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AI-ASSISTED TARGETED DRONE RE-INSPECTION OF PHOTOVOLTAIC PLANTS USING PHOTOGRAMMETRIC 3D MODELS – A PRACTICAL WORKFLOW

Wolfram Liese (corresponding author)

dronalise, Germany

wolfram.liese@dronalise.com

Summary

This paper presents a practical workflow that makes unmanned aerial vehicle (UAV)-based thermographic inspection of photovoltaic plants more efficient by letting the drone build its own understanding of the plant while it is still flying. Instead of a fixed, manually planned survey, the system uses an iterative image-to-flight-path loop: onboard imagery is analyzed by AI models that detect module areas and thermal anomalies, a geometric model of the plant is computed within seconds, and an optimized flight path is derived and translated into a new drone mission. Three coupled passes are used in the prototype: a coarse overview flight identifies regions of interest for thermographic re-inspection at IEC-compliant resolution; a second, targeted pass yields a precise 3D module model and true module-area thermal analysis; and a third pass captures exclusive close-up RGB and infrared imagery of the most conspicuous modules. The approach directly addresses a practical weakness of manual UAV inspection, where pilots regularly miss modules or capture insufficient imagery, which is discovered only during office-based evaluation and requires a costly re-flight. The underlying capability to build a georeferenced 3D module model from AI-segmented imagery has already been applied in more than 150 PV installations in Germany and Switzerland and supports the unambiguous localization of thermal findings in the final report. The full iterative, closed-loop re-inspection workflow across all three passes has been implemented and field-tested on one plant as a working prototype and still requires systematic validation across a larger number of installations.

Keywords: photovoltaic inspection, infrared thermography, drone inspection, photogrammetry, artificial intelligence, PV monitoring, iterative flight planning, autonomous re-inspection

Field of application for the findings: operation and maintenance of photovoltaic systems, thermographic inspection, automated monitoring and reporting

Addressed audience: researchers, PV plant operators, inspection providers, asset managers, and developers of AI-based monitoring systems

1. Introduction

The rapid expansion of photovoltaic (PV) capacity increases the need for inspection methods that are fast, reproducible, and useful for maintenance decisions. UAV-based infrared thermography can survey large areas efficiently and reveal thermal signatures associated with hotspots, bypass-diode-related anomalies, interconnection problems, and string faults. Prior work has demonstrated automated, single-pass pipelines that detect, classify, and geoposition such thermal defects from UAV-acquired IR and RGB imagery of a fixed, pre-planned survey (Fernández et al., 2020; Kuo et al., 2023). In conventional practice, however, a human pilot decides in the field which areas and modules deserve closer attention and which additional images to capture. This decision is made under time pressure, based on a small live-view display, and it is documented after the fact rather than derived from a systematic analysis. In practical experience, this manual approach is error-prone: pilots overlook conspicuous modules, forget to capture a required close-up, or acquire images at an unsuitable distance or angle. Such gaps are frequently discovered only during office-based post-processing, at which point a second site visit, re-flight and post-processing become necessary. This adds cost, delay, and coordination effort to the inspection process.

The work presented here addresses this problem by shifting the targeting decision from the pilot to an automated, iterative image-to-flight-path loop. Instead of a single, manually planned survey, the UAV first captures a small number of overview images. These are analyzed on the ground within seconds by AI models that detect PV module areas and thermal anomalies. From this analysis, the software automatically derives regions of the plant that warrant closer thermographic inspection, generates an optimized flight path through these regions, and translates it into a new drone mission. The same principle is then repeated at module level: once individual modules are reconstructed in 3D and analyzed thermally, the modules with the most conspicuous findings are automatically selected for an additional close-up mission. In this sense, the drone progressively "learns" where to look as the inspection proceeds, rather than relying on a flight plan that was fixed before take-off or on ad hoc pilot decisions.

The main contribution of this paper is the description and field demonstration of this iterative, self-refining inspection workflow, including the translation of automatically generated flight paths into DJI-compatible mission files. The paper outlines: (i) a detailed description of the three-pass acquisition, AI analysis, spatial mapping, and mission-generation chain; (ii) a practical account of a field-tested prototype that executed this loop under real operating conditions, including image transfer, on-the-ground processing, and mission upload within a single operational window; and (iii) a transparent separation between the practically established sub-workflow for building a georeferenced 3D module model from AI-segmented imagery for defect localization and the fully iterative, closed-loop re-inspection workflow, which still requires systematic validation across a larger number of plants.

2. Iterative Inspection Workflow

The core idea of the proposed system is that the UAV does not follow a single, pre-planned survey grid, but progressively refines its own flight plan based on what it detects during the mission. Each iteration follows the same principle: an image is captured, an AI model detects PV module areas or thermal anomalies within it, the software computes a geometric model of the observed scene within seconds, and a new, targeted flight path is derived from this model and translated into a drone mission file. Three coupled passes implement this principle in the field-tested prototype, moving from a coarse plant-level overview to individual module close-ups (Fig. 1).

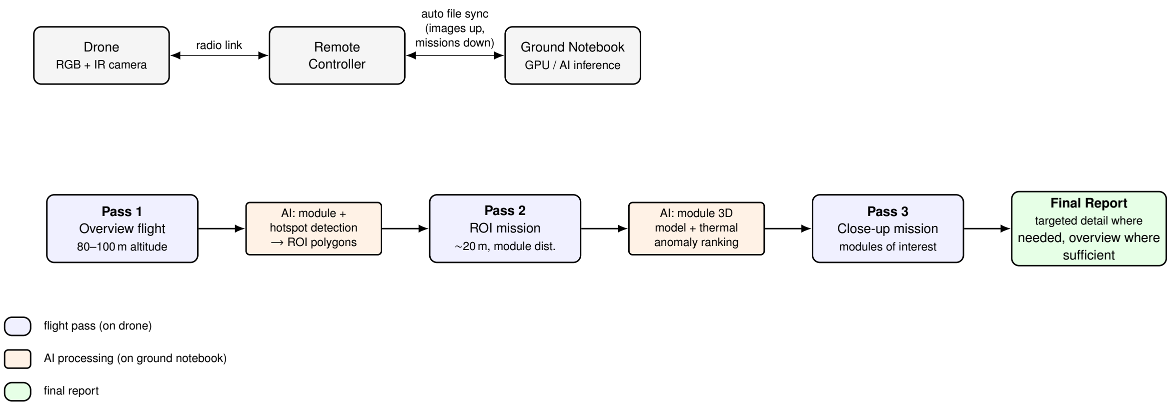

Fig. 1: Overview of the iterative, closed-loop inspection workflow: the drone, remote controller, and ground notebook form the hardware loop (top), while three coupled passes progressively refine the flight plan from a coarse overview to region-of-interest re-inspection and finally module-level close-ups (bottom).

2.1 Pass 1: Overview flight and region-of-interest generation

The mission begins with a small number of overview images acquired at 80–100 m altitude, which is sufficient to cover a typical plant section per image. These images are transferred from the aircraft through the remote controller to a ground notebook equipped with a GPU, using an automated file-synchronization mechanism so that processing can start while the aircraft remains airborne. On the ground, one AI model detects and segments

PV module areas in the RGB overview images and projects them onto the terrain model of the site, while a second, independent AI model detects thermally conspicuous regions (e.g., hotspots) in the corresponding infrared images. Combining both detections yields a set of regions of interest (ROIs): plant areas that are both confirmed as containing PV modules and flagged as thermally conspicuous. A flight mission is then generated that revisits exactly these ROIs, at the row-relative distance and viewing angle required for thermographic re-inspection (Fig. 2). The target distance of approximately 20 m corresponds to the maximum ground sample distance of 30 mm per IR pixel required by IEC 62446-3 (IEC, 2017) for module-level thermography.

Fig. 2: Region-of-interest generation from overview IR imagery and anomaly detection, RGB module area detection projected onto the terrain model, 3D modelling with optimal flight path generation

2.2 Pass 2: Targeted thermographic mission and module-level 3D model

The ROI mission acquires RGB and radiometric IR imagery at the thermographic target distance. On this imagery, further AI models detect and segment individual PV modules in both the RGB and the IR domain. Because the modules are now segmented at high resolution and from a closer, more consistent viewing geometry, the software computes a substantially more accurate 3D model of the individual modules in space, including their position, orientation, and extent within the plant layout. This complements existing photogrammetric approaches for the automated detection and tracking of PV modules from 3D UAV remote-sensing data (Cardoso et al., 2024).

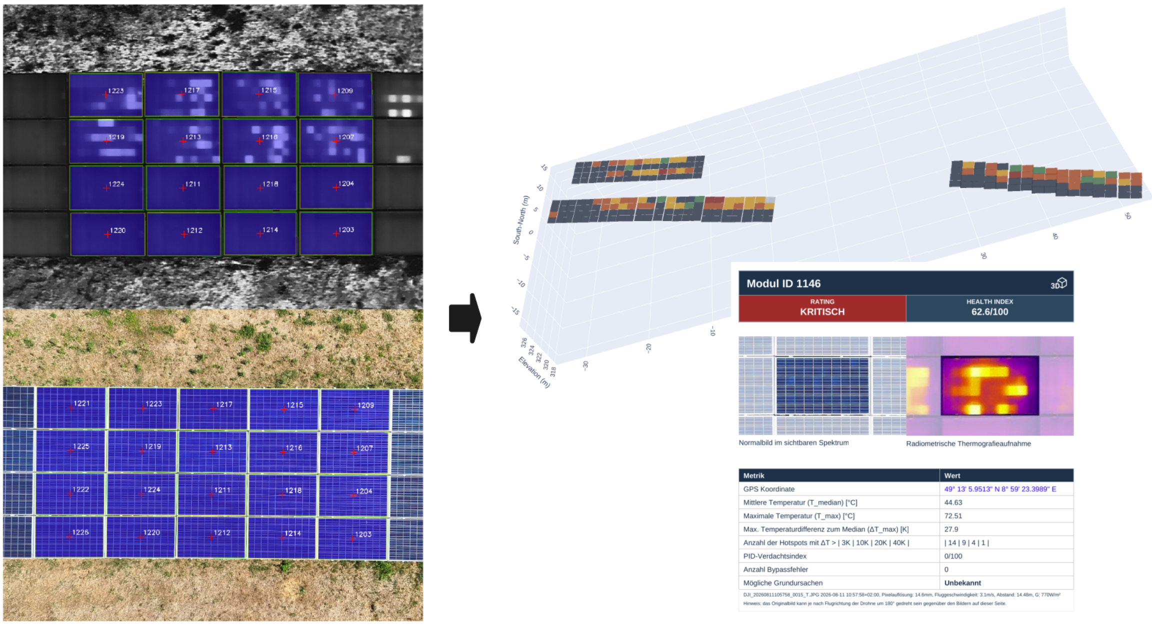

Fig. 3: Direct photogrammetric reconstruction of the module-level 3D model from a single image with known viewing distance: per-image module positions are overlaid and merged into a consistent 3D model of the array. Thermografic analysis for identification of modules of interest.

Two complementary approaches are used to compute this module-level 3D model, depending on which auxiliary information is available during the mission. If the distance to the modules is known and the modules are viewed at a near-perpendicular angle, a direct photogrammetric reconstruction is used: the true-scale 3D position of the segmented modules is computed directly from a single image, using the known viewing distance, focal length, and camera geometry. The per-image module reconstructions are then overlaid and merged into a single, consistent 3D model of the array (Fig. 3).

When this information is not available – for example, without an onboard distance sensor, without a terrain model of the site, or when the modules are not viewed head-on – a disparity-based reconstruction is used instead. Neighboring images are compared to determine the per-module pixel disparity between overlapping views, and the known GPS-derived baseline distance between the corresponding drone positions is then used to project each module, one at a time, into 3D space (Fig. 4).

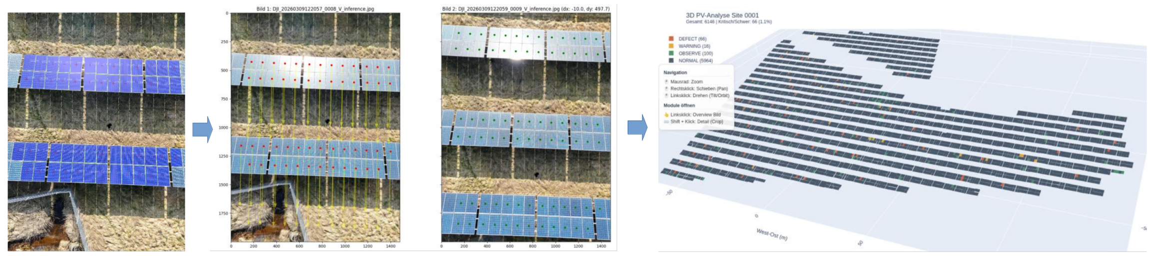

Fig. 4: Disparity-based reconstruction of the module-level 3D model: per-module pixel disparity between neighboring images, combined with the GPS-derived baseline distance between drone positions, projects each module individually into 3D space.

The segmentation of the infrared module area also enables a genuine module-area thermal analysis, in which pixel-level statistics are computed only over the actual active module surface rather than over a coarse bounding region. From this analysis, "modules of interest" are identified: modules exhibiting particularly pronounced or otherwise notable thermal anomalies relative to comparable modules in the same string or array.

2.3 Pass 3: Close-up inspection of modules of interest

In the third pass, the software generates a further mission that exclusively targets the modules of interest identified in Pass 2. The UAV navigates directly to each of these modules and captures dedicated close-up RGB and IR imagery. The resulting images have markedly higher effective resolution per module than the 20 m thermographic imagery (Fig. 5). This is particularly valuable for optically visible defects such as browning, cell defects, or connection faults, which are often difficult to identify reliably at the thermographic distance but become clearly visible in the close-up RGB imagery, complementing the thermal findings from Pass 2.

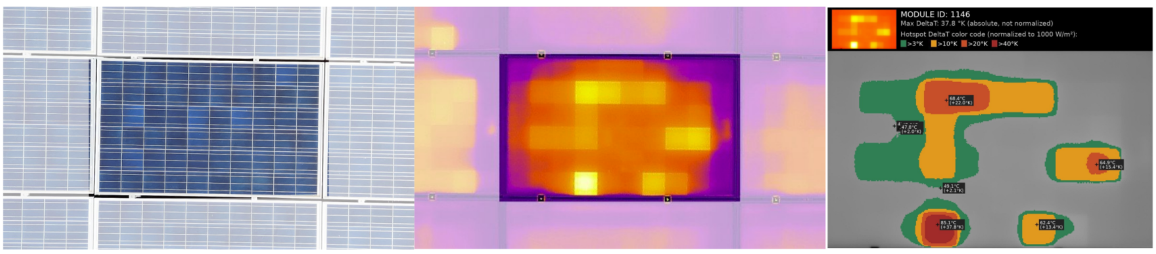

Fig. 5: Close-up RGB and IR imagery of a targeted module of interest, acquired during Pass 3. Ultra-high-resolution pics and thermal analysis.

The results of all three passes are combined into the final inspection report: the overview and ROI mission provide plant-wide context and rating for the majority of modules, while the close-up imagery from Pass 3 is inserted exactly where it is needed, for the specific modules of interest. This gives the report a targeted level of detail – detailed evidence where it matters, and a concise overview where a closer look is not required – without spending flight time or reviewer effort on close-up imagery of the entire plant.

2.4 Mission translation to a flyable format

After each pass, the software translates the computed waypoint sequence, including position, altitude, gimbal orientation, and viewing distance per target, into a DJI-compatible flight mission (KMZ format) that can be uploaded directly to the aircraft's flight controller. This step closes the loop between AI-based analysis and autonomous flight execution without requiring the pilot to manually plan the follow-up mission.

2.5 Rationale: reducing pilot-induced inspection gaps

Manual UAV inspection relies on a pilot who must decide, in real time and under time pressure, which parts of a plant deserve closer attention and which images still need to be captured. In practical experience, this process is error-prone: conspicuous modules are overlooked, planned close-ups are forgotten, or images are captured from an unsuitable distance or angle. These gaps are typically discovered only during office-based evaluation, at which point a further site visit is required. By deriving regions and modules of interest directly and consistently from the acquired imagery, and by automatically generating and uploading the corresponding follow-up missions, the iterative workflow is intended to make the inspection more efficient and more complete, independent of individual pilot attention during the flight.

3. Field Experience and Validation Status

Two levels of validation must be distinguished for this workflow, and the paper reports them separately to avoid overstating the current evidence.

First, the capability to build a georeferenced 3D module model from AI-segmented RGB and IR imagery, and to use it for the spatial localization of thermal findings in the final report, has been applied in more than 150 PV installations in Germany and Switzerland. For every one of these installations, module areas were detected and segmented from the acquired imagery and used to construct the 3D representation that supports the report reader in unambiguously assigning a given thermal finding to a specific module and its position in the plant layout. This large and diverse set of installations provides solid practical evidence for the underlying detection, segmentation, and 3D-mapping capability.

Second, the fully iterative, closed-loop re-inspection workflow described in Section 2 – comprising the overview flight, automated ROI-mission generation, the targeted thermographic pass, automated identification of modules of interest, and the automated close-up mission – has been implemented and field-tested as a working prototype. The test confirmed that the intended sequence of image transfer, on-the-ground AI processing, geometric-model computation, waypoint generation, and mission upload can be executed within a single operational window while the aircraft remains in the field. This demonstrates technical feasibility of the closed loop under real flight conditions. It does not yet constitute a systematic validation across multiple plants, plant types, and environmental conditions, and no controlled measurements of detection accuracy, localization accuracy, or time savings have been collected for the full iterative workflow to date.

4. Discussion and Limitations

The workflow combines several sources of uncertainty that must be considered separately for the two validation levels described above. For the 3D module-model sub-workflow, absolute georeferencing depends on the UAV navigation solution, camera metadata, image geometry, and the quality of the available spatial reference, while the relative assignment of a finding to the correct module has proven reliable in practical use. For the iterative re-inspection workflow, additional uncertainty arises from the automated selection of regions and modules of interest, which depends on detection thresholds, thermal contrast under the prevailing irradiance and wind conditions, and the consistency of viewing geometry between passes.

The AI models are trained on project-specific, self-labelled data; their generalization to unseen module types, mounting structures, climates, defect appearances, and acquisition conditions requires explicit evaluation on held-out data. The current prototype uses YOLO11 models (a segmentation variant for PV area and module segmentation, a detection variant for thermal anomalies). The prototype field test demonstrates feasibility but is not representative of the variability encountered across different plants. Future evaluation should therefore report, per model, precision, recall, and intersection-over-union on independent test data; the positional accuracy of the module-level 3D model; the completeness and correctness of automatically selected regions and modules of interest compared to expert review; end-to-end processing time per pass; and the mission success rate of automatically generated and uploaded flights across multiple plants. A paired comparison between the iterative workflow and a conventional, manually planned single-pass survey would make the claimed efficiency gain testable.

5. Conclusion and Outlook

This work presents an iterative, closed-loop UAV inspection workflow in which AI-based detection of module areas and thermal anomalies is used, within seconds, to compute a geometric model of the plant and to derive and upload targeted follow-up missions. Three coupled passes – plant-level overview, targeted thermographic re-inspection, and module-level close-up – progressively refine the acquired data from a coarse plant view to detailed imagery of the most conspicuous individual modules, without requiring the pilot to manually identify and revisit these locations.

The capability to construct a georeferenced 3D module model from AI-segmented imagery and to use it for defect localization is validated in practice across more than 150 installations in Germany and Switzerland. The fully iterative, three-pass re-inspection workflow, including automated mission generation and translation into DJI-compatible flight files, has been implemented and successfully demonstrated as a working prototype. This iterative flight workflow still needs to be validated in practice across a larger and more diverse set of plants before general performance or efficiency claims can be made. Planned next steps are a systematic multi-plant field study with independent ground truth, quantitative measurement of detection and localization accuracy, comparison of inspection duration and completeness against conventional manually planned flights, and extension of the underlying AI models to a wider range of defect types and site conditions.

6. References

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