DOI: 10.54254/2755-2721/2026.GU35083

Photovoltaic Cell Defect Detection Based on Machine Vision

Wenqian Li

School of Software, Xinjiang University, Urumqi, China
20242501319@stu.xju.edu.cn

Abstract. Defects in photovoltaic (PV) cells directly reduce photoelectric conversion efficiency. Automated defect detection using machine vision has become a core technology for quality control in PV manufacturing lines. This paper systematically reviews the research progress and engineering applications of machine vision-based defect detection for PV cells. First, typical defect types, formation mechanisms, and quantified impacts on PV cell performance are presented, and the principles and applicable scenarios of different imaging modalities are analyzed. Reasonable selection of imaging modalities and detection algorithms is crucial to improving detection stability and applicability in industrial scenarios. The technical principles and characteristics of traditional machine vision and deep learning methods are summarized in detail. Then, practical cases are used to compare different technical routes in terms of accuracy, real-time performance, and cost. Key solutions are proposed for challenges including lighting interference, limited defect samples, and real-time edge deployment. Finally, future trends are discussed, including vision large models, multimodal fusion, and integration with intelligent manufacturing.

Keywords: PV cells, defect detection, machine vision, deep learning

1. Introduction

In recent years, with the worsening global energy crisis and environmental pollution, photovoltaic power generation, as a clean and renewable form of energy, has attracted widespread attention. Relevant reviews have shown that photovoltaic module defect detection technology is developing toward the integration of multiple imaging methods, intelligent identification, and online monitoring [1]. The International Energy Agency also pointed out in its latest outlook that solar photovoltaics will remain one of the most important sources of newly added renewable electricity worldwide in the future [2].

Among the various types of defects in photovoltaic modules, micro-cracks are particularly critical because of their strong concealment and the difficulty of early detection. Relevant studies have indicated that methods based on gradient guidance and fine-grained feature modeling can help improve the accuracy of micro-crack detection, thus providing an important reference for subsequent defect diagnosis [3].

At present, computer vision methods have been widely applied to fault detection and performance evaluation in photovoltaic modules. For example, existing studies have conducted fault

DOI: 10.54254/2755-2721/2026.GU35083

identification and power loss estimation based on electroluminescence images, demonstrating that visual information has substantial value in defect localization and condition assessment.

This paper aims to provide a systematic review of machine vision-based PV cell defect detection technology, so as to comprehensively sort out the research status and development trends in this field. Firstly, it will systematically summarize the types, characteristics and influence mechanisms of common PV cell defects on power generation performance, and clarify the hazard levels and detection priorities of different defects. Secondly, it will compare the detection principles, imaging characteristics and applicable scenarios of mainstream imaging technologies including EL, IRT and PL in detail, and analyze their advantages, disadvantages and complementarity in different industrial scenarios. Thirdly, it will focus on reviewing the research progress, technical routes and application status of traditional image processing algorithms and deep learning algorithms in PV defect detection in the past five years, and deeply analyze the core ideas, key technologies and performance of various methods. Finally, it will analyze the main challenges faced by current technologies in complex industrial environments and prospect future development trends, so as to provide a comprehensive and systematic reference for researchers and industrial practitioners in related fields and promote the further development of PV intelligent manufacturing technology.

2. Fundamentals of PV cell defect detection

2.1. Typical defect types and causes

Defect detection of photovoltaic cells is an important step to ensure the quality and power generation efficiency of photovoltaic components. The main defects of photovoltaic cells can be divided into external defects and material defects according to their causes. External defects refer to surface damages of cells caused by manual operation, mechanical factors, or production processes, such as cracks, broken fingers, and smudges. Material defects are surface imperfections resulting from insufficient raw material quality or deviations in chemical reactions, such as spots, dark spots, and dark slices. Different defects exert different effects on cell performance.

This paper mainly introduces the four most typical defects of photovoltaic cells [4]. Figure 1 shows the EL imaging results of these four typical defects, which are, from left to right, crack, broken finger, dark spot, and dark slice.

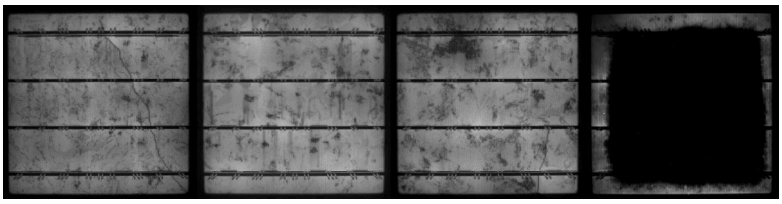

Figure 1. Examples of EL images of typical defects in PV cells [4]

Crack refers to the fine or wide fissures appearing on the surface of photovoltaic cells, which are slender and irregular in shape and easy to identify in captured images. Cracks are mainly caused by mechanical compression and physical collision during production and transportation, or improper use of chemical reagents and unstable process parameter control in processing steps such as cleaning and etching. Cracks directly damage the structural integrity of cells, block internal current paths, significantly reduce the output power of cells, and are one of the main defects leading to early module failure and poor longterm operational reliability. Broken finger refers to local fracture, gaps or discontinuous grid lines on the cell surface, which belongs to an electrode structure defect. This

DOI: 10.54254/2755-2721/2026.GU35083

defect mostly occurs in key production processes such as screen printing, sintering, laser cutting and soldering, and is also caused by improper handling such as severe vibration and friction during transportation. Broken fingers prevent the corresponding area from effectively collecting and transmitting carriers, resulting in the loss of local power generation capacity, significantly reducing the overall fill factor and conversion efficiency of the cell, and directly affecting power generation performance.

Dark spot refers to the irregular and fuzzy dark patches on the cell surface, which appear as distinct dark areas in EL and PL images with obvious characteristics. Dark spots are mainly caused by insufficient purity of silicon wafer raw materials, unstable coating process, uneven paste distribution or local contamination. The photoelectric reaction capacity in dark spot areas is greatly weakened and cannot participate in power generation normally, thereby reducing the effective lightreceiving area and lowering the overall photoelectric conversion efficiency. It is a common defect that affects cell uniformity and output stability. Dark slice refers to the serious darkening of a large area or the whole cell with abnormally low brightness, which is the most serious type of defect. Dark slices are caused by core process problems such as unqualified silicon substrate, abnormal diffusion, defective passivation film, excessive sintering or outofcontrol temperature profile. Dark slices completely lose normal light absorption and conductivity, and easily cause local overheating, thermal breakdown and even module burnout. They must be strictly screened and eliminated in the inspection stage to avoid entering subsequent packaging and application.

2.2. Mainstream imaging methods

Image acquisition is a critical preliminary step for PV panel defect detection. High-quality imaging significantly improves accuracy and efficiency while reducing false detection risks, and related technologies have been widely studied. Currently, the mainstream imaging methods are electroluminescence (EL), infrared thermography (IRT), and photoluminescence (PL), which differ greatly in principle and application.

To address the problems of detection efficiency and deployment cost, researchers have proposed a three-stage cascaded lightweight model that balances detection accuracy and real-time performance, thereby offering a feasible solution for online detection in industrial scenarios [5].

According to review studies, machine vision-based detection of surface defects in photovoltaic systems has developed along a relatively clear technical trajectory, and deep learning is gradually replacing traditional hand-crafted feature methods as the mainstream approach [6]. In addition, improved object detection architectures designed for small targets and weak defects under complex backgrounds also provide useful methodological insights for the model design of photovoltaic defect detection systems [7].

PL imaging requires no external voltage and relies on external light sources to excite cell luminescence. Defects appear as dark spots or lines. It is non-contact and non-destructive, enabling early defect screening in silicon wafer production to reduce losses and supporting quantitative defect analysis. Nevertheless, PL is costly, sensitive to light source stability and ambient stray light, and is currently used mostly in laboratory research and high-end silicon wafer inspection.

In summary, the three imaging methods have complementary strengths: EL excels at precise tiny defect detection, IRT suits large-scale rapid inspection, and PL focuses on raw material and early defect detection. Multimodal imaging fusion is widely adopted in industrial applications to lay a solid foundation for subsequent defect detection.

DOI: 10.54254/2755-2721/2026.GU35083

2.3. Core challenges in industrial inspection

Although various imaging detection technologies have become increasingly mature and widely used in industrial quality inspection, they still face many common challenges in practical application. First, environmental interference significantly affects detection accuracy. Dust, water mist, uneven lighting, and rain occlusion in industrial sites directly reduce image visibility and clarity, disturb defect feature extraction, and lead to obvious declines in detection accuracy and stability. Second, defect samples are scarce and extremely imbalanced in distribution. Although indoor controlled environments can reduce data deviation, they cannot adapt to large-scale outdoor inspection scenarios. Meanwhile, different imaging methods have inherent data biases: EL imaging is easily affected by ambient light and bias voltage fluctuations, IRT imaging is disturbed by ambient temperature and shadow occlusion, and PL imaging is highly sensitive to laser intensity stability and surface impurities. Third, there is a high dependence on hardware equipment. EL and PL imaging especially require high-resolution and high-stability professional cameras. Insufficient hardware performance directly causes blurred images and lost details, greatly reducing the recognition accuracy of tiny and hidden defects and restricting detection performance.

3. Mainstream methods for PV cell defect detection

3.1. Traditional machine vision detection methods

Traditional machine vision detection methods have been widely used in industrial defect detection for a long time. These methods mainly rely on manually designed image processing algorithms and feature descriptors to complete defect localization, segmentation and recognition. They do not require large-scale labeled datasets or high-performance computing hardware, and feature clear principles, low computation, simple deployment and strong real-time performance. They still undertake key inspection tasks in some automated production lines, and the main steps are shown in Figure 2. Traditional machine vision detection methods can be divided into two categories: spatial domain analysis methods and transform domain analysis methods. This section will elaborate on the research progress and improvements of these two methods made by relevant researchers in recent years.

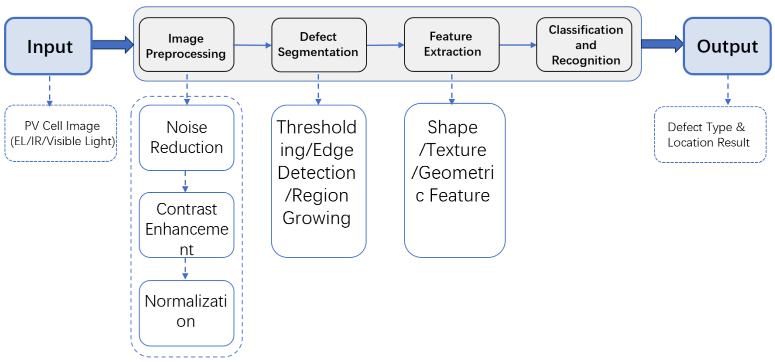

Figure 2. Traditional machine vision detection process (picture credit : original)

Although current methods for photovoltaic panel surface defect detection have continuously improved in accuracy, they still suffer from limitations in data diversity, adaptability to complex operating conditions, and real-time deployment, which has also been repeatedly emphasized in recent review studies [6].

DOI: 10.54254/2755-2721/2026.GU35083

Transform domain analysis converts images from the spatial domain to the frequency domain or low-dimensional feature space through mathematical transformations such as Fourier transform, wavelet transform, and principal component analysis (PCA), so as to enhance weak defect signals, suppress background noise, and eliminate redundant information. This kind of method can effectively mine hidden defect features that are difficult to be directly detected by human eyes, and has higher sensitivity to low-contrast defects, internal defects, and minor damages. In photovoltaic infrared thermal imaging fault diagnosis, discrete wavelet transform (DWT) is often used as a key preprocessing step. It highlights weak defect features and reduces noise interference through multi-scale decomposition, providing higher-quality input data for subsequent deep learning models, which fully verifies the practical value of transform domain methods in low-contrast defect recognition [7]. Nevertheless, such methods still have certain limitations: key parameters such as the selection of wavelet basis functions and the determination of decomposition levels highly rely on manual experience without a unified standard. Meanwhile, the computational complexity of transform domain is higher than that of direct spatial domain processing, which brings certain pressure in high-speed production line real-time detection scenarios.

In summary, spatial domain analysis and transform domain analysis jointly form the core technical system of traditional machine vision for photovoltaic cell defect detection. Spatial domain methods directly process pixel information, with simple process, convenient deployment, and good real-time performance. They perform reliably in scenarios with obvious defects and high contrast, but are easily limited by illumination changes, noise interference, and manual feature design. Transform domain methods mine deep hidden features through mathematical transformation, are more sensitive to weak and internal defects, and have stronger overall robustness, but with high computational cost and difficult parameter debugging. The two types of methods complement each other's advantages and jointly lay a solid theoretical foundation and engineering practice reference for the subsequent development of deep learning-based defect detection technology.

3.2. Deep learning detection methods

Deep learning has gradually become the mainstream direction for PV defect detection with its automatic feature extraction advantage, effectively overcoming the limitation of traditional machine vision relying on manual feature design. The deep learning-based detection process includes four core stages: data preprocessing, model inference, feature map analysis, and classification recognition. First, input PV images are preprocessed via cropping, data augmentation, and normalization. Then, feature maps are generated through model forward propagation. Next, feature vectors are extracted via activation map analysis and visualization. Finally, Softmax probability calculation completes defect classification and localization, as shown in Figure 3.

In the field of photovoltaic thermal image detection, the technical route combining discrete wavelet transform and convolutional neural network (CNN) has been extensively studied and applied. Using discrete wavelet transform for multi-scale decomposition and preprocessing of thermal images can effectively enhance weak defect features in the image and suppress noise interference from complex backgrounds, providing clearer and more prominent feature input for subsequent deep learning models and significantly improving the recognition of weak and hidden defects. This method shows strong robustness and stability in low-contrast defect detection, but also has obvious shortcomings. On the one hand, model training relies on a large number of high-quality labeled samples with high data acquisition cost; on the other hand, the overall computation is large and consumes high hardware resources, which is not conducive to rapid deployment on lightweight devices [7].

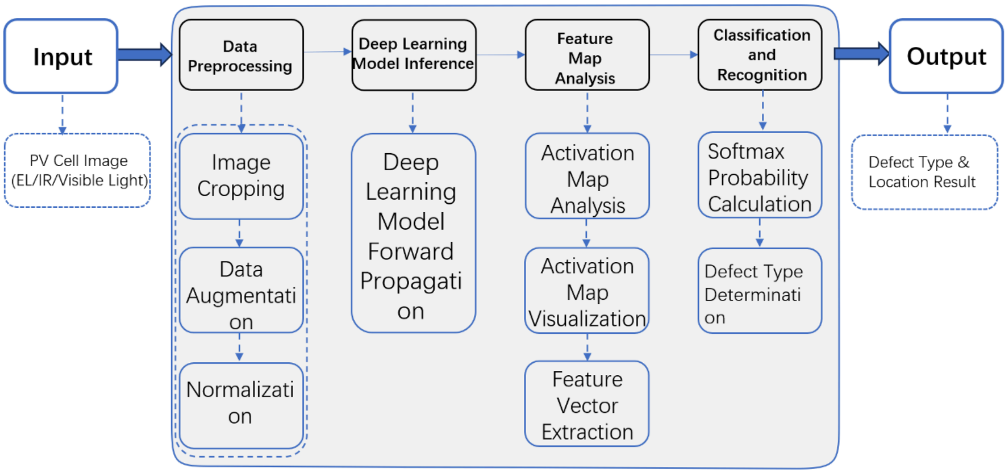

Figure 3. Overall framework of deep learning-based PV defect detection (picture credit : original)

At the methodological level, an improved YOLO framework based on adaptive complementary fusion has been applied to photovoltaic panel defect detection, indicating that feature fusion strategies can play a positive role in improving detection performance [8].

For infrared image-based scenarios, lightweight vision models help reduce model complexity and improve deployment efficiency [9]. Meanwhile, defect classification methods based on transfer learning have shown promising application potential under limited-sample conditions, although their performance can still be affected by source-domain differences and changes in data distribution [10].

Overall, with end-to-end automatic feature learning and classification capabilities, deep learning methods show significant advantages in the detection of multi-type mixed defects, tiny defects and hidden defects, providing a more advanced, reliable and intelligent technical path for efficient, intelligent and automated defect detection of photovoltaic cells.

4. Typical application cases and performance comparison

In electroluminescence image-based detection, researchers have further combined neural architecture search and knowledge distillation to build lightweight networks that balance accuracy and inference efficiency [11]. In addition, studies on automated defect detection for production-line scenarios have also shown that deep learning methods have strong potential for engineering applications [12].

For fault classification tasks based on electroluminescence images, the combination of convolutional neural networks and transfer learning has been proven to effectively improve the defect recognition performance of photovoltaic modules [13].

Performance comparison is the core method for evaluating technical routes. Comparing accuracy, real-time performance, and robustness provides a quantitative basis for technology selection.

From a broader perspective on technological development, recent systematic reviews of electroluminescence imaging have further summarized imaging conditions, hardware configurations, and artificial intelligence methods spanning from indoor to daylight environments, thereby providing guidance for the future development of more stable and practical photovoltaic defect detection systems [14].

In summary, different technical routes have respective strengths and weaknesses and should be selected based on line requirements for accuracy and real-time performance, providing a quantitative decision basis for practical applications.

DOI: 10.54254/2755-2721/2026.GU35083

5. Conclusion

This paper systematically reviews the research status and engineering application progress of machine vision-based defect detection for photovoltaic cells. Studies show that electroluminescence, infrared thermography, and photoluminescence imaging each have unique advantages in defect detection, and their integrated application is the key to improving detection robustness. In terms of detection algorithms, traditional machine vision methods feature fast computation and low deployment costs, presenting satisfactory real-time performance in stable production scenarios. However, they rely heavily on handcrafted features and exhibit weak generalization ability for weak and variable defects. In contrast, deep learning methods eliminate the need for manual feature design and achieve higher accuracy and adaptability in identifying complex defects such as micro-cracks, broken fingers, and dark spots, making them the mainstream solution. Lightweight networks and few-shot learning have further provided feasible routes for their industrial deployment.

The most prominent bottleneck in current industrial deployment lies in strong on-site environmental interference, scarce and class-imbalanced defect samples, and the difficulty in balancing high-precision models with real-time requirements and low-computation hardware on production lines. As a result, excellent laboratory performance can hardly be stably replicated in practical applications, which has become the main obstacle to large-scale implementation.

The most worthwhile directions for future advancement include three aspects. First, the combination of multi-modal imaging and large vision models will break the limitations of single-modal detection and comprehensively improve complex defect recognition capability. Second, the further development of few-shot learning, weakly supervised learning and data augmentation will alleviate the problem of insufficient samples and significantly reduce annotation costs. Third, the promotion of model lightweighting and edge computing collaborative deployment will achieve a better balance between high precision and high real-time performance. Ultimately, defect detection technology will be deeply integrated with the intelligent manufacturing system, evolving from online inspection to full-life-cycle quality traceability and closed-loop optimization of production processes, providing strong support for the efficient, stable and intelligent development of the photovoltaic industry.

References

[1] Maziuk, S., Wilson, G. M., Hammam, A., et al. (2023). A review on surface defect detection in photovoltaic systems. Solar Energy, 263, 111896.

[2] International Energy Agency. (2024). World Energy Outlook 2024. IEA.

[3] Dhimish, M., Badran, G., Houari, F., et al. (2024). Micro-cracks detection in photovoltaic modules based on a gradient-guided architecture. Expert Systems with Applications, 246, 123554.

[4] Su, B., Zhou, Z., & Chen, H. (2022). Photovoltaic cell anomaly detection dataset. IEEE Dataport. https://dx.doi.org/10.21227/pz6t-3s77

[5] Chen, Y., Ma, Z., Li, X., et al. (2025). Defect detection of photovoltaic cells using a three-stage cascade lightweight model. Laser & Optoelectronics Progress, 62(6), 0615006.

[6] Rana, A., & Arora, R. (2024). A review on surface defect detection in photovoltaic system. Artificial Intelligence Review, 57(8), 211.

[7] Guo, L., & Liu, Z. (2023). Improved YOLOv5-based defect detection in photovoltaic modules. Laser & Optoelectronics Progress, 60(20), 2015005.

[8] Pan, W., Liu, Y., He, C., et al. (2024). Enhanced photovoltaic panel defect detection via adaptive complementary fusion in YOLO-ACF. Scientific Reports, 14, 26425.

[9] Nowaczewski, M., Hołub, M., Pietruszka, S., et al. (2025). Infrared image analysis and lightweight vision models for photovoltaic panel defect detection. Swarm and Evolutionary Computation, 96, 101533.

DOI: 10.54254/2755-2721/2026.GU35083

[10] Akram, M. W., Li, G., Jin, Y., et al. (2020). Detection of photovoltaic module defects in infrared images with isolated and developed-model transfer deep learning. Solar Energy, 198, 175–186.
[11] Yang, Q., Wang, T., & Su, J. (2024). A lightweight network for photovoltaic cell defect detection in electroluminescence images based on neural architecture search and knowledge distillation. Applied Energy, 355, 122184.
[12] Tang, W., Yang, Q., Xiong, K., et al. (2020). Deep learning-based automatic detection of photovoltaic module defects in electroluminescence images on production line. Energy, 203, 117872.
[13] Korkmaz, D., Yildiz, C., Gulbag, A., et al. (2022). Efficient fault classification in photovoltaic modules using electroluminescence images based on convolutional neural network and transfer learning. International Journal of Energy Research, 46(11), 15764–15781.
[14] Aksoy, Y., Yıldırım, M. A., Ergani, B., et al. (2025). From indoor to daylight electroluminescence imaging for PV module diagnostics: A comprehensive review of techniques, challenges, and AI-driven advancements. Micromachines, 16(6), 610.