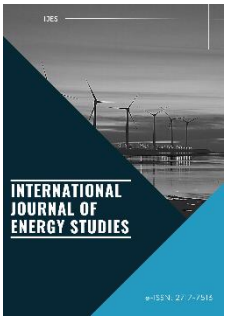
INTERNATIONAL JOURNAL OF ENERGY STUDIES

e-ISSN: 2717-7513 (ONLINE); homepage: https://dergipark.org.tr/en/pub/ijes



Research Article

Int J Energy Studies 2026; 11(3): 2157-2181

DOI: 10.58559/ijes.1961986

Received : 02 June 2026

Revised : 08 July 2026

Accepted : 30 July 2026

Conceptual introduction of a high-resolution image-based defect inspection method for photovoltaic panels

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Highlights

- A low-cost high-resolution image workflow is proposed for PV defect inspection.
- Image enhancement improves visibility of multiple PV surface defect categories.
- Enhanced defect images form a visual layer for future digital twin integration.

You can cite this article as: Çelik KB, Erat ÖÖ, Yeşilata B. Conceptual introduction of a high-resolution image-based defect inspection method for photovoltaic panels. Int J Energy Studies 2026; 11(3): 2157-2181

ABSTRACT

Photovoltaic (PV) systems require accessible and reliable inspection approaches to support quality control and defect diagnosis, especially in settings where advanced imaging systems such as electroluminescence may be unavailable, impractical, or cost-intensive. In this context, the present study introduces a systematic high-resolution image-based inspection workflow for the visual assessment of surface defects in PV panels and positions this workflow as a digital twin-oriented inspection layer rather than a fully synchronized digital twin implementation. Under controlled laboratory lighting conditions, defective PV panel regions were photographed using a high-resolution digital camera, and the acquired images were processed through a systematic enhancement workflow including brightness adjustment, contrast optimization, noise reduction, and edge sharpening. The enhanced images improved the visual interpretability of several visible defect categories, including ribbon deflection, EVA bubbles, uncut cells, cell particles, ribbon-tab defects, visible cell fractures, and non-laminated EVA regions. The findings indicate that high-resolution image enhancement can provide a low-cost and portable visual basis for defect-oriented PV inspection by increasing local contrast and defect readability under controlled conditions. However, the proposed approach functions as a qualitative and modular visual foundation for future digital twin integration, rather than as a complete digital twin system.

Keywords: Photovoltaic defect inspection, Image enhancement, Visual diagnostics, Panel surface anomalies, Digital twin-oriented inspection

INTRODUCTION

Industry 4.0 is usually described by pointing to the key technologies of today and the near future: big data, the internet of things, virtual and augmented reality, additive manufacturing (3D printing), digital design and modeling, artificial intelligence [1], all of which have led to industrial systems that are increasingly autonomous, smart, and highly interconnected [2]. At the core of this transformation, digital twin (DT) technology stands at the forefront of the fourth industrial revolution, offering a bridge between the physical and digital worlds [3]. While the first emergence of the digital twin concept can be traced back to Grieves in 2003 [4], it is also widely accepted that the logic behind the concept was applied earlier by the National Aeronautics and Space Administration (NASA) in the 1960s to simulate and program spacecraft [5]. Today, a Digital Twin is fundamentally conceptualized as an executable virtual model of a physical thing or system [6].

Current literature on DTs can be grouped into distinct analytical lines of research. Taxonomically, based on the integration level of DTs, Kritzinger et al. divided them into three subcategories: Digital Model, Digital Shadow, and Digital Twin [7]. Structurally, DTs can be broadly grouped into Asset Digital Twins (ADTs), which represent discrete assets and System Digital Twins (SDTs), which integrate multiple ADTs [8]. Methodologically, there are two main approaches for processing and interpreting these environments: physics-based modeling and data-driven approaches [9][10]. Across these lines of research, one of the main features that binds most definitions of DT -beyond being a virtual representation of a physical object- is the bidirectional transfer or sharing of data between the physical counterpart and the digital one [11]. In this sense, two characteristics distinguish a digital twin from conventional digital models: first, it represents a specific physical instance rather than a generic class of assets [12], second, it enables a dynamic linkage between physical and digital states [13].

However, applications of DTs diverge heavily across disciplines. Today, engineering and manufacturing predominantly use Digital Twins to provide accurate virtual representations of objects and simulations of operational processes [14]. Traditional simulation models have long supported system optimization when rigorously verified and validated [15][16]. However, purely physics-based digital twin implementations remain difficult to deploy in practice because high-fidelity models are computationally intensive and often unsuitable for real-time operation [17][18].

Despite its long-standing presence in industry, the digital twin (DT) concept remains ambiguous due to the wide variety of definitions and application workflows associated with it [19][20]. In addition, the implementation of hybrid DT architectures that combine physics-based models with data-driven methods remains technically challenging because of issues such as model coupling, calibration, computational cost, and real-time synchronization [21]. The practical effectiveness of DT systems further depends on scalable and seamless communication among heterogeneous hardware and software components [22]. These conceptual and implementation-related challenges indicate that more accessible, application-oriented, and modular approaches are still needed, especially in domains where full-scale DT deployment remains difficult. In this respect, renewable energy systems-and especially photovoltaic applications-represent an important area in which such practical DT-oriented approaches may offer clear value.

As the global demand for clean and renewable energy sources continues to rise, efficiency has become an increasingly critical issue in renewable energy systems because project design, planning, and implementation involve considerable costs related to material, labor, and installation area. Among renewable technologies, solar energy has gained particular importance in recent years, and in photovoltaic systems there is a direct relationship between the electrical energy produced and the total installation area. Although increasing the installation area generally increases the number of panels and therefore total power output, it is also technologically possible to achieve higher performance with fewer panels through improved design, monitoring, and optimization strategies [23]. In addition to design and monitoring strategies, previous photovoltaic performance studies have also emphasized the importance of grid-side power quality assessment and maximum power point tracking under variable irradiance and load conditions, indicating that PV system performance should be evaluated from both operational efficiency and grid-integration perspectives [24][25]. In this context, the extension of digital twin architecture into renewable energy systems offers a promising pathway for more efficient, adaptive, and data-driven PV operation.

The underlying logic of a PV digital twin relies heavily on real-time data ingestion and predictive analytics. Within this workflow, data can flow continuously from the Solar PV Array through SCADA into the digital twin platform [26], while environmental sensors measure variables such as temperature and humidity [27]. Based on twin insights, automated actions such as solar panel cleaning, wildfire risk alerts and efficiency optimization are executed [28]. In addition, to

maximize power output, Sehrawat et al. developed a DT-enhanced solar irradiance forecasting model that improved photovoltaic operational efficiency by leveraging machine learning forecasts of solar input [29]. In this way, DT-based PV systems move beyond passive monitoring and become active decision-support tools for performance management and fault diagnosis [30][31]. Nevertheless, the literature on digital twin applications in solar energy systems remains limited, even though solar deployment is expected to increase noticeably worldwide in the coming years [32]. In particular, portable image-based approaches that support visible defect representation and may later be integrated into broader digital twin architectures remain underdeveloped in the PV literature. In this context, high-resolution photographic inspection offers a portable, low-cost, and flexible route toward a digital twin-oriented visual representation of photovoltaic panel defects.

To clarify the current literature gap and to position the contribution of the present study more explicitly, Table 1 summarizes the main characteristics, limitations, and unresolved needs in digital twin applications for photovoltaic systems.

Table 1. Literature gap and positioning of the present study in Digital Twin applications for photovoltaic systems

Research Theme	**Current State of the Literature**	**Literature Gap**	**Positioning of This Study**
Application Domain and Sectoral Focus	Digital twin (DT) research has predominantly focused on industries such as manufacturing, aerospace, healthcare, smart cities, and architecture/engineering/construction-facility management (AEC-FM) [17]. In renewable energy systems-especially photovoltaic systems-studies typically emphasize functions such as power forecasting or anomaly detection based on time-series and SCADA data [28].	Although the capacity of DT applications in solar energy systems is expected to increase, image-based approaches that directly represent defect-oriented digital twins of PV panels remain highly limited. In particular, methodologies that integrate high-resolution instantaneous images into digital twin-oriented monitoring workflows have not yet been sufficiently developed [33].	This study provides a practical visual inspection foundation for existing renewable energy DT applications by utilizing high-resolution imaging and digital image enhancement techniques to detect and evaluate visible surface defects in PV panels.
Fault Detection and Data Acquisition Method	In industrial systems, fault diagnosis and condition monitoring largely rely on complex IoT networks, vibration analyses, and instantaneous electrical sensor data obtained from power converters (e.g., DC-DC converters) [34][35].	For the examination of structural and surface defects in PV panels, advanced electroluminescence (EL) systems are generally employed. However, the deployment, operation, and maintenance of these systems in remote installations or large-scale solar power plants are considerably challenging [36][37].	To overcome the limitations of conventional visual inspection, this study proposes a digital enhancement method that improves anomaly visibility-such as visible cell fractures, dark spots, and EVA bubbles on PV panel surfaces-by utilizing a standard digital camera (Canon EOS 600D) and open-source software (GIMP).

Table 1. Literature gap and positioning of the present study in Digital Twin applications for photovoltaic systems (Continued)

Research Theme	Current State of the Literature	Literature Gap	Positioning of This Study
Modeling Approach and Computational Cost	DT models are generally categorized into physics-based and data-driven approaches. High-fidelity theoretical physical models often require substantial computational power, making them impractical for real-time applications [17].	The development of hybrid DT architectures that integrate physical simulations with data-driven machine learning components involves significant technical challenges, including model integration, calibration, high computational cost, and real-time data synchronization [17].	Instead of relying on computationally intensive mathematical/physical modeling, this study proposes a practical and accessible conceptual workflow by integrating image-based defect detection with the core principles of digital twins (real-time monitoring, decision support, and data-driven maintenance), thereby enabling direct and efficient decision support.
Field Applicability and System Flexibility	The effectiveness of full-scale DT systems depends not only on scalability but also on the seamless integration of heterogeneous data flows, sensor networks, and software components, which often makes field implementation costly and complex [17].	There is a significant need for flexible evaluation tools that can operate in field conditions and production lines without requiring highly specialized test infrastructures, offering portability, low cost, and autonomous quality control capabilities [36][38][39].	This study positions a high-resolution digital imaging approach-practical instantly without the need for expensive equipment-as a portable and cost-effective complementary inspection option for both production-line quality control processes and field-level diagnostics in hard-to-access environments.
Digital Twins in Renewable Energy (PV Systems)	In PV systems, DT implementations are primarily based on continuous data streams obtained from SCADA systems and environmental sensors (e.g., temperature, humidity), as well as solar irradiance forecasting and automated actions such as panel cleaning and efficiency optimization [29][40][41][42][43]. Advanced design and monitoring approaches enable higher performance with fewer panels [43][44].	Despite the expected significant increase in solar energy capacity in the coming years, studies on the application of DTs in such systems remain limited [45][46]. In particular, image-based, defect-oriented approaches that enable the transition from high-resolution instantaneous photographs to functional digital twins are still underdeveloped [46][47].	By focusing on high-resolution digital imaging for the detection of surface anomalies-such as microcracks, EVA bubbles, and ribbon misalignments in PV panels - this study addresses the lack of visual/digital representation in the literature and provides a defect-oriented visual pathway for future digital twin-oriented inspection modules.

As summarized in Table 1, existing studies on digital twin applications in photovoltaic systems mainly emphasize sensor-based monitoring, predictive analytics, and system-level performance optimization, whereas comparatively limited attention has been paid to portable image-based approaches for panel-level defect representation. Against this background, the present study proposes a low-cost image-based inspection workflow and positions the resulting visual outputs as a modular digital twin-oriented inspection layer for future PV monitoring architectures.

Although advanced inspection techniques such as electroluminescence imaging and infrared thermography provide high diagnostic capability, their deployment often requires specialized equipment, controlled environments, and relatively high operational cost. In contrast, practical field-level and production-line applications frequently require more accessible and portable inspection approaches. To position the proposed workflow within the broader landscape of photovoltaic defect inspection methodologies, Table 2 presents a comparative overview of conventional and image-based inspection approaches.

Table 2. Positioning of the proposed qualitative image-enhancement workflow within existing photovoltaic defect inspection approaches

Method	Cost / Accessibility	Portability	Visible Defect Sensitivity	Subsurface Capability	Operator Dependence
Naked-eye inspection	Very high accessibility / very low cost	Very high	Low to moderate	Very limited	High
Electroluminescence (EL) imaging	Expensive / specialized	Limited	High	Very high	Moderate
Infrared thermography	Moderate to high cost	Moderate	Moderate to high	Indirect hotspot-related capability	Moderate
Proposed high-resolution image-enhancement workflow	Low cost / Accessible	High	Moderate to high for visible defects	Limited	Moderate

As summarized in Table 2, the proposed workflow is positioned as a low-cost, portable, and qualitatively interpretable inspection layer rather than a replacement for advanced subsurface diagnostic systems. While electroluminescence and thermographic techniques provide superior capability for detecting internal or thermally induced anomalies, the proposed image-enhancement

workflow offers a more accessible alternative for preliminary surface-level defect assessment under controlled imaging conditions.

This study makes three main contributions to the emerging intersection of photovoltaic defect inspection and digital twin-oriented monitoring. First, it introduces an accessible high-resolution imaging workflow for the qualitative evaluation of visible surface anomalies in photovoltaic panels. Second, it demonstrates that a structured sequence of image-enhancement operations can improve the visual discernibility of multiple defect categories under controlled laboratory conditions. Third, and more importantly, the novelty of the study lies in positioning the enhanced defect images not merely as processed inspection photographs, but as a modular visual information layer that can support future digital twin-oriented photovoltaic monitoring architectures. Unlike image-based PV inspection studies that primarily focus on defect visualization, algorithmic detection, or classification performance, the present study emphasizes the conceptual integration of enhanced visual defect information into a broader decision-support logic for production-line quality control and preliminary field diagnostics. Therefore, the proposed workflow should be understood as a low-cost, interpretable, and scalable visual foundation for future digital twin integration rather than as a fully synchronized digital twin implementation.

Based on this workflow, the study examines the extent to which low-cost photographic inspection combined with digital image enhancement can provide a practically useful visual basis for defect-oriented photovoltaic panel assessment. Rather than proposing a fully synchronized digital twin implementation, the study positions the resulting workflow as a scalable and application-oriented visual foundation for future integration with data-driven monitoring, machine-assisted analysis, and predictive maintenance environments.

2. EXPERIMENTAL SETUP

The materials and equipment used in this study consisted of photovoltaic panels with visible surface defects, a high-resolution digital imaging system, and computer-based image processing tools. The experimental setup was established to capture detailed visual data from defective PV panel surfaces and to support the development of an image-based digital twin workflow for defect detection and evaluation. Particular attention was given to surface anomalies such as ribbon irregularities, EVA-related defects, fracture-like regions, and local material discontinuities.

Image acquisition was performed using a Canon EOS 600D digital camera equipped with interchangeable Canon EF-S 18–55 mm and Canon EF-S 55–250 mm zoom lenses. The appropriate lens was selected according to the required field of view and imaging distance. During the experiments, the retained photographs were captured at an image resolution of 5202 x 3464 pixels, with an ISO value of 2000, a shutter speed of 1/40 s, an aperture of f/4, and an approximate shooting distance of around 2.3 m from the PV panel surface. The same camera body and controlled lighting conditions were maintained throughout the experimental procedure, while the interchangeable lenses were selected according to the required field of view and imaging distance. This optical configuration provided sufficient magnification and image clarity for the observation of small-scale surface defects on PV panels. A representative faulty photovoltaic panel analyzed in this study is shown in Figure 1.

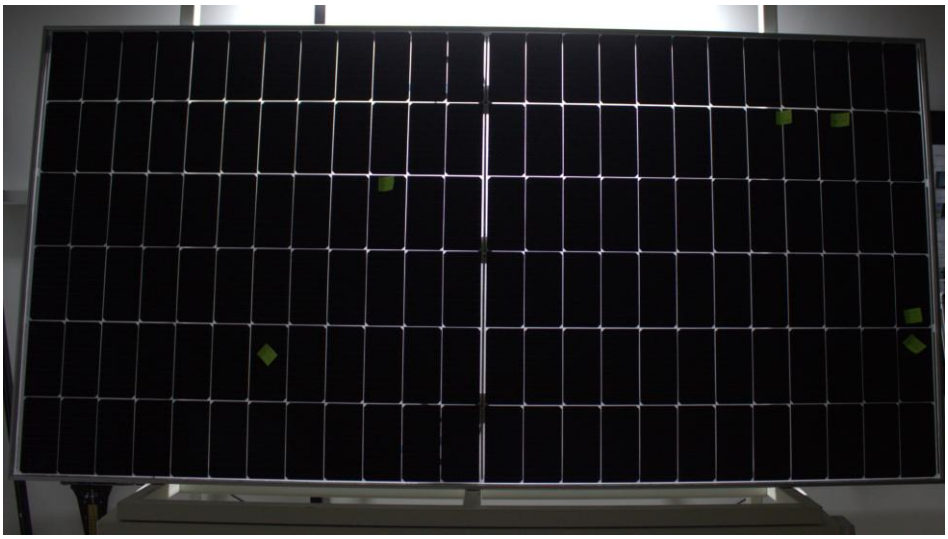

Figure 1. Representative faulty photovoltaic panel used for image-based defect analysis

All photographs were obtained under controlled laboratory lighting conditions to minimize glare, reduce external reflections, and ensure consistency in exposure and image quality. This controlled setup provided a stable basis for subsequent image enhancement and comparative visual analysis. For digital image processing and qualitative visual evaluation, GIMP was employed as the primary 2D image-enhancement platform. The software was used to perform brightness adjustment, contrast optimization, and noise-reduction operations in order to improve the visual discernibility of surface irregularities and defect-related features.

3. METHODOLOGY

The methodology of this study was designed as a systematic image-based workflow for detecting, enhancing, and interpreting visible surface defects on photovoltaic panels within a digital twin-oriented assessment perspective. Rather than relying solely on image capture, the proposed procedure integrates image acquisition, preliminary visual screening, image enhancement, visual/spatial interpretation, and defect-informed evaluation. To improve methodological clarity and to present the sequence of operations in a systematic manner, the overall workflow of the study is shown in Figure 2.



Figure 2. Overall methodological workflow of the proposed image-based inspection procedure

Figure 2 summarizes the sequential workflow progressing from controlled image acquisition to defect-informed qualitative assessment.

3.1. Image Acquisition and Preliminary Visual Screening

In the first stage of the methodology, high-resolution photographs of the photovoltaic panels were acquired in order to establish a reliable visual basis for surface defect identification. The aim of this stage was not only to document the visible condition of the panel surfaces, but also to generate image data suitable for subsequent enhancement and defect-oriented interpretation. Image acquisition was performed using the Canon EOS 600D camera setup described in Section 2. This optical setup provided sufficient magnification and image clarity for observing small-scale surface irregularities on the PV panels under controlled laboratory conditions.

To improve consistency across the dataset, all photographs were obtained under controlled lighting conditions designed to minimize glare, reduce external reflections, and maintain stable exposure. In addition, images were captured from multiple angles and distances in order to increase surface coverage and to support the preliminary identification of defect-prone regions. This stage therefore functioned as both an image acquisition procedure and an initial visual screening process, during which images were retained according to predefined criteria such as focus quality, reflection level, surface coverage, and preliminary visibility of the defect region.

In total, 120 high-resolution photographs were initially acquired under different viewing angles, distances, and lighting configurations. Following the preliminary screening stage, 85 images were retained for further analysis based on predefined selection criteria including focus quality, reflection level, illumination consistency, and visible defect coverage. The retained dataset supported subsequent enhancement and qualitative assessment procedures.
To illustrate the diversity of the defect patterns documented during this stage, representative raw-image examples are presented in Figures 3 and 4.

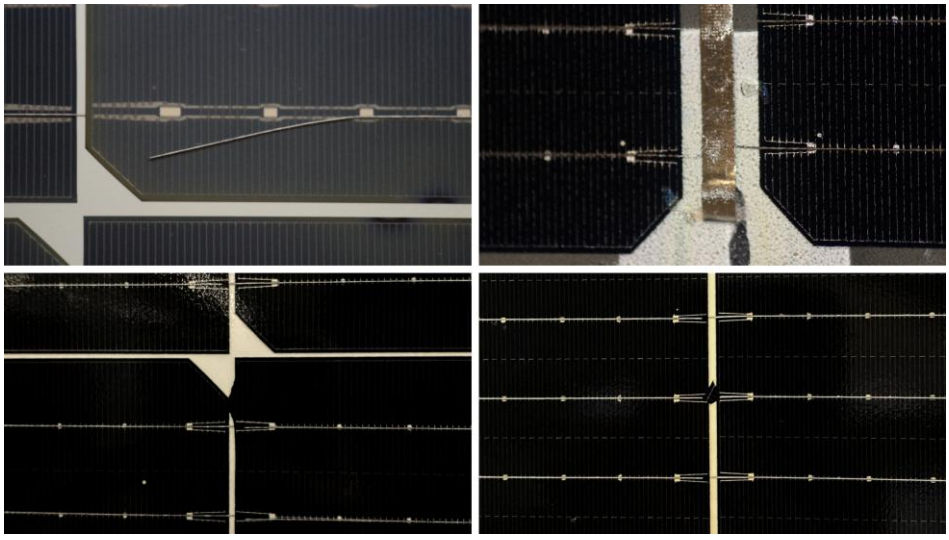

Figure 3. Representative Visible Defect Examples in Raw Images: Ribbon Deflection, EVA Bubble, Uncut Cell, and Cell Particle

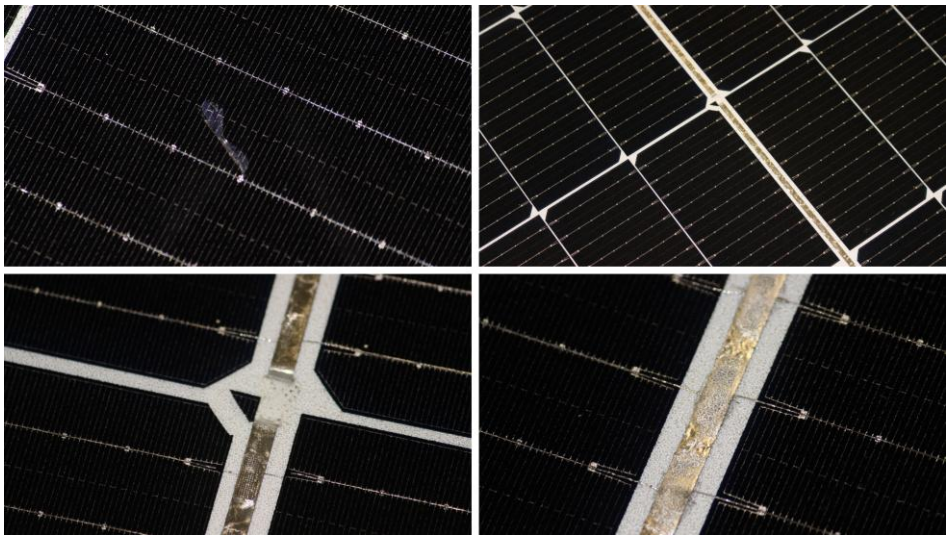

Figure 4. Representative Visible Defect Examples in Raw Images: Ribbon Tab Defect, Visible Cell Fracture, and Non-Laminated EVA

As shown in Figures 3 and 4, the acquired raw images revealed multiple defect categories, including ribbon deflection, EVA bubble formation, uncut cells, cell particles, ribbon tab defects, visible cell fractures, and non-laminated EVA regions. Nevertheless, the visual detectability of these defects was not equally strong in all cases, especially in terms of local contrast and boundary clarity. This limitation provided the methodological basis for the next stage, in which image enhancement techniques were applied to improve defect visibility and support more systematic interpretation.

3.2. Image Enhancement and Defect Identification

In the second stage, the captured images were processed using digital image enhancement techniques in order to strengthen the discernibility of surface irregularities that may not be easily distinguishable under standard visual inspection. GIMP was employed as the primary image-processing tool using a fixed sequence of operations, including brightness adjustment at a parameter level of -5, contrast adjustment at a parameter level of 45, noise reduction using the selected GIMP noise-reduction filter, and edge enhancement using the Sobel filter. The enhancement parameters were selected through preliminary visual trials performed on representative defective panel images. The main criterion for parameter selection was to increase the visibility of defect boundaries and local surface irregularities while avoiding excessive artificial distortion, over-sharpening, or loss of original image characteristics. Instead of optimizing the enhancement parameters for individual images or defect categories, a single set of

processing parameters was applied to the entire dataset. This standardized approach allowed visual differences to be associated with the underlying defect characteristics rather than variations in the image enhancement procedure.

Through this image reprocessing step, the visual detectability of anomalies including ribbon deflection, EVA bubble formation, uncut cells, cell particles, ribbon tab defects, visual cell fractures, and non-laminated EVA regions was improved. The purpose of this stage was not to alter the physical characteristics of the panels, but to improve image diagnostic clarity and support clearer defect localization.

As illustrated in Figures 5 and 6, the enhanced images enabled clearer visual identification of defect type and location on the panel surface. The defect regions are highlighted with red circles to improve readability and facilitate interpretation. To clarify the analytical role of each enhancement step, Table 3 summarizes the image-processing operations applied in this study and their expected contribution to visible defect identification.

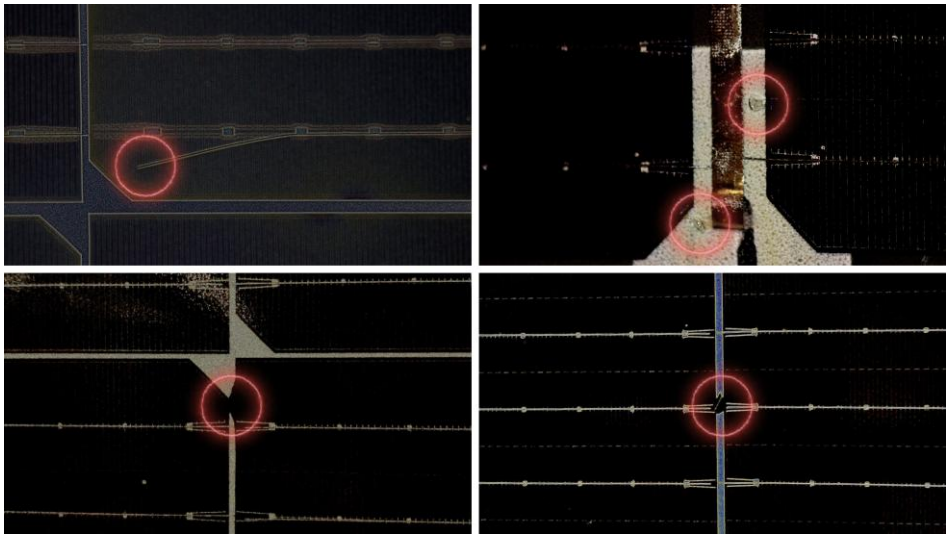

Figure 5. Enhanced counterparts of selected visible defects: ribbon deflection, EVA bubble, uncut cell, and cell particle. Red circles indicate the corresponding defect locations.

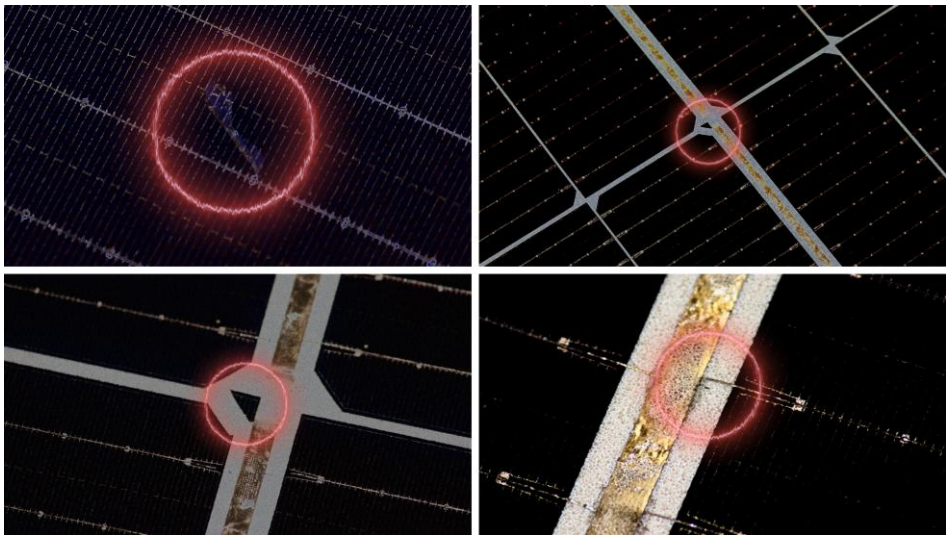

Figure 6. Enhanced counterparts of additional visible defect categories: ribbon tab defect, visible cell fracture, and non-laminated EVA. Red circles indicate the corresponding defect locations.

Table 3. Image enhancement operations and their expected contribution to visible defect identification

Image processing step	**Purpose**	**Expected contribution to defect detection**	**Defect types most visibly affected**
Brightness adjustment	Improve illumination balance	Make dark or low-contrast defects easier to notice	Dark spots, cell fractures, EVA-related anomalies
Contrast optimization	Increase distinction between damaged and intact regions	Strengthen separation of defect boundaries	Ribbon defects, uncut cells, non-laminated EVA
Noise reduction	Suppress visual interference	Improves interpretability of local surface patterns	Small particles, subtle irregularities
Edge enhancement	Clarify structural discontinuities	Makes cracks, line breaks, and borders more distinguishable	Visual cell fractures, connection line breaks, ribbon tab defects

As shown in Table 3, the enhancement workflow primarily improved interpretability by increasing local contrast, clarifying structural discontinuities, and reducing distracting visual noise. These operations did not alter the physical characteristics of the panel; rather, they improved the visual clarity of surface anomalies under controlled imaging conditions.

3.3. Proposed Digital Twin-Oriented Visual Inspection and Decision-Support Workflow

Building upon the visual data obtained through image acquisition and enhancement, this study proposes a digital twin-oriented conceptual decision-support workflow for photovoltaic panel inspection.

In the proposed framework, the enhanced image is not considered a complete digital twin by itself, but rather a visual data object that can be linked to a future cyber-physical PV monitoring environment. In a future implementation, each processed image could be associated with panel-specific metadata such as panel ID, inspection time, defect type, defect location, image acquisition parameters, and operator notes. These visual records could then be stored in a digital inspection database and connected with operational data streams obtained from IoT sensors, SCADA systems, environmental sensors, and inverter-level measurements. Through such an interface, the image-based inspection layer could support the updating of panel condition records, comparison of repeated inspections over time, and integration with maintenance decision-support modules. Therefore, the digital twin relevance of the present workflow lies in its potential role as a structured visual information layer within a broader real-time PV monitoring architecture, rather than in providing direct real-time synchronization in its current form. The main stages of the proposed digital twin-oriented decision-support workflow for photovoltaic panel evaluation are summarized in Table 4.

Table 4. Proposed digital twin-oriented decision-support workflow

Step	Input	Process	Output	Human Role
1. Visual inspection	Physical PV panel	High-resolution image capture	Raw image	Operator initiates capture
2. Image enhancement	Raw image	Brightness, contrast, noise, edge adjustments	Processed image	Operator verifies image quality
3. Defect interpretation	Processed image	Identification of visible defect characteristics	Defect-informed visual assessment	Expert checks plausibility
4. Optional future step: machine-assisted defect classification	Processed image	Automated quality support	Preliminary classification suggestion	Operator reviews suggestion
5. Final evaluation	Visual + assisted interpretation	Decision for inspection, maintenance, or quality grading	Final assessment	Humans make final decision

In this workflow, the processed image is treated as a structured visual representation of the physical panel surface and serves as the basis for defect-informed interpretation. The proposed model is especially relevant to quality control applications in production lines and to field diagnostics in environments where conventional electroluminescence-based inspection systems are not practical. Within the workflow, a panel first enters a visual inspection stage, where a high-resolution image is acquired and digitally enhanced. The processed image is then evaluated to identify visible defect characteristics and, as a possible future extension, may serve as an input for machine-assisted classification of panel condition. In this sense, the proposed workflow follows a hybrid assessment logic in which automated image-based analysis supports, rather than replaces, expert judgment. Such a structure offers a practical basis for faster quality classification, earlier defect recognition, and more accessible defect diagnosis in both production and operational contexts.

Compared with recent artificial intelligence and computer vision-based PV defect inspection systems, which commonly aim to automatically classify defects using annotated image datasets and trained deep learning models, the present workflow has a different scope [48] . It does not attempt to replace AI-based classification frameworks or provide fully automated defect recognition. Instead, it offers a low-cost and interpretable visual preprocessing layer that can improve the readability of defect-related image features before expert evaluation or future machine-assisted analysis. In this respect, the proposed approach may complement AI-based inspection systems by providing enhanced visual inputs and a structured defect-oriented image acquisition workflow, especially in cases where large labeled datasets, computational resources, or fully automated inspection infrastructure are not yet available.

4. RESULTS AND DISCUSSION

The results of the study show that high-resolution imaging and digital image reprocessing were effective in increasing the visibility of surface defects on photovoltaic panels. The acquired and enhanced images revealed several categories of anomalies, including ribbon deflection, EVA bubbles, uncut cells, cell particles, ribbon tab defects, visual cell fractures, and non-laminated EVA regions. Table 5 summarizes the observed defect categories and their qualitative visibility before and after enhancement. The visibility labels reported in Table 5 were assigned based on qualitative expert judgment considering local contrast, boundary clarity, and overall detectability of the defect region within the panel surface. Accordingly, these categories should be interpreted as systematic

qualitative observations rather than statistically validated metrics, and the reported relevance to panel condition is intended only as a literature-informed interpretive indication.

Table 5. Observed visible defect categories and qualitative visibility before/after enhancement

Defect type	**Figure reference**	**Visibility before enhancement**	**Visibility after enhancement**	**Potential relevance to panel condition**
Ribbon deflection	Fig. 3/Fig. 5	Moderate	High	May affect electrical continuity and local performance
EVA bubble	Fig. 3/Fig. 5	Low to moderate	High	May indicate encapsulation-related degradation
Uncut cell	Fig. 3/Fig. 5	Moderate	High	May be associated with manufacturing irregularities
Cell particle	Fig. 3/Fig. 5	Low	Moderate to high	May indicate localized surface anomaly
Ribbon tab defect	Fig. 4/Fig. 6	Moderate	High	May influence interconnection reliability
Visual cell fracture	Fig. 4/Fig. 6	Low to moderate	High	May contribute to efficiency loss over time
Non-laminated EVA	Fig. 4/Fig. 6	Moderate	High	May reflect lamination-related defect formation

As shown in Table 5, the most notable improvements were observed for defects that were initially difficult to distinguish in the raw images, especially EVA bubbles and visible cell fractures. Ribbon-related and lamination-related anomalies also became easier to localize after enhancement. Overall, these findings indicate that relatively simple image-processing operations appear to improve the interpretability of visible PV panel defects under controlled imaging conditions.

Although quantitative image-quality metrics were not calculated in the present conceptual study, future validation of the proposed workflow should include objective indicators to support the qualitative observations reported here. For example, local contrast ratios, contrast enhancement ratios, or defect-to-background intensity differences could be used to quantify the improvement in defect visibility after enhancement. Entropy and histogram-based analyses may also be used to evaluate changes in information content and tonal distribution between raw and enhanced images. In addition, metrics such as peak signal-to-noise ratio (PSNR) and structural similarity index measure (SSIM) could help assess whether the enhancement process improves defect readability without excessively altering the original image structure. The inclusion of such metrics in future

work would provide a more objective basis for comparing raw and enhanced images and for validating the workflow across larger datasets, different panel types, and variable imaging conditions.

The results of this study indicate that high-resolution photographic inspection, when combined with a systematic image-enhancement workflow, was observed to improve the visual interpretability of several visible surface defects in photovoltaic panels. The main value of the proposed approach lies not in replacing established diagnostic techniques, but in supporting earlier recognition of defect-prone regions through a low-cost image-based inspection workflow. In this respect, the workflow may be particularly useful for rapid screening, production-line quality control, and preliminary field diagnostics in environments where advanced electroluminescence-based systems remain impractical or cost-intensive.

A key implication of the findings is that relatively simple enhancement operations can make visually subtle anomalies easier to localize and interpret. Defects such as EVA bubbles, visible cell fractures, ribbon-related irregularities, and non-laminated regions became easier to distinguish after preprocessing, suggesting that enhancement procedures can strengthen the diagnostic clarity of standard photographic inspection.

At the same time, the study should be interpreted within its intended scope. The proposed workflow is qualitative and limited to visible surface features captured under controlled laboratory lighting. Therefore, its direct applicability to outdoor field conditions may be affected by uncontrolled illumination, changing solar incidence angles, shadows, dust accumulation, surface contamination, glare, and reflections from the glass surface of PV modules. These factors may reduce local contrast, obscure defect boundaries, or generate image artifacts that can be misinterpreted as surface anomalies. In addition, variations in camera angle, shooting distance, environmental brightness, and imaging hardware (including the camera lens and its optical characteristics) may influence image quality and, consequently, the consistency of the enhancement results. The present study does not provide direct electrical performance measurements, subsurface failure detection, or full physical-digital synchronization. Instead, the suggested procedure should be understood as a modular DT-compatible inspection component that may later be integrated with sensor data, expert-informed interpretation, and machine-assisted defect classification environments.

The study also has methodological limitations that define a clear agenda for future work. First, broader validation across larger image sets, additional panel types, and more diverse lighting conditions is necessary. Second, the qualitative interpretation of visible defects should be supported in future studies by systematic scoring, inter-reviewer agreement analysis, or basic image-quality metrics. Third, the practical transition from visual inspection outputs to functional digital twin environments will require stronger integration with operational data, fault history, and predictive maintenance logic. Overall, the findings suggest that image-enhanced visual inspection may provide a practical transition layer between conventional panel assessment and future data-driven photovoltaic monitoring architectures.

5. CONCLUSION

In a controlled laboratory setting, this study demonstrated a low-cost, high-resolution image-based inspection procedure for the qualitative evaluation of apparent surface irregularities in solar panels. The study presented a modular visual inspection layer designed to assist future digital twin-oriented monitoring and decision-support environments instead of suggesting a completely synchronized digital twin implementation.

The findings suggest that multiple categories of surface-related anomalies, such as ribbon irregularities, localized surface discontinuities, and non-uniform structural areas, may be made more visually discernible using structured image-enhancement processes. In this regard, the proposed workflow shows how accessible photographic inspection techniques may support defect-oriented solar panel evaluation without the need for specialist subsurface imaging tools.

The processed panel images obtained through enhancement may support future integration with sensor-assisted monitoring and machine-supported diagnostic environments. From this perspective, the proposed workflow may provide a scalable visual basis for further integration with sensor-supported monitoring structures, machine-assisted fault categorization, and predictive maintenance frameworks.

However, under standardized imaging settings, the current study is purposefully restricted to qualitative image-based interpretation. Real-time synchronization, automatic categorization, quantitative deterioration modeling, and operational sensor fusion are not included in the study. Therefore, for advanced photovoltaic digital twin settings, future research should concentrate on

bigger and more varied datasets, quantitative image-quality evaluation criteria, multimodal inspection integration, and real-time cyber-physical synchronization mechanisms.

Overall, the study indicates that portable and low-cost visual inspection workflows could be a useful first step in the larger development of digital twin-assisted photovoltaic monitoring systems, especially in applications where low deployment costs, accessibility, and interpretability are important factors.

DECLARATION ON THE USE OF GENERATIVE AI

ChatGPT was used for generating an illustrative visual used in the manuscript.

NOMENCLATURE

AEC-FM: Architecture, Engineering, Construction and Facility Management
ADT: Asset Digital Twin
AI: Artificial Intelligence
DC-DC: Direct Current to Direct Current
DT: Digital Twin
EL: Electroluminescence
EVA: Ethylene-Vinyl Acetate
GIMP: GNU Image Manipulation Program
IoT: Internet of Things
ISO: International Organization for Standardization
NASA: National Aeronautics and Space Administration
PSNR: Peak Signal-to-Noise Ratio
PV: Photovoltaic
SCADA: Supervisory Control and Data Acquisition
SDT: System Digital Twin
SSIM: Structural Similarity Index Measure
2D: Two-dimensional

ACKNOWLEDGMENT

The first author, Kaan Berk Çelik, received TÜBİTAK BİDEB BSc Student Graduation Project support (under contract number of 1919B012314529) for this work.

DECLARATION OF ETHICAL STANDARDS

The authors of the paper submitted declare that nothing which is necessary for achieving the paper requires ethical committee and/or legal-special permissions.

CONTRIBUTION OF THE AUTHORS

Kaan Berk Çelik: Performed the experimental work, image acquisition and processing, analysed the results, and contributed to the preparation of the manuscript.

Ömer Önder Erat: Contributed to the conceptualization and methodology of the study, supervised the research, interpreted the results, and reviewed and edited the manuscript.

Bülent Yeşilata: Contributed to the conceptual development of the study, provided scientific supervision and critical evaluation, and reviewed and edited the manuscript.

CONFLICT OF INTEREST

There is no conflict of interest in this study.

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