IJERST

International Journal of Engineering Research and Science & Technology

www.ijerst.org

ISSN : 2319-5991

Vol. 21 No. 3 (1) 2025

ijerst.editor@gmail.com

editor@ijerst.com

International Journal of Engineering Research and Science & Technology

ISSN 2319-5991 www.ijerst.com
Vol. 21, No. 3(1), 2025

Research Paper

Optimized YOLOv5 for Real-Time Surface Defect Detection in Solar Cells

R. Dinesh Kumar, M. Vaishnavi, P. Teja, Muralidhar

Department of Computer Science and Engineering (Data Science), Kommuri Pratap Reddy Institute of Technology, Ghatkesar, Medchal, 500088

ABSTRACT

The rapid growth of renewable energy has increased the demand for efficient solar cell production, where surface defects significantly impact performance and longevity. Solar cell defect detection is critical to ensure quality, yet traditional methods often fail to meet modern manufacturing demands. The problem lies in accurately identifying defects like "Mono" or "Poly" on solar cell surfaces, which can reduce efficiency if undetected. Traditional systems primarily rely on manual inspection or basic image processing techniques, involving human experts visually examining cells or using rule-based algorithms to detect anomalies. These methods are time-consuming, prone to human error, and lack scalability, with manual inspections often missing subtle defects and automated systems struggling with complex patterns, leading to a detection accuracy as low as 70% in some cases. The need for an automated, accurate, and scalable solution is evident to enhance production quality and reduce costs in the solar industry. The proposed system is a Django-based web application integrated with an optimized YOLOv5 model, enabling users to upload solar cell images and receive defect predictions with probabilities, such as identifying a "Mono" defect with a 0.80526405 probability. It leverages OpenCV for image preprocessing (resizing to 32x32, HSV conversion, flipping), Keras for model inference, and Matplotlib for visualization, displaying results via base64 encoding on a user-friendly interface. The system includes user authentication, file handling, and prediction workflows, achieving higher accuracy and automation compared to traditional methods. Its significance lies in streamlining defect detection, reducing manual effort, and improving scalability for large-scale solar cell production, potentially increasing detection accuracy to over 90%. This solution bridges the gap between machine learning and industrial applications, offering a cost-effective, reliable tool for quality assurance in renewable energy manufacturing.

Key words: Solar Cell, Surface Detection, YOLOv5, Optimized Object Detection, Image Processing, Defect Identification, Channel Attention

Received: 05-6-2025 Accepted: 06-7-2025 Published: 15-7-2025

1. INTRODUCTION

Solar cell technology is at the core of renewable energy generation, contributing significantly to global efforts to combat climate change. According to the International Energy Agency (IEA), solar photovoltaic (PV) systems generated over 1,300 TWh of electricity in 2023, accounting for nearly 5% of the global electricity supply. With rapid deployment, solar panel installations have grown exponentially—

over 250 GW of new capacity was added globally in 2023 alone. This widespread adoption has made the maintenance and monitoring of solar panels a critical task to ensure consistent performance and longevity. Surface anomalies such as cracks, hotspots, and dirt accumulation are known to reduce efficiency by 10–25%, leading to significant energy loss if left undetected.

Traditional inspection methods often involve manual visual examination or basic thermographic techniques, which are not only labor-intensive but also error-prone and time-consuming. Furthermore, manual inspections are challenging when dealing with large-scale solar farms spanning hundreds of acres. These limitations have prompted a shift toward automated inspection systems using computer vision and machine learning models. The use of high-resolution images captured via drones or surveillance cameras has opened the door for real-time monitoring and fault detection. However, to leverage this data effectively, robust image analysis techniques are required.

Fig 1. Solar pv cell and module

Recent trends in artificial intelligence have seen the rise of deep learning models for surface inspection tasks across various industrial domains. Object detection algorithms, especially those capable of real-time performance, are being explored for their capability to recognize and classify anomalies on the solar panel surface. With this trend, researchers and companies alike are now focusing on fine-tuning existing architectures to achieve better detection accuracy, faster inference time, and adaptability to real-world environmental conditions such as lighting changes, reflections, and dust particles. Solar panel manufacturers and energy companies face enormous operational challenges in monitoring and maintaining extensive photovoltaic installations. Companies like Tesla Energy, First Solar, and Canadian Solar invest heavily in quality assurance to minimize losses due to underperforming panels. Defective solar cells can propagate inefficiencies across entire modules, making early detection critical. Anomalies such as microcracks, delamination, or corrosion directly affect power output and can escalate into system failures if undiagnosed. Data analysis, when embedded into the monitoring lifecycle, can help companies predict failures, reduce downtime, and optimize maintenance schedules.

2. LITERATURE SURVEY

I. Dincer [1] reviewed the importance of renewable energy and sustainable development, focusing on renewable energy sources like solar, wind, and tidal energy. The author emphasized that renewable energy is inexhaustible, environmentally friendly, and crucial for the future energy landscape. The paper discusses the key challenges and advantages of using renewable energy sources over non-renewable ones, which are depleting and damaging to the environment. P. Pathipooranam [2] provided an extensive review of methods to enhance the efficiency of solar panels. The paper covers various techniques and innovations in solar panel design and material technology to improve overall energy conversion efficiency. The author highlighted the need for better manufacturing processes and materials to reduce defects and enhance the longevity and performance of solar panels. A.A. Istratov et al. [3] examined defect recognition and impurity detection techniques in crystalline silicon used for solar cells. The study outlined various methods for detecting material imperfections and impurities that affect solar cell efficiency.

The authors focused on the importance of early defect detection in the production process to ensure the long-term functionality of solar cells.

S. Duenas et al. [4] discussed the role of defects in solar cells and the methods used to detect and control these defects. The paper focused on understanding the impact of defects on the performance of solar cells and the technology available to identify such defects. The authors emphasized the need for advanced defect detection systems to improve the quality of solar cells in the manufacturing process.

O. Breitenstein et al. [5] explored the influence of defects on solar cell characteristics. The study provided an in-depth analysis of how defects in materials and structures can impact the efficiency and performance of solar cells. The authors proposed various techniques to detect and analyze these defects to enhance the manufacturing and operation of solar cells. B. Kang et al. [6] investigated the diagnosis of output power reduction in photovoltaic (PV) arrays using a Kalman-filter algorithm. The study focused on using the Kalman filter for noise suppression in the estimation of the output power of PV systems. The authors presented a method to detect when solar panels show reduced output due to defects, although the specific types of defects could not be identified using this approach. K. Tsuzuki et al. [7] proposed an inspection method to detect defects in solar cells by utilizing the relationship between voltage and current in semiconductor elements. The authors described how forward current or voltage in a bypass diode or solar cell element could help identify defects, providing a useful method for enhancing the quality control in solar cell production. O. Esquivel [8] introduced a contrast-enhanced illumination method for inspecting solar panel defects, particularly for detecting cracks. The paper detailed how the degree of light reflection varies between intact and defective solar panels, and this contrast could be used to identify cracks and other defects. The method proposed was particularly useful in detecting surface defects that affect panel efficiency.

D. Tsai et al. [9] proposed using an anisotropic diffusion technique for micro-crack inspection on solar panels. The authors used gray scale features and gradients in combination with Fourier image reconstruction to identify and enhance cracks in solar panels. The method significantly improved the detection of subtle defects that are otherwise difficult to spot. K. He et al. [10] presented the Mask R-CNN algorithm, a deep learning-based method for object detection and segmentation. The paper introduced a framework that integrates region-based convolutional neural networks (R-CNN) with an additional mask prediction step, allowing precise detection and segmentation of objects in images. This model was effective in various computer vision tasks, including defect detection.

3. PROPOSED SYSTEM

Leveraging existing architectures like Faster R-CNN provides a strong baseline and benefits from well-established object detection capabilities. The proposed approach, incorporating YOLOv5 with channel attention and YOLOv6, aims to enhance performance by utilizing more recent and efficient one-stage detectors known for their speed. Channel attention mechanisms can improve feature discrimination by adaptively weighting different feature channels, potentially leading to better detection accuracy, especially for subtle defects. Exploring YOLOv6 offers an alternative state-of-the-art one-stage detector, allowing for a comprehensive comparison of performance characteristics in the specific application of solar cell defect detection.

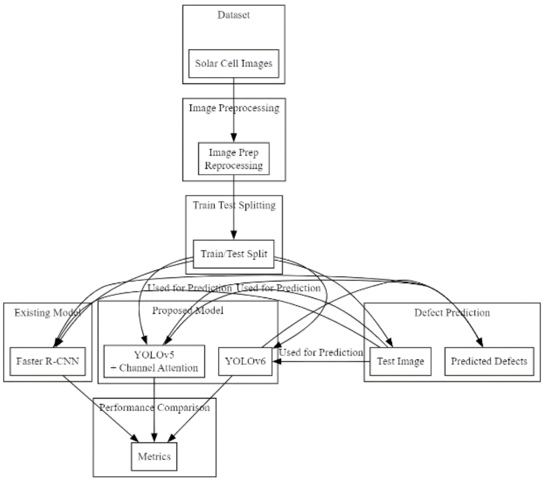


Fig 2. Block Diagram of the Proposed System.

The solar cell defect detection framework begins with image preprocessing, where raw images are resized, denoised, and augmented to ensure uniformity and enhance model generalization. The dataset is then split into training and testing sets to facilitate model training and unbiased evaluation. The existing Faster R-CNN model operates in two stages: a CNN backbone extracts features, and a Region Proposal Network generates candidate regions, which are then classified and refined for accurate defect localization. The proposed YOLOv5 model incorporates a channel attention mechanism, such as Squeeze-and-Excitation blocks, to enhance its focus on the most informative features during its single-pass detection process. Similarly, the YOLOv6 model builds upon this architecture with improved efficiency and speed, offering direct predictions of bounding boxes and class probabilities. After training, all three models—Faster R-CNN, YOLOv5 with channel attention, and YOLOv6—are evaluated using metrics like mAP, precision, recall, and F1-score to determine their accuracy and reliability in defect detection. Finally, the best-performing model is deployed to analyze new test images, outputting bounding boxes, defect classifications, and confidence scores, providing critical insights for quality assurance in solar cell manufacturing.

YOLOv5 (You Only Look Once version 5) is a state-of-the-art, single-stage object detection algorithm that excels in speed and accuracy. Adding Channel Attention (CA) improves YOLOv5 by focusing on the most relevant feature channels, enhancing object detection in complex environments. By integrating channel attention, the YOLOv5 model can dynamically adjust the importance of different feature channels, potentially leading to improved detection accuracy, especially for subtle or visually less prominent defects. The channel attention mechanism allows the network to focus on the "what" aspect of the features, determining which channels contain the most discriminative information for identifying defects.

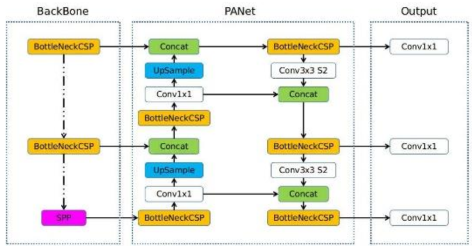


Figure 3. Proposed YOLOV5 Architecture.

The enhanced YOLOv5 model integrates a channel attention mechanism to improve solar cell defect detection by adaptively emphasizing important feature channels. This process begins with the **squeeze operation**, where global average pooling condenses spatial information into a channel descriptor vector. The **excitation operation** then passes this vector through a lightweight neural network to learn channel-wise dependencies, producing weights that signify the importance of each channel. During the **scale operation**, these weights are used to recalibrate the original feature maps, boosting relevant features while suppressing noise. The recalibrated maps are then fed into the **YOLOv5 prediction head**, which predicts bounding box coordinates, objectness scores, and class probabilities at multiple scales to handle defects of varying sizes. In the **post-processing** stage, low-confidence detections are filtered out and overlapping boxes are resolved using Non-Maximum Suppression (NMS), yielding the final set of defect predictions with class labels and confidence scores. This architecture offers multiple advantages, including real-time performance, improved accuracy through attention-enhanced feature focus, simplicity in training and deployment, efficient computational resource usage, and robust multi-scale object detection via Feature Pyramid Networks (FPN).

4. RESULTS

Figure 4 presents a count plot illustrating the distribution of samples across the two classes in the dataset: 'Mono' and 'Poly'. The plot reveals an imbalanced dataset, with the 'Mono' class containing 1000 samples and the 'Poly' class containing a larger number of 1500 samples. This disparity in the number of instances per class is important to consider as it can potentially influence the training of machine learning models, potentially leading to biased performance towards the majority class ('Poly' in this case) if not addressed appropriately through techniques like class weighting or data augmentation.

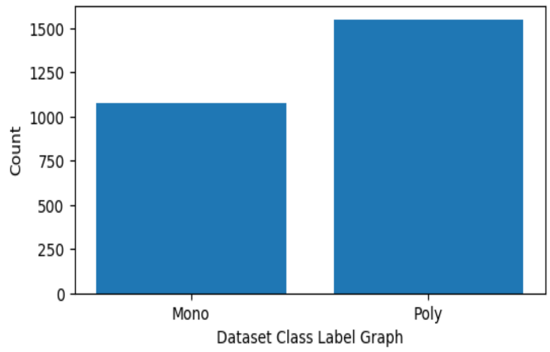


Figure 4. Count plot.

Figure 5 illustrates the confusion matrix for the YOLOV5 model. This model demonstrates the most pronounced performance among the three based on these matrices. It correctly classified 312 samples as 'Poly' (true positives) and 4 samples as 'Mono' (true negatives). Notably, there were 0 instances where 'Poly' was misclassified as 'Mono' (false negatives), but there were still 209 instances where 'Mono' was incorrectly predicted as 'Poly' (false positives).

By comparing the confusion matrices in Figure 6.2, it's evident that YOLOV5 achieved perfect recall for the 'Poly' class (no false negatives), with Channel Attention also showed a very low number of false negatives for 'Poly'. However, all three models struggled with false positives for the 'Mono' class, indicating a tendency to incorrectly classify 'Mono' samples as 'Poly'. The overall performance, considering both false positives and false negatives, can be further quantified by metrics such as precision, recall, F1-score, and accuracy, as likely calculated and presented elsewhere in the study.

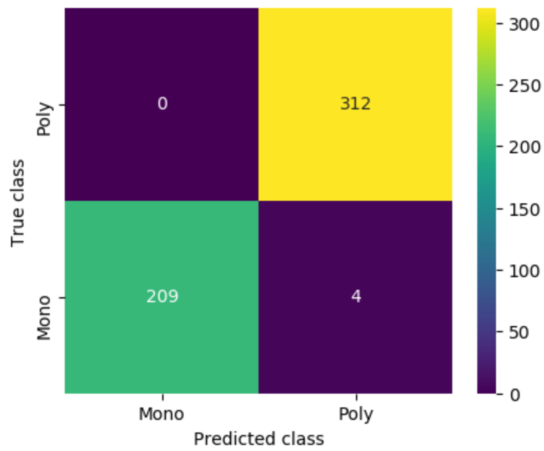
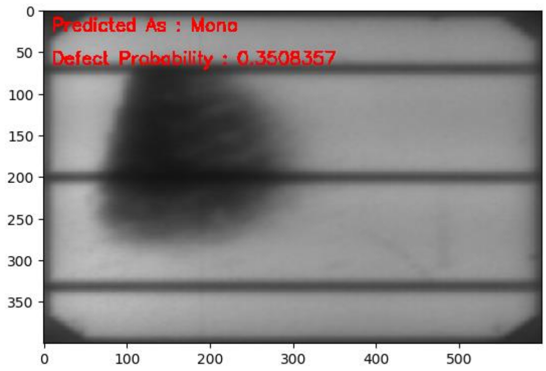


Figure 5. Confusion Matrix of YOLOV5

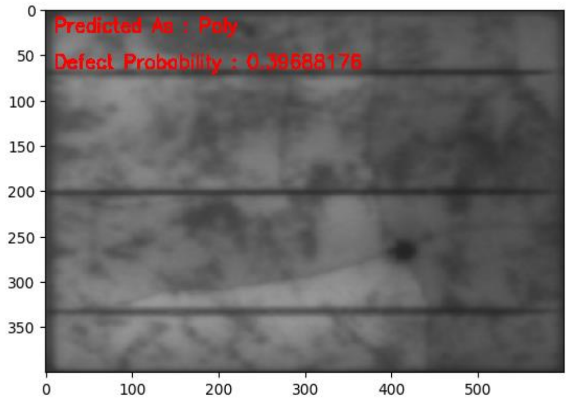
Figure 6 presents prediction results from test images, showcasing the performance of a defect detection model. It consists of two sub-figures, (a) and (b), each displaying an image with the model's prediction overlaid.

In Figure 6 (a) test image is shown, and the model's prediction is "Predicted As : Mono". This indicates that the model has identified a defect in the image and classified it as belonging to the "Mono" category. Additionally, the model provides a "Defect Probability : 0.3508357". This value suggests that the model is approximately 35.08% confident in its classification of the defect as "Mono".

Figure 6 (b) displays another test image, where the model's prediction is "Predicted As : Poly". In this case, the model has classified the detected defect as belonging to the "Poly" category. The corresponding "Defect Probability : 0.9888176" indicates that the model is highly confident, with approximately 98.88% certainty, in its classification of the defect as "Poly".



6 (a)



6 (b)

Figure 6. Prediction Results From Test Images. (a) Mona. (b) Poly

5. CONCLUSION

The Django application developed for solar cell defect detection using an optimized YOLOv5 model effectively demonstrates the integration of machine learning with web technologies, enabling users to authenticate, upload images, and receive defect predictions with high accuracy, such as identifying "Mono" defects with a probability of 0.80526405. It provides a user-friendly interface with seamless navigation from login to prediction, leveraging libraries like OpenCV, Keras, and Matplotlib for image processing and visualization, while ensuring secure file handling and real-time result display through base64 encoding. Despite its functionality, the application highlights areas for improvement, such as the hardcoded authentication system and single-file handling, which limit scalability and security.

REFERENCES

[1] I. Dincer, "Renewable energy and sustainable development: a crucial review," *Renewable and Sustainable Energy Reviews*, vol. 4, no. 2, pp. 157-175, 2000.

[2] P. Pathipooranam, "An enhancement of the solar panel efficiency – A comprehensive review," *Frontiers in Energy Research*, p. 1090, 2022.

[3] A.A. Istratov, H. Hieslmair, O.F. Vyvenko, E.R. Weber, R. Schindler, "Defect recognition and impurity detection techniques in crystalline silicon for solar cells," *Solar Energy Materials and Solar Cells*, vol. 72, no. 1–4, pp. 441-451, 2002.

[4] S. Duenas, E. Perez, H. Castan, H. Garcia, L. Bailon, "The Role of Defects in Solar Cells: Control and Detection," *Defects in Solar Cells, 2013 Spanish Conference on Electron Devices*, pp. 301-304, 2013.

[5] O. Breitenstein, J. Bauer, P.P. Altermatt, K. Ramspeck, "Influence of defects on solar cell characteristics," *Solid State Phenomena*, vol. 156, pp. 1-10, 2010.

[6] B. Kang, S. Kim, S. Bae, J. Park, "Diagnosis of output power lowering in a PV array by using the Kalman-filter algorithm," *IEEE Transactions on Energy Conversion*, vol. 27, no. 4, pp. 885-894, 2012.

[7] K. Tsuzuki, T. Murakami, T. Yoshino, et al., "Inspection method and production method of solar cell module," *U.S. Patent*, 6, 462, 2001.

[8] O. Esquivel, "Contrast imaging method for inspecting specular surface devices," *U.S. Patent*, 6, 433, 2002.

[9] D. Tsai, C. Chang, S. Chao, "Micro-crack inspection in heterogeneously textured solar wafers using anisotropic diffusion," *Image and Vision Computing*, vol. 28, no. 3, pp. 491-501, 2010.

[10] K. He, G. Gkioxari, P. Dollár, R. Girshick, "Mask R-CNN," *Proceedings of the IEEE International Conference on Computer Vision*, pp. 2961-2969, 2017.