Chapter 10

AI and Robotic techniques for PV inspection

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10.1 Introduction

The growing interest in renewable energy sources, particularly solar energy, has highlighted the importance of maintaining the efficiency and reliability of photovoltaic (PV) systems. PV systems are subjected to various environmental and operational stresses that can cause defects over time. If not detected and addressed promptly, these defects can lead to significant energy production losses and, in some cases, safety hazards. Therefore, regular inspections and maintenance are essential to ensure the long-term efficiency and reliability of PV systems [1].

Faults in PV modules can arise from various sources, including manufacturing defects, environmental factors, and operational wear and tear. For instance, defects such as microcracks, potential-induced degradation, and hot spots can severely impact the performance of PV modules [2]. These faults are not always visible to the naked eye and require advanced diagnostic techniques for accurate detection. External factors like shading, soiling, and mechanical damage can further complicate the inspection process. Regular and detailed inspections are crucial for identifying and mitigating these issues before they escalate into more significant problems, ensuring PV systems operate efficiently and safely over their intended lifespan.

Traditional inspection methods, such as manual visual inspections and electrical testing, have proven inadequate for the comprehensive and efficient maintenance of large-scale PV installations [3]. They are often time-consuming, labor-intensive, and prone to human error, making them unsuitable for the dynamic and extensive monitoring required for optimal PV system performance. The increasing scale of PV installations underscores the need for innovative and automated inspection solutions. Large-scale PV plants, which can span extensive regions and easily comprise thousands of PV modules, present a significant challenge for traditional inspection methods (e.g., one of the solar farms in Rajasthan, India, comprises 10 million solar panels and extends over about 57 square kilometers [4]). The logistical difficulties of manually accessing and inspecting each module are substantial, leading to inef-

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ficiencies and potential oversight. Moreover, the dynamic nature of environmental conditions means that defects can develop and change rapidly, which requires frequent and comprehensive inspections to ensure system performance.

Inspection tasks involve executing a well-coordinated sequence of operations: planning how to survey the plant's elements, positioning sensors close to the panels, employing advanced sensing technologies to gather accurate data, and processing these data to identify potential issues. Data processing can either be integrated into a closed-loop system, enabling real-time adaptation of the sensing process, or performed offline, where insights are derived post-inspection for later adjustments. Integrating AI and robotic technologies offers a promising solution to implement this chain of operations while addressing existing challenges effectively. The combined use of advanced imaging technologies, machine learning algorithms, and autonomous robotic systems can significantly improve the detection and diagnosis of PV module faults in vast installations, ultimately improving the reliability and performance of solar energy systems.

This chapter provides an overview of the application of AI and robotics in inspecting PV systems, showcasing their potential to address these challenges. Unlike manual inspections, the combination of AI and robotics offers scalable, accurate, and efficient solutions for detecting and diagnosing faults, enabling timely intervention and optimizing energy production.

While several reviews in the literature focus on specific aspects of AI and robotics for PV inspection, this chapter adopts a more integrated perspective. It does not aim to serve as a comprehensive review of all existing works—a daunting task given the rapid advancements in the field—but rather as a concise overview of the predominant tasks and most effective techniques. The chapter also highlights key research gaps and identifies potential underexplored applications, aiming to inspire future developments in this transformative domain.

Our approach involves diving deeper into the systematic processes that underpin AI- and robotics-driven PV inspections, from sensor-level decisions and data collection strategies to advanced data processing techniques. By framing these discussions within the context of the challenges faced by modern PV installations, this chapter underscores the importance of embracing innovative, technology-driven approaches to ensure the long-term sustainability and efficiency of solar energy systems.

10.1.1 Recent Survey Papers on AI and Robotics for PV Inspection

Research on AI and robotics for PV system inspections has grown significantly in recent years, with numerous review papers categorizing advancements and identifying emerging trends. These reviews collectively underscore the transformative potential of AI and robotics in enabling efficient fault detection, predictive maintenance, and optimization of PV systems, particularly for large-scale installations. Recent efforts emphasize integrating imaging technologies, machine learning algorithms, and unmanned aerial vehicles (UAVs) to effectively implement the required chain of operations of inspection tasks and overcome the limitations of traditional inspection methods.

A recurring theme in existing reviews is the importance of fault detection for ensuring the reliability and efficiency of PV systems. Several works focus on the application of advanced imaging modalities, such as electroluminescence (EL), infrared thermography (IRT), and photoluminescence (PL), to identify defects that are not visible by conventional means or regular visual inspection. For instance, [5] explores deep learning techniques for visual fault diagnosis, emphasizing the role of imaging technologies for improving defect detection accuracy. Similarly, [6] highlights the advantages of using aerial drones equipped with imaging sensors—both UAVs and remotely piloted drones—over IoT-based approaches, where sensors are typically installed directly on the panels. Integrating imaging techniques via UAVs with IoT data collection (e.g., electrical and environmental data) and data streaming methods is emphasized as beneficial, if not essential. Additionally, the study stresses the importance of tailoring approaches to the unique characteristics of different imaging modalities. Overall, these imaging-based methods underscore the critical role of advanced diagnostic tools in addressing the complexities and challenges of modern PV systems.

AI and machine learning techniques feature prominently across these reviews as enablers of more efficient and accurate fault detection. El-Banby et al. [7] highlights the role of AI in thermography-based fault detection, categorizing faults and emphasizing the need for timely detection to sustain system performance. [8] broadens this perspective by reviewing machine learning applications, including fault detection, performance prediction, and energy management, demonstrating the versatility of AI in PV system optimization.

Adopting UAVs for PV inspections is another key focus area, reflecting a shift towards automation and scalability. [9, 10] examine UAV-based inspection strategies, discussing their potential to provide high-resolution imaging and efficient coverage of large-scale installations. These works also address practical challenges, such as path planning, battery life, and integrating UAVs with other inspection technologies. [11] extends this discussion to concentrating solar thermal systems, highlighting UAV applications in fault inspection, mirror soiling detection, and flight path optimization. These studies illustrate how UAVs can complement AI and imaging technologies to streamline inspection workflows.

While some reviews adopt a focused approach, such as [7, 5] on specific fault detection methods, others, like [12, 3], take a broader view, encompassing operation and maintenance strategies. These broader reviews emphasize the need for systematic approaches integrating AI, IoT, and robotics to address the multifaceted challenges of PV system inspection and maintenance. The role of autonomous systems in combining visual inspection with real-time analytics emerges as a promising direction for future research.

A common conclusion in these reviews is that several gaps remain in the literature despite technological advancements and challenges. For example, while imaging technologies and UAV-based inspections have been extensively studied, integrating AI for real-time analytics and decision-making requires further exploration. Reviews such as those by [13, 14] highlight the need for advanced algorithms and hybrid approaches to enhance the accuracy and efficiency of PV inspections. Table 10.1 summarizes recent reviews on applications of AI and robotics to PV inspection.

Ref.	Year	No. Works	Scope and Applications	Research Gaps Identified
[7]	2023	54	Specific techniques for fault detection and maintenance, focusing on thermography and AI integration	Lack of standard benchmarks for thermographic data
[5]	2023	229	Imaging-based fault diagnosis using EL, IRT, and PL with deep learning for improved detection accuracy	Integration of multimodal imaging for diagnosis
[6]	2024	153	Broad overview of imaging, IoT-enabled UAV inspections, and tailored approaches for scalable PV maintenance	Scalability of UAV inspections in large PV farms
[3]	2024	249	Comprehensive strategies for predictive maintenance, combining AI with system reliability practices	Lack of integration between AI and maintenance tools
[9]	2023	108	UAV-specific methodologies focusing on predictive maintenance and fault detection in large-scale PV systems	Battery life, flight path optimization
[13]	2023	128	Image acquisition, pre-processing, and defect detection using various imaging techniques such as RGB, LWIR, and SWIR.	Comprehensive datasets, advanced imaging techniques and machine learning models

Table 10.1 Summary of key survey papers on AI and Robotics for PV inspection

10.1.2 A Systematic Perspective on PV Panel Inspection: Sensing, Data Collection, Data Processing

Compared to existing reviews, this chapter takes a more systematic approach, offering readers a concise and focused overview of how AI and robotics are applied to PV inspections. Building on the observation that inspection tasks are typically organized as a coordinated sequence of operations, as outlined in the Introduction, the chapter frames the discussion of the complex landscape of AI and robotics applications around three interrelated pillars: sensor selection, data collection strategies, and data processing.

This framework is designed to guide readers through the critical elements of the inspection process, ensuring a coherent discussion while providing practical insights to support decision-making for real-world implementations. The chapter systematically explores these pillars and emphasizes how these technologies streamline workflows, overcome key challenges, and optimize inspection outcomes. Furthermore, this approach helps identify emerging opportunities and research gaps, equipping readers with actionable insights into how AI and robotics revolutionize PV inspection practices.

The process of a practical PV inspection task begins with selecting the appropriate sensors to capture relevant data. Visual sensors, such as high-resolution cameras, enable the detection of surface-level defects like cracks, discoloration, and soiling. Thermal cameras are indispensable for identifying temperature anomalies that signify electrical faults or shading issues. Electrical sensors complement these by monitoring voltage, current, and temperature to identify performance issues. In Section 10.2, we show that AI is critical in optimizing sensor configurations and adapting them to specific environmental conditions, defect types, and inspection goals.

Once the sensors are selected, an effective data collection strategy is vital for comprehensive inspection. Static inspection methods involve fixed cameras regularly capturing images of specific areas and providing continuous monitoring. Drone-based inspections offer a comprehensive overview of the PV plant, capturing high-resolution photos and videos efficiently. Dynamic inspection employs mobile data collection devices with sensors to autonomously navigate the PV plant, allowing for close-up inspections of individual panels. In Section 10.3, we examine the main strategies that involve AI and robotics in collecting data for PV inspection.

In Section 10.4, we focus on the last stage of the inspection process: data processing. In this stage, image processing and computer vision techniques, including image segmentation, feature extraction, and machine learning algorithms, can help to detect and classify potential defects.

AI and robotics can be utilized independently or synergistically within these phases of operations. In sensor selection, AI can optimize the choice of sensors based on environmental conditions, panel types, and desired inspection granularity. Robotics automates data collection, ensuring consistent and comprehensive coverage of the PV plant, while AI optimizes robotic path planning and task scheduling. In data processing, AI algorithms efficiently process the acquired data, identifying defects and providing actionable insights. The combination of AI and robotics facilitates early detection of potential issues, maximizing energy output and minimizing downtime.

10.2 Sensor-Level Decisions in PV Inspection

The success of PV panel inspection depends mainly on the ability to capture accurate and meaningful data regarding potential defects. This process begins with crucial decisions at the sensor level, including the selection, design, composition, and calibration of the sensors. These decisions establish a foundation for high-quality raw data acquisition, directly impacting the subsequent analysis needed for defect detection and system maintenance.

Sensor-level decisions also encompass the preprocessing strategies of the raw data gathered by the sensors. This includes using intelligent sensing techniques that optimize the data quality by improving sensor performance, filtering out noise, and prioritizing relevant features. For instance, when gathering images of PV panels, preprocessing may involve image segmentation (e.g., aerial imagery) to identify the regions of interest, such as the PV panels or their individual cells. It may also include combining multiple images when capturing all areas of interest in a single image is neither possible nor practical.

Sensor-level tasks are critical steps to combine raw sensing and data processing by isolating meaningful areas and highlighting the most relevant data for further analysis. This initial stage ensures the resulting dataset is cohesive and ready for practical analysis, bridging the gap between data acquisition and actionable insights.

There is growing evidence that AI is being integrated to optimize sensor performance and data acquisition for many tasks at the sensor level. To systematically survey the advancements in sensor-level decisions for PV inspection, we have identified three major tasks highlighting the integration of AI and robotics in this domain. The first task focuses on automated parameter tuning and sensor calibration, optimizing sensor configurations and performance to meet specific inspection requirements. The second task involves PV panel segmentation, primarily using deep learning techniques, to enable precise identification of areas of interest within complex environments. The third task addresses the creation of orthomosaics for PV inspection. Orthomosaics – high-resolution images generated by stitching multiple individual photos together – provide a seamless and geometrically accurate representation of large-scale installations. This technique is essential for inspecting photovoltaic systems, enabling detailed analysis across extensive areas.

The remainder of this section will discuss these tasks in detail, highlighting the most representative works and their contributions to improving the accuracy, efficiency, and scalability of PV inspection processes.

10.2.1 Automated Sensor Calibration and Parameter Tuning

The application of AI and robotics for sensor-level decision-making and automated data preprocessing in PV panel inspections remains a relatively underexplored area. Yet, it holds immense potential to revolutionize the field. By automating traditionally manual tasks such as parameter tuning and sensor calibration, these technologies can significantly enhance the accuracy and efficiency of inspections.

For instance, [15] noted that a significant limitation of using RGB, thermal, and hyperspectral cameras to inspect PV installations is the requirement for manual parameter adjustments, including thresholds in edge detection and kernel sizes in morphological operations. Another study [16] found that automatic gain control algorithms of commercial infrared cameras hinder the accurate identification of PV panels. Switching to fixed manual gain and offset settings improved quantitative analysis. This reliance on manual tuning introduces subjectivity and requires user intervention.

The work in [17] explores critical sensor-level decisions for UAV-based thermal inspections of PV modules, focusing on factors like infrared wavelength selection, emissivity settings, drone distance, orientation, and flight speed. It highlights the impact of these parameters on radiometric accuracy and emphasizes the need for careful calibration to minimize errors.

10.2.2 PV Panel Segmentation

PV panel segmentation is crucial in ensuring that subsequent analyses focus exclusively on the regions of interest, such as PV panels, while effectively filtering out irrelevant data (e.g., terrain data). Recent advancements in AI and computer vision have revolutionized this process, enabling highly accurate and efficient segmentation, even in complex scenarios. These innovations have been particularly impactful in applications involving thermal or visible light imagery captured by UAVs, where variability in environmental conditions and image resolutions poses significant challenges.

The literature on PV panel segmentation is extensive, particularly with the growing adoption of deep learning methods. This section highlights and discusses key studies that represent significant advancements in the field. By leveraging deep learning techniques, these modern approaches have greatly improved the precision and scalability of PV panel segmentation in remote sensing applications.

Bommes et al. [18] developed a semi-automated computer vision tool to extract PV modules from thermographic UAV videos. This tool addresses the challenge of identifying PV panels in thermal imagery, where temperature differences between panels and their surroundings are exploited. The tool segments PV modules from the background and facilitates the creation of large, high-quality datasets for further anomaly detection. One of the key contributions of this work is its ability to generalize across different PV plants, demonstrating robustness in diverse environmental conditions. This ensures the accurate identification of panels, setting a strong foundation for subsequent thermal anomaly detection and defect classification.

Similarly, Di Tommaso et al. [19] introduced a multi-stage model based on the YOLOv3 (You Only Look Once) deep learning framework, designed explicitly for PV panel extraction from aerial imagery. The model integrates two detection phases: first, to locate the PV panels within the image, and second, to identify and classify potential defects. This pipeline supports visible light and infrared imagery, ensuring versatility across different sensing modalities. Technical highlights include the model's real-time processing capabilities, average inference time of less than one second per image, and ability to handle large-scale PV farms efficiently. This approach significantly enhances operational efficiency, enabling rapid identification of defects and prioritization of maintenance activities.

Vlaminck et al. [20] use a region-based convolutional neural network (R-CNN) framework to extend the capabilities of aerial image analysis by focusing on extracting and classifying anomalies in PV power plants. Unlike traditional methods that process entire images, R-CNN employs region proposals to isolate specific areas of interest, such as individual PV modules, before applying deep learning models for defect detection. This approach ensures high accuracy in identifying anomalies, such as hotspots, cracks, and soiling, while reducing false positives. A notable technical contribution of this work is its integration of aerial imagery with advanced object detection algorithms, which allows for more precise localization of defects, even in complex or cluttered environments.

Guo et al. [21] introduced a robust framework to tackle the challenges of PV panel detection, particularly in scenarios with significant data imbalance and resolution disparities. The proposed segmentation approach employs a deep-learning architecture to address variations in PV panel sizes, shapes, and spatial distributions across diverse environments. One of the key problems highlighted in the study is the imbalance in spatial resolution within training datasets, where high-resolution imagery offers more detailed information crucial for deep learning model training.

Still, such data is often costly and limited in scope. Conversely, datasets from lower-resolution sensors, while more readily available, may lack the granularity required for precise segmentation. To address these challenges, the framework leverages advanced data augmentation techniques and customized loss functions to mitigate the effects of resolution and class imbalances. A notable innovation is the integration of multi-scale feature extraction, which allows the model to capture fine-grained details from high-resolution imagery and broader contextual information from lower-resolution data. This capability is particularly beneficial for detecting small-scale PV panels within complex or cluttered imagery, ensuring robust performance across various scenarios. The model achieves superior accuracy and generalizability by effectively handling resolution disparities and dataset imbalances, marking a significant advancement in PV panel segmentation for real-world remote sensing applications.

Gasparyan et al. [22] proposes a hyperspectral solar segmentation network (HSS-Net) method to address challenges such as low image quality, varying resolutions, and computational inefficiencies. Their approach uses a Chebyshev Transformation to enhance image quality and Hyperspectral Synthetic Decomposition to optimize band selection. Both techniques are integrated into a deep neural network architecture. The reported results outperformed state-of-the-art methods, including CNN and transformer-based networks. Key novelties include demonstrating the application of hyperspectral decomposition to refine spectral details and using Chebyshev transformers to improve scalability and computational efficiency.

Other applications of deep learning methods to refine the segmentation of PV panels include leveraging contextual understanding, particularly prior knowledge of the color of PV panels, to enhance the accuracy and shape regularization of segmented regions [23]. In addition, using vision-transformer-based methods for PV segmentation tasks has recently shown promising results [24].

While most studies focus on visible light imagery, some have explored segmenting PV panels in the infrared domain. One of the earliest deep learning-based approaches for PV segmentation in the infrared spectrum is Deep Res-UNet [25], a semantic segmentation neural network to extract PV panels in aerial infrared images. Building on such foundational work, more advanced methods have been developed, including the approach by Shen et al. [26], which presents a modified U-Net architecture specifically tailored for segmenting PV panels in complex infrared scenes. This adaptation improves performance in scenarios where PV panels are surrounded by challenging environmental features, such as objects with varying temperatures or emissivity, that complicate segmentation tasks. The authors benchmark their method against [25], demonstrating superior performance in these challenging environments.

10.2.3 Orthomosaics and Image Stitching

Orthomosaics from multiple aerial photographs are invaluable in extensive PV plant inspections. They provide expansive, high-resolution views of PV installations, facilitating precise PV panel detection, segmentation, and comprehensive analysis [27]. Most approaches for creating orthomosaics in PV plant inspections rely on computer vision techniques for image stitching [28, 29]. These methods highlight the reliance on image stitching as a critical step for further processing and analysis.

Deep learning algorithms have the potential to automate and enhance image stitching, ensuring seamless integration of images captured from different angles and under varying lighting conditions. For instance, using AI-driven feature matching techniques could allow for accurate overlapping image alignment, resulting in high-quality orthomosaics that accurately represent the spatial characteristics of PV panels [30]. Deep learning frameworks have demonstrated the potential to surpass traditional methods in estimating homography transformations between overlapping infrared images of PV panels captured at close range —a crucial task for stitching multiple images from the panels without relying on precise GPS localization [31].

In PV plant inspections, UAVs with visible and IRT sensors are increasingly utilized. These UAVs can capture comprehensive datasets with thermal information critical for identifying anomalies such as hotspots and calculating the temperature and efficiency of PV panels [32]. Deep learning can also facilitate the fusion of visible and IR images, enhancing the quality and informational content of the resulting orthomosaics. For example, integrating thermal data into orthomosaics enables the visualization of temperature distributions across the PV array, aiding in the early detection of potential issues [33].

Integrating AI and robotics into creating orthomosaics for PV plant inspections presents significant advantages, yet it remains underexplored. Traditionally, computer vision algorithms have been the dominant approach for creating orthomosaics and stitching images, relying on feature matching and geometric corrections. While these methods have been effective, they have inherent limitations, such as sensitivity to lighting conditions, occlusions, and computational inefficiencies. Despite growing evidence that AI-based methods can outperform traditional techniques—offering greater accuracy, robustness, and adaptability—many PV inspection workflows still rely on conventional approaches.

One promising direction for integrating AI and robotics is optimizing UAV trajectories to enhance the real-time construction of orthomosaics. Unlike traditional methods, where orthomosaics are generated offline after all images have been collected, AI-driven systems can dynamically adjust flight paths based on real-time image analysis. This ensures better coverage, reduces redundant data collection, and improves the overall quality of the final orthomosaic. Additionally, AI can enhance multi-spectral data fusion, allowing for more precise defect detection by intelligently aligning and processing images from different sensors. These advancements can make PV inspections more efficient, accurate, and scalable, ultimately optimizing solar energy production and improving system maintenance.

10.3 Data Collection Strategies for PV Inspection

Inspecting PV plants requires effective data collection strategies to ensure accurate, efficient, and scalable monitoring of large-scale installations. With the increasing deployment of solar farms in remote and expansive areas, manual inspection methods are becoming less practical due to their time-consuming nature, high costs, and safety concerns. Autonomous robotic systems, particularly UAVs and remotely operated aerial vehicles, have emerged as a transformative solution, efficiently collecting high-quality data across vast infrastructures. With advanced sensors, UAVs can capture visible light, thermal, and hyperspectral images, enabling comprehensive assessments of PV panel performance and condition [9].

Several studies have explored using UAVs, either individually [34] or in fleets [35], to inspect PV plants. These systems leverage their maneuverability to capture detailed imagery from different, highly informative perspectives, overcoming limitations posed by stationary cameras or ground-based robots. Furthermore, UAVs guided by advanced path-planning algorithms can ensure efficient PV installation coverage while minimizing travel time and energy consumption [36]. Integrating AI and robotics into these systems streamlines data collection and paves the way for automated processing and analysis, ultimately enhancing the accuracy and reliability of PV inspections.

Robust data collection strategies are critical to exploiting aerial imaging capabilities, especially in extensive and intricate PV plants and power facilities. These strategies must ensure thorough data acquisition and optimize efficiency, dependability, and scalability. Robotic systems, whether operating individually or in multi-robot configurations, rely on meticulously crafted data collection workflows to tackle issues related to coverage, sensor accuracy, and environmental changes.

For single-robot systems, data collection strategies involve precise path optimization and adaptive data acquisition techniques [37, 38, 39]. In PV inspections, UAVs must follow efficient flight paths that balance coverage and energy consumption while maintaining safe distances from obstacles [40, 41]. Additionally, the integration of machine learning algorithms for real-time image processing and boundary detection enhances the accuracy of inspections, allowing UAVs to work in closed-loop with data acquisition, adapting their paths dynamically based on the identified locations of dirt or defects [42].

Specific mission goals of data collection strategies include capturing high-resolution imagery at appropriate angles and distances to improve defect detection and thermal analysis [43]. Additionally, strategies can emphasize minimizing errors caused by environmental factors like wind turbulence or electromagnetic interference by dynamically adjusting flight parameters, such as altitude and speed [44]. Incorporating redundancy and error-checking mechanisms further ensures data reliability, reducing the need for repeated flights and enhancing overall inspection efficiency [35].

In this section, we first discuss works on path planning, a prominent task in the context of data collection strategies. We then consider research works using multi-robot systems, where additional challenges arise in coordinating the data collection efforts across a fleet of autonomous and possibly diverse agents. Finally, we highlight general operational issues of autonomous aerial platforms.

10.3.1 Path Planning

When using one or more UAVs, thorough path planning is crucial for optimizing the efficiency and effectiveness of the inspection process. Various criteria are employed to ensure that the UAVs cover the entire area of the PV plant while minimizing energy consumption and time. Standard methods include coverage path planning (CPP) techniques [41], which systematically calculate flight paths to ensure that all modules are inspected without leaving gaps. For instance, Pérez-González et al. [45] proposes three CPP methods—boustrophedon exact cellular decomposition, grid-based spanning tree coverage, and wavefront coverage—demonstrating their effectiveness in automating UAV flight paths for PV inspections.

Other path optimization approaches for UAV-based inspections include modeling the problem as a Traveling Salesman Problem (TSP), which seeks to determine the shortest route that visits a set of locations and returns to the origin point. This method is particularly relevant in PV plant inspections to minimize travel distance while ensuring comprehensive coverage of all modules. Salahat et al. effectively utilized the TSP framework to optimize waypoint planning for autonomous aerial inspections, demonstrating its applicability in enhancing operational efficiency in large-scale solar farms [39]. Heuristic approaches such as particle swarm optimization (PSO) have also been employed to address UAV path planning challenges, taking into account factors such as flight attitude and gimbal limitations to improve the reliability of the inspection system [38].

Another notable example of path optimization is presented in [46], which introduces a multi-module system that manages boundary detection, path planning, and dynamic flight control. This coordinated approach allows UAVs to operate efficiently over extensive solar arrays, eliminating the need for manually programmed routes. The software autonomously adapts flight paths in real time based on the plant's layout, ensuring comprehensive coverage and reducing inspection time. The system enables seamless transitions between data collection tasks and flight maneuvers by communicating via the MAVLink protocol with multi-rotor flight controllers like Pixhawk.

Further emphasizing robust path planning, Morais at al. [47] demonstrate how vertical takeoff and landing capabilities can be combined with fixed-wing flight. This dual-mode operation tackles the unique requirements of floating PV installations, where environmental constraints such as wind and moving water surfaces demand adaptable flight strategies. Once the UAV transitions to a fixed-wing mode, it can traverse more considerable distances more efficiently, thus optimizing the overall duration and energy consumption of the inspection mission. These works collectively underline the importance of flexible navigation algorithms that can handle diverse operating environments on land-based fields or offshore floating solar plants.

10.3.2 Multi-robot systems

Due to the vast spatial distribution of PV panels, inspecting large-scale PV installations presents significant challenges. To address this, researchers have explored using multi-robot systems (MRS), which can leverage the scalability and parallelism offered by coordinated teams of aerial and ground vehicles.

In MRS, typical tasks include path planning, navigation, and allocation algorithms to allow a fleet of unmanned vehicles to cover large PV sites efficiently [35]. Existing works explore optimization techniques to plan inspection paths and task assignments for multiple agents, such as linear temporal logic (LTL) [36], and market-based approaches [35]. Proposed algorithms consider factors like battery life, charging stations, temporal constraints, and obstacle avoidance to ensure the feasibility and efficiency of robotic inspection missions.

The use of heterogeneous MRS, particularly of teams combining UAVs and unmanned ground vehicles (UGVs), has gained attention due to their ability to combine the strengths of different platforms for enhanced operational efficiency. UAVs excel in aerial inspections, covering large areas quickly, while UGVs provide logistical support, such as energy supply and landing platforms [48]. This collaboration addresses the limitations of each platform, optimizing inspection processes in large-scale PV installations where traditional methods are impractical.

In this context of heterogeneous MRS, De Benedetti et al. [35] proposed a market-based task assignment algorithm that optimally distributes inspection tasks among a fleet of UAVs and UGVs. The goal was to minimize the overall energy consumption while accounting for battery degradation and vehicle deterioration. The authors used a decentralized approach where each robot computes the cost of executing individual tasks, and a central auctioneer assigns tasks to the robot with the lowest bid.

Similarly, Liao and Liu [48] developed a path-planning method that prioritizes meeting points between UAVs and UGVs. In their scenarios, the UAVs perform aerial inspections, while the UGVs provide landing platforms and energy supplies for the UAVs. They use an improved genetic algorithm to plan the inspection path for each UAV. The resulting paths are then clustered to determine the optimal number and location of meeting points. An adaptive PSO algorithm was employed to find the best locations for the meeting points within the road network.

Focusing on long-term missions, Huang et al. [36] introduced LTL-based path planning algorithms that consider the need for charging, multiple visits to PV equipment, a single visit to communication equipment, and the avoidance of restricted regions when using a fleet of UAVs. The authors also proposed a heuristic algorithm to optimally deploy a charging station for the long-term monitoring of PV solar farms.

A common challenge highlighted in these works is the need to address the complex and dynamic environments of large-scale photovoltaic plants. The works emphasize the importance of accurate positioning and navigation, as well as the ability to handle obstacles, no-fly zones, and the changing orientation of the PV modules due to sun tracking [35, 36, 39]. Addressing these challenges is crucial to ensure the reliability and effectiveness of MRS for PV inspection tasks.

10.3.3 Operational Issues of Robotic Platforms for PV Inspection

Beyond navigation and path planning, the success of using robotic platforms for PV inspections relies heavily on integrating reliable hardware platforms with software mechanisms for real-time decision-making. In [9], the authors highlight several practical challenges for autonomous flights, including regulatory frameworks, operational safety, and real-time communications. UAV platforms must be equipped with sensors capable of monitoring flight conditions and adapting accordingly—such as adjusting altitude to avoid obstacles or modifying flight speed to ensure high-resolution data capture. These considerations become even more critical for large solar farms or remote locations, where GPS signals may be unreliable [39], and weather conditions can change unexpectedly [42].

System modularity is another key aspect. The diverse range of sensors used for PV inspection supports a compartmentalized design, enabling quick upgrades or replacements of sensors, cameras, or onboard processors without requiring a complete UAV overhaul [49, 12]. This modularity is particularly valuable in dynamic environments where equipment requirements evolve over the lifespan of a PV plant.

Different UAV platforms offer unique advantages: multirotor drones provide stability and maneuverability for close-up inspections while fixed-wing aircraft are better suited for conducting broad surveys over vast landscapes [50]. In either case, tailoring the UAV hardware to the specific inspection mission can significantly enhance the efficiency of data collection.

These studies underscore that well-chosen platforms and robust operational protocols are critical for advancing robotics in PV inspections, regardless of the deployment environment.

10.4 AI Techniques for Data Processing in PV Inspection

At the core of AI-powered PV inspection lies the ability to analyze diverse data modalities—such as electroluminescence (EL), photoluminescence (PL), and infrared thermography (IRT) to identify a wide range of defects. For example, EL imaging reveals micro-cracks [51] and cell degradation [52], while IRT detects hot spots [53] and thermal anomalies indicative of electrical issues or shading.

The adoption of AI in PV inspection supports the scalability of solar energy solutions and advances their sustainability by improving reliability and minimizing energy losses. This section explores the various AI techniques employed for data processing in PV inspection, including supervised and unsupervised learning methods, state-of-the-art imaging modalities, and emerging approaches such as generative adversarial networks (GANs). By understanding these technologies, we can better address the challenges and opportunities in maintaining the efficiency and longevity of solar energy systems.

This section explores key AI techniques used in PV inspection, structured to first introduce the imaging modalities that provide the foundational data for inspection methods, including electroluminescence, photoluminescence, and infrared thermography. With these imaging techniques established, the discussion moves to fault detection and classification, focusing on identifying and categorizing defects for effective maintenance. Next, it examines hot spot detection, a crucial process for preventing power losses and safety risks using deep learning-based object detection techniques. Anomaly detection follows, addressing deviations from normal PV module behavior to enable proactive fault management. Finally, the section concludes with synthetic data augmentation using generative adversarial networks, which enhances AI model performance by generating diverse and realistic training samples, overcoming data scarcity challenges in PV inspection.

By organizing the discussion this way, we create a clear progression—from data acquisition to imaging modalities, AI-driven fault detection and classification, proactive anomaly identification, and methods for enhancing model robustness.

10.4.1 Imaging Techniques for AI-Driven PV Inspection

Different imaging methods can significantly contribute to identifying a wide range of defects in PV modules, each offering unique advantages and insights. Visible light imaging allows for detecting surface-level defects such as discoloration, physical damage, and soiling, providing a straightforward and cost-effective method for routine inspections. IRT is instrumental in identifying thermal anomalies like hot spots, which can indicate electrical issues or shading effects, thereby preventing potential fire hazards and efficiency losses. EL imaging excels in detecting micro-cracks, cell degradation, and other subtle defects not visible through conventional means, making it essential for in-depth diagnostic assessments. PL imaging further enhances defect detection by identifying issues related to series resistance and minority carrier lifetime, offering detailed insights into the internal quality and performance of PV cells. Together, these imaging techniques provide a comprehensive diagnostic toolkit, enabling accurate and efficient identification of various defects, ultimately ensuring the optimal performance and longevity of PV systems.

The data from IR images often require different preprocessing techniques, such as normalization, colorization, and temperature calibration, to ensure that the models can accurately interpret the thermal data [54, 55]. Furthermore, the architecture may need to be adapted to handle the inherent noise and variability of thermal images [49, 35].

EL imaging provides high-resolution images that can reveal defects not visible through conventional means. Deep learning models leveraged for analyzing EL images often utilize architectures capable of handling high-resolution data and distinguishing subtle variations in brightness that indicate defects [56]. The literature highlights the need for specialized deep-learning architectures that can effectively leverage the high-resolution and nuanced information provided by EL imaging for comprehensive fault detection and classification in PV modules. Several deep learning architectures are employed for defect detection in photovoltaic modules through EL image analysis. CNNs are widely used because they can effectively extract local features and detect subtle brightness variations indicative of defects [51, 57]. Region-based CNNs (R-CNNs) extend this approach by incorporating region proposal networks to identify and classify defects in EL images automatically [58].

The deep learning models applied to PL images may require different preprocessing and augmentation techniques to account for the lower signal strength compared to other imaging types. This can influence the choice of architecture, as models may need to be more robust to noise and variations in illumination [59]. The comparative analysis of PL and EL imaging techniques in the literature suggests that while both can visualize similar faults, the choice of architecture may depend on the specific characteristics of the images being analyzed [59].

In summary, the type of imaging used in PV module inspection directly impacts the design and effectiveness of deep learning architectures. Works like [51] discuss the implications of image type on model performance, emphasizing the need for specialized architectures that can effectively process the unique features of each imaging modality.

10.4.2 Fault Detection and Classification

Ensuring the efficiency and reliability of solar energy systems heavily relies on fault detection and classification in photovoltaic (PV) modules. These two tasks, though related, serve distinct purposes. Fault detection identifies the presence of anomalies or defects in PV systems, while fault classification determines the specific type of fault, often at the cell level.

Fault detection involves locating defects such as hot spots, shading, and material degradation that impact the performance of PV modules. Several studies have leveraged both standard [60] and advanced deep learning architectures for this purpose. For instance, [61] utilized a Faster R-CNN framework combined with thermal imaging to localize defects in PV modules effectively. Advanced architectures have refined detection capabilities, significantly enhancing fault detection by employing attention mechanisms [62].

Fault classification, distinct from detection, focuses on identifying the specific type of fault, typically at the cell level. This task is crucial for targeted maintenance and system optimization. Various studies have proposed methodologies to classify faults in PV modules using advanced machine learning techniques, particularly deep learning models. For example, [63] addresses the classification of 11 different fault types, achieving an impressive average accuracy of 93.51%. This work highlights the importance of comprehensive datasets encompassing diverse fault types to improve classification performance.

In [64], authors classify anomalies into eight distinct classes, achieving a testing classification accuracy of 78.85%. The study underscores the challenges posed by high within- and between-class variations, which can complicate classification. The authors also emphasize the role of data augmentation techniques in enhancing their CNN model's performance.

10.4.3 Hot Spot Detection

Hot spot detection is crucial for maintaining the efficiency and reliability of PV systems, as these defects, often caused by shading, material degradation, or electrical mismatches, can result in significant energy losses and safety hazards. Recent advancements in machine learning and deep learning techniques have greatly enhanced hot spot detection accuracy and efficiency.

Object detection models are pivotal in automating the identification and localization of hot spot defects in PV modules. Among these, the YOLO framework excels with its balance of speed and accuracy, making it ideal for real-time fault detection in large-scale PV installations. YOLO's single-stage detection approach processes high-resolution images efficiently, ensuring timely identification of hot spots that could cause power losses or safety hazards. Studies such as [65] demonstrate its effectiveness when combined with semantic segmentation, enhancing the precision of hot spot localization in thermal images. Similarly, [66] highlights YOLOv5's ability to detect and classify multiple defect types within PV modules, showcasing its scalability and versatility in addressing complex diagnostic tasks.

YOLO's adaptability to various imaging modalities, including IRT and EL imaging, further enhances its applicability. For instance, [56] demonstrates YOLO's robustness in analyzing EL images to detect and categorize defects that affect power output, while [65] shows its effectiveness in handling thermal data under challenging PV inspection conditions. These attributes, combined with YOLO's real-time processing capabilities, make it an invaluable tool for optimizing PV maintenance. Future research, such as integrating attention mechanisms and feature fusion strategies outlined in [67], can further improve YOLO's performance by addressing challenges like data imbalance and enhancing its robustness in operational conditions.

Challenges in PV hot spot detection systems have driven the exploration of novel neural network architectures and strategies to enhance detection accuracy, efficiency, and adaptability. These cutting-edge designs address critical challenges in PV monitoring through innovative mechanisms and frameworks. One notable contribution is the bi-branch collaborative training algorithm introduced in [68]. This framework employs a teacher-student paradigm using a knowledge distillation mechanism, allowing lightweight yet highly accurate detection systems. By incorporating a YOLOX-based student network optimized for speed and a HorNet-enhanced teacher network for robust feature representation, their model achieves high accuracy, demonstrating its applicability in real-world UAV-based PV inspections.

APM^{2}Det [69] addresses challenges in angle distortion and small-scale characteristics in infrared images by introducing an angle perception module and a model migration mechanism. The angle perception module mitigates distortions from varying camera angles, ensuring consistent feature capture, while model migration leverages pre-trained weights to enhance performance on small-scale datasets. These innovations enable APM^{2}Det to perform robustly under diverse imaging conditions, making it suitable for real-world applications.

The selective kernel mechanism is another area of innovation, as highlighted in SK-FRCNN [61]. This model improves traditional Faster R-CNN networks by integrating a selective kernel attention mechanism, enabling adaptive feature extraction across scales. Adding a region-of-interest align layer further enhances localization precision, addressing the challenges of small-scale fault detection in complex environmental conditions. Experimental results reveal an accuracy improvement over baseline models, making SK-FRCNN a practical choice for field applications.

These advancements above highlight the diverse strategies employed in modern PV hot spot detection. Each deep learning architecture addresses unique challenges in detection precision, environmental adaptability, and computational efficiency, paving the way for more reliable and scalable PV monitoring solutions.

10.4.4 Anomaly Detection

In the context of PV systems, anomaly detection is a critical process aimed at identifying defects, inefficiencies, or faults that could jeopardize the performance and reliability of solar energy systems. This process seeks to uncover deviations from expected operational patterns that may signal potential system malfunctions or indicate the need for maintenance interventions.

The practical implementation of anomaly detection enhances the operational efficiency of PV systems and contributes to the longevity and sustainability of solar energy production. Advances in machine learning have significantly improved anomaly detection in PV systems, and many works [70, 71, 72, 73] have reported successful applications of AI in this area. Despite their shared focus, studies vary in methodologies and data types, reflecting the diversity of challenges in this domain.

Many approaches utilize unsupervised [74] or semi-supervised learning to address the common issue of limited labeled data. For example, weakly-supervised methods like feature map conversion and hypersphere transformation[75] and Positive and Unlabeled (PU) learning with generative adversarial networks[76] demonstrate robust anomaly detection using minimal labeled samples. Similarly, deep learning models such as SeMaCNN[71] accurately identify defects in EL images. Pipelines combining weakly-supervised and unsupervised approaches have also been used to create annotated datasets for anomaly detection [74].

Time-series data offers another avenue for unsupervised learning. Methods like LSTM autoencoders [77] reconstruct standard operational patterns to identify anomalies. At the same time, spectral clustering[70] adapts to environmental variations in PV power plants without requiring additional weather data.

10.4.5 Synthetic Data Augmentation with GANs

While CNNs have significantly advanced the automation of defect detection, these models require large, annotated datasets to achieve high accuracy. The scarcity of annotated defect images presents a substantial bottleneck. GANs offer a compelling solution by generating high-quality synthetic images that enrich training datasets, thereby enhancing the performance of defect detection models [78, 79, 80, 57].

The motivation for using GANs in PV inspection stems primarily from the need to overcome the limitations of small and imbalanced datasets. As highlighted by [78], the paucity of defective PV images constrains the training of deep learning models. They propose using a Wasserstein GAN (WGAN) to synthesize realistic defect images, demonstrating through extensive experiments that including these synthetic images significantly improves the classification accuracy of CNN-based models. Their work lays the foundation for employing GANs as an effective data augmentation strategy in PV inspection. By leveraging the Wasserstein distance metric, WGANs ensure stable training and better convergence, critical for generating high-quality synthetic images.

Building on this idea, [57] integrates GAN-generated images with traditional data augmentation techniques to enhance datasets of EL images. They employ a high-resolution network (HRNet) for defect identification, achieving notable improvements in defect classification. This approach demonstrates the potential of combining multiple augmentation methods to tackle the scarcity of annotated datasets and highlights the adaptability of GANs in complementing other techniques. HRNet further ensures the preservation of fine-grained details in EL images, which is crucial for accurate defect detection.

The study in [79] presents further advancements, introducing an innovative feature moving method combined with a YOLOv5S model. This approach aligns the features of GAN-generated images with those of real samples, effectively reducing the distribution gap between synthetic and real data. The improved alignment results in higher defect recognition accuracy, underscoring the importance of ensuring the representational fidelity of synthetic data in real-world applications. Their study also demonstrates how integrating GANs with state-of-the-art object detection models can enhance overall system performance, making it a promising direction for future research.

In [80], authors propose the AC-PG GAN model, which progressively generates high-resolution EL images for PV inspection. Their experiments demonstrate that this approach enhances the quality of generated images and significantly improves classification accuracy, with gains of up to 14% in specific defect categories. This study highlights the advantages of progressive generation methods in refining the resolution and diversity of synthetic images, further solidifying the role of GANs in advancing PV inspection technologies. The AC-PG GAN model also employs attention mechanisms to focus on critical regions of the PV modules, improving the relevance and utility of the generated images.

Despite these promising advancements in using GANs to generate synthetic data and help advance the field of AI-driven PV inspection, several challenges remain. The training of GANs is often unstable and computationally expensive, posing barriers to their scalability and practical deployment. Additionally, while GANs can generate realistic images, ensuring the diversity and accuracy of these images to represent the full range of defect types remains an open research problem. Future work should explore hybrid approaches that integrate GANs with other generative models, such as variational autoencoders, to enhance the robustness of data augmentation. Moreover, addressing computational efficiency through techniques like model pruning or quantization could make GANs more viable for real-time applications. The validation of these methods on larger and more diverse datasets, coupled with their testing in real-world operational settings, is essential for their widespread adoption in the energy industry.

10.5 Challenges and Future Directions

Despite significant advancements in the application of AI and robotics in PV inspection tasks, including fault detection and maintenance of PV modules, numerous challenges still hinder the efficient and reliable operation of PV systems. Addressing these issues is essential for improving the accuracy, scalability, and integration of AI- and robotics-based inspection technologies. This section explores key challenges and outlines possible future directions.

One of the most significant challenges in AI-driven PV fault detection is the scarcity of labeled data, particularly for rare fault types. Deep learning models, which have demonstrated high accuracy in fault detection, rely heavily on large, well-balanced datasets to perform effectively. Techniques such as data augmentation and GANs have shown promise in artificially expanding datasets, enhancing model generalization, and addressing data imbalance [78, 80]. Additionally, weakly-supervised learning approaches have leveraged both labeled and unlabeled data to improve anomaly detection capabilities while mitigating the dependency on extensive labeled datasets [71, 74]. Yet it remains an open question whether these approaches generalize well to various imaging modalities and environmental contexts.

Deploying fault detection systems in large-scale PV installations necessitates real-time processing and scalability. Traditional deep learning models often incur high computational costs, making them unsuitable for resource-constrained environments. Recent studies have proposed lightweight CNNs to reduce computational requirements while maintaining detection accuracy [81, 82]. Edge computing frameworks have enhanced real-time processing by enabling localized data analysis on UAVs or other edge devices, reducing latency and the need for centralized data transmission [73]. Additional work in this area is needed to show that these systems can be utilized in cost-effective, resource-limited devices to support large-scale PV installations.

Effective integration of fault detection systems with predictive maintenance frameworks and IoT technologies can potentially improve the reliability and efficiency of PV operations. Future research should focus on predictive models that identify potential failures based on historical and real-time data, enabling proactive maintenance strategies. Moreover, advancing the autonomy of UAVs for inspection tasks could enhance the efficiency of maintenance operations [83, 73].

While deep learning models have achieved impressive accuracy in fault detection, their interpretability and robustness remain areas for improvement. Techniques such as attention mechanisms and feature fusion have been explored to enhance model interpretability and detection accuracy, particularly for subtle defects in complex environments [79, 58]. Additionally, noise reduction techniques are critical for improving model reliability under diverse operating conditions.

Using robotics and autonomous systems for PV inspection also presents several research gaps and challenges that must be addressed to enhance their effectiveness and reliability. One of the significant challenges in robotic systems is optimizing energy consumption and battery management. The current literature highlights the impact of battery degradation on operational efficiency and the need for strategies to maximize recharge cycles during inspections [35, 36]. Future work should focus on dynamic energy-sharing frameworks between ground and aerial robots and adaptive energy-saving algorithms. Furthermore, deploying robotic systems across large-scale PV installations remains cost-prohibitive [35]. Future research should also focus on modular, low-cost robotic platforms and scalable inspection algorithms to enhance affordability without compromising performance.

Path planning for collaborative ground-air robotic teams in dynamic environments is another persistent challenge. Effective coordination is challenging when considering obstacles, no-fly zones, and the need for efficient meeting points for energy resupply [48]. Novel approaches could include multi-agent reinforcement learning for real-time adaptive path planning and developing robust coordination algorithms that handle heterogeneous robot capabilities.

Fusing data from multiple sensors (e.g., thermal, visual, and LiDAR) is critical for comprehensive inspections. However, data alignment, synchronization, and processing challenges persist [39]. Developing standardized protocols for sensor integration and employing AI techniques for multi-modal data fusion could improve inspection accuracy.

Effective collaboration between human operators and robotic systems is essential for the success of autonomous PV inspections. Current gaps include the design of intuitive user interfaces and interaction protocols [84]. Future research should explore augmented reality (AR) interfaces and adaptive collaboration frameworks that enhance operator understanding and control. Emerging challenges include integrating real-time data processing with autonomous decision-making and creating standardized benchmarks for evaluating multi-robot inspection systems. Future directions should also emphasize interdisciplinary research combining robotics, artificial intelligence, and domain-specific knowledge to develop robust, scalable, and adaptable solutions for PV inspection.

10.6 Conclusion

This chapter presented a systematic view of the application of AI and robotics in PV inspection, focusing on the key tasks involved—sensor selection, data collection strategies, and data processing. By structuring the discussion around these fundamental components, we provided a coherent framework highlighting both the technological advancements and the practical challenges faced in real-world implementations. Integrating AI and robotics has proven to be a powerful approach for addressing the limitations of traditional inspection methods, enabling more accurate, scalable, and efficient monitoring of PV systems.

The application of AI and robotics for PV inspection is becoming an increasingly active area of research and development. Numerous survey papers are published each year, each with a distinct focus, reflecting the rapid advancements and growing interest in this field. However, while these surveys provide valuable insights into state-of-the-art techniques, there remains a gap between theoretical advancements and practical deployment. This chapter aimed to bridge that gap by focusing on the practitioner's perspective, emphasizing the technical challenges that arise in real-world applications, and discussing how AI and robotics can be effectively implemented in PV inspections.

Despite the progress, significant challenges remain. Ensuring the reliability and robustness of AI-driven inspection systems, addressing data limitations, improving real-time processing capabilities, and optimizing robotic autonomy for large-scale PV farms are critical issues that need further research. The chapter underscored these challenges, highlighting the need for continued innovation in multi-modal data fusion, adaptive AI models, and collaborative robotic inspection strategies.

By presenting a structured and application-oriented overview, this chapter serves as a resource for researchers and practitioners looking to implement AI and robotics in PV inspection. As this field continues to evolve, bridging the gap between theoretical advancements and practical deployment will be crucial in realizing the full potential of these technologies in ensuring the efficiency, reliability, and sustainability of solar energy systems.

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