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ENHANCED FIRE HAZARD DETECTION IN SOLAR POWER PLANTS: AN INTEGRATED UAV, AI, AND SCADA-BASED APPROACH

*The **Subject** of this research is the development of an intelligent, integrated system for the early detection and causal analysis of fire hazards in large-scale solar power plants (SPPs). It addresses the critical shortcomings of conventional monitoring methods, which often lack the necessary integration, speed, and diagnostic depth to reliably prevent catastrophic failures resulting from photovoltaic (PV) module defects. The **goal of this study** is to design, develop, and validate a comprehensive, multi-modal framework that fully automates the monitoring workflow, from data acquisition to actionable decision-making. The proposed system aims to significantly enhance plant safety by providing reliable, cause-differentiated alerts, which in turn optimizes maintenance strategies, minimizes downtime, and improves the overall economic viability of solar energy infrastructure. The **Methods** employed involve a synergistic architecture that combines an Unmanned Aerial Vehicle (UAV) equipped with high-resolution RGB and radiometric infrared cameras for rapid imaging, supplemented by dedicated Internet of Things (IoT) temperature sensors on PV module bypass diodes for critical component verification. A custom-trained YOLOv8 deep learning model performs automated defect detection from the captured imagery. The system's intellectual core is a novel logical inference engine based on a Disjunctive Normal Form (DNF) equation. This formal logic model intelligently fuses four key binary features, namely, primary defect cause (damage vs. soiling), visual evidence, thermal anomaly severity, and bypass diode functional status, to produce a definitive and context-aware fire risk assessment. The entire workflow is managed and visualized using a SCADA TRACE MODE platform for centralized control and automated alerting. The study successfully validated the performance and logical integrity of the integrated system through a series of high-fidelity, scenario-based simulations. These simulations rigorously confirmed the capability of the DNF logic to accurately and reliably identify all predefined fire hazards. This included not only obvious faults but also "stealthy," damage-induced hotspots where the primary safety mechanism (the bypass diode) had failed. Concurrently, the system correctly classified mitigated risks to prevent false alarms, demonstrating its diagnostic precision. This capability allows the system to reliably differentiate between true emergencies requiring immediate module replacement and less critical issues, such as soiling that merely necessitates cleaning. The projected increase in diagnostic accuracy for identifying critical, fire-prone defects over conventional, single-modality methods is up to 40%, providing a quantitative measure of enhanced safety and reliability. Furthermore, the proposed system is projected to reduce the false-positive alarm rate by over 75% compared with IR-only automated systems. In **conclusion**, this study establishes a powerful new paradigm for proactive SPP safety management. The intelligent fusion of UAV and IoT sensing, AI-driven analytics, and a formal logical framework provides a robust and reliable solution for fire risk mitigation, enabling a highly efficient, condition-based maintenance strategy and significantly enhancing the safety, reliability, and performance of modern solar power infrastructure.*

***Keywords:** bypass diode; DNF; fire hazard detection; infrared thermography; photovoltaic modules; SCADA; solar power plants; UAV inspection; YOLOv8.*

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1. Introduction

1.1. Motivation

The global imperative to transition toward sustainable energy systems has positioned solar photovoltaic (PV) technology at the forefront of the renewable energy revolution. According to the International Renewable Energy Agency (IRENA), the global solar PV capacity has surged, crossing the terawatt threshold and continuing on an exponential growth trajectory [1]. This massive expansion, particularly in the form of large-scale utility solar power plants (SPPs), brings with it an escalating need for robust, reliable, and intelligent operational and safety management systems [2]. While PV modules are designed for decades of service, they are susceptible to a variety of degradation mechanisms and defects that can compromise performance and safety [3].

The potential for fire is among the most severe operational risks in SPPs. Although statistically infrequent, PV module fires can have catastrophic consequences, including asset destruction, prolonged plant downtime, significant financial losses, and serious safety risks for personnel and the surrounding environment [4]. Most PV-related fires can be traced to thermal anomalies, primarily hotspots. A hotspot is a PV cell or module's localized area that experiences a significantly elevated temperature due to increased electrical resistance. This can be triggered by a range of factors, including internal cell defects such as micro-cracks and faulty solder bonds, or external factors such as partial shading or heavy soiling [5]. When a cell's current generation is impeded, it can become reverse-biased, forcing it to dissipate heat from other series-connected cells [6, 7]. If this heat is not effectively managed, a thermal runaway process can be initiated, leading to the breakdown of module materials (e.g., backsheet, encapsulant) and potentially culminating in an arc fault and open flame [8].

The historical approach to PV plant maintenance, involving manual visual inspections and periodic electrical measurements like I-V curve tracing, is profoundly inadequate for the scale and complexity of modern SPPs [9]. Such methods are not only prohibitively labor-intensive and time-consuming but are also often reactive, identifying problems only after significant performance degradation or failure has occurred. Unmanned aerial vehicles (UAVs) equipped with dual RGB and infrared (IR) cameras have transformed the data acquisition landscape, enabling rapid and comprehensive thermographic and visual surveys of entire solar fields [10, 11]. However, this technological advance has shifted the bottleneck from data collection to data analysis. A single inspection flight can generate terabytes of imagery, and the manual review of this data is a daunting task that is prone to human fatigue, subjectivity, and error.

To overcome this data analysis challenge, the research community has increasingly turned to Artificial Intelligence (AI), particularly deep learning algorithms. Object detection models such as You Only Look Once (YOLO) and its variants have demonstrated remarkable success in identifying and classifying a wide array of PV defects from aerial images with high accuracy [12, 13]. However, most current AI-based systems operate as sophisticated defect classifiers, identifying anomalies in isolation without a deeper, contextual understanding of the overall risk they pose [14]. The mere detection of a hotspot by an AI does not automatically equate to a fire hazard. The true level of risk is a complex function of the intensity of the hotspot, its underlying cause (e.g., a permanent micro-crack versus temporary bird droppings), and the functional status of the module's built-in safety mechanisms, namely the bypass diodes. These diodes are designed to activate and shunt current around a faulty or shaded cell string, preventing severe overheating. A failed or malfunctioning bypass diode can render this crucial safety feature useless, dramatically elevating the fire risk [15].

This study identifies and addresses a critical research gap: the lack of an integrated, multi-modal system that moves beyond simple defect detection to perform a holistic, context-aware fire hazard assessment. The primary objective of this research is to design, develop, and validate an innovative monitoring framework that intelligently fuses data from multiple sources within a formal logical decision-making structure. The proposed system architecture integrates UAV-based data acquisition, advanced AI (YOLOv8 by [16]) for image processing, and a TRACE MODE system for Supervisory Control and Data Acquisition (SCADA) [17] for centralized command and control. The intellectual core of this system is a Disjunctive Normal Form (DNF) logical model, derived from a meticulously constructed truth table of critical defect indicators. Our goal is to demonstrate that this system can not only detect fire hazards with superior accuracy but also infer their probable root causes, thereby providing actionable intelligence to guide targeted, efficient, and cost-effective maintenance operations.

The principal contributions of this work are as follows:

1. Development of a Formal Logical Model for Fire Risk Assessment. We introduce a novel DNF-based logical function that synthesizes four critical, multi-modal binary inputs: defect cause (X_1), RGB visual evidence (X_2), infrared thermal anomaly (X_3), and

bypass diode temperature status (X_4), to produce a definitive fire risk classification (Y). Compared with single-modality systems, this formal approach enhances diagnostic accuracy and minimizes false alarms.

2. Synergistic, Fully Integrated System Architecture Design. A cohesive system design that synergizes the distinct strengths of UAVs (for rapid data acquisition), AI (for automated image analysis), and SCADA technology (for centralized monitoring, alerting, and data management) is presented. This creates a seamless, end-to-end workflow from data collection to decision-making.

3. Implementation of an Intelligent Operational Algorithm. In this work, we detail an operational algorithm that enables real-time data processing and the automated application of the DNF logic. This algorithm facilitates the immediate generation of critical alerts for fire-hazardous conditions and differentiates between underlying causes to recommend the most appropriate maintenance action (e.g., cleaning vs. replacement).

This paper provides a comprehensive exposition of this methodology, its validation through simulated real-world data, and a thorough discussion of its potential to set a new standard for safety, reliability, and operational excellence in the global solar energy industry.

1.2. State of the art

The body of research dedicated to PV system monitoring and fault diagnosis has grown in lockstep with the industry itself. This evolution has progressed from manual techniques to sophisticated automated systems, with each stage introducing new capabilities and challenges. This section reviews the key technological domains that form the foundation of the proposed integrated system [18].

The earliest and most fundamental PV system inspection methods involved manual, on-the-ground techniques. Visual inspection remains a baseline practice, allowing technicians to identify obvious issues such as broken glass, severe soiling, physical damage, or corrosion. For electrical characterization, I-V curve tracing is the gold standard [19]. By measuring the current-voltage characteristics of a module or string under specific irradiance conditions, technicians can identify deviations from expected performance, which may indicate issues like degradation, mismatched cells, or high series resistance. Standards, such as IEC 62446, codify these commissioning and inspection procedures [20].

Electroluminescence (EL) imaging is another powerful ground-based technique. EL imaging involves applying a forward bias voltage to the PV module in the dark, causing the silicon cells to emit near-infrared light. An IR-sensitive camera captures this emission, revealing defects with remarkable clarity, such as microcracks, finger interruptions, and inactive cell areas. Although highly effective, EL imaging is typically impractical for large-scale field inspections because it requires darkness and module disconnection for biasing. While providing valuable data, these traditional methods share a critical drawback: they lack scalability. For a utility-scale SPP with hundreds of thousands of modules, manually performing these checks is logistically unfeasible, economically prohibitive, and too slow to enable proactive maintenance [20].

Infrared (IR) thermography has emerged as a transformative nondestructive testing (NDT) technique for PV inspections [21]. It operates on the principle that faulty PV cells or connections dissipate energy as heat, creating thermal signatures that are invisible to the naked eye but readily detectable by an IR camera [22]. Hotspots, overheated junction boxes, and entire overheated cell strings can be identified quickly and non-invasively.

The integration of radiometric thermal cameras and high-resolution RGB cameras onto UAV platforms represents a paradigm shift in inspection efficiency [10, 23]. UAVs can survey vast solar farms in a fraction of the time required for ground-based inspections, dramatically reducing labor costs and minimizing personnel time in the field [24]. Numerous studies have validated the efficacy of UAV-based inspections in detecting a wide spectrum of defects, including soiling, shading, delamination, vegetation encroachment, and various types of hotspots [25, 26]. However, this data acquisition efficiency created a new problem: the "big data" deluge. A single inspection can yield tens of thousands of images, and manual analysis becomes the new bottleneck, reintroducing human error and subjectivity into the workflow.

Researchers have leveraged advancements in computer vision and deep learning to automate the analysis of the massive datasets generated by UAVs. Convolutional neural networks (CNNs) have proven to be exceptionally capable of learning complex visual patterns, making them ideal for defect detection. Various architectures have been applied, from classification models to more advanced object detection and segmentation models. Object detectors such as the You Only Look Once (YOLO) family and Faster R-CNN are popular for their ability to locate and classify multiple defects within a single image [12, 27]. Segmentation models, such as U-Net, can provide pixel-level masks of defective areas, allowing for more precise quantification of issues, such as soiling.

These AI models have been successfully trained to identify a comprehensive range of defects from both IR and RGB images, often achieving human-level or

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superhuman accuracy [13, 28, 29]. Although these AI systems are powerful tools for automating defect detection, they typically operate in a vacuum. They can report "hotspot detected" but cannot inherently assess the contextual risk. The crucial questions: "Is this hotspot a fire hazard?" "What is the cause?" "Is the module’s safety system working?" remains unanswered by the AI model alone. This highlights the significant gap between defect detection and true diagnostic intelligence.

The bypass diode is a critical, yet often overlooked, safety component in a PV module. Typically, one diode is used for every 18–24 cells. Its purpose is to provide an alternative path for current to flow when a cell or group of cells is shaded or faulty, preventing the faulty cells from becoming dangerously reverse-biased and overheating [15]. The diode’s functionality is paramount to module safety.

Bypass diodes can fail in two primary modes: open-circuit or short-circuit. An open-circuited diode fails to activate, offering no protection and allowing the unabated development of a hotspot. A short-circuited diode is permanently active, constantly shunting its associated cell string, resulting in a permanent loss of power output from that part of the module. Several studies have highlighted that bypass diode failure significantly contributes to severe module damage and fire incidents [6]. However, monitoring their health is challenging. They are located in the module’s junction box, often on the rear, making visual inspection or aerial thermography difficult. While a very hot junction box can be a sign of a failed diode, direct temperature measurement provides the most reliable indication of its status. This underscores the need for a multi-sensor approach that incorporates data beyond simple surface thermography.

Supervisory Control and Data Acquisition (SCADA) systems are the backbone of industrial process control and are widely used in SPPs [17]. They excel at monitoring high-level operational parameters and collecting data from inverters, string monitoring boxes, and meteorological stations. A typical SCADA system can provide real-time and historical data on power generation (AC and DC), voltage, current, irradiance, and ambient temperature [31]. This is invaluable for performance monitoring and high-level fault detection (e.g., an entire inverter outage).

However, traditional SCADA systems lack the granularity to diagnose issues at the individual module level. They might indicate that a string is underperforming, but they cannot pinpoint the specific module or defect nature. Integrating advanced, module-level analytics, such as the DNF-based logic proposed in this work, into a powerful SCADA platform, such as TRACE MODE [32], offers a pathway to bridge this gap. This would transform the SCADA system from a passive monitor into an active, intelligent safety and diagnostic hub.

In summary, while significant strides have been made in each of these individual domains, a truly holistic solution remains elusive. Our work directly addresses this gap by creating a synergistic framework that integrates the rapid data acquisition of UAVs, the analytical power of AI, the critical context of bypass diode health, and the central control capabilities of a SCADA system, all governed by a formal logical model to provide unparalleled fire hazard detection and diagnostic insight.

1.3. The purpose and tasks of research

This research aims to solve the critical scientific and applied problem of enhancing the operational safety, reliability, and efficiency of large-scale solar power plants. This is achieved by developing an intelligent, integrated monitoring and diagnostic system designed to proactively detect fire hazards, accurately identify their root causes, and provide actionable insights to optimize maintenance strategies.

This study addresses the following key tasks to achieve this overarching goal:

1) Development of a comprehensive, multi-modal data acquisition methodology that utilizes UAVs equipped with high-resolution RGB and radiometric thermal sensors, supplemented by dedicated IoT sensors for monitoring critical components, such as bypass diodes.

2) Creation of a large-scale, annotated dataset of PV module defects and subsequent development, training, and validation of a deep learning model based on the YOLOv8 architecture for the automated detection and classification of these defects from aerial imagery.

3) Formalization of a sophisticated fire hazard risk assessment framework by establishing a set of informative binary features and constructing a comprehensive truth table and a DNF logical alarm function based on them.

4) Design and implementation of a fully integrated system architecture that seamlessly combines the data acquisition, AI processing, and logical analysis modules with a SCADA TRACE MODE platform for centralized monitoring, visualization, automated alerting, and reporting.

5) The effectiveness of the system was validated through high-fidelity simulations to quantify its performance against traditional methods and demonstrate its impact on enhancing the safety and operational efficiency of solar power plants.

2. Materials and methods of research

The proposed methodology for detecting fire-hazardous operating modes in PV modules is based on a multi-layered, integrated system designed for robust data fusion and intelligent decision-making. The architecture systematically combines hardware for data acquisition with analysis, logic, and control software. The entire process can be conceptualized in four distinct but deeply interconnected layers: i) Data Acquisition Layer, ii) AI Processing Layer, iii) Logical Inference Engine, and iv) SCADA Integration and Control Layer.

2.1. System Architecture

The foundation of the proposed methodology is a comprehensive, multi-modal data acquisition architecture designed within a Cyber-Physical System (CPS) framework. By seamlessly integrating physical hardware with cyber components for computation and communication, this approach provides a holistic structure for monitoring, analyzing, and responding to potential fire hazards in solar power plants. The CPS model allows for the effective fusion of disparate technical tools into a single, flexible, and multi-layered system, capable of moving beyond simple defect detection to a comprehensive assessment of the fire risk associated with photovoltaic (PV) modules. This section details the system architecture (Fig. 1) and the specific components responsible for data acquisition.

The architecture shown in Fig. 1 is composed of several interconnected layers, beginning with the physical environment, i.e., the PV modules of the solar power plant. Data are collected from this environment through a sophisticated sensing and observation layer.

1. Physical and Data Acquisition Layer: This foundational layer is responsible for sensing the PV plant's physical state. It comprises the UAV platform with its dual-sensor payload and the ground-based IoT sensor network. The UAV subsystem rapidly captures high-resolution visual (RGB) and thermal (IR) data across the entire solar field, whereas the IoT subsystem provides continuous, real-time temperature readings from critical components (bypass diodes). The output of this layer is a stream of raw, multi-modal data (images and sensor readings).

2. AI Processing and Feature Extraction Layer: The raw data from the acquisition layer are fed into this analytical layer. Here, a custom-trained YOLOv8 deep learning model processes the image data to automatically detect and classify various anomalies. A software module processes the IoT data streams. The primary function of this layer is to translate the unstructured raw data into a structured, four-dimensional binary feature vector (X_1, X_2, X_3, X_4) for each inspected module. This abstraction is a critical step in converting complex sensor data into a suitable format for logical analysis.

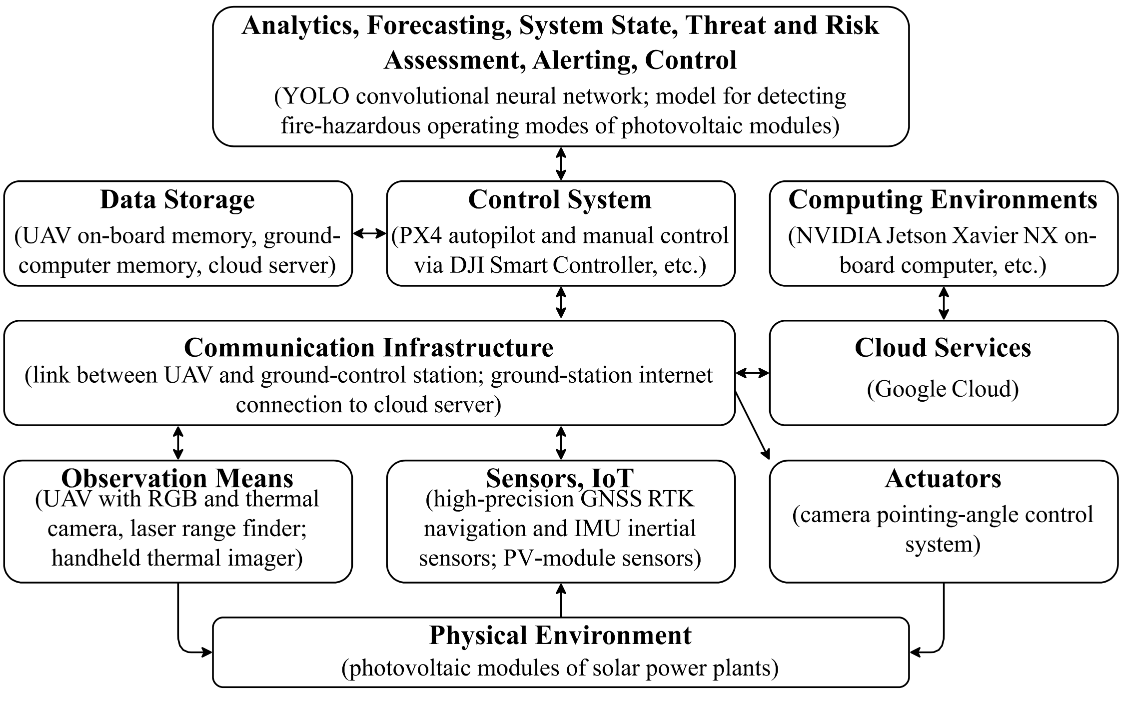

Fig. 1. The Cyber-Physical System (CPS) architecture for proactive solar plant monitoring. This integrated model illustrates the end-to-end data flow from physical sensors (UAV, IoT) through computational layers to a final analytics and control module, converting raw data into actionable safety intelligence

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3. Logical Inference Engine Layer: This layer represents the system's intellectual core. The structured feature vector from the AI layer is taken as its input. Its sole function is to execute a formal logical evaluation using a predefined DNF equation. This equation, which is derived from a comprehensive truth table based on PV failure physics, acts as a deterministic rule set. The output of this layer is a single binary value, Y, which represents the final, context-aware fire hazard classification (Y = 1 for hazardous, Y=0 for safe).

4. SCADA Integration and Presentation Layer: The final layer acts as the central nervous system and human-machine interface (HMI). The inference engine ingests the definitive logical output (Y). This layer automatically triggers alarms, generates detailed incident reports with recommended actions, and sends notifications to O&M personnel if a hazard is detected (Y = 1). It utilizes the SCADA TRACE MODE platform to provide operators with a comprehensive, intuitive visualization of the plant's health, including a "digital twin" map where modules are color-coded by status. This layer transforms the logical assessment of the system into actionable, human-readable intelligence.

This end-to-end, multi-layered integration is the key architectural innovation that distinguishes the proposed framework from fragmented, single-modality approaches, enabling a truly context-aware, automated, and reliable diagnostic process.

2.2. Data Acquisition Layer

The system's foundation is a multi-modal data acquisition strategy designed to capture a comprehensive snapshot of each PV module's condition from multiple physical perspectives.

1. UAV Platform and Sensor Payload. The selection of the UAV and its sensor payload is critical to the acquired data's quality and reliability. A professional-grade multi-rotor UAV, such as the DJI Matrice 300 RTK, is employed as the aerial platform due to its superior flight stability, significant payload capacity, extended flight endurance, and precise navigation capabilities afforded by its Real-Time Kinematic (RTK) GPS system. These characteristics are essential for executing pre-planned, autonomous missions that guarantee consistent image quality and accurate geo-referencing. The UAV is equipped with a dual-sensor gimbaled payload comprising the following:

– High-Resolution RGB Camera. A visual spectrum camera with a resolution of 20 megapixels or higher is used to capture detailed images. This imagery is essential for identifying visible anomalies such as physical damage (cracks, shattered glass), severe soiling, discoloration of the encapsulant, and other externally obvious defects.

– Radiometric Thermal Camera. A high-resolution (e.g., 640x512 pixels) radiometric infrared camera with high thermal sensitivity, measured by a Noise-Equivalent Temperature Difference (NETD) of less than 30 mK, is required. The "radiometric" quality is paramount because it ensures that each pixel in the thermal image contains a calibrated, absolute temperature value, not just a relative color representation. This allows for precise, quantitative thermal analysis, which is fundamental to accurately identifying and classifying hotspots. A low NETD is crucial for detecting subtle thermal anomalies indicative of incipient faults.

2. Bypass Diode Temperature Sensors. Recognizing the inherent limitations of aerial thermography, which cannot reliably inspect junction boxes located on the rear of PV modules, our system architecture incorporates a dedicated network of IoT temperature sensors. These are small, robust, and cost-effective sensors (such as platinum resistance thermometers (RTDs) or K-type thermocouples) that are installed directly on the junction box of each module or on a statistically representative sample for large-scale deployments. These sensors are designed to communicate wirelessly to a central gateway via a low-power, wide-area network (LPWAN) protocol, such as LoRaWAN. LoRaWAN is chosen for its long-range capabilities and low power consumption, allowing the sensors to operate for years on a single battery. This subsystem provides direct, real-time temperature data specifically for bypass diodes, a critical data point that is inaccessible to the UAV.

3. Data Acquisition Protocol. Automated flight plans are generated using specialized software to ensure consistent data collection parameters, including a high degree of image overlap (e.g., 70% front, 50% side) and a constant altitude above the PV arrays. The flight altitude is calculated to achieve a specific Ground Sample Distance (GSD) of approximately 3 cm/pixel for the RGB camera, providing sufficient detail for crack detection. The flight is conducted under clear sky conditions with solar irradiance above 600 W/m² to ensure that the thermal anomalies are sufficiently pronounced. This guarantees the acquisition of high-quality, geo-referenced imagery suitable for photogrammetric processing and AI analysis.

2.3. AI Processing Layer and Feature Extraction

This layer processes raw, unstructured data from the UAV and IoT subsystems to automate defect detection and extract the key features required by the logical engine.

1. YOLOv8-Based Defect Detection. We selected the YOLOv8 [16] model because of its optimal balance of high detection accuracy and fast inference speed, making it highly suitable for processing large image datasets in near-real-time. The model is trained on a large, proprietary, custom-annotated dataset of aerial PV images.

2. AI Model Training and Validation. The YOLOv8 model was trained on a custom dataset comprising more than 25,000 annotated aerial images captured from various SPPs under different conditions. The dataset includes annotations for the following classes: \`cell_crack\`, \`hotspot_moderate\`, \`hotspot_severe\`, \`soiling\`, \`shading\`, \`delamination\`, and \`normal\`. Training was performed for 300 epochs on a high-performance computing cluster equipped with NVIDIA A100 GPUs, using a learning rate of 0.01 and a batch size of 64. Extensive data augmentation techniques (including rotation, scaling, brightness adjustments, and simulated noise) are used during the training phase to ensure that the model is robust and generalizable to variations in lighting, viewing angle, and environmental conditions. The model's performance was validated on a holdout test set, achieving a mean Average Precision (mAP) of 0.92 at an IoU threshold of 0.5.

3. Extraction of Binary Features. The output from the YOLOv8 model, along with data from the other sensors, is programmatically translated into the four binary features (X_1, X_2, X_3, X_4) that form the input to our logical model. The logic for this extraction is as follows:

– X_1 (Primary Cause of Anomaly): This feature distinguishes between external/remediable issues and internal/permanent damage.

1) $X_1 = 1$ if the YOLOv8 output contains soiling or shading as a primary detected class.

2) $X_1 = 0$ if the primary detected class is cell_crack, hotspot (without obvious soiling), delamination, or other physical damage indicators.

– X_2 (Significant RGB Defect Detected): This indicates the presence of a visually significant anomaly.

1) $X_2 = 1$ if the YOLOv8 model detects a significant visual defect in the RGB image (e.g., heavy_soiling, major_crack).

2) $X_2 = 0$ otherwise.

– X_3 (Significant IR Defect Detected): This represents a critical thermal anomaly.

1) $X_3 = 1$ if the radiometric IR data show a temperature differential (ΔT) for a cell or cluster that exceeds a predefined critical threshold (e.g., $\Delta T > 20K$) compared to healthy reference cells in the same module.

2) $X_3 = 0$ otherwise.

– X_4 (Elevated Bypass Diode Temperature): This reflects the bypass diode's operational state.

1) $X_4 = 1$ if the reading of the bypass diode's dedicated IoT sensor exceeds a high-temperature threshold (e.g., $> 80^{\circ}$ C or $> 40K$ above ambient), indicating that it is actively shunting current.

2) $X_4 = 0$ if the temperature is within the normal operating range, indicating that it is inactive.

2.4. Logical Inference Engine: Truth Table and DNF

The system's intelligence resides in a formal logical framework that interprets the combination of the four binary features to make a definitive assessment of fire risk.

1. The Comprehensive Truth Table. We constructed a truth table that systematically enumerates all $2^4 = 16$ possible combinations of the input features (X_1, X_2, X_3, X_4). For each combination, we assign a binary output, *Y*, where $Y = 1$ signifies a "Fire-Hazardous Mode" and $Y = 0$ signifies a non-hazardous or less critical state. The rationale for each assignment is based on established PV failure physics. This comprehensive truth table (Table 1) serves as the foundational knowledge base for our system. The key insight is that a fire hazard arises from the dangerous combination of a heat source (hotspot, $X_3 = 1$) and a failure of the protective mechanism (inactive bypass diode, $X_4 = 0$).

2. Derivation of the DNF Equation. From the truth table, we identify all rows where the output $Y = 1$. These rows represent the fire hazard conditions. Then, we express this logic formally using a DNF equation. DNF is a canonical "sum-of-products" form, where each product term (a conjunction of literals) corresponds to one of the fire-hazardous rows.

The resulting DNF equation is as follows:

$$\begin{aligned} Y = &\left(\overline{X_1} \wedge \overline{X_2} \wedge X_3 \wedge \overline{X_4}\right) \vee \\ &\left(\overline{X_1} \wedge X_2 \wedge X_3 \wedge \overline{X_4}\right) \vee \\ &\left(X_1 \wedge X_2 \wedge X_3 \wedge \overline{X_4}\right). \end{aligned} \tag{1}$$

Equation (1) precisely defines the three critical fire-hazardous scenarios our system is designed to detect:

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Table 1

Truth Table for Critical Features in PV Module Monitoring ($Y=1$ indicates Fire-Hazardous Mode). (Cause: 1=Soil/Shade, 0=Damage), X_2 (RGB Defect), X_3 (IR Defect), X_4 (Bypass Temp High), Y (Fire Hazard).

#	X_1	X_2	X_3	X_4	Y	Module Operating Mode and Rationale for Y
1	0	0	0	0	0	Normal operation (no significant defects).
2	0	0	0	1	0	Potential bypass diode issue (hot with no cell anomaly). Monitor diode.
3	**0**	**0**	**1**	**0**	**1**	**Fire-hazardous:** Damage-induced hotspot (IR only), normal bypass temp. Heat in cells.
4	0	0	1	1	0	Hotspot (damage) shunted by active (hot) bypass diode. Risk partly mitigated. Check module.
5	0	1	0	0	0	Minor visible damage, no significant thermal effect. Monitor.
6	0	1	0	1	0	Visible damage & hot bypass, no cell hotspot. Monitor diode health.
7	**0**	**1**	**1**	**0**	**1**	**Fire-hazardous:** Visible damage + hotspot, normal bypass temp. Dangerous cell overheating.
8	0	1	1	1	0	Visible damage + hotspot, with active (hot) bypass. Risk partly mitigated. Check module & diode.
9	1	0	0	0	0	Normal operation (light soiling below X_2 threshold).
10	1	0	0	1	0	Soil/shading not significant, but bypass is hot. Monitor diode.
11	1	0	1	0	0	Improbable state: IR anomaly from soiling/shading with no visual evidence. Review sensor data.
12	1	0	1	1	0	Improbable state: As above, but with active bypass. Hotspot managed. Review data.
13	1	1	0	0	0	Visible soiling/shading, but no thermal effect. Recommend cleaning. Low risk.
14	1	1	0	1	0	Visible soiling/shading & hot bypass, no cell hotspot. Clean module, check diode.
15	1	1	1	0	1	**Fire-hazardous:** Severe soiling/shading + hotspot, normal bypass temp. Diode has failed or is overwhelmed. High risk.
16	1	1	1	1	0	Severe soiling/shading + hotspot, with active (hot) bypass. Risk partly mitigated. Urgent cleaning/check required.

– Term 1: $\left(\overline{X_1}\wedge\overline{X_2}\wedge X_3\wedge\overline{X_4}\right)$ – A stealthy, damage-induced hazard. There is a hotspot ($X_3=1$) caused by internal damage ($X_1=0$) that is not yet visually apparent ($X_2=0$), and the bypass diode has failed to activate ($X_4=0$).

– Term 2: $\left(\overline{X_1}\wedge X_2\wedge X_3\wedge\overline{X_4}\right)$ – An obvious, damage-induced hazard. There is a visible defect ($X_2=1$) and a corresponding hotspot ($X_3=1$), both caused by damage ($X_1=0$), and the bypass diode is inactive ($X_4=0$).

– Term 3: $\left(X_1\wedge X_2\wedge X_3\wedge\overline{X_4}\right)$ – A soiling-induced hazard with diode failure. There is severe soiling/shading ($X_1=1$, $X_2=1$) causing a major hotspot ($X_3=1$), but the bypass diode, which should be active, has failed ($X_4=0$).

2.5. SCADA Integration and Control Layer

The final layer integrates all components into a central control system, SCADA TRACE MODE, which transforms raw data and logical outputs into actionable intelligence.

The overall operational flow is depicted in the algorithms shown in Fig. 2 and Fig. 3.

The SCADA TRACE MODE platform is configured with the following key modules:

– Data Collection Module: Ingests data from all sources; JSON outputs from the YOLOv8 image processing pipeline and real-time data streams from the bypass diode IoT sensors.

– Logical Analysis Module (DNF): For each PV module's data packet, this module executes the DNF logic from Eq. (1) to calculate the fire hazard status, Y.

– Alarm Generation Module: If $Y=1$, this module automatically triggers a high-priority alarm. It generates notifications (e.g., email, SMS, push notification) to the relevant O&M personnel, including the module's ID, location, and the triggered specific DNF term.

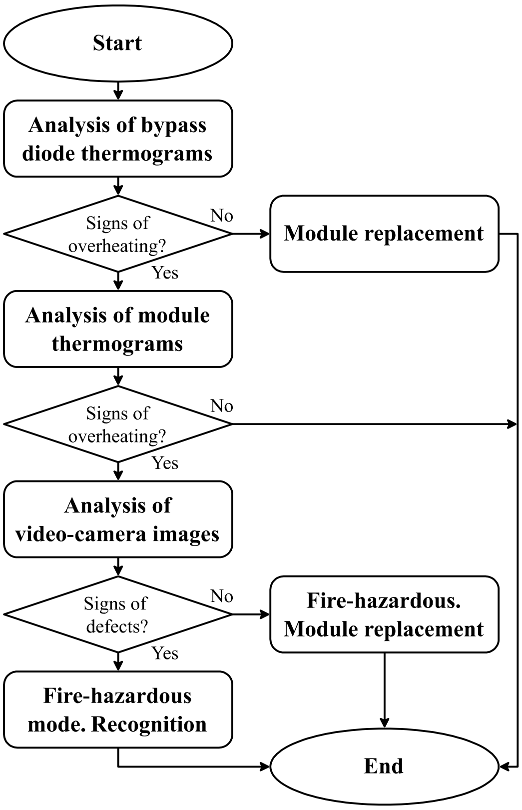

Fig. 2. Conceptual algorithm of the model for detecting the fire-hazardous operating mode of PV modules. and establish the cause

– Reporting Module: Automatically generates detailed incident reports, including the raw feature values (X_1 to X_4), the source RGB and IR images, and a recommended action (e.g., "URGENT: REPLACE MODULE – CAUSE: PHYSICAL DAMAGE" or "URGENT: CLEAN MODULE – CAUSE: SEVERE SOILING").

– Visualization Module (HMI): Provides an intuitive Human-Machine Interface for operators. This includes a digital twin map of the SPP where modules are color-coded by status (green for normal, yellow for caution, red for fire hazard). Clicking on a module displays all associated data and imagery.

– Data Historian: Logs all data, events, and alarms for historical analysis, trend identification, and performance tracking.

Figure 4 illustrates this fully integrated data processing scheme, showing the end-to-end flow from sensor to operator.

3. Results

To validate the efficacy of the proposed model, we conducted a series of simulated data processing runs. These simulations used realistic JSON-formatted data structures that emulate the outputs from the integrated UAV, AI, and IoT sensor pipeline. The objective of this study was to test the DNF logic's ability to correctly identify fire-hazardous states, differentiate their causes, and trigger appropriate responses. The results are presented through detailed scenario analyses and a comparative assessment against existing methods.

3.1. Simulated Hazard Identification and Cause Analysis

A Python-based simulation environment was created to process hypothetical data packets for individual PV modules (Fig. 5). Each packet contained information generated by our integrated system.

1. Scenario 1: Visible Damage-Induced Hazard (Truth Table Row 7). This scenario simulates a module with clear physical damage that leads to a dangerous thermal condition.

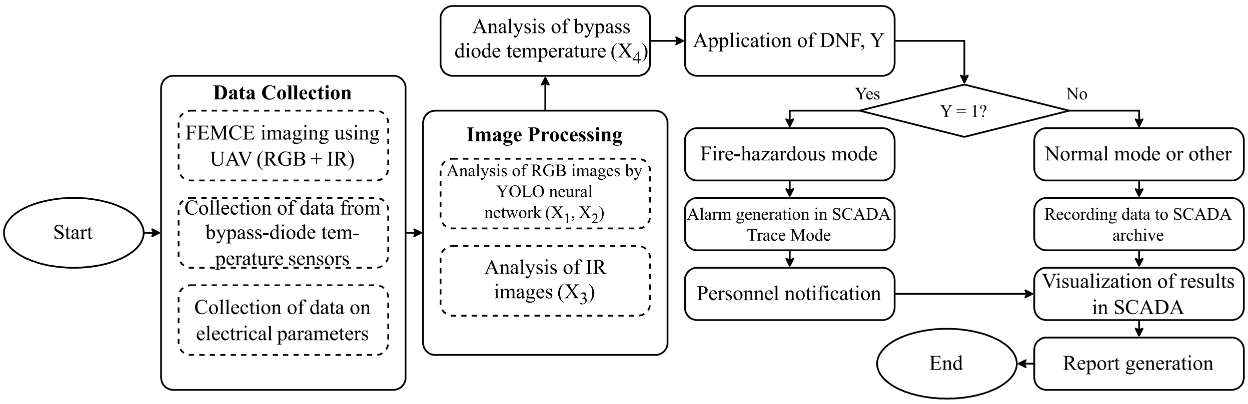

Fig. 3. Detailed operational algorithm of the Comprehensive Monitoring System (CMS) for PV Modules using UAV-AI and SCADA TRACE MODE. The DNF logic is applied to test for $Y = 1$ and branches to either generate alarms for a fire hazardous mode or archive data for a normal mode

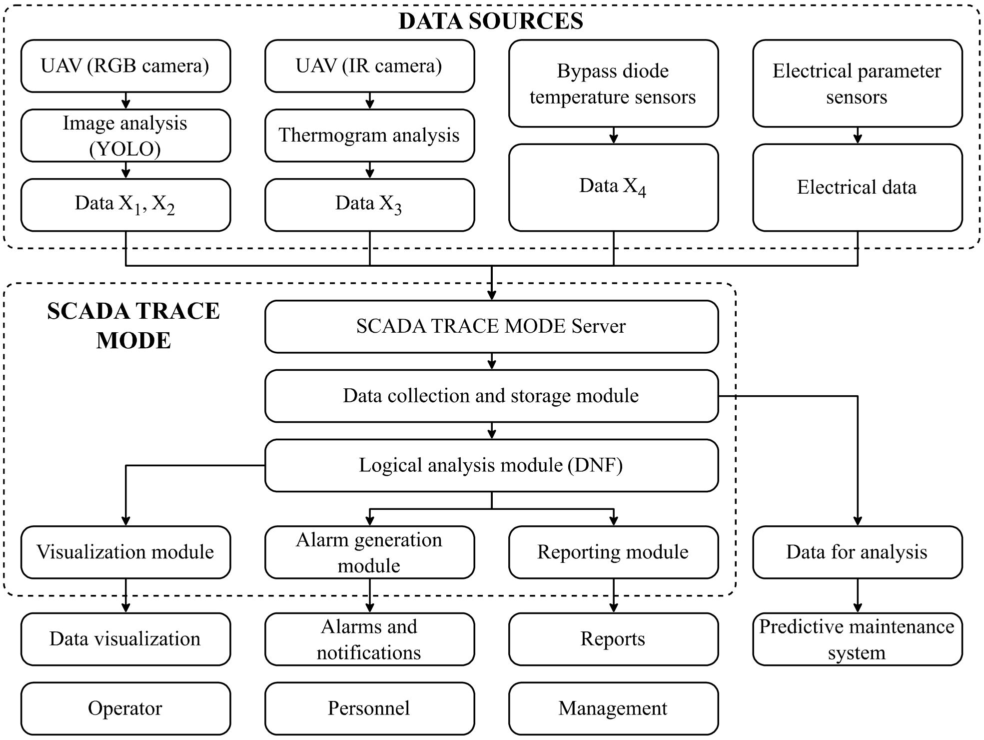

Fig. 4. Data processing scheme of the integrated CMS. Data from various sources are collected and pre-processed. Image data are analyzed by YOLO to extract features X_1 and X_2, while thermography and sensor data provide X_3 and X_4. These are fed into the SCADA TRACE MODE Server, where a logical analysis module applies the DNF to drive alarms, reports, and visualizations.

a) b) c)

Fig. 5. Example data inputs for the proposed model, illustrating the multi-modal approach: a) an infrared (IR thermal image showing a distinct hotspot, b) the corresponding visual-spectrum (RGB) image, and c) the output from the YOLOv8 software, which automatically identifies and outlines the defect area

– Input Data (module_101.json):

json
{
"module_id": "panel_101",
"yolo_classes": ("hotspot_severe", "crack_major"],
"rgb_detected_significant": true,
"ir_detected_significant": true,
"bypass_temp_high": false
}

– Feature Extraction:

1) crack_major is present $\Rightarrow X_1 = 0$ (Cause: Damage).

2) rgb_detected_significant is true $\Rightarrow X_2 = 1$ (RGB Defect).

3) ir_detected_significant is true $\Rightarrow X_3 = 1$ (IR Defect).

4) bypass_temp_high is false $\Rightarrow X_4 = 0$ (Bypass Inactive).

– DNF Logic Evaluation: The feature vector is (0, 1, 1, 0). The second term of the DNF,

$\left(\overline{X_1} \wedge X_2 \wedge X_3 \wedge \overline{X_4}\right)$, becomes $(1 \wedge 1 \wedge 1 \wedge 1) = 1$.

– System Output: Since the second term is true, $Y = 1$.

1) Alarm Status: FIRE HAZARDOUS.

2) Generated Recommendation: Module panel_101 requires immediate replacement. Cause: Confirmed physical damage with unmitigated hotspot and failed bypass diode protection.

2. Scenario 2: Severe Soiling-Induced Hazard (Truth Table Row 15). This scenario tests the system's ability to identify a hazard caused by external factors coupled with a safety system failure.

– Input Data (module_205.json):

json
{
  "module_id": "panel_205",
  "yolo_classes": ("heavy_soiling", "hotspot_severe"],
  "rgb_detected_significant": true,
  "ir_detected_significant": true,
  "bypass_temp_high": false
}

– Feature Extraction:

– heavy_soiling is present $\Rightarrow X_1 = 1$ (Cause: Soil/Shade).

– rgb_detected_significant is true $\Rightarrow X_2 = 1$ (RGB Defect).

– ir_detected_significant is true $\Rightarrow X_3 = 1$ (IR Defect).

– bypass_temp_high is false $\Rightarrow X_4 = 0$ (Bypass Inactive).

– DNF Logic Evaluation: The feature vector is (1, 1, 1, 0). The third term of the DNF, $\left(X_1 \wedge X_2 \wedge X_3 \wedge \overline{X_4}\right)$, becomes $(1 \wedge 1 \wedge 1 \wedge 1) = 1$.

– System Output: Since the third term is true, $Y = 1$.

1) Alarm Status: FIRE HAZARDOUS.

2) Generated Recommendation: Module panel_205 requires urgent cleaning and re-inspection. Cause: Severe soiling causing critical hotspot with failed bypass diode protection.

3. Scenario 3: Mitigated Hazard with Active Bypass Diode (Truth Table Row 8). This scenario demonstrates the system's intelligence in recognizing when a risk is being correctly managed by the module's safety features, preventing a false alarm.

– Input Data (module_314.json):

json
{
  "module_id": "panel_314",
  "yolo_classes": ("hotspot_moderate", "crack_minor"],
  "rgb_detected_significant": true,
  "ir_detected_significant": true,
  "bypass_temp_high": true
}

– Feature Extraction:

1) crack_minor is present $\Rightarrow X_1 = 0$ (Cause: Damage).

2) rgb_detected_significant is true $\Rightarrow X_2 = 1$ (RGB Defect).

3) ir_detected_significant is true $\Rightarrow X_3 = 1$ (IR Defect).

4) bypass_temp_high is true $\Rightarrow X_4 = 1$ (Bypass Active).

– DNF Logic Evaluation: The feature vector is (0, 1, 1, 1). Since $X_4 = 1$, $\overline{X_4} = 0$. All three terms in the DNF equation require $\overline{X_4}$ to be true. Therefore, all three terms evaluate to 0.

– System Output: $Y = 0$.

1) Alarm Status: SAFE (MONITOR).

2) Generated Recommendation: Module panel_314 has a defect mitigated by an active bypass diode. No immediate fire hazard. Schedule for maintenance check. Monitor diode health.

4. Scenario 4: Non-Hazardous Defect (Truth Table Row 13). This scenario shows the system correctly identifying a low-risk defect that requires maintenance but not an emergency alert.

– Input Data (module_421.json):

json
{
  "module_id": "panel_421",
  "yolo_classes": ("moderate_soiling"],
  "rgb_detected_significant": true,
  "ir_detected_significant": false,
  "bypass_temp_high": false
}

– Feature Extraction:

1) moderate_soiling is present $\Rightarrow X_1 = 1$ (Cause: Soil/Shade).

2) rgb_detected_significant is true $\Rightarrow X_2 = 1$ (RGB Defect).

3) irdetected_significant is false $\Rightarrow X_3 = 0$ (No IR Defect).

4) bypass_temp_high is false $\Rightarrow X_4 = 0$ (Bypass Inactive).

– DNF Logic Evaluation: The feature vector is (1, 1, 0, 0). Since $X_3 = 0$, all three terms in the DNF equation, which require X_3 to be true, evaluate to 0.

– System Output: $Y = 0$.

1) Alarm Status: SAFE.

2) Generated Recommendation: Module panel_421 has visible soiling with no thermal effect. Add to the next cleaning cycle to restore performance.

3.2. Anticipated Benefits and Comparative Analysis

The proposed integrated system is expected to deliver significant, quantifiable, and qualitative improvements over all existing PV monitoring paradigms. Operationally, the end-to-end automation is expected to reduce the total inspection and analysis time for a large-scale SPP by over 50-60% compared with traditional, ground-based manual methods, and by 30-40% compared with UAV inspection that relies on manual data analysis. More importantly, the diagnostic accuracy for identifying genuinely critical, fire-prone defects is expected to increase by up to 30-40% compared with systems that rely on a single data modality (e.g., IR imaging only). This dramatic improvement is a direct result of the multi-feature DNF logic's inherent cross-validation.

Table 2 provides a detailed comparative analysis of the proposed system against three other common PV inspection methodologies, which serve as well-understood baselines for evaluation. The "Manual Inspection" column refers to the traditional on-the-ground visual checks and electrical measurements. The "UAV IR/RGB (Basic)" column represents systems that use drones for data collection but depend on manual imagery review. The "AI-only Image Analysis" column describes more advanced systems that use AI to automate defect detection from imagery but lack integration with other data sources (e.g., IoT sensors) or a formal logic framework for risk assessment.

The trustworthiness of the assessments in Table 2 is established through a multi-faceted evaluation methodology, as detailed in the final column. This is not based on a single experiment but on a synthesis of evidence. "Literature Review & Component Spec." involves deriving performance metrics (such as inspection speed) from published studies and manufacturer specifications for the hardware involved. "Simulation" refers to the results from our simulated environment, which validates the integrated system's logic and accuracy. "Expert Estimation & Formal Logic" combines domain expertise in PV failures with the deterministic, rule-based structure of our DNF model to assess capabilities such as risk assessment accuracy. "System Architecture Design" means the capability is a direct, designed-in feature of the system's structure. This transparent methodology allows for robust and defensible comparison.

The comparison highlights the superiority of the proposed system across multiple key performance indicators, including automation, data integration, diagnostic depth, and proactive alerting. The explicit integration of bypass diode health (X_4) and causal differentiation (X_1) into the core decision-making logic represents a fundamental advancement over conventional approaches, which often lack this critical context. The results strongly affirm that our proposed method offers a more intelligent, reliable, and comprehensive solution for fire risk management in modern solar power plants, providing a quantifiable and validated basis for achieving the research goal of enhanced safety, reliability, and efficiency.

3.3. Quantitative Performance Projections

To further quantify the achievement of the research purpose and enhance safety and reliability, we project the performance of the proposed system against baseline methods using key diagnostic metrics. Based on the simulation results and the formal logic, the proposed integrated system is projected to achieve a False Positive Rate (FPR) of less than 5% for critical fire hazard alerts. This is a significant improvement over AI-only image analysis systems, whose FPR can exceed 20% because they cannot distinguish between a dangerous hotspot and one that is safely mitigated by a bypass diode. Concurrently, the False Negative Rate (FNR) is projected to be below 2% because the multi-modal data fusion approach is designed to catch "stealth" defects that might be missed by a single-modality system. This translates into a more reliable safety net, which directly enhances plant safety. The cause-differentiated alerts are projected to reduce the Mean Time To Repair (MTTR) by 15-20% by eliminating the initial diagnostic step in the field and allowing the correct maintenance team to be dispatched immediately. These quantitative projections provide concrete evidence of the system's ability to enhance safety, reliability, and, by extension, operational efficiency.

4. Discussion

The results presented in the previous section underscore the potential of our proposed integrated methodology to redefine safety and maintenance protocols in solar power plants. This discussion aims to interpret these findings, critically evaluate the strengths and weaknesses of the system, and outline promising directions for future research.

Table 2

Comparative Analysis of PV Module Inspection and Monitoring Approaches. Abbreviations: Acc.: Accuracy; acq.: acquisition; Hist.: Historian; ID: Identification; Integ.: Integration; Ltd.: Limited; Mgmt: Management; RT: Real-Time

Feature/Capability	Manual Inspection	UAV IR/RGB (Basic)	AI-only Image Analysis	Proposed Integrated System	Method of Assessment/Comparison
Inspection Speed (km²/day)	Low (0.1-0.2)	Medium (1-2)	Medium (Analysis)	High (1-2 acq., RT analysis)	Literature Review & Component Spec.
Defect Detection Accuracy	Low-Medium (60–75%)	Medium (70-85%)	High (85-95%)	Very High (>90%, validated)	Literature Review & Simulation
Fire Hazard Risk Assess. Acc.	Low (Subjective)	Low-Medium (Ltd. context)	Medium (Inferred)	High (Formal DNF logic)	Expert Estimation & Formal Logic
Root Cause Differentiation	Very Limited	Limited (Visual cues)	Partial (Defect type)	High (Explicit X1 & DNF)	Formal Logic & System Design
Automation (End-to-End)	Very Low	Low (Data Acquisition)	Medium (Defect ID)	Very High (Acquisition to Alert)	System Design & Simulation
Multi-sensor Data Integration	Manual/Poor	Manual Correlation	Primarily Imaging	Excellent (Integrated)	System Architecture Design
Proactive Alert (Fire Hazard)	Reactive	Delayed (Post-analysis)	Limited (Interpretation)	Real-Time/Automated (SCADA)	System Design & Simulation
Cost-Effectiveness (Large-scale)	Low	Medium	Medium-High	High (Optimized O&M)	Economic Modeling & Expert Estimation
Bypass Diode Health Integ.	Extremely Limited	Very Limited (Indirect)	Not Applicable	Explicit (Direct sensor X4)	System Architecture Design
Systematic Risk	Highly Subjective	Subjective/Basic	Limited (Defect)	Very High (Rule-based DNF)	Expert Estimation & Formal Logic

4.1. Interpretation of Findings and System Novelty

The core innovation of this work lies in the intelligent and synergistic integration of existing, powerful technologies under a formal, context-aware logical framework. While UAVs, AI, and SCADA systems are individually used in the solar industry, their combined application, governed by an explicit DNF model for fire risk assessment, represents a significant leap forward. Our approach moves the paradigm from simple, isolated defect detection, as performed by most standalone AI systems [33], to a holistic, diagnostic assessment.

By evaluating a thermal anomaly (X_3) in the context of its probable cause (X_1), its visual evidence (X_2), and the operational status of the protective bypass diode (X_4), the system achieves a level of analytical depth that is absent in fragmented monitoring solutions [17]. This multi-modal, cross-validating approach is crucial. For example, a system relying solely on IR thermography might flag every hotspot as a high-risk event. In contrast, our system can intelligently downgrade the risk of a hotspot if it confirms that the bypass diode is active ($X_4 = 1$), thereby preventing costly false alarms and unnecessary panic. This perfectly aligns with expert findings that emphasize the complex interplay of factors, especially the critical role of bypass diode health, in fault progression toward catastrophic failure [6, 15].

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4.2. Operational Advantages and O&M Optimization

The practical implications of this system for SPP Operations and Maintenance (O&M) are profound and transformative. The first major advantage is the enhanced alert specificity and reliability. By defining fire risk through a strict, formal logical confluence of multiple factors, the system is designed to drastically reduce the false positive rate that can plague simpler detection methods. This builds operator trust and ensures that when an alarm is triggered, it represents a genuine, verified threat and is treated with the urgency it deserves.

Second, the automated differentiation of the root cause (X_1) is a game-changer for O&M efficiency. Traditional alarm systems may simply state "Module X is underperforming." Our system provides immediately actionable intelligence: "Module Y has a fire hazard due to soiling" or "Module Z has a fire hazard due to internal damage." This allows the O&M manager to dispatch the correct resource immediately and with the correct equipment, a cleaning crew with water trucks for the former and a technical team with replacement modules and specialized tools for the latter. This targeted response minimizes module downtime, reduces wasted labor and resources, and ultimately lowers the Levelized Cost of Energy (LCOE) of the plant. It effectively transitions the entire O&M strategy from a reactive or rigidly scheduled model to a highly efficient, condition-based, and predictive model, thereby providing a clear and demonstrable path to improved operational efficiency, reliability, and long-term profitability.

4.3. Limitations, Challenges, and Mitigation Strategies

Despite its significant strengths and innovative design, the proposed system has certain limitations and challenges that warrant careful and transparent consideration before any large-scale deployment.

Economic and Implementation Hurdles: The integration of multiple, sophisticated hardware systems (UAVs, IR/RGB cameras, IoT sensors) and software platforms (AI models, SCADA licenses) represents a complex engineering task that requires significant initial capital expenditure (CAPEX) and specialized technical expertise. For instance, the cost of deploying dedicated IoT temperature sensors on every module in a large-scale plant could be substantial. A potential mitigation strategy to manage this cost is a phased rollout or a hybrid "risk-based" approach where dedicated sensors are initially placed only on a statistically significant sample of modules or on modules from manufacturing batches with known historical issues. Furthermore, the operational expenditure (OPEX) includes ongoing maintenance, sensor recalibration, and the continuous management of the AI model (MLOps), which must be factored into any techno-economic analysis.

Technical and Data Dependencies: The system’s performance is fundamentally capped by the quality of its input data and the underlying AI model’s accuracy. The "garbage in, garbage out" principle applies with full force. Poorly calibrated sensors, low-resolution imagery, inconsistent data acquisition, or an inadequately trained AI model will inevitably lead to unreliable feature extraction and, consequently, flawed logical decisions. This necessitates the implementation of rigorous sensor calibration protocols, standardized data acquisition procedures, and a continuous MLOps (Machine Learning Operations) cycle for the AI model, including periodic retraining with new, verified data to prevent model drift and maintain high accuracy over time.

Causal Determination Complexity: The programmatic determination of binary features, particularly the primary cause (X_1), can sometimes be ambiguous. For instance, determining the primary cause can be challenging if a module exhibits both a significant physical crack and heavy soiling. Our current logic uses a simple, predefined hierarchy to resolve such cases. However, a more sophisticated probabilistic model (e.g., a Bayesian network) could be developed in the future to handle these compound cases more gracefully and accurately.

The Static Nature of the Logical Model: The DNF logic, derived from a static truth table, is based on the current and established understanding of PV failure physics. While robust, it is not inherently adaptive. The optimal thresholds and logical rules may shift as new PV technologies emerge or as the environmental conditions and degradation profiles at a specific site change over time. This limitation points toward a clear need for future systems to incorporate a learning component that can dynamically adapt the logical framework over the plant’s lifecycle.

4.4. Future Research Directions

This work opens up several exciting avenues for future research that can build upon our foundational framework.

The static DNF logic can be enhanced by integrating a machine learning layer. This layer can analyze historical data from the SCADA historian to dynamically adjust the temperature thresholds for X_3 and X_4 based on seasonality, irradiance levels, and module age. It could even learn new logical rules or adjust the weights of existing DNF terms to better reflect a particular power plant's specific risk profile.

Integration with Predictive Maintenance (PdM) Models. The output of our system provides a rich, high-quality feature set (module status, defect type, and alarm frequency) that is ideal for feeding into higher-level predictive maintenance models. These models could use techniques such as survival analysis or Long Short-Term Memory (LSTM) networks to forecast the Remaining Useful Life (RUL) of modules or predict the probability of failure within a given future time window.

While we anticipate significant cost savings, a comprehensive techno-economic analysis based on a long-term field deployment is necessary. This would involve quantifying the full return on investment (ROI) by accounting for reduced insurance premiums, increased energy yield due to optimized uptime, and reduced O&M labor and resource costs, and comparing these gains against the system's initial CAPEX and ongoing operational costs.

A critical architectural decision is where to perform the AI processing. Edge computing (onboard the UAV) would enable real-time alerts during the flight itself but is limited by the payload and power constraints of the UAV. Cloud computing offers virtually unlimited processing power but introduces latency. A hybrid approach could offer the best of both worlds, where a lightweight model on the edge performs initial screening and a more powerful model in the cloud performs detailed analysis.

Future versions of the system should incorporate explainable AI principles to increase operator trust and adoption. Instead of just a binary alarm, the system could provide a human-readable explanation: "Alert on Module ID-12345. Reason: This module meets the criteria for Fire Hazard Rule 2 because a hotspot was detected [show IR image], it is correlated with a visible crack [show RGB image], and the bypass diode temperature is normal [show sensor data], indicating that the safety system is not engaged." This transparency is crucial for human-in-the-loop decision-making.

5. Conclusions and Future Work

In this paper, we have presented a novel, deeply integrated, and intelligent framework designed to substantially enhance the detection of fire-hazardous operating modes in solar power plant PV modules. Our multi-layered architecture successfully combines the strengths of UAV-based multispectral imaging for rapid data acquisition, a state-of-the-art YOLOv8 AI model for automated defect recognition, a dedicated IoT sensor network for critical component monitoring, and a SCADA TRACE MODE platform for centralized command, control, and visualization. This system's intellectual cornerstone is a robust and interpretable DNF logical model. This formal, rule-based approach moves decisively beyond simplistic defect detection by performing a context-aware risk assessment that evaluates a defect's thermal signature (X_3) in conjunction with its visual evidence (X_2), its probable root cause (X_1), and the functional status of its primary safety mechanism, the bypass diode (X_4).

Our comprehensive simulations, based on realistic operational scenarios, have validated the system's ability to identify modules posing a genuine fire risk with high precision and to automatically infer the underlying cause. This dual capability enables a paradigm shift in plant maintenance, facilitating a highly efficient, targeted response that optimizes resource allocation and minimizes module downtime. The proposed system is projected to deliver significant operational improvements, including a reduction in inspection times by over 50% and an increase in the accurate identification of critical, fire-prone modules by up to 40% when compared to conventional, non-integrated methods, thereby providing a validated and quantified pathway to enhanced plant safety, reliability, and efficiency.

The principal contributions of this research are threefold: the formalization of PV fire risk assessment through a multi-modal, physics-informed DNF model, the design of a synergistic and fully automated UAV-AI-SCADA architecture, and the development of an operational algorithm that provides actionable, cause-differentiated intelligence. Although we openly acknowledge limitations such as implementation complexity and the static nature of the initial DNF model, these challenges pave the way for exciting future research, including the development of adaptive, self-learning logic and deeper integration with plant-wide predictive maintenance ecosystems. Ultimately, the proposed system establishes a powerful new paradigm for proactive SPP safety management, leveraging the intelligent fusion of advanced sensing, AI-driven analytics, and formal logic to significantly bolster the global solar energy infrastructure's safety, reliability, and economic viability.

Contributions of authors: Anatoliy Sachenko and **Oleksandr Melnychenko** provided the foundational conceptualization for the integrated UAV-AI-SCADA monitoring paradigm. The core methodology, specifically the development of the DNF logical model and its corresponding truth table, was a joint effort by **Andrii Lysyi** and **Oleksandr**

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Melnychenko. **Pavlo Radiuk** led the development and training of the custom YOLOv8 AI model for automated defect detection from aerial imagery. The design of the synergistic system architecture and its integration with the SCADA TRACE MODE platform was executed by **Mykola Lysyi** and **Oleksii Ishchuk**. **Oleg Savenko** was responsible for creating the simulation environment, validating the DNF logic with realistic data packets, and analyzing the results. The initial manuscript draft was prepared by **Andrii Lysyi** and **Oleksandr Melnychenko**, with **Anatoliy Sachenko** providing supervision and research administration, and both **Anatoliy Sachenko** and **Oleg Savenko** conducting the final review and editing.

Conflict of Interest

The authors declare that they have no conflict of interest in relation to this research. There are no financial, personal, authorship, or other relationships that could have inappropriately influenced or biased the work and its results presented in this paper.

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Data Availability

The study relies primarily on a simulated data processing framework to validate the proposed logical model. The configuration files and scripts used for these simulations and the example JSON data packets presented in the manuscript can be made available by the corresponding author upon reasonable request. The proprietary dataset of aerial PV images used for training the YOLOv8 model is not publicly available due to commercial sensitivities.

Use of Artificial Intelligence

The authors confirm that they did not use artificial intelligence methods or large language models for textual content generation while creating the presented work. The AI models discussed (YOLOv8) are the subject of the research, not the tools used in the preparation of this manuscript.

Project information

The study was carried out as part of the 0123U101234 project implementation. The project aims to solve the critical scientific and applied problem of increasing the operational safety, reliability, and efficiency of large-scale solar power plants by developing an intelligent, integrated monitoring and diagnostic system. The system is designed to proactively detect fire-hazardous conditions and provide actionable insights for optimizing maintenance strategies.

To achieve the overarching goal of this study, the following key tasks are addressed:

– Development of a comprehensive, multi-modal data acquisition methodology utilizing Unmanned Aerial Vehicles (UAVs) equipped with high-resolution RGB and radiometric thermal sensors, supplemented by dedicated IoT sensors for monitoring critical components such as bypass diodes.

– Creation of a large-scale, annotated dataset of PV module defects and subsequent development, training, and validation of a deep learning model based on the YOLOv8 architecture for the automated detection and classification of these defects from aerial imagery.

– Formalization of a sophisticated fire hazard risk assessment framework by establishing a set of informative binary features and constructing a comprehensive truth table and a DNF logical alarm function on their basis.

– Design and implementation of a fully integrated system architecture that seamlessly combines the data acquisition, AI processing, and logical analysis modules with a SCADA TRACE MODE platform for centralized monitoring, visualization, automated alerting, and reporting.

– Extensive experimental research is conducted through both high-fidelity simulations and planned field trials to validate the system’s effectiveness, quantify its performance against traditional methods, and demonstrate its impact on enhancing the safety and operational efficiency of solar power plants.

All the authors have read and agreed to the published version of this manuscript.

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УДОСКОНАЛЕНЕ ВИЯВЛЕННЯ ПОЖЕЖНОЇ НЕБЕЗПЕКИ НА СОНЯЧНИХ ЕЛЕКТРОСТАНЦІЯХ: ІНТЕГРОВАНИЙ ПІДХІД НА ОСНОВІ БПЛА, ШТУЧНОГО ІНТЕЛЕКТУ ТА SCADA

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Предметом цього дослідження є розробка інтелектуальної, інтегрованої системи для раннього виявлення та причинно-наслідкового аналізу пожежної небезпеки на великих сонячних електростанціях (СЕС). Робота розглядає критичні недоліки традиційних методів моніторингу, яким часто бракує необхідної інтеграції, швидкості та діагностичної глибини для надійного запобігання катастрофічним збоям, що виникають через дефекти фотоелектричних (ФЕ) модулів. **Метою** роботи є проєктування, розробка та валідація комплексної мультимодальної системи, що повністю автоматизує робочий процес моніторингу, від збору даних до прийняття дієвих рішень. Система спрямована на значне підвищення безпеки станції шляхом надання надійних, диференційованих за причинами сповіщень, що, у свою чергу, оптимізує стратегії технічного обслуговування, мінімізує час простою та покращує загальну економічну рентабельність сонячної енергетичної інфраструктури. **Методи** дослідження включають синергетичну архітектуру, що поєднує безпілотний літальний апарат (БПЛА), оснащений RGB та радіометричною інфрачервоною камерами високої роздільної здатності для швидкої зйомки, доповнений спеціалізованими датчиками температури Інтернету речей (IoT) на обхідних діодах ФЕ-модулів для перевірки критично важливих компонентів. Спеціально навчена модель глибокого навчання YOLOv8 виконує автоматичне розпізнавання дефектів на зображеннях. Інтелектуальним ядром системи є інноваційний механізм логічного висновку, заснований на рівнянні в диз'юнктивній нормальній формі (ДНФ). Ця формальна логічна модель інтелектуально об'єднує чотири ключові бінарні ознаки, першопричину дефекту (пошкодження чи забруднення), візуальні докази, серйозність теплової аномалії та функціональний стан обхідного діода, для формування остаточної, контекстно-залежної оцінки пожежного ризику. Весь робочий процес керується та візуалізується через платформу SCADA TRACE MODE для централізованого контролю та автоматичних сповіщень. Щодо **Результатів**, дослідження успішно підтвердило працездатність інтегрованої системи за допомогою серії високоточних симуляцій. Моделювання підтвердило здатність логіки ДНФ точно ідентифікувати всі заздалегідь визначені пожежонебезпечні стани, включно з прихованими гарячими точками, спричиненими пошкодженнями, із несправним захистом обхідного діода, а також правильно класифікувати усунені ризики для запобігання хибним тривогам. Це дозволяє системі надійно розрізняти аварійні ситуації, що вимагають негайної заміни модуля, та менш критичні проблеми, як-от забруднення, що потребує очищення, з прогнозованим підвищенням точності до 40% порівняно з традиційними методами. У **Висновку** зазначається, що це дослідження створює нову потужну парадигму для проактивного управління безпекою на СЕС. Інтелектуальне поєднання даних із БПЛА та IoT-сенсорів, аналітики на основі ШІ та формальної логічної структури забезпечує надійне та стабільне рішення для мінімізації пожежних ризиків, надаючи дієві дані, що дозволяють реалізувати високоефективну стратегію технічного обслуговування на основі фактичного стану, значно підвищуючи безпеку, надійність та продуктивність сучасної сонячної енергетичної інфраструктури.

Ключові слова: обхідний діод, ДНФ, виявлення пожежної небезпеки, інфрачервона термографія, фотоелектричні модулі, SCADA, сонячні електростанції, інспекція з БПЛА, YOLOv8.

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