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Defect inspection of photovoltaic solar modules using aerial electroluminescence (EL): A review

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ABSTRACT

In recent years, aerial defect inspection methods have emerged as cost-efficient and rapid approaches, proving to be reliable techniques for detecting failures in photovoltaic (PV) systems. These methods are designed to swiftly conduct comprehensive monitoring of PV power plants, spanning from the commissioning phase to the entire operational lifetime. This paper presents a literature review on reported the aerial EL framework for PV system inspection. EL inspection on PV modules can be used to detect of defects, cracks, shunting, etc., with the aim of assisting to overcome any possible future major breakdown in the modules. While there are comprehensive review articles covering subjects such as infrared thermography (IRT), digital image processing (DIP), EL inspection classification, and deep learning techniques, there is currently no focused review exclusively on aerial EL inspection. In this mini review, we delve into the latest articles on aerial EL inspection, highlighting both the advantages and drawbacks of this technique. The contribution of this paper is to provide a focused review of the aerial EL inspection technique as a cutting-edge solution for evaluating module quality and identifying defective modules or problem areas.

1. Introduction

Growing awareness of environmental issues worldwide has led to a surge in interest in renewable energy sources, among which solar energy stands out as a particularly promising option.

Concurrently, the market for solar PV plants is experiencing a robust increase, drawing keen interest from both researchers and governments, amid fierce competition within the PV sector.

In this regard, efforts should be concentrated on three pivotal areas: enhancing conversion efficiency, lowering costs, and improving reliability through fault mitigation, which can arise at any stage from manufacturing and transportation to assembly and operation.

Notably, PV modules can develop a range of defects due to inadequate sorting of electrical performance in the manufacturing process, improper handling during transportation and installation, and intense thermo-mechanical stresses throughout their operational lifespan, if promptly detected, can be rectified to prevent significant reductions in energy output and potential safety hazards.

Therefore, this necessitates advanced research and development in areas such as reliability and efficiency optimization, fault detection and diagnosis, and maintenance, especially for PV modules. In response, extensive studies and technical analyses have been conducted, employing various detection methods through both indoor and outdoor testing [1,2].

The International Energy Agency (IEA) projects that by 2030, sustainable energy will make up 30 % of global power production, reaching 50 % by 2040. Solar PV energy is expected to contribute 10 % and 20 % of this total, respectively [1].

Currently, identifying and diagnosing problems in large-scale systems, particularly in real-world settings, is a major challenge. This has led scientists to propose various inspection techniques, which can be broadly categorized into imaging-based methods, such as infrared thermography and EL, and electrical testing methods, such as voltage and current analysis. While voltage/current methods can identify a wide range of issues, they are invasive and often struggle to pinpoint the exact location of faults, which is crucial for large solar installations. On the other hand, camera-based inspections benefit from advances in robotics and drones, providing quick fault detection and accurate localization. With the use of drones and sophisticated processors, monitoring capabilities have improved, leading to better fault detection and localization [2–5]. Numerous scholarly review articles have delved into the latest methods for identifying defects in solar modules.

A notable contribution by Mahdi et al. [6] offers an in-depth review of cutting-edge research aimed at understanding PV system failures,

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categorizing them, and pinpointing their origins across the spectrum of PV module components, from the protective glass to the junction box. Similarly, Hijjawi et al. [7] explored various data analysis techniques for automated defect detection in solar photovoltaic systems, focusing on the primary categories of imaging-based and electrical testing methods. Meribout et al. [1] provided a comprehensive overview of advanced fault detection techniques for solar panels, further elucidating the underlying principles of these methods. In a similar vein, Puranik et al. [8] discussed advancements in module-level quantitative EL imaging for crystalline silicon PV modules.

In addition, Mansouri et al. [9] concentrated solely on the application of Deep Learning (DL) in fault diagnosis and detection within PV systems, evaluating the methodology and five principal architectures: stacked autoencoder network, deep belief network, Convolutional Neural Network (CNN), recurrent neural network, and deep transfer learning.

Moreover, Rana and Arora [10] reviewed Machine Learning (ML)-based strategies for detecting surface defects on solar cells, focusing exclusively on imaging techniques. Al-Mashhadani et al. [11] similarly examined DL-based research employing only imaging methods.

In turn, Oliveira et al. [12] dedicated their review to aerial IRT for inspecting PV plants, while Herraiz et al. [13] focused on the use of solar thermography for PV plant condition monitoring. Additionally, Mellit et al. [14] analyzed electrical testing methods for diagnosing faults, particularly within PV arrays. Finally, Triki-Lahiani et al. [15] investigated fault detection and monitoring systems, emphasizing electrical signal analysis and circuit simulation techniques. The most recent review by Tanda and Migliazzi [16] presented two distinct techniques for aerial infrared thermography (aIRT) inspection of PV plants, utilizing remote sensing via unmanned aerial vehicles (UAVs) and aircraft platforms.

Their comparative results showed that inspections with airplanes equipped with high-speed thermal cameras closely aligned with routine monitoring by UAVs using standard, uncooled thermal cameras in detecting thermal defects at two PV installations. In contrast, the primary aim of this review paper is to synthesize and analyze existing methodologies and findings related to aerial EL inspection for photovoltaic modules, rather than proposing a novel methodology. By consolidating recent studies, the paper provides a focused review of the current state of knowledge, identifies key research gaps, and discusses challenges and opportunities for future developments in the field. Unlike previous reviews that briefly address multiple techniques, this paper focuses specifically on aerial EL inspection, critically examining its use for evaluating module quality, detecting faults, and identifying problem areas. The advantages and limitations of this state-of-the-art technique are also evaluated, making this review a valuable reference for researchers and industry professionals.

The structured approach used to identify and analyze relevant studies is outlined in the subsequent sections. The 'Technology and Components for Aerial EL Inspection' section discusses the technology used, including drones and cameras. The 'Aerial Inspection Planning and Data Collection' section outlines the drone routes over photovoltaic arrays to ensure complete coverage of all modules under various conditions. The 'EL Image Analysis' section addresses different types and classifications of defects. Finally, the 'Results' and 'Conclusion' sections are reorganized to discuss both the current and future applications of the drone-based EL method.

2. Technology and Components for Aerial EL inspection

This section discusses the components used in aerial EL inspections, including UAVs and their various types, along with the associated challenges, benefits, and limitations. Additionally, we explore the different types of cameras suitable for aerial EL imaging and briefly touch upon the power supply requirements.

2.1. Unmanned aerial vehicles (UAVs)

The use of UAVs for monitoring and inspection in the PV industry has gained significant attention in recent years due to their potential to improve cost-effectiveness, accuracy, speed, and efficiency. To briefly explain UAVs, there are different types, including fixed-wing and multi-rotor UAVs. Fixed-Wing UAVs are designed to fly like airplanes, featuring wings that provide lift and a tail section for stability and control. These UAVs are typically larger and more complex than their rotary-wing counterparts and require a runway or another smooth, flat surface for take-off and landing.

On the other hand, Multi-Rotor UAVs, also known as quadrotors or quadcopters, are characterized by their use of multiple rotor usually four to lift and propel the aircraft. These UAVs can vary based on the number of rotors, such as hexacopters (six rotors) or octocopters (eight rotors). They are further categorized by size and payload capacity, with larger, more powerful models capable of carrying heavier payloads like high-resolution cameras or specialized sensors.

While multi-rotor UAVs are highly agile, able to hover in place, and easy to deploy and operate by a single person, making them cost-effective, they generally offer less range and speed compared to fixed-wing UAVs. Moreover, they are typically less efficient, have shorter flight times, and their payload capacity is usually more limited.

Despite the potential benefits of using UAVs, there are still some challenges and limitations that need to be addressed, including regulatory and legal issues, technical limitations, data processing challenges, training and expertise, and safety concerns. To overcome these issues, a collaborative effort between industry stakeholders, regulatory agencies, and academic researchers is required. Using UAVs for inspection is subject to a complex set of regulations and laws, which can vary depending on country or region. Regulatory bodies typically impose requirements related to pilot certification, UAV registration, flight restrictions, and data privacy, restrictions on flying over certain areas, such as airports or prisons. One of the primary technical limitations of UAVs is their limited flight time. Most commercial UAVs can only fly for approximately 20–30 min, restricting the amount of data that can be collected in a single flight [17]. Another issue affecting the effectiveness of UAVs inspections is weather conditions. Rain, high winds, and other adverse weather can make it difficult or unsafe to fly UAVs, hindering the ability to obtain timely and accurate data [18]. However, UAV imaging has emerged as a noteworthy technique due to its cost-effectiveness, accuracy, and speed, especially in solar module defect inspection using aerial EL imaging systems, which will be discussed in the next section.

2.2. Camera types for aerial EL imaging

EL imaging is a particularly useful method of quality control of solar modules. When an external electric field is introduced, solar cells reverse bias and generate light which is mostly in the near-infrared (NIR) region. For most widely used crystalline silicon solar cells, the EL emission is within range from near 900 nm to about 1300 nm with a notable peak at 1150 nm. It is due to the recombination of the charge carriers that are made within the solar cell material, the energy is emitted in form of photons. For other solar cell technologies including thin film, the spectrum of emission may be a bit different but still falls under the NIR emissions [19].

Since EL light falls outside the visible spectrum and is instead within the NIR range, EL images used for analysis and defect detection are captured using NIR-sensitive charge-coupled device (CCD) cameras, complementary metal-oxide-semiconductor (CMOS) silicon cameras, or indium gallium arsenide (InGaAs) camera chips [19,20]. Each camera detector has its own advantages and limitations, such as resolution, exposure time, and other factors. This diversity in camera detectors reflects the broader range of sensors and optimization procedures that have been developed, each offering distinct characteristics in terms of sensitivity, resolution, cost, and spectral response [21]. To enhance EL imaging, coatings or lenses can be applied to increase quantum efficiency, while filters are typically used to block unwanted light and isolate the light emitted from the solar cells at specific wavelengths [21]. A long-pass filter with a cut-on of 850–950 nm is typically encumbered for crystalline silicon cells while a band pass filter of about 1150 nm can be used for more precise imaging. For thin-film modules, filter selection is varied by the nature of the material's emission. EL imaging is a very disruptive and rapidly worn process in that it provides a unique level of detail about the structures of solar modules, making it possible to identify and locate all of the defects with impeccable precision. This enables adverse operators to target the areas that need to be dealt with, repaired or maintained, which in turn enhances the operability and service life of the solar modules [22]. Additionally, the camera angle should be adjustable, and the UAV should be equipped with a GPS-guided system to precisely determine its position.

2.3. Power supply

A DC power supply capable of delivering the short-circuit current (I_{SC}) of the module, or a series string of cells or modules being imaged, is essential for EL inspections. The power supply must provide sufficient voltage to achieve the I_{SC}. Depending on the module technology, the required voltage may be approximately equal to the module's open-circuit voltage (V_{OC}), but it can be significantly higher for certain PV modules, such as those utilizing thin-film technology [23,24].

In fact, one of the major challenges in performing rapid EL measurements is providing the necessary power supply to energize the PV string. Modern PV modules, typically rated at 400–500 Wp, and strings comprising up to 30 modules, require power supplies exceeding 15 kW to power a single PV string. The current used in EL measurements usually ranges from 0.5 to 1 times the short-circuit current of the modules. Consequently, a suitable DC power supply unit must be programmable and meet the specifications of 0–15 A, 0–1.5 kV, and 0–15 kW [25]. Meanwhile, the power supply can be sourced either from a 3-phase grid connection or a mobile petrol generator transported to the PV installation. However, future advancements may alleviate this limitation as some inverter manufacturers develop new models capable of powering individual strings, potentially accelerating EL inspections and reducing costs. In this regard, to enhance throughput and lower costs for night-time EL imaging, high-power multiplexer-switch systems can connect up to 100 strings to a single power source. Wiring is typically pre-installed to avoid re-wiring in the dark, with power switched between strings via remote control during measurements.

Connecting these systems to the PV installation requires a certified electrician [26]. Therefore, a power supply integrated with a multi-box system is highly recommended to address the limited flight duration of the UAV [27].

The following section explains aerial inspection planning and data collection, and the subsequent part will describe the aerial EL image.

3. Aerial inspection planning and data collection

In the following subsections, the aerial EL imaging technique and its methods are explored. The discussion is divided into two parts: night-time aerial EL imaging and daytime aerial EL imaging, each addressing specific applications and considerations for these timeframes. This section also covers aerial inspection planning, highlighting the importance of route planning for complete coverage of photovoltaic arrays, the impact of weather conditions, and the optimal times for conducting EL inspections.

3.1. Aerial EL imaging

EL imaging is a precise technique for identifying defects in PV modules, such as cracks and broken connections. However, it's mainly used indoors or outdoors at night since sunlight greatly overpowers the silicon luminescence signal. This constraint limits its utility for large-scale inspections, highlighting the need for developing tools for efficient outdoor EL imaging [28].

Currently, Unmanned Aerial Vehicles (UAVs) or Systems (UASs) are increasingly utilized for equipment inspections across a variety of sectors such as civil engineering, environmental surveillance, disaster relief, and more, extending to energy infrastructure and power plant inspection. Their appeal lies in their lightweight design, cost-effectiveness, comprehensive area coverage, swift monitoring capabilities, and ability to carry diverse cameras and sensors for precise data collection and malfunction identification. Specifically, their effectiveness in providing real-time imagery and their capability to fly close to objects at low speeds enhance their suitability for detailed inspections, including PV system monitoring, making them a pivotal tool in modern reconnaissance operations [29–32].

Over the years, numerous researchers have diligently explored the utilization of UAVs in various methodologies, notably including thermal imaging and visual cameras. Extraordinary contributions in this field include the work of Aghaei et al. [33], Leva et al. [34], and others [35–45], extending to infrared measurement techniques by Addabbo et al. [46] and in other articles [47–49] and digital mapping innovations and real-time inspection by Grimaccia et al. [50] and other researchers [51–54]. Additionally, Ozer and Türkmen [55] focused on developing an AI-based drone as a cost-effective and functional method for detecting dusty, damaged, and normal solar panels. These studies collectively demonstrate the application of lightweight UAVs equipped with thermal and visual cameras for the inspection of photovoltaic systems, revealing a broad range of potential defects.

The integration of thermal imaging and visual inspections via UAVs has proven to be a significant advancement in monitoring the health of photovoltaic plants. These techniques facilitate extensive area coverage and provide a detailed assessment of PV systems' conditions. Through visual monitoring, a diverse array of defects such as discoloration, lamination problems, the presence of bubbles, glass cracks, yellowing, misalignment, and even oxidation and corrosion in connectors have been identified.

Despite significant advances in defect detection through innovative approaches, challenges persist, with reports of abnormal degradation rates in PV modules. These issues stem from various failures, including cracks, breaks, interrupted contacts, and process failures such as shunts or defects in the anti-reflection layer. Notably, EL imaging has emerged as a potent technique for detecting such failures, as highlighted in recent studies [56,57]. Consequently, aerial EL imaging has become a powerful tool for outdoor defect inspection in PV solar modules, applicable both during the day and at night.

In a typical UAV inspection system for large-scale photovoltaic farms, it is essential to capture images of all PV modules and accurately identify those with defects using efficient image processing techniques.

Without an effective path generation algorithm, simply following a series of waypoints may result in unsatisfactory image acquisition, potentially missing areas that require inspection [58]. Performing a drone EL inspection requires a methodical approach to ensure both safety and accuracy. Key considerations include monitoring weather conditions to ensure drone stability and selecting an appropriate time with low ambient light, such as early morning, late evening, or night-time. Start by preparing the drone to ensure it is in optimal condition. Then, conduct a site assessment to design the flight path and identify potential hazards. Before proceeding, de-energize the solar array by turning off the AC switch, disconnecting the DC circuit breaker, and isolating the array from the combiner box. Each array should then be connected to an external power supply to induce EL. Once energized, the drone can be deployed to capture high-resolution EL images of the solar modules. Maintaining a consistent altitude and ensuring sufficient image overlap are crucial for effective drone-based inspections, as is the association between the incidence angle and the selection of appropriate imaging methods. Once the inspection is complete, power should be safely shut off, the arrays reconnected to the combiner box, and the system restored.

There are two primary methods for drone-based inspections.

- **Stop and Go:** This method involves flying the drone over the modules and pausing above each individual PV module to capture images.
- **Drone Scan:** This method involves flying the drone continuously across an entire PV string, capturing EL images without stopping.

These inspection methods highlight the essential role of UAV technology in enhancing diagnostic capabilities for photovoltaic systems. By employing these techniques, we can achieve more reliable and efficient energy production, demonstrating the significant advancements in UAV technology and its impact on photovoltaic system diagnostics [57]. To review aerial EL imaging, the following subsections address nighttime and daytime aerial EL imaging, each presenting unique advantages and considerations.

3.1.1. *Nighttime aerial EL imaging*

In 2016, Koch et al. [59] examined the use of EL scanning as an effective method for identifying defects in solar cells and modules. They proposed utilizing a drone to capture EL videos of solar plants, presenting a promising solution for comprehensive investigations of entire solar plants. Their research included a comparative analysis of manual inspections at ground level including a manual ground-level inspections consist of the scanning of PV modules by means of fixed EL cameras on portable constructions, which are manually moved by field engineers and a tripod system consists of one tripod and one camera or multiple cameras versus drone-based aerial methods, aiming to highlight the advantages of employing UAVs in such contexts. They demonstrated that ground-level inspections are not only inapplicable for large-scale analysis but also very time-consuming [59,60]. They developed through collaboration with Fladung Aerial PV Inspection, utilizes an octocopter drone outfitted with a high-resolution, remotely adjustable EL camera. The drone was capable of capturing images ranging from individual module shots to comprehensive plant overviews, with flight altitude easily adjustable to accommodate varying needs. However, challenges arise from solar winds, which can disrupt the drone's GPS navigation, leading to issues with positional stability and occasional image blurring.

These researchers mentioned that for drone based EL analysis, the brief flight duration necessitates rapid switching between strings, prompting the requirement for an automated, wirelessly controlled power supply. Given the limited flight times, hovering around 60 min, maximizing the number of shots taken becomes imperative. They indicated that the drone, in combination with the string boxes which enable connection of up to 100 module strings (500 kWp), makes it possible to measure up to 1 MW per night [59]. In turn, Oliveira et al. [61] designed and utilized a low-cost drone equipped with EL imaging and a lower-quality camera to detect faults quickly and efficiently. They designed and utilized a low-cost drone equipped with EL imaging setup involving a GoPro HERO 3 Plus Black® camera mounted on a DJI Phantom 4 Pro drone to detect faults. The drone's original camera was replaced with the GoPro using a tripod mounting buckle, allowing angle adjustments in sync with the tilt of the PV modules. The GoPro's CMOS sensor, which initially had low quantum efficiency for the emission range of crystalline silicon PV modules, was modified by removing its infrared filter to capture electroluminescent effects.

Their experimental setup involved eight multi-Si, double-glass, frameless 325 Wp PV modules set to a horizontal alignment. They used a 6 kW power supply to energize one string at a time for their proposed method to emit EL radiation. The UAV typically flies for 20 min, but it was reduced to 15 min due to the added weight of the GoPro setup. They used manual route planning at an altitude of 2 m, and according to their results, it is possible to inspect thousands of modules on a single battery.

In this regard, according to various published research studies on silicon camera-based drone EL inspection, where individual module EL images are extracted from recorded videos, approximately 150–300 modules can be inspected per drone per hour. This estimate accounts for the time needed to swap out drone batteries, which typically last around 20 min per charge. By increasing flight speeds, faster image acquisition is possible, albeit at a lower image quality that suffices for Potential-Induced Degradation (PID) detection but not for identifying smaller features. In contrast, an InGaAs camera-based drone EL system can inspect about 1200–1500 modules per hour, achieving an average of 12,000 module inspections per night. This increased speed is facilitated by the use of short exposure times (less than 5 ms), automated route planning based on site layout, and autonomous drone piloting and PV string scanning [26,62,63]. In term of rout planning, Moradi Sizkouhi et al. [62] proposed an automatic boundary extraction method for large PV installations using a fully convolutional network (FCN). This method utilized RGB aerial images from PV plants worldwide and was based on a Mask R-CNN architecture with a fine-tuned VGG-16 model for precise boundary detection. Pérez-González et al. [64] proposed coverage path planning (CPP) methods for automating UAV flight paths in PV plants. They utilized a DL server to segment the region of interest in each PV plant image and compared three CPP techniques: boustrophedon exact cellular decomposition, grid-based spanning tree coverage, and wavefront coverage. The results indicated that the boustrophedon exact cellular decomposition and grid-based wavefront coverage methods were the most effective approaches. Xi et al. [65] developed a vision-based inspection strategy using an autonomous UAV, tailored for large-scale PV farms. The strategy encompassed three main components: mission area acquisition, line detection and calculation, and velocity control. Boundary information was initially obtained from design drawings, GPS, and aerial images, supplemented by geographic information system (GIS) data. This information was used to derive the "Regional Polygons" of the PV plant and establish a starting point based on the northern or southern vertices of these polygons. For line detection, RGB images were converted to Hue, Saturation, and Value (HSV), and edges of PV strings were extracted using the Canny edge detector. The Hough transformation was then employed to identify straight lines, and the slope and offset of the edge lines were estimated. Velocity control during tracking and turning was adjusted to minimize deviation from the image center and ensure accurate tracking of PV strings.

In line with this approach, Livera et al. (2023) [66] recently introduced a decision-making platform for UAVs designed specifically for precise diagnosis and optimal operation and maintenance (O&M) of PV plants. The UAV systems they employed have a maximum take-off weight (MTOW) of 9 kg and can hover for approximately 30 min when equipped with both thermal (H20T) and EL payloads. Their experimental results were gathered from a PV power plant with a capacity of 772.8 kWp, located in Santa Marta, Spain. The study site consists of 800 monocrystalline PV modules, each capable of generating a peak power output of 375 Wp at 24 V. For the flight planning application, they also developed a user-friendly graphical user interface (GUI).

The captured EL images were subsequently processed using bespoke diagnostic algorithms. The findings underscored the efficacy of the integrated algorithms in identifying potential issues such as PID, cracks, bypass diode failures, and malfunctioning cells within the tested PV modules, including pinpointing the problematic cell locations. The algorithm processed a total of 100 EL images showcasing various defects, achieving an average precision rate of 89 %.

In 2024, Bakır [67] conducted a comparative study of UAV-based EL inspection and Infrared Thermal Imaging (IRT) for panel failure detection. The study analyzed panel failures using the EL test, renowned for its high reliability in detecting micro-cracks, identifying 11 failures. The EL imaging conditions were as follows: applied voltage of 49 V, applied current of 2 A, camera resolution of 6000x4000 pixels, and focus length

Table 1
Comparison of the number of solar modules inspected per hour using different EL inspection methods.

Study	Number of Modules Inspected Per Hour	Remarks
Kunz et al. (2022)	150–300	The CMOS camera-based drone includes the time required for battery swaps, as each battery lasts only about 20 min per charge [26].
Bedrich (2022)	1200–1500	The InGaAs camera-based drone EL system can inspect 12000 modules per night [68].

of 18 mm. The findings indicated that the EL test, known for its accuracy, demonstrated a 90–95 % higher detection rate of micro-cracks compared to the IRT test, underscoring its superiority. While IRT scanning offers faster and more cost-effective remote measurements using thermal cameras, its effectiveness in detecting micro-cracks is limited to 5–10 %. In Table 1, you can observe a comparison of the number of solar modules inspected per hour using EL inspections, including those performed by EL drones equipped with CMOS cameras and those equipped with InGaAs cameras.

In the next subsection, we focus on the daytime aerial EL imaging technique to review its pros and cons.

3.1.2. *Daytime aerial EL imaging*

As previously mentioned, the EL technique can be used both during the day and at night. EL imaging is a potent method for identifying defects in solar PV modules, but its limitations in daytime can make it intractable to use in certain situations contexts. Under these conditions, thermal imaging or other non-destructive evaluation techniques might be more suitable for inspecting solar PV systems during the day. According to the International Electrotechnical Commission (IEC) technical specification and field experiences mandate that EL measurements should be taken when the outdoor light intensity is below 100 W/m^2. This limitation not only restricts the timing for inspections but also introduces several challenges, such as limited access to the site, constraints on UAV operation times, and safety issues related to making electrical connections in dark and potentially damp conditions [28,59,69].

To overcome the daylight limitations of EL imaging, researchers have developed various state-of-the-art systems, including optical systems that function as filters for EL cameras [70–72]. Developing a system capable of performing EL inspections during daylight, using UAVs for image capture, is critically important. In conditions of bright sunlight (with global horizontal irradiance—GHI—exceeding 100W/m^2), simply employing daylight filters and subtracting a background image typically fails to produce a clear EL image. The EL signal is much weaker than sunlight, resulting in a significantly low signal-to-noise ratio (SNR). However, capturing multiple EL/background image pairs from a fixed position and applying post-processing averaging and background subtraction for each pair can enhance the SNR to an acceptable level. For EL inspections outdoors, a minimum SNR (a simplified measure of image quality) of above five is desirable [28]. Furthermore, for situations requiring averaging, an adjusted SNR formula suggests that the average SNR (SNRAVG) should also exceed five to achieve satisfactory quality in outdoor EL images [28]. A key requirement for successful daylight EL imaging is rapid acquisition of images with short exposure times to prevent motion blur and overexposure from sunlight. This can be achieved with cameras equipped with InGaAs-based detectors. In this regard 2020, Benatto and his team developed a method focused on quickly acquiring EL images in daylight. In their article, they introduced a drone-based system capable of capturing EL images at a frame rate of 120 frames per second, allowing the acquisition of 120 EL/BG modulated images per second. Even under high irradiance conditions, this system can gather enough pairs of EL and background images in just a single second to create an EL PV module image. It results images which are contained sufficient diagnostic information to identify faults associated with power loss. In 2023, Santamaria et al. [70] conducted research utilizing a C-RED 3 InGaAs camera from First Light Imaging for various experiments, including indoor EL, daylight EL with a tripod, and drone-based EL. The camera was equipped with a 25 mm focal length sapphire lens and an optical bandpass filter with a center wavelength of 1150 nm and a bandwidth of 25 nm. For the daylight EL inspection conducted with a tripod, the camera operated at 480 frames per second (fps), capturing 16 image frames per modulation period—eight at short-circuit current (Isc) and eight at negative short-circuit current (-Isc). During drone-based inspections, the camera operated at 320 fps, capturing eight image frames per period at a modulation frequency of 40 Hz, with four images at Isc and four at -Isc. The drone inspection involved a DJI Matrice 600 Pro carrying the same InGaAs camera, lens, and filter. The drone flew approximately 630 cm from the PV string at a height of 270 cm, with the PV modules tilted at an angle of 27°. The researchers specifically investigated the "Stop and Go" methodology [73]. Meanwhile recently, Dhimish and Tyrrell [72] published an innovative system that filters out visible light, allowing only near-infrared light, which EL cameras use, to pass through. This development broadens the applicability of EL imaging to a wider array of conditions, enhancing defect detection capabilities in solar PV modules.

Despite having suitable hardware, enhancing the SNR for UAV-captured images presents additional challenges [72,74]. In this regard, Stoicescu et al. demonstrated that using stationary camera carriers for EL inspections can achieve high image throughput. According to their investigation, an optimized setup can obtain EL images equivalent to inspecting 400 kWh per 8-h working day, which corresponds to approximately 1 min per module [75]. While systems designed for daylight operation enhance availability, they demand more advanced equipment and sophisticated image processing techniques.

In summary, the reviewed literature emphasizes the importance of effective flight planning and environmental conditions for successful aerial EL inspections, whether conducted during the day or at night. Optimizing drone routes to ensure comprehensive coverage of photovoltaic arrays is crucial, typically using grid or serpentine patterns to prevent gaps in inspection, particularly for large-scale solar farms [76]. Regardless of the time of day, weather conditions play a critical role in ensuring high-quality inspections. Low ambient light is preferred to enhance the contrast between defects and the rest of the module, with early morning, late evening, or nighttime often recommended for this purpose. Clear skies and calm weather conditions are also vital to avoid wind-induced instability, which can degrade image quality. Moreover, maintaining a consistent flight altitude and speed is essential for capturing clear and accurate EL images in all lighting conditions.

4. EL image analysis

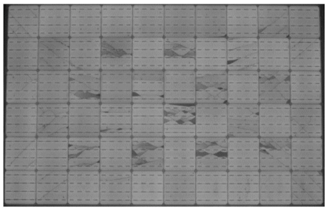
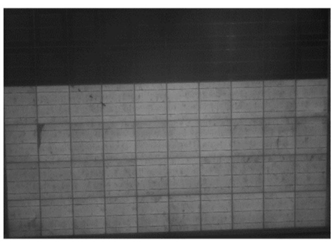
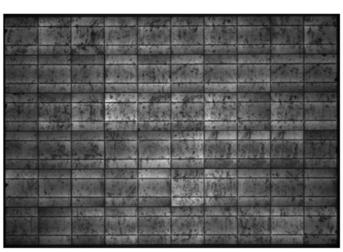
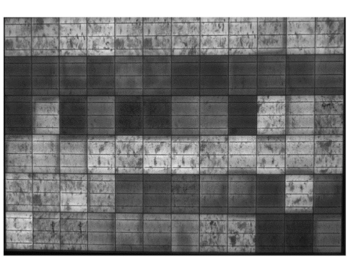
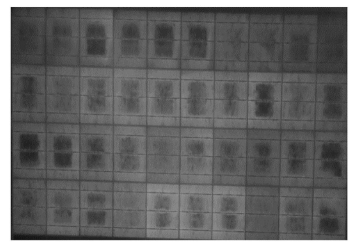
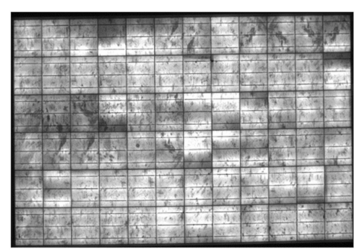
EL imaging was first introduced by Fuyuki et al. [77] for studying cells, and it has become a popular method for identifying defects since then. EL imaging is also a sophisticated technique utilized for assessing the health of PV modules, identifying underperformance in solar plants, and evaluating damage resulting from force majeure events.

Operating on a principle akin to that of a Light Emitting Diode (LED), EL imaging involves injecting current into a solar module while it's under a forward bias condition. This process induces light emission in the near-infrared spectrum, which peaks at a wavelength of around 1.15 μm. This emission is then captured in an EL image [78,79].

The intensity of light emitted from different regions of the module correlates directly with their voltage potential, rendering inactive or defective areas visibly darker in EL images. EL imaging offers a comprehensive visualization of damage to PV modules, detecting defects that are imperceptible to the naked eye and beyond the detection capabilities of conventional thermal imaging techniques [80–82]. The EL imaging technique is widely utilized both indoors and outdoors.

The acquisition of EL images indoors is conducted in dark conditions,

Table 2
Distinguishable different defects and degradations in EL images.

Defect/ Degradation	EL Image	Description
Crack		Cracks may manifest as line defects or display increased resistance, resulting in a uniform decrease in EL intensity. Additionally, cracks can electrically isolate the affected area, causing it to appear entirely dark in EL images [85].
PID shunting		In the last decade, PID has emerged as a significant reliability concern for PV systems. Voltage stress experienced by a PV module relative to the ground leads to the generation of leakage current [86]. PID in EL imaging often reveals dark areas near the edges or corners of the module, clearly showing the affected cells with reduced or no luminescence.
LID		LID leads to an increase in bulk recombination due to the presence of boron-oxygen defects, resulting in a decrease in the EL intensity of a cell [87].
LeTID		LeTID represents a type of degradation observed in solar modules in the field, which is accelerated by high irradiance at higher temperatures after hundreds of hours of light exposure. Without proper preventative measures, this degradation can lead to efficiency losses of up to 10 %. LeTID in EL imaging might present as a subtle, more uniform, and widespread reduction in luminescence across the module, without distinct or specific patterns typically observed [88,89].
Delamination		Delamination results in a gap between the cell and the glass, diminishing the EL intensity in the affected region. Furthermore, the obstruction caused by delamination lacks a consistent correlation between the dark areas observed in EL images and the extent of the delamination [90].
BIF		Failure in busbar interconnects causes an uneven distribution of current across a cell. As a result, areas near an active busbar show the brightest EL. The intensity of the EL decreases as the distance from the busbar increases due to the non-uniform distribution of current [91].

with the sample excited by a current source, ensuring that the EL current (IEL) is less than or equal to the Isc. The Outdoor EL inspection performed in day and night conditions.

So Low-cost Si-CCD camera can be used in night for capturing high-definition EL images and InGaAs camera can be preferred in daytime. This technique can be mounted on a stationary, ground-based setup, such as a tripod or a multi-bridge system, to capture high-resolution EL images of modules for detailed performance analysis. Alternatively, it can be employed in drone-based aerial inspections to scan a large volume of PV systems in a short time or to access installations that are difficult to reach [1,3,83,84]. The following section elaborates on the various types of defects that can be detected using the EL method.

4.1. Defects detected by EL imaging

Defects and degradations within crystalline silicon (c-Si) PV modules can be analyzed through EL imagery, identifying them by their unique patterns or characteristics in the images, such as cracks, potential-induced degradation shunting (PID-s), finger breakages, light-induced degradation (LID), light and elevated temperature-induced degradation (LeTID), delamination and busbar interconnect failure (BIF). Table 2 presents the identifiable image characteristics associated with various commonly seen defects and degradations.

EL imaging systems, including tripod-based and UAV EL systems, can detect electrical and nonelectrical defects that are not visible to the human eye and may not be detectable by other methods such as thermal imaging. However, distinguishing between different types of degradation solely based on EL images can be challenging. For example, both LeTID and PID can appear as darker cells in EL images. While both result in power loss, their degradation patterns are distinct: LeTID typically causes a more uniform and gradual performance reduction across the module, whereas PID often results in more localized damage, particularly at the edges. To address these challenges, artificial intelligence (AI) and machine learning techniques are increasingly being employed to enhance automated defect detection and differentiation.

4.2. Defect classification by EL imaging

According to the literature, EL imaging is a powerful diagnostic tool used to detect various types of defects in PV modules. These defects can be classified using different ML and DL methods and algorithms. Accurate classification of defects is crucial for understanding their impact on the performance and longevity of PV systems, as well as for determining appropriate maintenance actions. As discussed in the previous subsection, defects detected by EL imaging can manifest in several forms, each with distinct characteristics and causes. These defects may arise from mechanical stress, environmental conditions, manufacturing imperfections, or aging of the module, among other factors. Classifying these defects is essential for evaluating their severity. Accurate classification helps determine the urgency of corrective actions and allows operators to trace back to the possible causes of defects, whether they stem from installation issues, operational conditions, or inherent material properties of the modules. By identifying specific defect types, operators can prioritize repairs and schedule preventive maintenance more effectively, thereby optimizing maintenance protocols. This subsection explores the classification of different types of defects based on their characteristics and their implications for photovoltaic module performance.

To automatically and consistently identify faults and degradation modes in EL images, deep learning methods, such as CNNs, can be employed [92]. These CNNs are trained on thousands of images from various module types, where faults have been previously annotated by human experts. This allows the algorithms to automatically detect faults in new images, regardless of cell sizes and module layouts. The defects identified and classified by ML include micro-cracks, PID, BIF, shunts, and other defect types [92–95]. Additionally, ML techniques like principal component analysis (PCA) can be used to categorize modules based on specific features and faults [96]. After defect classification, the modules are sorted into quality categories, with ratings based on the identified defects and degradation features.

In other words, EL imaging is a highly effective technique for acquiring both qualitative and quantitative insights into defects and degradation in PV modules. The emerging field of quantitative EL imaging enables the evaluation of the impact of these defects and degradation on module performance through the analysis of EL images [97].

4.2.1. Quantitative analysis of EL images

Quantitative analysis of EL images has been extensively studied in recent years [98–100], employing various strategies. These include constructing a series of dark I-V curves for individual solar cells from EL images of PV modules [101] and determining operating voltages to extract electrical parameters for each cell [99,102]. Additionally, researchers have leveraged both analytical and ML methods to predict PV module light I-V characteristics and, subsequently, power loss from EL images [103,104]. For example, Rajput et al. [100] proposed methods strongly validated for outdoor conditions. By capturing EL images using both Si-CCD and InGaAs cameras at night and during daylight, they demonstrated the effectiveness of their approach in accurately generating the module I-V curve, with a relative error of less than 3 % in output power. Similarly, Castaneda et al. [105] made the first attempt to quantify performance loss due to cell breakages using EL images. In their study, the active area of a cracked cell was statistically calculated from the EL image. Based on this calculated active area, the ideal Isc of the cracked cell was determined using the nameplate Isc rating (Ideal Isc = nameplate Isc × normalized active area). To estimate the actual Isc of a cracked cell, quantum efficiency was used to calculate the current density of the active area (Actual Isc = current density × active cell area). By comparing the Ideal Isc with the Actual Isc, the Isc loss due to cracking was estimated. The study demonstrated that cell isolation caused by cracking results in Isc loss proportional to the inactive area. However, the work was limited to estimating Isc loss at the cell level and did not provide a method for quantifying the impact of cell breakages at the module level [105,106].

Kropp et al. [108] estimated the power loss in hail-damaged PV modules using a method that requires two EL images of the defective module—one captured at high current (>0.3Isc) and the other at low current (0.1Isc). For the analysis, it was assumed that mechanical cracks primarily affect the cell's series resistance (Rs). By using the two EL images, an Rs map of the PV module was generated by solving analytical equations. The authors demonstrated that this approach could estimate the module's output power with a relative error of less than 4.3 %. However, a key limitation of this method is that it requires specific cell parameters, such as the saturation current and ideality factor, which must be obtained from the module's datasheet. In the case of field-aged modules, these parameters may no longer be accurate due to aging effects. Therefore, for optimal accuracy, this method is most suitable for evaluating cracks in newly installed or unaged PV modules, where the necessary parameters can be reliably sourced from the module datasheet. They also developed a method for predicting the output power of a PV module affected by PID shunting, using an analytical approach. This method estimates the module's output power based on a single low-current EL image to determine the cell's shunt resistance, offering a straightforward way to estimate the shunt resistance of a PV module [108]. In contrast, Bedrich et al. [109] reported an empirical approach for quantifying PID shunting losses, utilizing two EL images of the test module, either taken at different EL currents or before and after degradation. By calculating the logarithmic ratio of the two EL images, they estimated spatially resolved PID shunting power loss, which depends on factors such as cell size, the number of cells, cell technology, and series resistance.

In parallel, for quantitative machine learning, Rodrigues et al. proposed a DL algorithm to predict the I-V curves of three multi-crystalline PV modules with varying degrees of cell cracking. As a result, quantitative luminescence image analysis has made significant advancements in recent years, and this knowledge is expected to be applied to outdoor luminescence measurements of fielded PV modules [105].

Classifying defects in photovoltaic modules is essential for understanding their effects on overall energy generation. Different types and severities of defects, such as cracks, PIDs, LeTID etc. can significantly affect module performance. Even minor defects can aggregate to impact the global energy output of photovoltaic systems. It is important to consider how different semiconductor technologies, such as silicon and thin films, respond to these defects to assess their overall impact. Evaluation protocols like the National Renewable Energy Laboratory (NREL) Test-to-Failure (TTF) Protocol provide a structured approach for quantifying these effects and developing maintenance strategies to enhance system performance and longevity.

While certifications such as IEC 61215 and IEC 61646 demonstrate a

Table 3
Power losses due to PV module failures in baseline and worst-case scenarios [97,98].

Failures	Min Power Loss	Max Power Loss
Cell Crack	1 %	15 %
Delamination	1 %	30 %
PID	10 %	70 %
Failure bypass diode and junction box	33 %	33 %
Hotspot	2 %	20 %
LeTID	7 %	10 %
Improperly Installed	5 %	20 %

module's ability to withstand environmental exposure, they are limited in evaluating long-term reliability and comparing different technologies.

The NREL TTF Protocol addresses these gaps by enabling comparative testing of new module technologies under accelerated conditions. This protocol allows for a thorough evaluation of performance against existing designs, identifies potential reliability issues for high-voltage systems, and facilitates a comprehensive assessment of various technologies before committing significant capital to photovoltaic power plants [110,111].

According to their results, a crack in the cell was imaged using EL during thermal cycling, and again after 200 cycles. This stress sequence resulted in a 5.3 % power loss, which was not considered significant [110,111]. Thermal and EL imaging of their tested modules revealed shunting patterns that varied depending on the module design. One of the models, which incorporates glass with an anti-reflective (AR) coating, frequently exhibited localized hot spots, with affected cells showing significantly reduced EL indicative of shunted cells. The presence of shunting was further confirmed through light I-V tests, where cells were individually shaded for characterization [110].

In contrast, modules without AR-coated glass demonstrated more extensive and uniform shunting under the negative Damp Heat (DH(−)) stress test, where a negative 600V bias was applied during a DH test. DH testing simulates the environmental conditions that PV modules may encounter, typically involving exposure to high temperatures (85 °C) and high humidity (85 % relative humidity) [110,111]. Moreover, the impact of cell cracking on reliability can vary widely, from negligible to significant. Cracking can potentially lead to the formation of hotspots and dead areas, which contribute to module power loss. Degradation rates associated with cell cracking are influenced by several factors, including module architecture, loading conditions, and environmental factors. While some cell cracks may remain stable without affecting performance, others can cause immediate power loss [112]. In this regard, also Moser et al. [98] and Høiaas et al. [97] reported power losses associated with PV module failures for both baseline and worst-case scenarios, as presented in Table 3.

Therefore, to ensure high reliability and long-term usage of PV modules, there has been an emphasis on developing standards and best practices for solar PV operation and maintenance (O&M) activities. Power losses resulting from specific PV module failures can be challenging to quantify and may increase over time. Additionally, both existing and emerging failures can present safety risks that are often not addressed in initial assessments [97,98].

Three main maintenance strategies for solar PV systems are categorized as follows: First, corrective maintenance addresses unexpected failures and damages, often resulting in high costs and power generation losses. It involves unscheduled repairs and increased expenses, especially in remote locations. Second, preventive maintenance aims to prevent failures through scheduled inspections (time-based) or real-time monitoring (condition-based) to address minor issues before they escalate. Third, predictive maintenance uses data analysis and forecasting models to predict failures, identify trends, and estimate component lifespan, allowing for early detection of issues [113]. Efficient fault detection is crucial for minimizing disruptions and maintaining system performance.

In the context of using aerial EL imaging for inspecting photovoltaic systems, corrective maintenance involves addressing issues identified during inspections, such as repairing defects or replacing damaged modules to restore system functionality. It also includes managing any equipment failures that occur during the inspection process. Preventive maintenance aims to avert potential issues before they occur by routinely calibrating and maintaining the EL equipment, performing scheduled inspections to detect minor problems early, analyzing historical data to forecast and address potential issues, and ensuring that personnel are well-trained and procedures are current. These measures collectively enhance the efficiency and reliability of both the inspection process and the photovoltaic system. Therefore, to ensure continuous improvement and quality control in aerial EL inspections, it is essential to regularly update procedures and utilize advanced tools. This includes refining inspection methods based on the latest standards, adopting state-of-the-art imaging equipment, and integrating advanced data analytics. Regular tool maintenance and personnel training are also crucial for maintaining high standards. These practices collectively enhance the accuracy and reliability of EL inspections.

5. Results

Most PV plants employ a combination of corrective and preventive maintenance strategies, adhering to manufacturer guidelines and industry best practices. While immediate corrective maintenance ensures high system availability, it may not always be cost-effective. Thus, a systematic approach to optimizing maintenance strategies is essential for balancing various objectives within PV systems. Key goals include maximizing reliability and availability, minimizing costs, optimizing scheduling operations, and efficiently allocating resources [113].

In this context, advanced inspection technologies, such as drone-based EL imaging, are instrumental in enhancing maintenance strategies. Integrating drones equipped with EL imaging capabilities enable more precise and efficient inspections. These technologies facilitate proactive defect detection and detailed assessment of module conditions, supporting both corrective and preventive maintenance efforts. The use of drones for EL inspections helps identify and address issues before they escalate, ultimately improving maintenance schedules and resource allocation, and thereby enhancing the overall reliability and cost-effectiveness of PV operations.

This work provides comprehensive insights into the inspection of PV modules using aerial EL imaging. The findings indicate that employing advanced techniques for image capture and data analysis allows for a detailed and accurate assessment of module conditions, thereby optimizing maintenance efforts and extending module lifespan while monitoring the overall performance of solar farms. EL imaging is crucial for detecting defects at both the cell and module levels, with UAVs emerging as a promising tool for such inspections.

However, UAV-based EL inspections face several challenges. Firstly, inspections are typically conducted at night to avoid daytime NIR interference, complicating UAV control and increasing regulatory and training requirements. Nighttime operations also introduce additional risks and require skilled operators. Secondly, the need to connect PV module strings to a DC power supply makes the process labor-intensive, particularly when moving between distant DC combiner boxes at night. Thirdly, commercial silicon sensor cameras' limited sensitivity to NIR wavelengths necessitates long exposure times, raising the risk of blurred images due to UAV movement. In contrast, InGaAs cameras, with their superior NIR sensitivity and video recording capabilities, facilitate daytime inspections and streamline operations. However, their use involves more complex image processing for defect detection and comes with a higher cost.

Moreover, selecting the appropriate UAV-to-panel distance and lens type depends on specific analysis objectives, such as micro-crack detection or broader assessments of submodule or string functionality.

Table 4
Summary of the aerial EL imaging system.

Time of imaging	Technical requirements	Advantages	Disadvantages	References
Nighttime	• Si camera (low cost) or InGaAs (high cost). • Power supply with multiplexer switch and generator (or 3-phase A/C power connection). • Site preparation to connect equipment to PV strings	• No Ambient Light Interference: Clearer EL images. • Accurate Defect Detection: Enhanced sensitivity for cracks etc. • Lower Equipment Cost: Standard silicon cameras are less expensive. • Consistent Imaging Conditions: Uniform lighting improves image consistency.	• Higher Operational Risk: Increased risk due to low visibility. • Complex Logistics: Requires extra approvals, safety measures, and training. • Labor-Intensive Setup: Difficult to connect PV strings in the dark. • Limited Operational Hours: Only feasible at night, extending inspection time.	[28,69,70, 97,107, 113]
Daytime	• InGaAs camera (high cost); • Power supply with multiplexer switch and generator (or 3-phase A/C power connection); • Site preparation to connect equipment to PV strings	• Flexible scheduling during working hours. • Enhanced safety with reduced nighttime risks. • Lower labor costs, avoiding nighttime personnel. • Easier coordination with ongoing site activities.	• Ambient light interference affecting image quality. • Complex image processing needed for noise reduction. • High cost of advanced equipment • Lower sensitivity of silicon cameras requiring longer exposure	

Each scenario presents unique challenges that require tailored solutions. Despite these difficulties, studies have demonstrated that drone-based inspections significantly reduce module inspection time, and the benefits generally outweigh the challenges.

Table 4 provides a summary of the aerial EL imaging system, including its advantages and disadvantages.

6. Conclusion

Qualifying PV power plants in the field is essential for understanding their performance and degradation mechanisms, which is crucial for improving their reliability and extending their lifespan. Utilizing portable testing equipment for on-site inspections proves to be an effective approach in identifying factors contributing to the underperformance of PV power plants. This review focuses on aerial EL imaging and provides a brief exploration of various inspection techniques, including manual/tripod EL, visible light inspections, and thermographic drone inspections. Each method has its advantages and limitations, influenced by system size, required detail, environmental conditions, and the availability of equipment and personnel.

Among these techniques, aerial EL imaging has emerged as a notable method due to its cost-effectiveness, accuracy, and speed in identifying a range of defects such as PID, cracks, and inactive sections within PV modules. This approach not only detects issues like overvoltage effects, short-circuiting of bypass diodes, and interconnection failures in substrings but also reduces inspection time and the need for human resources. By streamlining the defect detection process, aerial EL testing stands out as a powerful tool for maintaining the health and efficiency of solar modules.

In the context of optimizing maintenance strategies for PV systems, aerial EL imaging integrates well with both corrective and preventive maintenance approaches. It supports proactive defect detection and detailed assessment of module conditions, which is essential for balancing various objectives within PV maintenance, such as maximizing reliability, minimizing costs, optimizing scheduling operations, and efficiently allocating resources. Despite its advantages, aerial EL imaging does have drawbacks, including regulatory and legal concerns, technical limitations, data processing challenges, the need for specialized training, and safety considerations. Additionally, the number of published papers on EL drone inspections and detailed reports on detected panels is limited, constraining the breadth of available research and data.

Recent advancements in technology and methodology are addressing these issues, but ongoing research is needed to further refine the technique. Various studies indicate that while drones significantly reduce inspection time, their use presents certain challenges. Nevertheless, the benefits of aerial EL imaging generally outweigh these challenges, solidifying its role as a paramount method for quality assessment in photovoltaic systems. Future research could focus on overcoming current limitations and exploring new applications to enhance the effectiveness and efficiency of aerial EL inspections.

Declaration of competing interest

The authors declare the following financial interests/personal relationships which may be considered as potential competing interests:

Zeinab Mahdavipour reports financial support was provided by TT Vision Technologies Sdn Bhd. If there are other authors, they declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Data availability

No data was used for the research described in the article.

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