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Enhanced solar panels fault detection approach using lightweight YOLO

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ABSTRACT

Artificial intelligence (AI)-driven fault detection improves the reliability of solar energy by reducing the chances of system failures. However, existing single-stage object detection methods excel in accuracy but demand high computational resources, preventing seamless integration into embedded systems. This paper introduces a lightweight approach using YOLOv5, which incorporates a multi-backbone design, specifically tailored for accurate fault detection in solar cells. It evaluates YOLOv5 and TinyYOLOv5. The findings emphasize the effectiveness of YOLOv5l with Ghost backbone, particularly notable for its precision rates of 96% for faulty and 93% for non-faulty instances. Additionally, it showcases commendable mean average precision (mAP) scores, achieving 78% at an intersection over union (IoU) threshold of 0.5 and 72% at an IoU of 0.95. Additionally, YOLOv5_Ghost emerges as the optimal selection, showcasing competitive precision, processing speed of 42.1 giga floating point operations per second (GFLOPS), and remarkable efficiency with 2.4 million parameters. This evaluation underscores the effectiveness of YOLOv5 models, thereby leading to advanced solar energy technology significantly.

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1. INTRODUCTION

In recent years, solar power has surged as a primary renewable energy source, attracting global attention and investment. This shift emphasizes its potential to provide energy independence. Solar power's significance is particularly notable in addressing global energy demands while reducing reliance on fossil fuels [1]. Indeed, it can significantly mitigate greenhouse gas emissions and combat climate change. This is especially crucial in areas most affected by environmental degradation. Moreover, the economic benefits of solar power are substantial. The solar industry is experiencing rapid growth [2]. As the cost of solar panels continues to decline and government incentives encourage investment in solar infrastructure, the economic feasibility of solar power becomes increasingly evident. However, the effectiveness of solar energy systems faces significant challenges due to potential faults that can occur during the manufacturing or operation of solar cells [3]. Various faults, including microcracks, hot spots, soiling, shadowing, and bird droppings, pose critical difficulty to the efficiency of solar energy systems within the photovoltaic (PV) system [4]. Addressing these faults is paramount for improving the efficiency of PV generation [5]. Consequently, the development of methods for smart detecting faults in solar cells holds significant importance [6]. In the literature, various techniques have been explored for detecting faults in solar cells, broadly categorized into image processing techniques, traditional methods such as visual inspection and I-V curve tracing, and artificial neural networks (ANNs) [7]. Each of these approaches has its own set of limitations: Conventional visual inspection of solar cells requires specialized equipment and manual examination, leading to labor-intensive tasks and subjective outcomes [8]. Image processing techniques struggle with complex faults and environmental changes, primarily detecting surface-level issues. Infrared and Electroluminescence imaging, though effective, are costly and require specialized training, mainly suitable for surface-level detection [9]. Artificial intelligence (AI), particularly deep learning (DL) methods, is a powerful approach for fault detection in solar cells. However, it requires significant amounts of data and computational resources. Moreover, it faces limitations in environments where data is scarce or resources are constrained [10].

Leveraging AI, particularly DL, is essential for improving the performance and durability of solar energy systems by enabling the automated and precise identification of various faults in solar panels [11]. AI methods offer an efficient solution for early fault detection, capable of analyzing large datasets accurately and in a timely manner [12]. This led to significant research efforts focused on detecting anomalies in PV systems. Janarthanan *et al.* [13] presented a methodology in their study aimed at advancing the development of resilient fuzzy logic systems (FLSs) and ANNs for PV fault detection. Their research highlights the effectiveness of fault identification approaches in accurately identifying distinct fault categories, including impaired PV modules and partial shading of PV units. Akram *et al.* [14] conducted research on automating the detection of defects in PV modules using infrared images. Their study employed isolated DL and develop-model transfer learning techniques. They achieved a high average accuracy of 98.67% using a light CNN architecture for an isolated trained model. Additionally, they utilized transfer learning by pre-training a base model on electroluminescence images of PV cells and fine-tuning it on infrared images. Prabhakaran *et al.* [15] introduces the real-time multi variant deep learning model (RMVDM). The model demonstrates improved performance while requiring less computational time, underscoring its efficiency and practical applicability. Ramírez *et al.* [16] introduces an innovative method for monitoring PV panel condition by integrating a radiometric sensor with an unmanned aerial vehicle (UAV). This approach detects various faults, including hot spots and faulty cells, with commendable accuracy, advancing fault detection for PV systems. Han *et al.* [17] propose a cutting-edge method for detecting solar panel defects using thermal imaging, employing principal component analysis (PCA) and independent component analysis (ICA) techniques. This facilitates easy defect identification without costly electrical detection circuitry, reducing time and costs associated with detection procedures.

In this study, we introduce an improved YOLO detection model with an architecture fine-tuned for efficient and precise faults detection in PV modules. The contributing points of this research include, employing a range of data augmentation methods to offer practical suggestions for effective data augmentation, enhancing the accuracy of the training models. Exploiting the benefits of YOLOv5, we introduce an adopted YOLOv5 network designed for defect detection in PV panels. The objective is to create an automated detection system that excels in accuracy, computational efficiency, and model size compactness. Integrating a modified YOLOv5 tiny model by substituting the original backbone with ghost, MOBILENET, pre-processing and localization control (PPLC), SHUFFLE, and YOLOv5lEfficientLit architectures. The results of the proposed approach demonstrate that the YOLOv5Ghost-lightweight model successfully detects faults in PV systems, achieving the highest average precision of 95%, outperforming YOLOv5s which reached 74.8%.

The rest of the document is structured as follows: section 2 outlines the YOLO models we propose. Section 3 contains the presentation and discussion of the experimental results. Lastly, in section 4, we delve into the conclusion and future work.

2. METHOD

The process begins with data acquisition, as shown in the Figure 1 describing the architectural blueprint of the proposed methodology, where a variety of data are collected from solar panel installations. This data is then processed and pre-processed to ensure its quality and suitability for training. Subsequently, the models are trained using advanced algorithms, leveraging techniques such as DL and pattern recognition to detect subtle faults within the solar panels. Through iterative training, the models learn to identify anomalies indicative of potential faults. The ultimate output of this comprehensive approach is a smart fault detection system capable of accurately identifying issues within solar panel arrays.

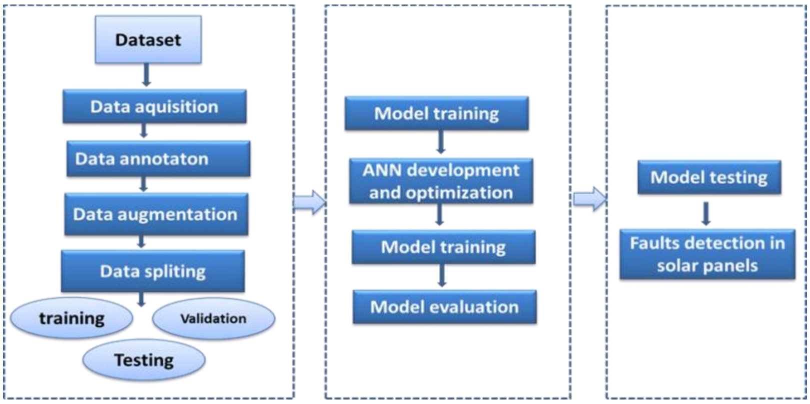
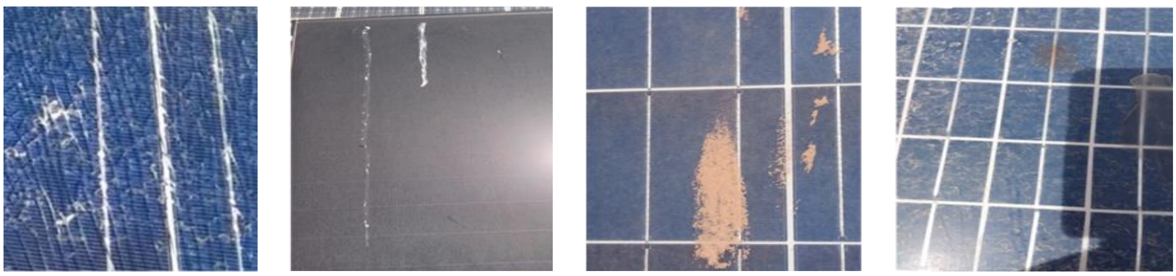


Figure 1. Comprehensive overview: architectural blueprint of the proposed methodology

In this research, data acquisition involved utilizing a database from three PV module technologies monocrystalline (m-Si), polycrystalline (p-Si) and amorpha (a-Si) in Errachidia, Morocco as shown in Figure 2. Images captured with a high-resolution camera depicted various anomalies like dust accumulation, shading, cracks, and bird droppings as illustrated in Figure 3. The dataset was expanded to 6,300 images using augmentation techniques, with 80% allocated for training and 20% for testing. This dataset was merged with another Roboflow dataset to improve training [18]. Augmentation techniques included horizontal flipping, cropping with zoom (0%-20%), and brightness variation (-25% to +25%).



Cracks Bird droppings Dust accumulation Shading

Figure 3. An array of solar panel faults: a visual guide to common issues

2.1. YOLO: algorithms and architectural frameworks

The YOLO architecture consists of three main components: the backbone, neck, and head [19]. These elements, which may vary across different YOLO versions, play crucial roles in determining the model's speed and accuracy [20]. This subsection offers an insight into the network architecture of YOLOv5, well-known for its advanced detection capabilities across diverse scales [21]. The core architecture, depicted in Figure 4, relies on a backbone serving as a feature extractor, employing a convolutional neural network (CNN) trained on extensive datasets such as ImageNet. YOLOv5 utilizes the CSPDarknet53 backbone, chosen for its effectiveness in capturing features from input images. Additionally, YOLOv5 integrates techniques like feature pyramid network (FPN) and path aggregation network (PAN) [22]. FPN involves up-sampling the output feature map (C3, C4, and C5) from various convolutional down-sampling operations [23], generating multiple new feature maps (P3, P4, and P5) to enhance target detection across a variety of scales [24].

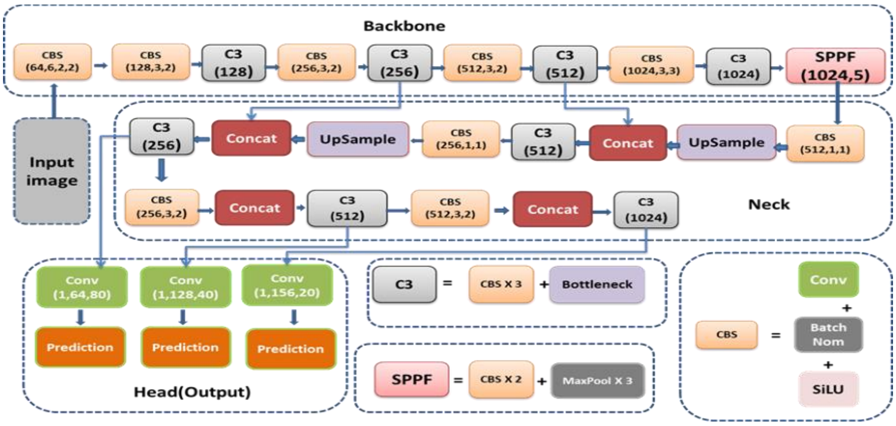


Figure 4. YOLOv5 architecture

This paper focuses on Lightweight YOLOv5 models, aiming to enhance defect detection in solar panels. Various YOLOv5-Multibackbone models were utilized as shown in Figure 5, including YOLOv5lEfficientLite, YOLOv5lGhost, YOLOv5lMobilenetv3Small, YOLOv5lPP-LC, and YOLOv5lShuffle. YOLOv5lEfficientLite integrates a customized EfficientNetLite backbone, while YOLOv5lGhost features a Ghostnet-based backbone for multi-scale feature fusion. YOLOv5lPP-LC utilizes MobileNetv3Small architecture, and YOLOv5lPP-LCNet employs PP-LCNet architecture, both enhancing object detection capabilities. Lastly, YOLOv5lShuffleNetV2 uses ShuffleNetV2_InvertedResidual modules for feature extraction, each with specific parameters tailored for improved detection accuracy.

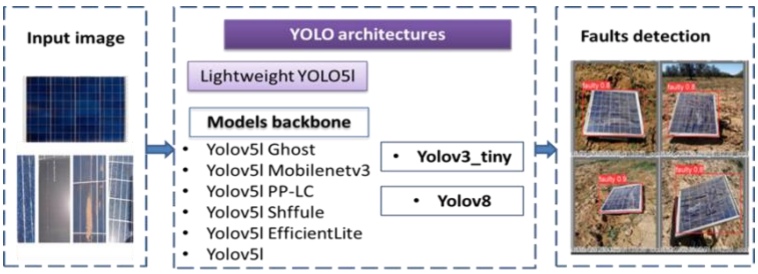


Figure 5. General framework for fault detection in solar panels

2.2. Performance assessment

To evaluate the effectiveness of each model, diverse performance metrics including accuracy, precision, recall, F1-score [25], and mean average precision (mAP) are calculated [26].

$$Accuracy = \frac{(TP + TN)}{(TP + TN + FP + FN)} \quad (1)$$

$$Precision = \frac{TP}{(TP + FP)} \quad (2)$$

$$Recall = \frac{TP}{(TP + FN)} \quad (3)$$

$$F1 - score = 2 \times \frac{(Precision \times Recall)}{(Precision + Recall)} \quad (4)$$

$$mAP = \frac{1}{N}\sum_{i=1}^{N} APi \quad (5)$$

Where N is the total number of classes and AP_i is the average precision for class i.

3. RESULTS AND DISCUSSION

In examining the results of the proposed models for fault detection in solar panels, it is clear to focus on various critical aspects of their performance. Among these considerations, computational costs associated with training each variant emerge as a significant factor. Table 1 summarizes the performance metrics of YOLOv5, YOLOv5Light, and YOLOv8 models on the validation set. YOLOv5Ghost achieves the highest precision of 0.95, followed by YOLOv5EfficientNet with 0.92. YOLOv8 demonstrates the highest recall at 0.89, while YOLOv5 and YOLOv5Light models exhibit recalls between 0.61 and 0.68. In terms of mAP@50, YOLOv8 leads with 0.94, followed closely by YOLOv5s with 0.85. YOLO_Ghost excels in processing speed at 42.1 giga floating point operations per second (GFLOPS), with 24,226,831 parameters. Despite having fewer parameters, YOLOv5Ghost maintains competitive precision and processing speed, making it a strong choice. YOLOv5Ghost stands out with a precision value of 0.95, showcasing its ability to minimize false positive detections defects on solar panels, closely followed by YOLOv5EfficientNet at 0.92. YOLOv8 excels in recall at 0.89. However, YOLOv5 and YOLOv5Light models show lower recall values (0.61 to 0.68), suggesting limitations in capturing true positive instances. YOLOv8 leads in mAP@50 with 0.94, followed by YOLOv5s at 0.85, while YOLO Ghost among YOLOLight models scores 0.77. These results highlight various strengths and trade-offs across models. In terms of parameters and processing speed, YOLOGhost balances well with 24,226,831 parameters and a processing speed of 42.1 GFLOPS. Despite operating with more parameters (46,113,663 and 43,608,150), YOLOv5 and YOLOv8 exhibit faster processing speeds at 107.7 GFLOPS and 164.8 GFLOPS. This indicates YOLO_Ghost's commendable trade-off between parameters and processing efficiency.

Figure 6 illustrates the experimental results, showcasing mAP_{50} and mAP_{95} performances. YOLOv8 demonstrated the highest values, followed by YOLOv5. In the case of the light model, YOLOGhost exhibited the best performance, while YOLOShuffle showed lower values. Loss values for YOLOGhost and YOLOEfficient were around 0.006 as shown in Figure 7. This paper employs diverse methods to enhance backbones, explaining performance enhancements and potential applications.

Table 1. The performance metrics of the proposed models

Model backbone	Precision	Recall	mAP@ 0.05	mAP@ 0.95	NP	Model layers	CPU time	Processing speed (GFLOPS)
YOLOv5l Ghost	95	63	77	70	24226831	552	45.5	42.1
YOLOv5l Mobilenetv3	85	60	75	67	20317981	337	40.5	38.2
YOLOv5lPP-LC	90	60	75	67	21588991	294	44.2	41.5
YOLOv5l Shuffle	87	64	76	68	21210447	361	43.2	40.4
EfficientLite	92	61	76	67	22958935	298	42.5	44
YOLOv5l	96	68	84	79	46113663	267	48.4	107.7
YOLOv3_tiny	94	64	78	66	8669002	38	32.7	12.9
YOLOv8	90	89	94	89	43608150	268	30.2	164.8

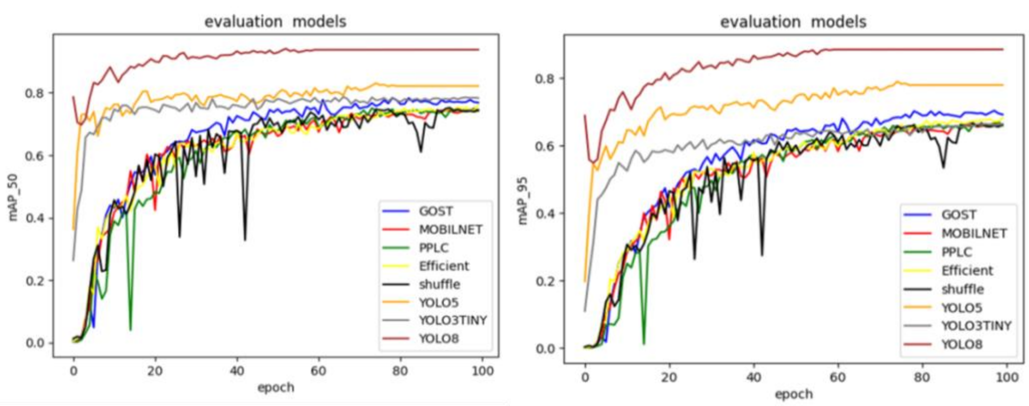


Figure 6. mAP_{50} and mAP_{95} of each models

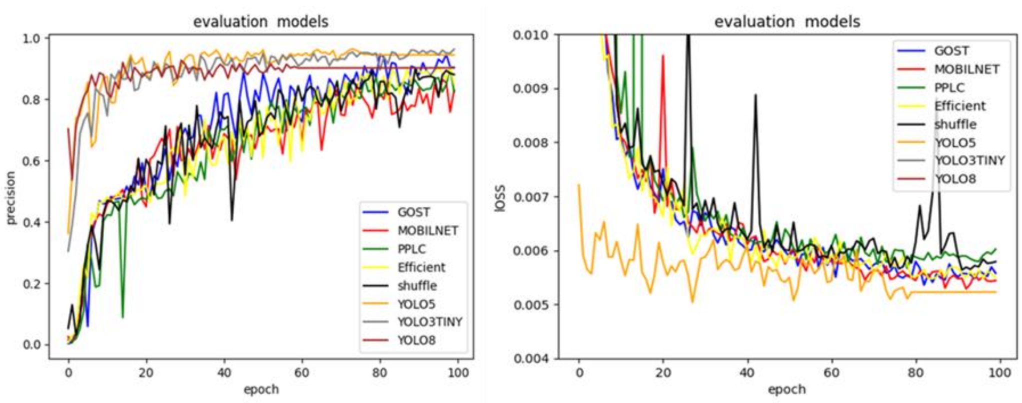


Figure 7. Precision and recall of the models

The precision-confidence curve and recall-confidence curve prominently exhibit elevated values, specifically 0.98 and 0.96, respectively, underscoring the model's efficiency in accurately identifying both faulty and non-faulty solar panels. These metrics reflect a robust performance in terms of precision and recall, crucial for ensuring a reliable identification process. Furthermore, the precision-recall values of 0.96 for faulty panels and 0.90 for non-faulty panels, as illustrated in Figure 8, emphasize the model's ability to maintain high precision while effectively capturing instances of both faulty and non-faulty solar panels. These findings highlight the model's balanced performance in achieving accurate detection across diverse scenarios, contributing to its overall efficacy in solar panel defect detection. After examining the validation batch predictions, it becomes evident that the model accurately identifies and delineates defects like cracks, soiling, shadow, and bird dropping, as depicted in Figure 9. This underscores the proficiency of lightweight YOLO models in detecting and categorizing such anomalies.

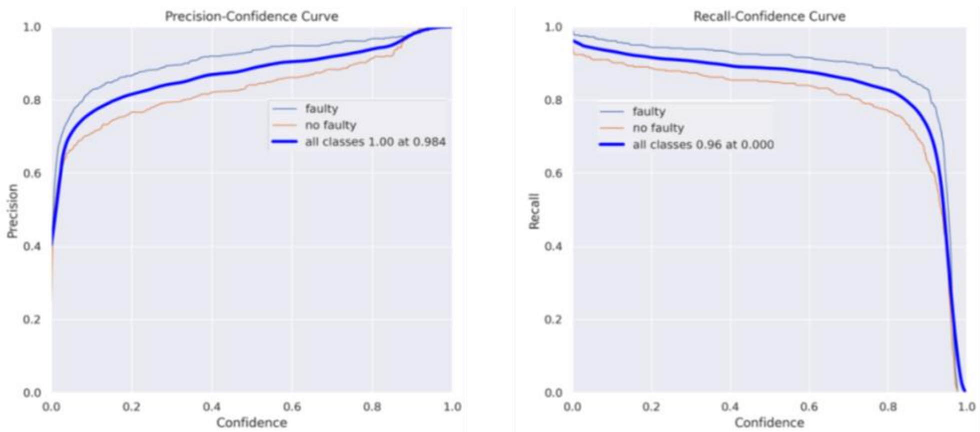


Figure 8. The precision-confidence curve and recall-confidence curve of the best light model

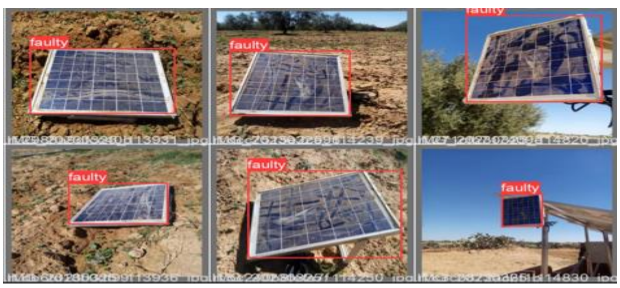


Figure 9. Results of detected faults in solar panels

4. CONCLUSION

In this study, the application of multiple YOLO models for defect detection on the surfaces of solar panels was explored. Considering the set of 5040 images used to train the models, the research results provide compelling evidence that the YOLOv5Gost-lightweight model successfully achieves the goal of defect detection in PV systems, with the highest average precision of 95% compared to YOLOv5s which reached 74.8%. The comparative results between YOLOv5l Ghost and YOLOv5l highlight significant differences in terms of precision, number of parameters, CPU time, and processing speed. While YOLOv5l achieves a slightly higher precision of over 96%, YOLOv5l Ghost attains a precision of 95%. However, YOLOv5l Ghost features a lighter architecture with only 24,226,831 parameters compared to 46,113,663 for YOLOv5l, which can be advantageous for embedded systems with limited resources. Future directions include exploring a more concise backbone structure and an efficient feature fusion method for improved speed.

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AUTHOR CONTRIBUTIONS STATEMENT

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C : **C**onceptualization
M : **M**ethodology
So : **So**ftware
Va : **Va**lidation
Fo : **Fo**rmal analysis
I : **I**nvestigation
R : **R**esources
D : **D**ata Curation
O : Writing - **O**riginal Draft
E : Writing - Review & **E**diting
Vi : **Vi**sualization
Su : **Su**pervision
P : **P**roject administration
Fu : **Fu**nding acquisition

CONFLICT OF INTEREST STATEMENT

Authors state no conflict of interest.

DATA AVAILABILITY

The data that support the findings of this study are available from the corresponding author, N.E.Y., upon reasonable request.

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