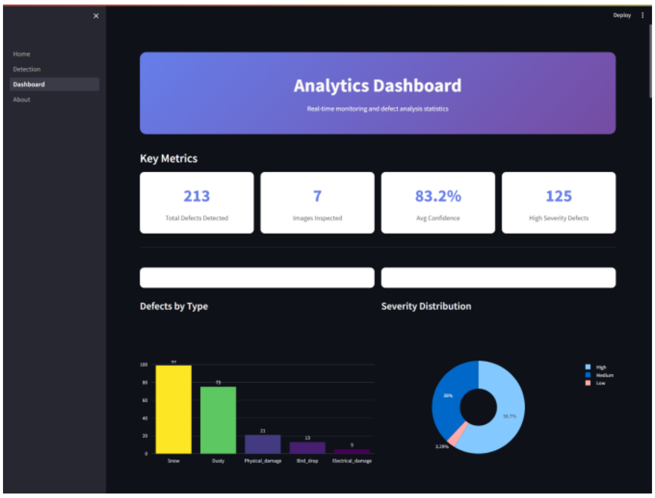

Fig. 4. Dashboard interface showing detection visualization and performance metric

Fig. 5. Dashboards recent detection history over time

The developed dashboard offers a comprehensive visualization of detection results and performance metrics. Figure 4 illustrates the interface displaying detected defects, confidence scores, and class-wise analysis.

VIII. ADVANTAGES OF THE PROPOSED SYSTEM

The proposed system provides multiple benefits compared to traditional and baseline methods.

It delivers high detection accuracy while preserving real-time performance, making it ideal for practical applications. By integrating attention mechanisms to prioritize defect regions and employing multi-scale feature fusion for robust detection across varying sizes, the system achieves improved performance [10]. Key advantages include:

- Accurate detection of small and complex defects
- Robust performance across diverse datasets
- Scalability for large solar farms
- Reduced manual inspection effort

IX. LIMITATIONS

Although the proposed system offers several benefits, it also has some limitations. Training deep learning models demands substantial computational resources, particularly when dealing with large datasets and intricate architectures.

Although GAN-based augmentation offers benefits, it can cause training instability if not carefully tuned. Furthermore, the system's performance is contingent upon the quality and diversity of the dataset.

X. FUTURE WORK

Future improvements may prioritize enhancing efficiency and broadening the system's capabilities. Lightweight models can be created for edge devices, allowing real-time processing in resource-limited settings. Further improvements may include:

- Integration with UAV-based inspection systems
- Use of multi-modal data such as thermal imaging
- Optimization for low-power hardware
- Development of real-time monitoring dashboards

XI. CONCLUSION

This paper introduces an improved deep learning approach for detecting defects in photovoltaic panels using YOLOv8m. The proposed system achieves enhanced detection accuracy and robustness by integrating attention mechanisms, multi-scale feature fusion, and GAN-based data augmentation.

The experimental results show that the model can identify various defect types while maintaining real-time performance. This proposed approach offers a scalable and efficient solution for automated solar panel inspection, thereby enhancing maintenance and energy efficiency in photovoltaic systems.

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