Image-Based Sensor-Free Diagnostics and Performance Analytics in Photovoltaic Systems: A Comprehensive Review

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Abstract

The perennial operation of the photovoltaic systems essentially relies on their capacity to withstand the heterogeneous environmental and operational stressors. Among them, the processes of partial shading, accumulation of soil, thermal anomalies, and structural degradation processes become the most prominent causes of power losses and reliability degradation. The traditional monitoring systems are based on internal electrical sensors, radiation measuring devices and thermographic devices which cumulatively raise the cost of capital and limit the scalability of large solar systems. Photovoltaic monitoring has been transformed by sensor-free, image-based diagnostics that utilize optical imaging, artificial intelligence, and physics-informed analytics to assess system health discreetly. The review makes photovoltaic diagnostics a purposeful area of study and summarises the developments related to imaging modalities, classical computer vision, machine-learning classification, deep-learning segmentation, illumination-field modelling, multimodal fusion, UAV inspection, edge-ai deployment, digital-twin integration, and predictive-maintenance ecosystems. The maturity, interpretability, complexity of computation, and its deployability of all paradigms are critically discussed. Issues about research, standardisation requirements, as well as innovative directions are stated to direct the creation of autonomous, scalable, and intelligent photovoltaic asset-management systems.

Keywords: Photovoltaic Monitoring; Sensor-Free Diagnostics; Computer Vision; Deep Learning; Solar Panel Fault Detection

1. Introduction

1.1 Photovoltaic Infrastructure Spread to the World.

The rapid decarbonisation of the world energy infrastructure has set photovoltaic (PV) technology as the leading energy source in terms of renewability. Governments, utilities, and other interested parties are aggressively expanding solar implementation in order to achieve net-zero emission policies, energy-security policies, and electrification. A wide variety of installation typologies are included in this proliferation, which is not just limited to conventional ground-based solar gardens. These include floating photovoltaic platforms on reservoirs, building-integrated photovoltaics within architectural envelopes, agrivoltaic systems that are situated alongside agricultural activities, and hybrid microgrid ecosystems that cater to isolated or remote communities. With cumulative installed capacities in the process of moving into multi-gigawatt levels, the operational paradigm of PV systems is shifting to fleet-level performance optimisation [1]. Even small error in efficiency on a module scale in such high-density deployments combine to large deficits on the energy yield levels at the plant scale. As a result, operational efficiency is not only a local maintenance concern anymore, but a systemic issue, which determines the stability of the grid, financial gains on investment and the long-term sustainability indicators. Such a macro-scale growth requires sophisticated monitoring systems that will be able to guarantee the same level of performance even in geographically spaced and environmentally diverse installations. In addition, the incorporation of PV assets in smart grids bring in to the scene more performance accountability. Vision-Driven Photovoltaic Diagnostics is presented in Fig.1.

New solar plants are currently involved in demand response, frequency-regulation and real-time markets in energy-trading. In this type of grid-interactive relation, the performance uncertainty due to an unnoticed degradation has a direct effect on dispatch planning and market participation. Therefore, the scalable, precise and cost-effective monitoring systems have started to become an essential part of the contemporary photovoltaic networks [2].

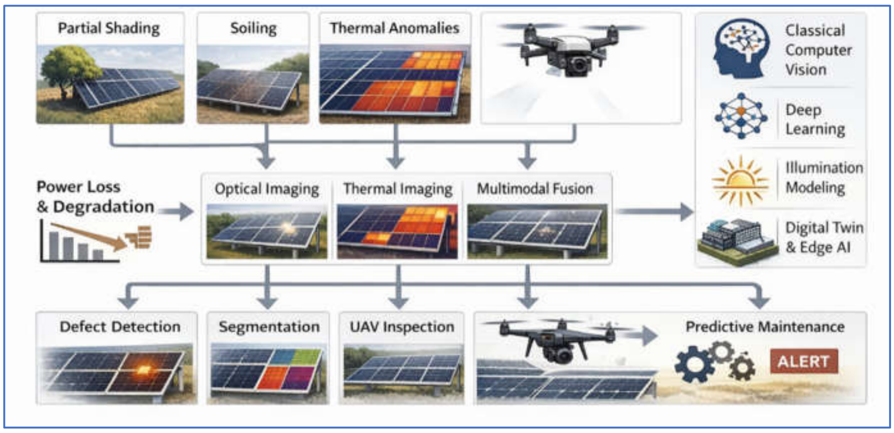

Fig.1. Vision-Driven Photovoltaic Diagnostics

1.2 Field Conditions Operational Vulnerabilities

Although photovoltaic modules have the ability to be designed to endure over a long period, their performance in the field is still susceptible to environmental and operational stressors. The laboratory characterisation presupposes standardised conditions of testing including homogeneous irradiance, constant temperature and free of contaminants on surfaces. But the operating environments in reality differ significantly with these idealised environments. PV arrays that are deployed in the field are subject to stochastic variations in irradiance that are caused by transient clouds, seasonal changes in solar-angle, and atmospheric scattering effects. These variations cause temporal and spatial non-uniformity of illumination on surfaces of modules. Along with atmospheric effects, the airborne particulate matter including dust, industrial emissions and pollen gradually deposes on the panel glass, reducing the incident radiation. Such deposits are ecologically different and more severe and their structure varies across geographical areas with arid and industrial regions reporting an increased rate of soiling [3].

Another degradation vector is the biological contaminant. The bird droppings, the formation of algae in the wet climatic condition, and the litter generation of leaf in the vegetative areas generate local shading-patches which interfere with the cell-level irradiance homogeneity. These obstructions have very nonlinear effects of electrical mismatch, as compared to uniform soiling. Mechanical stresses also make operations even more vulnerable. Microcracks in silicon wafer or solder interconnects can be caused by wind caused vibrations or thermal expansion cycles or by structural loading. These microstructural defects spread with time, and the electrical conductivity and thermal dissipation properties as well change. These environmental and mechanical stress factors collectively cause distortion of the homogenous light and thermal balance that is necessary to produce the maximum amount of photoelectric conversion. Its resultant performance decline can be spatially heterogeneous and temporally evolving, which requires diagnostic models that can solve fine-grained variability at PV arrays [4].

1.3 Weaknesses of Traditional Monitoring Paradigms

- The conventional photovoltaic monitoring systems are sensor-based systems that are mostly sensor-centric and use a distributed network of instrumentation to record electrical and environmental measurements. Pyranometers are used to measure the incident solar irradiance and thermocouples are used to monitor the module temperature and current voltage tracers to determine the electrical output characteristics. These measurements supply supervisory control and data acquisition systems which support performance analysis as well as the detection of faults.
- Although sensor-based diagnostics offers high measurement fidelity, it has numerous infrastructural limitations. The cost of installation of dense sensors networks on large solar farms involves huge investment in capital, complexity in the wiring and system integration overhead. Furthermore, the sensors themselves are prone to calibration errors, contaminations, and other environmental degradation and require periodic maintenance and recalibration.
- Another significant weakness is spatial resolution. In order to capture localized shading or contamination effects at sub-module scales, the sensors often measure the electrical or environmental conditions at their

discrete locations, which are not necessarily the best. As a result, there is a tendency of incipient faults to go without detection until a stage where they grow up to be measurable electrical losses.

- Infrared imaging Techniques such as thermographic inspection can be useful in identifying hotspots, however they need specialised equipment to take the infrared images and controlled acquisition conditions, which can be done manually or through a drone-based survey. This episodic inspection model does not have the capability of continuous monitoring.
- The sum of cost and logistics cost of installation, maintenance and calibration of sensor infrastructures is prohibitive in big, geographically dispersed, PV installations. These drawbacks have fueled the creation of sensor-free diagnostic tools that assess a system's health non-invasively using optical imaging and computer analytics.
- Image-based monitoring infrastructures mitigate most of these shortcomings by offering a high spatial resolution, less hardware reliantness and scalable deployment channels. With the development of camera technologies and artificial intelligence algorithms, the role of vision-based diagnostics in the context of the possible successor or supplement to existing sensor-based monitoring paradigms is growing.

2. Photovoltaic Degradation Mechanisms

In practice, photovoltaic modules undergo a wide range of degradation processes which all reduce electrical functionality, thermal and structural stability. These mechanisms as opposed to abrupt failures normally develop over time, interacting with the environmental stressors and operational loading conditions. The most exaggerated and performance-dominant processes are that of electrical mismatch due to partial shading, thermally fueled hotspots, optical attenuation by soiling, and mechanical and material degradation processes. The operations of such mechanisms and their intricate viewpoints at the cell and module levels are vital in the design of successful diagnostic and monitoring models particularly in image-based, sensor-free paradigm where visual and thermal images are the main predictors of loss of performance [5]. These mechanisms will be explained in Fig. 2.

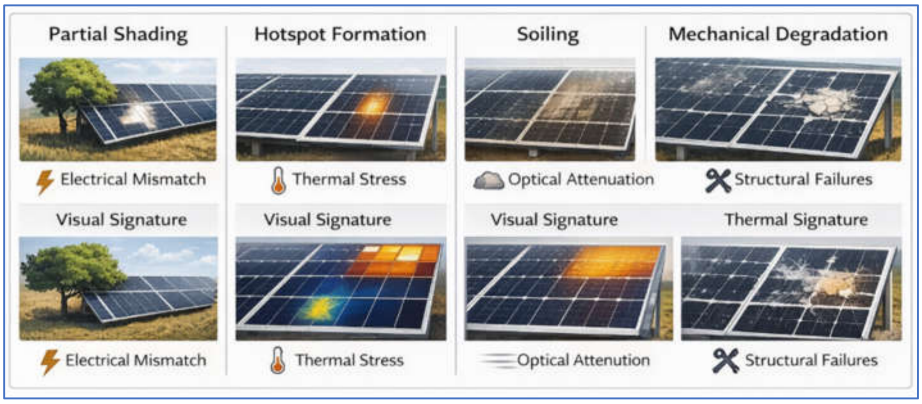

Fig.2. Photovoltaic Degradation Mechanisms

2.1 Electrical Mismatch Induced by Partial Shading

One of the most disruptive electrically discontinuous phenomena in photovoltaic arrays is partial shading, and this is mainly due to the series-interconnection geometry of solar cells in modules. All the cells produce current in the same proportion to the total current at the same irradiance. But, in situations whereby a small population of cells is illuminated by irradiance blocked by debris or plant cover or structural shadows, the light receptive cells produce smaller photocurrent amounts compared to the shadowed cells. Since series connected circuits impose current continuity the smaller current output of shaded cells limits the amount of current flowing through the string [6]. To sustain the functioning of the circuit, the shaded cells are pulled into reverse bias where they use instead of producing electrical energy. The shaded cell becomes a resistive load as a result of this inversion, internalizing energy instead of contributing to external power delivery. Nonlinear distortions of the current voltage (IV), and power voltage (PV) characteristics are electrically equivalent to this mismatch. The P-V curve has multiple local maxima making it difficult to follow maximum power point algorithms which are usually optimized on single mode power profiles. Beyond the obvious shading effect, the energy yield losses can be exacerbated by the conventional MPPT controllers' tendency to approach non-optimal operating positions.

Moreover, a recurring exposure to mismatch stress enhances the speed of degradation of bypass diodes, interconnect ribbons and metallization pathways. With time, this causes the irreversible degradation of electrical performance related to the initial shading source even in cases where the source of shading has been eliminated. Partially shaded, therefore, is not an isolated loss factor but an initiator of long-term issues with the reliability of modules [7].

2.2 Dynamics of Thermal Hotspots Formation

The thermoelectrical effect of a partial shading operation (or partial reverse-bias operation) is the formation of thermal hotspots. Local conversion of electrical energy into heat occurs when the shaded cells absorb electrical power inside them to create temperature gradients on the face of the module. The gradients are very strong and they create microscale thermal hotspots which can reach tens of degrees Celsius higher than the surrounding cells. It has long-term material consequences of persistent exposure to hotspots. High temperatures increase the decay of polymers in encapsulation layers like ethylene-vinyl acetate (EVA) layers. Hotspot conditions (thermal cycling) cause expansion-contraction fatigue in solder joints, which leads to the amplification of the risk of interconnect fractures. Also, long-term heat concentration can also lead to browning of encapsulant material, decreasing optical transmittance and further diminishing performance loss [8]. Reliability wise, thermal stresses caused by hotspots may cause irreversible damage to cells such as cracking of silicon wafers, metallization burn-out and blistering of back sheets. In worst-case situations, hotspots are a fire hazard especially in large utility scale arrays of high voltages. Hotspots have a unique infrared emission spectrum, thus can be identified by thermographic images. Nevertheless, secondary signs, including discoloration or burn patterns, can be detected with the help of visual imaging, and thermal degradation is associated with diagnostic possibilities using image-based methods [9].

2.3 Accumulation and Optical Attenuation of Soiling

The accretion of soiling is one of the most widespread and spatially diffused degradation processes in PV. Dusts in the air, industrial wastes, automobile emissions, farm waste, and bio deposits gradually increase on the surfaces of the modules. Surface soiling on the other hand unlike uniform atmospheric attenuation offers localized optical impediments, which obstruct incident solar radiation even before reaching the active semiconductor junction. The attenuation of the light caused by soiling is achieved in many ways, among which are absorption, scattering and reflection loss. The spectral transmittance reduction is determined by particle size distribution, chemical composition and density of deposition. An example is that the particulates having high absorption such as carbon are more absorptive compared to mineral dust which can scatter incident photons, changing the angular irradiance distribution. Avian pollutants like droppings of birds appear especially harsh attenuation impacts because of their impenetrability and sticky morphology [10]. Likewise, clusters of pollen and algae films form semi-transparent layers of shading, which distort intensity and spectral properties of incident light. The diversity in soiling deposition delivers complicated fields of attenuation of illumination on the PV surfaces. These areas are not proportional to energy loss but localized high density can cause some electrical mismatch effect like a partial shading. In turn, the soiling impact cannot be well quantified with the use of aggregate transmittance estimation but with the help of spatially resolved diagnostics. Soil losses are also high, in the arid and semi-arid climates and may rise to over 20 per cent in a year when cleaning cycles are not properly regulated. This financial effect has motivated serious study in soiling detection by robotics, automated cleaning, and image-based contamination analytics [11].

2.4 Mechanical and Material Degradation

The sources of mechanical degradation and material degradation sources are both manufacturing defects and exposure to operational stress. Photovoltaic modules undergo continuous thermal cycling as a result of day to day change in temperature, seasonal change in climate and heating caused by irradiance. Mechanical stress in the module laminate is created by different thermal expansion between glass and silicon and interconnect layers of metals. In long lifespan operations, this stress is in form of micro cracks in the crystalline silicon wafers. These cracks are microscopic, electrically latent, and gradually widen further as the loads applied on them cycle in nature breaking the pathways of current conduction eventually. The crack propagation changes the local resistivity, the active cell area and creates local heat areas [12].

Delamination is another important degradation route whereby the adhesives between the encapsulant layers and the glass substrates degrade. This isolation allows the entry of moisture that enhances the corrosion process of metallic connections and facilitates the existence of potential-induced degradation (PID) effects. Optical properties are also affected due to the presence of moisture infiltration that creates discontinuities in refractive indices in the laminate layers. In high-resolution photos, this can be seen visibly as haze, bubbling, or discolouration. The mechanical degradation mechanisms are frame deformation, mounting stress fracture, and back-sheet cracking. These structural distortions do not only affect the durability of modules, but also open the internal elements to environmental pollutants. Notably, most mechanical and material degradation indicators are detectable optically before electrical activity deteriorations can be detected. This chronological precedence highlights the diagnostic importance of image-based inspection systems in predictive maintenance systems. PV Diagnostics Infrastructure: Imaging [13].

3. Photovoltaic Diagnostics Imaging Infrastructure

Image-based sensor-free diagnostics is a fundamental step in the functioning of a photovoltaic system because its efficacy depends on the imaging infrastructure used to gain access to data. Imaging platforms require diagnostic accuracy, inspection scale, time-tracking capability, and spatial performance. In general, there are three basic categories of photovoltaic imaging infrastructures ground-based and fixed, aerial imaging systems and mobile robotic inspection systems. All of the paradigms have their own benefits regarding coverage, resolution, the cost of operation, and applicability in large-scale solar installations. Fig.3 shows how photovoltaic imaging infrastructures have been designed.

Fig.3. Photovoltaic Imaging Infrastructures

3.1 Ground-Based Imaging Systems

The visual monitoring infrastructure within photovoltaic plants is the most basic and the most extensively deployable, ground-based imaging systems. These systems usually include fixed high-resolution cameras in rows of photovoltaic arrays or a support structure or perimeter surveillance poles. Throughout the operational cycles, visual inspection is possible thanks to the imaging nodes' strategic placement and continuous line of sight coverage of the module surfaces. The main opportunity of fixed ground-based systems is that it is continuous in time. In contrast to episodic inspection modalities, time-series images of stationary cameras can be used to carry out longitudinal studies of degradation phenomena. Such a time-based data can be used to monitor the rate of soiling amass, seasonal pollution patterns and the gradual shading progression due to plant development or infrastructure barriers [14]. Change-detection methods that may identify subtle alterations in the surface structure are analytically supported by continuous imaging. Frame-differencing, background modelling and temporal texture analysis can be used to detect incremental dust deposition, beginning of discoloration, or developing hotspots discoloration. This anomaly identification at this early stage is essential to predictive maintenance.

Ground-based systems are also capable of being combined with edge-computing hardware deployed on-site on photovoltaic facilities. Real-time shading notifications, contamination severity scoring and cleaning activation automation can be done on-site in real-time without cloud connection. Additionally, electrical control mechanisms and permanent imaging systems can be cross-registered to enable cross-correlation between markers of visual degeneration and changes in power delivery. The shape of the camera field-of-view and mounting height, however, inevitably restrict the coverage of ground-based imaging. The inaccessibility of the rear module surfaces, perspective distortion, and occlusion effects can all reduce the diagnostic completeness. Resultantly, ground systems are commonly accompanied by aerial or robotic platforms in order to obtain a comprehensive inspection coverage [15].

3.2 Aerial Imaging Platforms

Platforms based on aerial imaging, mostly through the use of unmanned aerial vehicles (UAVs), have transformed the inspection of large-scale photovoltaic by facilitating the rapid and high-coverage data collection of large-scale solar installations. Hundreds of megawatts of installed capacity can be surveyed by drone-mounted imaging payloads in the course of a single flight mission, compared to a significant amount of time in inspection compared to manual or ground-based inspection methods. UAVs are fitted with high-resolution RGB cameras, thermal sensors, or multispectral imaging systems to have a detailed surface view of the surface at high altitudes. It has autonomous flight-planning software, which allows pre-meditated flight paths along photovoltaic array paths to guarantee a systematic coverage with well-defined overlap ratios necessary to support image stitching. One of the major technological innovations in aerial PV diagnostics is the orthomosaic reconstruction. Aerial frames are geometrically patented and assembled with the help of photogrammetric algorithms to create large-scale geo-referenced composite maps of complete solar plants [16]. These orthomosaics offer macro-scale visualisation of clusters of the shading, the contamination sites, the structural abnormalities and the vegetation encroachment patterns. In computational terms, orthomosaics datasets make it possible to segment anomalies in plants, perform spatial clustering of defects, as well as to prioritize maintenance areas. Accurate mapping of detected defects to module-string specific faults, in conjunction with GPS-tagging, enables targeted field interventions.

Thermal drone diagnostics is another improvement of aerial diagnostics that can identify resistive heating patterns due to cell mismatch, diode failure or interconnect degradation. Optical-thermal aerial surveys, when combined, therefore, give surface and underground performance. UAV platforms have regulatory limitations of airspace, weather reliance and battery life challenges despite their scaling benefits. Extreme weather conditions such as high wind speeds, precipitation, and extreme temperatures could limit the number of flights. However, utility-scale PV diagnostics cannot be done without aerial imaging because this method has unique coverage of inspection and spatial analysis capabilities [17].

3.3 Robotic Crawlers and Autonomous Rovers

Robotic crawlers and autonomous ground rovers are a new area of photovoltaic imaging infrastructure, especially in high-resolution, close-range objects of interest. Such mobile robotic systems move along rail or wheel-guided or track-driven locomotion systems across rows of photovoltaic panels. Robotic crawlers are fitted with high-definition optical cameras, thermal imager, LiDAR sensors and in some cases hyperspectral payloads to take ultra-high-resolution images that cannot be attained using aerial platforms. They can detect microcracks, encapsulant discolouration, delamination edges, and fine-grained soiling morphologies because of their proximity to the module surfaces. The two-fold nature of robotic inspection is one of its characteristics. The systems are often combined with automated cleaning systems, i.e. rotating brushes or electrostatic dust cleaning systems [18]. This enables both the contamination sense and cleaning process to be performed in a single maintenance process. To move around the panel arrays without assistance from a person, the autonomous rovers use GPS-based path planning, infrared control, or machine vision. The obstacle-detection algorithms are made to guarantee safe passage along structural joints and mounting frames. Robotic imaging datasets are especially suitable in deep learning diagnostic model training because they have high spatial resolution and controlled geometry of acquisition. These data sets increase the accuracy of segmentation in contamination classification and localisation of defects. Nevertheless, robotic systems have greater mechanical complexity, cost of deployment and maintenance costs compared to stationary cameras. They are slower than aerial surveys in their operational speed thus should be used in specific inspection and not in scanning the whole plant. Platforms for robotic, ground-based, and aerial photography are all hierarchical components of an inspection ecosystem. This type of cameras offers permanent control, UAV offers macro-scale mapping, and robotic crawlers offers micro-scale defect analytics. This synergistic interconnection between these infrastructures guarantees multi-resolution diagnostics coverage which can provide the end-to-end sensor-free performance monitoring of photovoltaic installations in modern installations [19].

4. Optical Imaging Modalities

The basis of sensor-free photovoltaic diagnostics of the image is optical imaging. The imaging modality used has a direct effect on the detectability of defects, spatial resolution, spectral sensitivity and the diagnostic interpretability. Photovoltaic degradation is a mixture of morphological, thermal, and variations in material properties, many of which are optically visible at various parts of electromagnetic spectrum [20]. As such, the infrared thermography, multispectral sensing, and hyperspectral analytics have been added to the traditional visible imaging of PV imaging research. All the modalities have their own benefits in terms of the ability to identify certain signatures of degradation, and their joint use can provide a multi-dimensional performance evaluation. Fig.4. indicates the various Photovoltaic Imaging Modules.

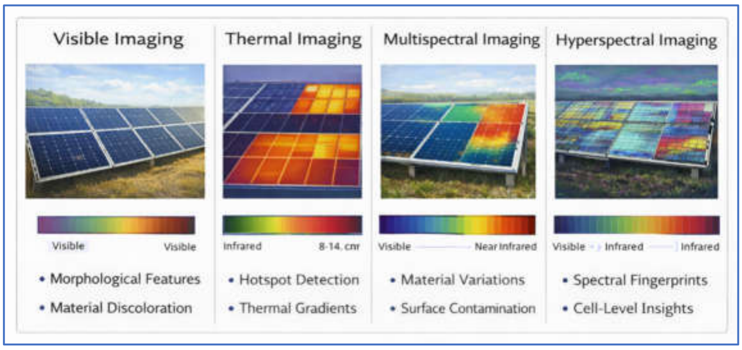

Fig.4. Photovoltaic Imaging Modules

4.1 Visible Spectrum Imaging

The most available modality with lower costs of implementation, which is visible spectrum imaging, is mostly introduced by the use of RGB cameras. RGB imaging, working in the 400-700 nm wavelength range, measures reflected solar energy on the surface of PV modules, thus representing visual data on shading, contamination, discolouration and structural defects. The capacity of the RGB imaging to record morphological signatures of surface soiling is one of the main diagnostic utilities of the imaging technique. The surface texture and reflectance intensity is changed by dust formation, resulting in quantifiable pixel brightness and colour distributions deviation. Likewise, the droppings of birds, and the deposits of leaves and pollen form localized opaque areas which appear as sharp contrast anomalies to the homogenous photovoltaic cell background. Dark mapping is yet another important use [21]. Fig.5. is clear evidence of the Visible Spectrum Imaging of PV Diagnostics.

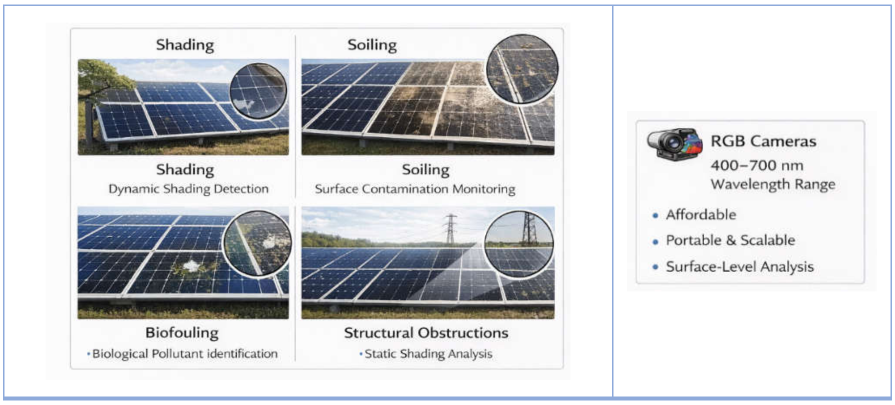

Fig.5. Visible Spectrum Imaging for PV Diagnostics

Geometric shading of structural obstructions can include transmission poles, mounting frames and vegetation, due to their unique geometries which can be bifurcated with intensity gradient analysis. Additionally, temporal RGB imaging makes it possible to track the passage of shadows, which facilitates the dynamic assessment of the effects of shading effects on daytime and nighttime sun pathways. Chromatic distortions that are measurable using colorimetric analysis are caused by biological contaminants such as algae films and fungal growth in moist climates. This kind of biofouling is not only attenuative of irradiance but can also degrade other protective coatings, which can be done chemically. The low cost, compact size and high spatial resolution of the RGB cameras render it very scalable into large solar farms. The deployment is also made more flexible with the integration with drone platforms and fixed monitoring systems. Nevertheless, visible imaging is fundamentally only surface diagnostics and susceptible to the changes in ambient light, which requires radiometric normalization in the preprocessing step [22].

4.2 Infrared Thermographic Imaging

Infrared thermographic IR imaging represents a photovoltaic diagnostics operation that is extended to the thermal emission spectrum, typically at the 8-14 µm wavelength range. In contrast to visible imaging, which is based on reflected radiation, thermography uses emitted infrared energy based on the distribution of temperature of the surface. Thermal imaging has been found to be especially useful in identifying emissivity anomalies that can be related to electrical and material defects. Local resistive heating occurs in those cells that are shaded and experience electrical mismatch conditions when they are reverse-biased. Such thermally stressed areas are indicated by high-temperature hotspots that can be differentiated with the rest of the cells. Shading on a cell string may also cause activated bypass diodes that leave characteristic thermal signatures visible in infrared images [23]. Likewise, solder bond failures, interconnect corrosion and metallization fatigue enhance electrical resistance, which results in heat concentration areas. Latent electrical faults which are not yet apparent optically can be detected by thermographic surveys in a non-contact way. In order to prevent catastrophic encapsulant melting failures, back sheet blistering, or fire dangers in high-voltage arrays, early hot spot identification is crucial. Operationally, thermal imaging can be done via thermal monitoring stations that are permanently installed, sensors mounted on drones, or handheld cameras. Nonetheless, precise thermographic interpretation presents a need of emissivity calibration and controlled irradiance conditions and little wind interference since the convective cooling may lead to temperature misreadings. Although more expensive equipment is required compared with RGB imaging, thermography is essential in the overall PV diagnostics because it can be used to detect electrical faults beneath the surface [24].

4.3 Multispectral Imaging

MSI fills the diagnostic gap between visible and hyperspectral imaging by recording reflectance data at a discrete number of spectral bands (outside the human eye visual spectrum). Common multispectral systems capture imagery in the short-wave infrared, near-infrared and visible wavelengths. Photovoltaic substances have wavelength-sensitive reflectance and absorption properties. These spectral signatures are altered due to the degeneration effect of encapsulant discoloration, wear of anti-reflective coating, and wear of glass surface. Multispectral imaging uses these differences to identify the material aging process that is not easily observable in the RGB space. As an example, transmittance in particular NIR bands is altered by encapsulant browning formed by the years of UV exposure. Equally, spectral scattering anomalies that can be detected using band ratio can be introduced by ingress of moisture and delamination. Shading by vegetation is also spectrally differentiable since the reflectance of vegetation matter has characteristic reflectance peaks of near-infrared wavelengths. The ability allows the distinction of both biological shading and inorganic contaminants. Multispectral data help in the advanced monitoring of vegetation encroachment, contamination, and degradation mapping of large PV fields. Although more sensitive to material than RGB imaging, multispectral systems have more expensive sensors and need more complicated calibration than RGB imaging [25].

4.4 Hyperspectral Imaging

Hyperspectral imaging is the richest optical diagnostic modality that can be used in photovoltaic inspection. Hyperspectral sensors have the ability to record continuous spectral data with hundreds of narrow wavelength ranges in three-dimensional spectral cubes, unlike multispectral systems which record spectral data at a limited number of bands. The full spectral signature of an object is contained in each pixel of a hyperspectral image, in effect a fingerprint of the material of the object. This spectral resolution allows observing the minute physicochemical processes in the PV materials, such as encapsulant degradation at the early stage, microfracture in silicon wafer and chemical changes in the back sheet. Subsurface flaws may cause additional spectrum absorption and scattering effects, which RGB imaging may not be able to detect. Latent degradation can therefore be seen at hyperspectral level before it is electrically/thermally manifested. Anomalies in material composition, such as corrosion byproducts or residues of pollutants, can be accurately recognized by their spectral signature. State-of-the-art machine learning algorithms on hyperspectral cubes result in an improved level of defect detection [26]. Nevertheless, hyperspectral imaging presents a significant amount of data and processing. The expensive acquisition cost, reduced capture rate, and extensive computational demands have led to the limitation of the high-field deployment at the moment. However, hyperspectral diagnostics have a great potential in research grade inspection, failure diagnostics, and monitoring of high value assets. The optical modality has its own contribution to photovoltaic diagnostics. The visible imaging is the most successful in the surface morphology examination, thermography imaging senses electrical and thermal stress, multispectral sensing imaging senses material aging, and hyperspectral imaging senses sub-surface physicochemical defects. These modalities can be strategically combined to allow multi-layered performance measurement across surface, thermal and material planes, which make up the technological foundation of sensor-less PV monitoring systems of the future [27].

5. Image Acquisition and Preprocessing Pipelines

Image quality and consistency of obtained imagery is the root cause of diagnostic reliability of imaging sensor-free photovoltaic monitoring structures. Raw images that are collected using ground cameras, UAV platforms or robotic crawlers are automatically affected by environmental variations, sensor constraints and acquisition geometry distortions. These artifacts may create an introduction of analytical bias, loss of segmentation quality and impairment of defect detection sensitivity without systematic preprocessing. The image acquisition and preprocessing pipelines are then the lowest computational layer that converts raw visual data into representations that can be analysed to provide reliable analytical information. These processes include radiometric calibration, geometric correction, and noise suppression, and additional processes like illumination normalization, lens distortion correction and image registration. Preprocessing helps improve on the physical meaning and statistical consistency of image datasets so that the diagnostic algorithms that follow can work on physically meaningful data [28]. In Fig.6, Image Acquisition & Preprocessing Pipeline illustrates the manner in which the images are taken.

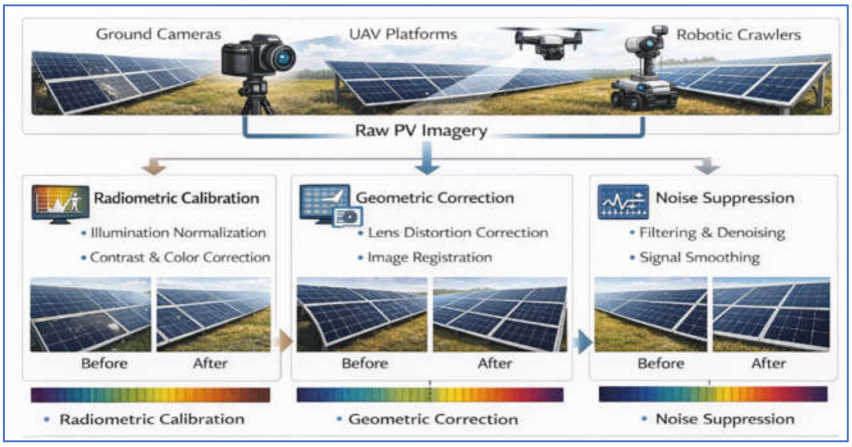

Fig.6. PV Image Acquisition & Preprocessing Pipeline

5.1 Radiometric Calibration

Radiometric calibration, also known as radiometric normalization, is an important preprocessing step which is necessary to make the values of the pixel intensities reflect surface reflectance properties and not acquisition artifacts. Captured pixel brightness in photovoltaic imaging applications does not only depend on the module surface conditions but also varies due to external sources like the variability of the solar irradiance, the atmospheric scattering, sensor exposure parameters and camera gain parameters. Radiometric inconsistency is especially a major threat to temporal imaging datasets. The photos taken on various times of the day undergo changes in solar angle and spectral composition and irradiance level. Due to the absence of calibration, the same contaminant on the surface can be displayed under different values of intensive value, falsifying the comparative diagnostics and change detection algorithms [29].

By transforming raw pixel values into normalized reflectance values, radiometric normalization techniques compensate for these discrepancies. Flat-field correction is widely used to eliminate sensor illumination gradients and histogram matching is used to match intensity distributions across time frames. The more sophisticated calibration processes include reference reflectance panels installed in PV fields, which allow to do absolute radiometric correction with known albedo values. In aerial imaging, radiometric calibration should also take into consideration effects of vignetting created by lens falloff, and effects of bidirectional reflectance distribution function (BRDF) that vary with viewing angles. Correction of these distortions gives calibrated imagery so that the deviation of the intensities are directly proportional to physical events like shading or contamination but not to the variation between acquisitions. Radiometrically scaled data sets cannot be replaced in quantitative analytics such as the shaded area estimation, soiling severity indexing and machine learning feature extraction [30].

5.2 Geometric Correction

Geometric correction is used to focus on spatial discrepancies which are caused during the acquisition of the image. Photovoltaic imaging systems especially UAVs and mobile robots rarely obtain the images in the perfectly orthogonal viewing conditions. Perspective distortions created by camera tilt and variation of altitudes and platform movement as well as terrain undulation modify the geometry of PV modules as perceived. Such distortions are in the form of trapezoidal shapes of the panel, non-uniformity of cell dimensions and misalignment of space between image frames. Without repair, these geometric irregularities make it difficult to properly segment, quantify, and locate flaws. Geometric rectification is based mathematically on homographic transformation. By projecting the distorted picture coordinates onto a planar reference grid, homograph can be utilized to restore the actual spatial proportions of PV modules. This change is based upon the determination of the matching control points between distorted image and reference geometry, which are usually defined using the panel corner coordinate or other structural mount structure [31].

Geometric correction is also applied in orthorectification processes in large-scale aerial inspections. In this case, digital elevation models and GPS telemetry are added so that the distortions of terrain are eliminated allowing the creation of geospatially correct Ortho mosaic maps. Another geometric preprocessing is Lens distortion correction. Radial and tangential distortions are inherent in wide-angle and fisheye cameras often used in UAV images, and have to be corrected with matrixes of camera calibration. Precise geometric correction is critical to pixel to physical area conversion, defect localization and date alignment of multi date imagery. It makes sure that the spatial analytics is based on the real geometry of modules and not perspective artifacts [32].

5.3 Noise Suppression

Another essential preprocessing step intended to enhance signal fidelity in the photovoltaic image is noise suppression. PV imaging noise has many different causes, e.g. atmospheric interference, sensor electronics, compression artifacts and motion induced blur. Haze effects are brought on by atmospheric scattering in wet or dusty environments, which reduce contrast and mask small surface details. On the same note, high ISO images taken in low light increase sensor noise and make pixel variability discrete to create contamination-like textures. Thermal imager systems add on extra noise elements like fixed-pattern noises, thermal drift and artifact of emissivity variation. When left uncorrected, these distortions may cause the false hotspots detection or estimation of temperature. The use of adaptive filtering methods is common to reduce such noise and still retain some features that are diagnostically useful. The median filtering is very effective in removing salt and pepper noise without blurring edges and hence it can be applied in preservation of contamination boundaries. Gaussian filters suppress sensor noise in the high frequency range, but have to be parameter-tuned to prevent fine cracks to be lost. There are more advanced denoising methods, like bilateral filtering, which takes into account both spatial proximity and intensity similarity, and hence edges discontinuities. By dividing images into frequency bands with different resolutions, wavelet-domain denoising enables local noise attenuation without sacrificing structural detail. To eliminate sensor band noise and atmospheric absorption artifact, noise suppression is further extended in spectral smoothing and dimensionality reduction in hyperspectral imaging. Noise reduction methods increase the accuracy of segmentation, enhance stability in machine learning features, and make dependable degradation signatures extraction of PV imagery [33].

Raw photovoltaic imaging is transformed into analytically sound datasets by combining radiometric calibration, geometric correction, and noise reduction. By restoring spatial fidelity, uniformizing illumination, and enhancing signal clarity, these preprocessing pipelines serve as the processing foundation for more crucial diagnostic operations like shading segmentation, contamination classification, and defect detection. With PV monitoring systems moving to autonomous and real-time operation, there is a growing optimization of preprocessing algorithms to operate at the edge to provide the ability to run high-quality image analytics directly at the hardware infrastructure of the field [34].

6. Classical Computer Vision Frameworks

Before the popularization of deep learning-based systems, photovoltaic defect diagnostics heavily has been based on classical computer vision algorithms based on deterministic image processing and statistical patterns analysis. These models are based on manually crafted feature extraction and rule-based segmentation concepts and present computationally efficient and interpretable models of shading detection, soiling quantification and defect localization. Classical vision algorithms are also still useful in photovoltaic monitoring especially in edge-computing platforms that have limited hardware resources. Fig.7 displays Classical Vision Algorithms of PV Analysis.

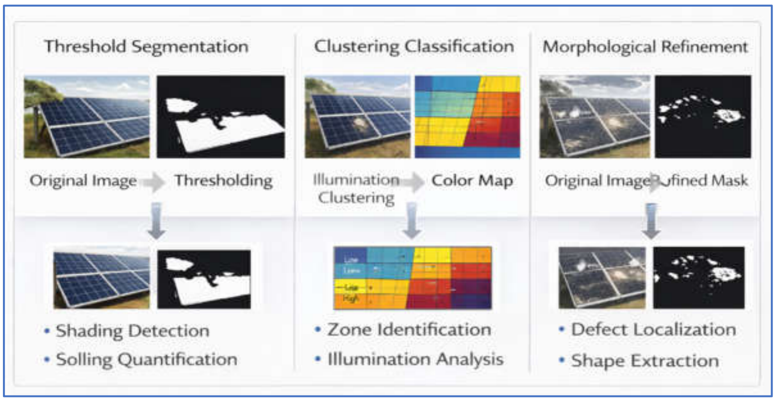

Fig.7. Classical Vision Algorithms for PV Analysis

Their low calculative cost gives them real-time analytics in embedded processors used in UAV payloads, robotic crawlers or on a fixed monitoring station. Moreover, classical models present explainable results, and thus operators can trace diagnostic results to explicit image characteristics, e.g. intensity gradients, texture discontinuities, or morphological boundaries. There are three major classical vision constructs through which PV imaging pipelines are typically offered: threshold-based segmentation, clustering-driven illumination classification and morphological analytics of structural refinement [35].

6.1 Threshold-Based Segmentation

One of the simplest methods of photovoltaic image analysis is the threshold-based segmentation. The procedure assumes that stained, dirty or dirty areas have characteristic grayscale variation or colour intensity differences compared to the standard panel surfaces which are lit up. In global thresholding, one intensity value threshold is used throughout the image to divide the pixels into binary classes that are typically illuminated and obstructed areas. The method is computationally inexpensive and is suitable to uniformly lit scenes and the illumination gradients are small. Nevertheless, installations of PVs do not work in perfectly homogeneous lighting conditions, which restricts the strength of global thresholds. Adaptive thresholding is a solution to this shortcoming that uses local threshold values in sliding window neighbourhoods. This makes possible dynamic segmentation that considers the spatially varying irradiance, cloud shadows and brightness gradients due to perspective. Gaussian adaptive thresholding and mean adaptive thresholding are some of the techniques that are normally used to improve the segmentation quality in the presence of non-uniform illumination. Another popular threshold optimization method, developed by Otsu is its method. It automatically establishes the threshold value which reduces the intra-class variance and maximises inter-class separability. Otsu segmentation is also effective in the PV diagnostics of dense soiling spots or bird droppings with high contrast against the module glass. Although simple, threshold-based methods are very prone to radiometric variations and noise effects thus requiring strong preprocessing pipelines. Through proper calibration, threshold segmentation gives a quick and understandable distinction to the stippled areas that can be further quantified in terms of areas [36].

6.2 Clustering Algorithms

Compared to binary partitioning, clustering-based segmentation has the capacity to do multi-class illumination and contamination classification. These methods enable a more nuanced representation of PV surface conditions by grouping pixels based on similarity metrics, such as intensity, chromaticity, or texture metrics. One of the most popular unsupervised learning algorithms used in the photo-voltaic image diagnostics is k-means clustering. It divides pixel data sets into K clusters by reducing the variance within the clusters via a series of centroid optimization. Shading analytics Clusters can be associated with completely lit cells, semi-shaded areas, thick obstruction and background artifacts. Fuzzy C-means cluster brings the concept of probabilistic membership modelling whereby the pixels can be members of many clusters with differing levels of membership. In PV imaging, where shade transitions are gradual rather than abrupt, such a soft clustering paradigm offers unique advantages. An example is the semi-transparent dust decks or dark cloud shadows, which form unclear intensity boundaries which can be better represented by fuzzy clustering than by hard segmentation. Advanced PV analytics include spectral clustering and Gaussian mixture models too especially when a multispectral input (imaging) is incorporated. These approaches make use of multidimensional space of features to enhance cluster separability in complicated patterns of degradation. The frameworks of clustering play an important part in measuring shading severity by estimating the soiling density gradients and producing illumination heatmaps. They depend however on the ability to select the optimum number of clusters and the design of feature space, which in many cases, needs domain-specific calibration [37].

6.3 Morphological Analytics

Morph image processing gives structural refining opportunities that increase the accuracy and interpretability of segmented photovoltaic areas. Based on mathematical morphology, they are spatial analysis operations whose transformation processes examine the pixel neighbourhood structures through a kernel-based process. Erosion and dilation are the fundamental morphological operators. his technique can be used to remove individual pixel misclassifications brought on by reflecting glare or sensor noise. In order to reconjugate broken stippled areas and restore structural continuity, dilation is the opposite procedure of extending region boundaries. plied in sequence erosion, then dilation, called opening gives up noise information but leaves primary region morphology intact. Dilation and erosion on the other hand, seals minor gaps in segmented shading areas. Contour extraction algorithms are applied to morphologically advanced masks in order to define accurate contours of shaded or polluted areas. These contours allow geometric analysis like the computation of shaded area, modelling of obstructions shape and defect localization at cell or sub-cell resolution. In more sophisticated morphological procedures, skeletonization can be used to examine patterns of crack propagation, whereas watershed segmentation can be used to isolate overlapping clusters of contamination. The morphological analytics boost the accuracy of the estimations of the shaded areas and delineations of defect boundaries in order to achieve structural coherence, which in turn enhances the trustworthiness of classical computer vision diagnostics in photovoltaic monitoring devices.

The computational basis of classical photovoltaic image analysis is comprised of threshold segmentation, clustering algorithms and morphological analytics. Individually constrained in their response to large variations of illumination or a complex degradation signature, their combination allows effective interpretation, interpretable and hardware-light diagnostic solutions. Classical computer vision models are still used in modern AI-based surveillance systems as accelerators of preprocessing or extracting features or validating layers to support deep neural inference networks [38].

7. Feature Engineering for PV Image Analytics

The analysis between the raw photovoltaic images and a computational intelligence system is the feature engineering. Before the capabilities of deep neural networks of end-to-end learning, diagnostic inference used features extracted by hand, which has the capacity to mathematically encode visual signatures of degradation Even in contemporary AI ecosystems, engineered features are helpful in interpretability-driven analytics, hybrid systems, and lightweight AI models. In photovoltaic monitoring, feature engineering aims at converting visual expression of soiling, shading, contamination and structural defects into quantifiable descriptors. These descriptors should be insensitive to illumination variation and at the same time should be sensitive to degradation morphology. Multidimensional representations of PV surface conditions are offered by the use of texture, colorimetric, and frequency-domain feature spaces, and allow strong contamination classification and performance inferences. In Fig.8, Feature Engineering of Classical PV Diagnostics is demonstrated.

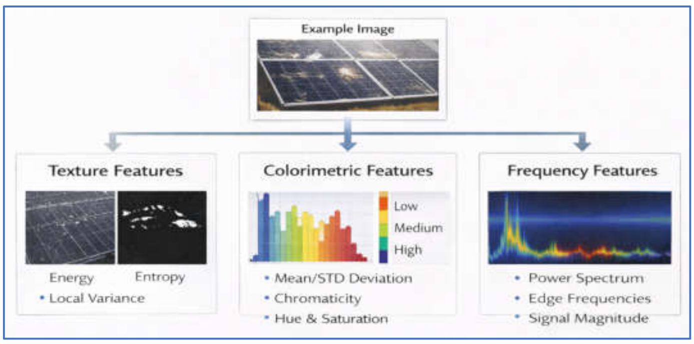

Fig.8. Feature Engineering for Classical PV Diagnostics

7.1 Texture Feature Spaces

The texture analysis is instrumental to the photovoltaic contamination diagnostics, with lots of degradation factors leaving a trace on the surface granularity and spatial roughness change. The stochastic micro-patterns are induced by dust deposition, pollen deposition and industrial particulate matter, and alter uniformity of panel reflectance. Statistical texture measures like Gray-Level Co-occurrence Matrices (GLCM) are used to measure spatial pixel relations of several parameters, including contrast, homogeneity, entropy and correlation. In order to distinguish between equally dispersed haze-like soiling and the concentration of deposition, the metrics are employed to measure the density and dispersion distribution of pollutants. Local Binary Patterns (LBP) is a rotationally invariant micro-texture encoding, which is especially useful at identifying fine layers of particulate dust. Gabor filters extend this feature of texture characterization by breaking images down into orientation sensitive bands of frequencies, making it easier to detect directional streaks due to dust being blown along by the wind or due to cleaning residues being left behind. Texture feature spaces allow the detection of preliminary soiling even in cases when macroscopic soiling evidence is faint by statistical modelling of granularity and surface roughness of contaminants.

7.2 Colorimetric Feature Modelling

Colorimetric analysis takes advantage of chromatic deviations that contamination agents add to be used in categorizing degradation typologies. Though the appearance of photovoltaic modules might seem to be homogeneous in the clean conditions, it is possible to observe spectral change induced by the deposition of materials. The geographical variation in dust composition has been identified with desert sand, industrial soot and agricultural particulates having unique colour signatures. High-albedo white spots are added by bird droppings whereas spectral anomalies of greenish spectral view is a biological pollutant of algae or moss in humid climates. Colour feature extraction is normally performed in various colour spaces, such as: RGB, HSV, and CIELAB. HSV breaks down components of hue and saturation that improve the separation of organic and inorganic contaminants. The space of CIELAB is specially developed to provide uniformity in perceptions, therefore, allowing a more accurate measurement of small deviations in chromatics. Spectral shifts caused by contamination are represented in colour histograms, chromatic moments and colour coherence vectors. These descriptors underpin monitored classification systems that are able to differentiate dust deposition with the biological foulage or structure shading artifacts.

7.3 Frequency-Domain Descriptors

An alternative form of representation Photovoltaic imagery is represented by frequency-domain analytics, which convert the distribution of spatial pixels into spectral data. The transformation is effective especially to detect large-area illumination attenuation phenomena which might be less visible in the spatial space. Fourier Transform analysis breaks-down PV images into sinusoidal frequency components which allows low-frequency intensity attenuation of broad-area shadings (as caused by cloud cover or structural obstruction) to be detected. High-frequency content, in its turn, defines small-scale texture features, e.g. dust speckling or microcrack edges. Wavelet transforms improve this by adding multi-resolution decomposition, which preserves both the frequency characterisation and the spatial localization. This is particularly useful to the PV diagnostics tasks, in which the degradation patterns can be at more than one spatial scale at a time. Periodicity of shading, distribution of contamination, and degradation of uniformity in illumination can be quantified with frequency-domain descriptors, which create a solid analytical basis of both classical and machine learning diagnostic pipelines [39].

8. Machine Learning Classification Ecosystems

Machine learning models are constructed based on feature spaces that are engineered to support automated photovoltaic degradation classification and classification of performance. Through the acquisition of statistical connections between visual metrics and operational performance, these models transform untapped images into diagnostic intelligence. Fig.9 represents Machine Learning to Diagnose Photovoltaic.

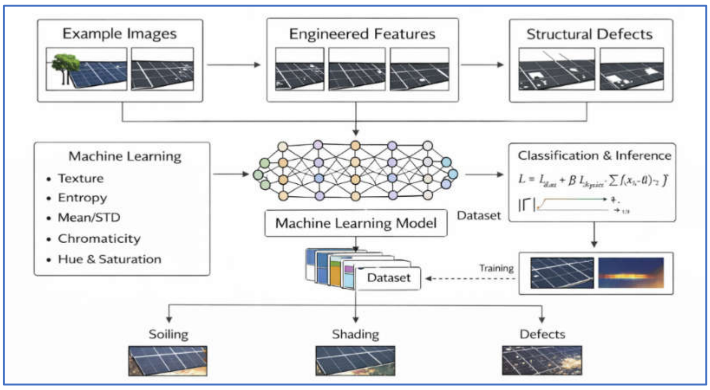

Fig.9. Machine Learning for Photovoltaic Diagnostics

8.1 Supervised Contamination Classification

Supervised learning models require annotated photovoltaic datasets in which the types of contamination and the shading categories are annotated. Feature vectors that represent images based on their texture, colour, and frequency attributes are used to train classifiers such as Support Vector Machines (SVM), Random Forests, k-Nearest Neighbours, and Gradient Boosting architectures. Such classifiers get to learn decision boundaries that distinguish between the typologies of contamination such as dust layers, bird droppings, leaf shadows, and structural obstructions. Dataset diversity, annotation fidelity and feature discriminability are very important in model performance. The implementation of supervised classification allows mapping the contamination of solar arrays across the arrays automatically and helps prioritize maintenance needs and allocate resources to cleaning. Nevertheless, the limitations to its scalability are based on the labour-intensive nature of dataset labelling.

8.2 Regression Models for Power Loss Estimation

Machine learning regression models provide quantitative correlations between electrical performance attenuation and visual degradation descriptors in addition to categorical classification. hrough comparison of the features of the extracted images with the measured power output data, regression schemes are used to estimate the energy yield losses due to shading or soiling. Base line feature-to-power relationships are obtained using linear regression frameworks and more complicated nonlinear structures include Artificial Neural Networks, Support Vector Regression, and Ensemble Regressors are used to capture intricate interactions between degradation and performance. These models can estimate power loss in real-time directly using the imagery and therefore power loss estimates no longer require invasion electrical measurements. This becomes useful especially in sensor-free monitoring schemes in which the density of the electrical instrumentation is constrained [40].

9. Deep Learning Architectures

Deep leaning has been used to transform photovoltaic image diagnostics, removing the manual feature engineering. Neural networks learn features that are degradation relevant, and solely those features, without any manual or human intervention in hierarchical representation learning. In Fig.10 Deep Learning on Photovoltaic Diagnostics is shown.

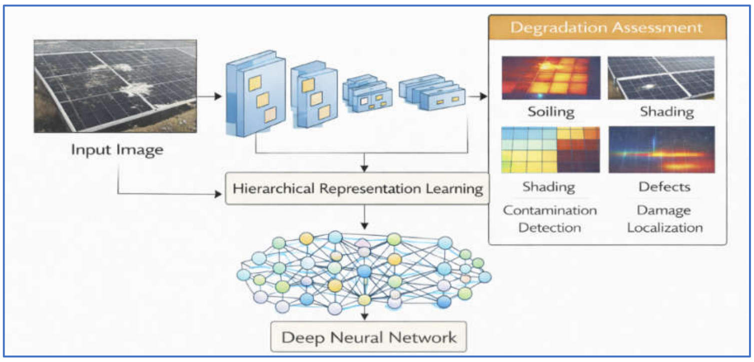

Fig.10. Deep Learning for Photovoltaic Diagnostics

9.1 Convolutional Feature Hierarchies

The basis of deep PV analytics is based on CNNs. CNNs teach features that are hierarchical, i.e. edge and gradient at the lowest levels and morphology of the contaminant at the highest levels. The first few convolutional layers encode early visual primitives, including shading edges and dust textures, whereas later convolutional layers encode complicated obstruction patterns and degradation semantics. The application of pretrained architectures like ResNet, VGG, and EfficientNet speeds up the model convergence in datasets related to PV. The CNN-based classifiers have higher recognition accuracy in contamination when compared to the classical feature-based models, especially when there is a variation in illumination and in complicated environmental settings.

9.2 Semantic Segmentation Networks

The semantic segmentation is an extension of CNN functions, which are applied to classify images, to pixels. U-Net, DeepLab and SegNet architectures produce dense prediction masks that identify the location of shaded, soiled and defected areas at a high level of spatial resolution. Finer-grained analytics like localized efficiency estimation, a contamination densitymap, and the measurement of darkened areas can benefit from segmentation down to the pixel level. The maintenance planning depends upon this spatial resolution in order to determine areas of high-impact degradation. Annotated aerial orthomosaics or ground images can be utilized to train segmentation networks, and encoder-decoder architectures are typically employed to guarantee the preservation of high contextual and spatial information.

9.3 Instance Segmentation Frameworks

The instance segmentation goes a step further by isolating discrete entities of obstructions in photovoltaic images in addition to semantic labelling. Mask R-CNN and Yolo based segmentation models are frameworks that detect and partition individual contaminants. The object-centric representation has been especially useful in distinguishing between overlapping sources of degradation e.g. in separating bird droppings and leaf shadows in the same region of the panel. Analytics at the instance level are useful to aid obstruction counting, size estimation and targeted deployment of robotic cleaners and increase precision of maintenance [41].

10. Illumination Non-Uniformity Modelling

Non-uniformity of illumination is one of the most severe causes of loss of performance in photovoltaic systems. Predictive estimation of electrical mismatch severity has been made possible by modeling the variability of illumination with the use of quantitative descriptors. The Fig.11 illustrates Illumination Mapping of Mismatch Analysis.

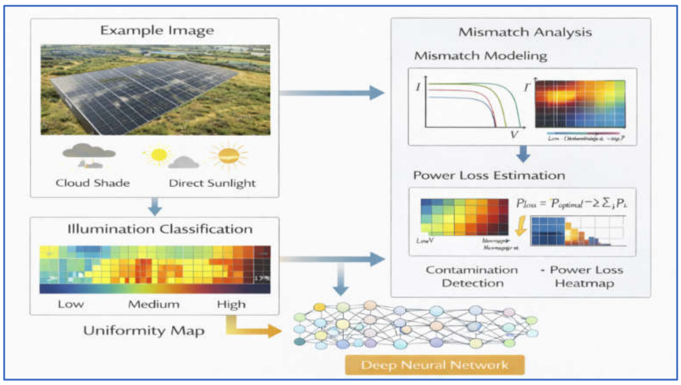

Fig.11. Illumination Mapping for Mismatch Analysis

10.1 Spatial Illumination Gradients

Spatial gradient analysis is used to measure changes in pixel intensity over PV surfaces to measure sudden shading discontinuities. Sobel and Scharr filters are gradient operators, which identify sharp edges of illumination that are indicative of structural shadows or dense obstructions. Gradient magnitude mapping allows to detect large contrast shading edges, which help to estimate the severity of mismatch in series-connected cell networks.

10.2 Global Intensity Variance Metrics

Measures of statistical dispersion such as variance, standard deviation, and coefficient of variation are used to describe the general imbalance of illumination on PV modules. Large values of variance are associated with strong irradiance heterogeneity, which in many cases translates to low efficiency of maximum power point tracking. Globally metrics offer real-time plant-scale shading severity indices that are applicable in massive monitoring observatory boards.

10.3 Frequency Distortion Indices

The Frequency-domain illumination modeling is used to measure the harmonic distortions caused by large attenuation fields. The spectral dominance of low frequencies shows extensive coverage of the shading and mixed-frequency distributions are heterogeneous distributions of obstructions. These indices make macro-scale diagnostics of illumination and prediction of energy yield impact [42].

11. Physics-Guided AI Hybrid Models

Physics-guided AI is a new paradigm that entails the incorporation of photovoltaic illumination physics in the neural learning models. Instead of using data-driven inference only, hybrid models incorporate physical constraints like irradiance-current laws, diode behaviour and laws of thermal dissipation into training of networks. Such integration makes predictions made by AI more interpretable, which guarantees physically plausible predictions. It also decreases the dependency of datasets as it limits the space of solutions with the domain knowledge. Several forms of differentiable PV performance models, simulation-augmented training datasets, and loss functions guided by physics are some of the key components of this hybrid system. These models are especially useful in terms of extrapolating diagnostics in the unobserved environmental conditions [43]. Fig.12 illustrates Physics-Guided AI on Photovoltaic Diagnostics.

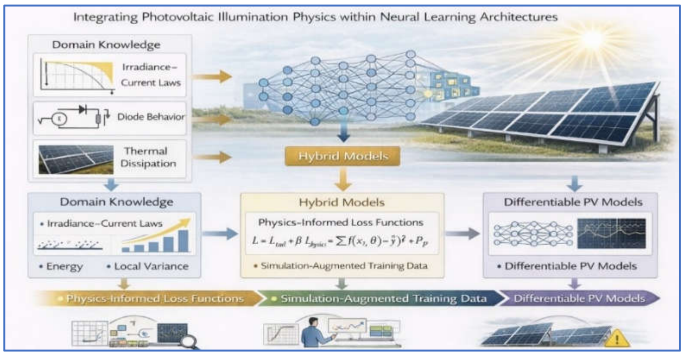

Fig.12. Physics-Guided AI for Photovoltaic Diagnostics

12. Multimodal Fusion Diagnostics

Because multimodal fusion frameworks (Fig. 13) integrate disparate data streams to enable cross-domain evaluation of photovoltaic deterioration signals, they increase diagnostic confidence.

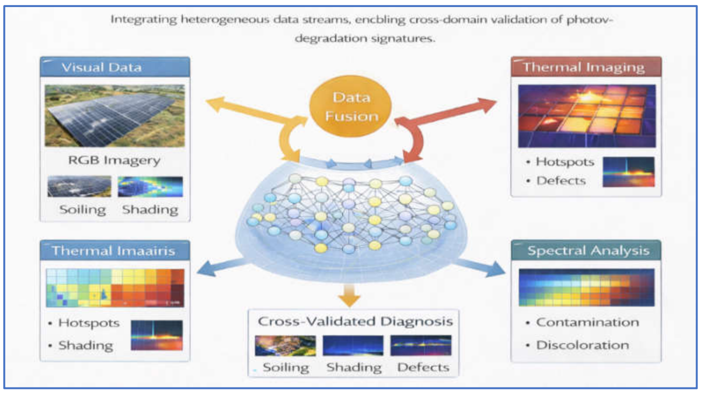

Fig.13. Multimodal Fusion for Photovoltaic Diagnostics

12.1 RGB–Thermal Fusion

Vis-IR thermographic imaging allows optical contamination and thermal anomalies to be studied together, because of the fusion of the two imaging modes. Whereas the RGB imaging systems are used to identify the morphology of shading and soiling, the thermal imaging system identifies resistive heating, bypass diode activation, and interconnect stress. Data fusion can be at pixel, feature or decision based, and deep multimodal networks are progressively being used to learn joint representations. This combination strategy also drastically lowers the false positive and improves the strength of defect detection.

12.2 Vision–Electrical Data Coupling

Image analytics are coupled with SCADA telemetry, bringing about a cyber-physical diagnostic paradigm. Visual degradation indicators are related to electrical parameters of a string current, voltage mismatch, and inverter efficiency. Instance validation of root causes, such as determining whether observed shading is caused by detectable power attenuation, is made possible by cross-domain fusion. It is an integrated analytics model that enables high confidence fault diagnostics and performance attribution modelling [44].

13. Edge Computing and Embedded AI

Image-based photovoltaic diagnostics has proliferated and this has required computational architectures that are able to handle high volume flows of visual information with low latency. In this regard, edge computing has become a revolution by empowering on-field inferences in direct field monitoring devices. Embedded AI systems can do real-time analytics at the data acquisition site, using significantly less bandwidth and communication latency than transferring raw photos to centralized cloud servers. On-board inference systems are customarily based on power-saving hardware accelerators, including GPUs, TPUs, FPGAs or neuromorphic processing units installed in UAV payloads, robots' crawlers or stationary inspection nodes. Fig.14 represented the Edge Computing of Photovoltaic Diagnostics.

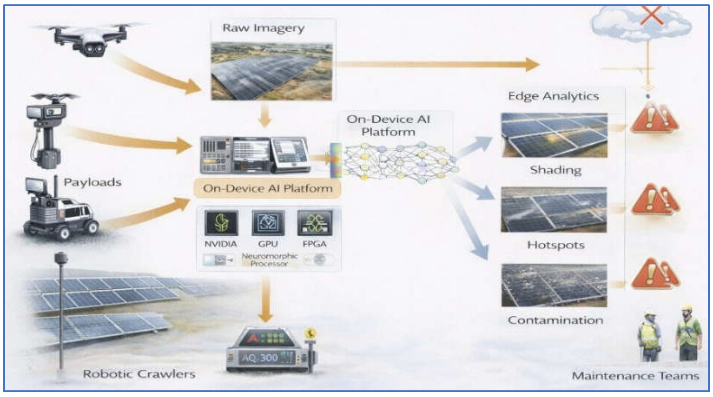

Fig.14. Edge Computing for Photovoltaic Diagnostics

These platforms are optimized convolutional neural networks and classical vision pipelines that are customised on shading detection, hotspot recognition and contamination segmentation. The ability to process in real-time allows real-time generation of anomaly notifications that can be used to trigger a response to the maintenance team in case of a performance degradation event. Additionally, edge analytics will improve operational stability in remote solar farms where network connectivity may be seasonal or have capacity constraints. Embedded AI architectures also enhance privacy of data and lower the costs of cloud infrastructure by decentralizing the computational workloads and allow scalability to gigawatt-scale photovoltaic fleets [45].

14. Autonomous UAV Swarm Inspection

The inspection missions of a single drone cannot be operationally efficient as the solar parks grow to ultra-large size plants which occupy thousands of hectares. Autonomous UAV swarm inspection suggests a cooperative aerial robotics paradigm in which several drones carry out cooperative survey tasks. Swarm systems use distributed mission planning algorithms that are used to break up solar fields into optimized inspection grids. The UAVs are deployed with a spatial sector and adapt dynamically their flight plan reacting to telemetry in the real time, battery conditions, and obstacle detection. The inter-drone communication is guaranteed to provide collision avoidance, reduction of coverage redundancy and coordinated data acquisition. The swarm units carry high-resolution imaging payloads to record visible and thermal datasets, which would allow defects to be detected and the hotspots to be mapped on the thermographic of a component at the same time. Ortho mosaic reconstruction algorithms are then used to integrate multi-drone footage into single-plant diagnostic maps. Swarm inspection minimally cuts down the time required to achieve a survey, at day times, to hours, and the spatial resolution is high. This quick inspection system is highly important especially after a severe weather or a sandstorm or grid fault when instant determination of the condition is in order. Combining swarm intelligence, autonomous navigation, and PV imaging analytics is one major step towards fully automated solar asset inspection ecosystems [46]. Fig.15 is the Swarm Inspection of Photovoltaic Diagnostics.

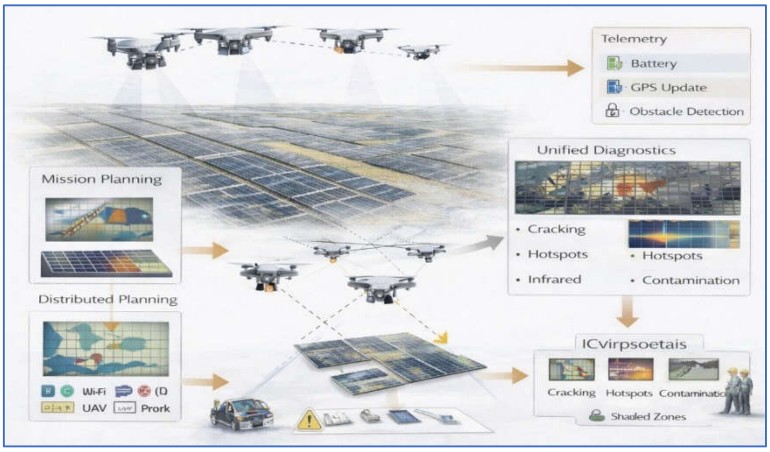

Fig.15. Swarm Inspection for Photovoltaic Diagnostics

15. Digital Twin-Driven PV Analytics

A cyber-physical replication model is made possible by digital twin technology, in which virtual models replicate the climatic, electrical, and structural characteristics of actual photovoltaic resources. In order to simulate plant activity under varying situations, these digital replicas continuously consume real-time image diagnostic data, sensor metadata, and operational telemetry. Models of performance decay are fitted with images degradation measurements maps of soiling density, crack propagation, and hotspots patterns that are introduced in twin settings. Physics informed simulation engines are then used to measure the effect of observed defects on energy yield, thermal stress and component life. Digital twins make it possible to analyze maintenance strategy optimization through scenario optimization. Simulation of cleaning schedules can be done at a range of rates of soiling accumulation, and repair prioritization may be informed by the estimated impact of energy loss. Also, lifecycle forecasting models are estimates of long-term degradation when subjected to various environmental exposure regimes. Digital twin ecosystems can assist the management of photovoltaic portfolios by converting fixed inspection data to flowing predictive intelligence to assist in data-driven management of assets, financial projection, and optimization of reliability [47]. Digital Twin Photovoltaic Management is indicated in Fig.16.

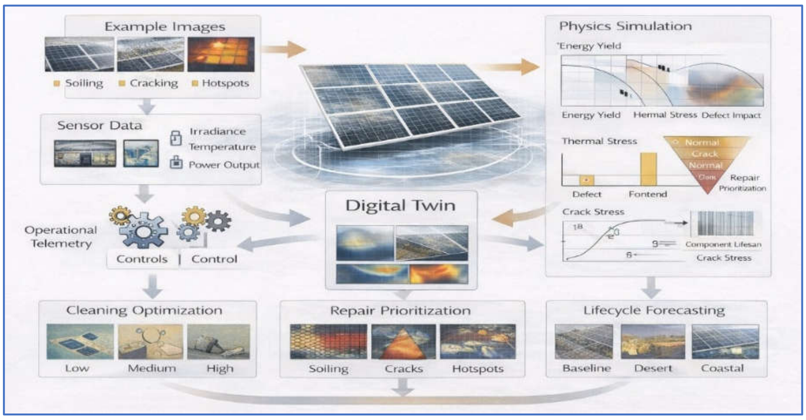

Fig.16. Digital Twin for Photovoltaic Management

16. Predictive Maintenance Frameworks

Predictive maintenance is a shift in the paradigm of reactive or timetable-based servicing to condition-based intervention approach. In PV monitoring systems based on images, AI-based prognostic models are used to predict the future progression of faults based on the temporal degradation pattern. Machine learning methods can generate information regarding soiling accretion dynamics, hotspot probabilities, and fracture propagation speeds using time series picture data. Such prognostic analytics are increasingly being implemented using recurrent neural networks, temporal convolutional architectures and transformer-based sequence models. Prognostic models make prediction advisories depending on the risk levels. Among them are cleaning operations, which can be initiated when estimated soiling losses are negative to economic breakeven values (and hotspots mitigation which can be initiated before risks of thermal runaway occurrence. This is an expectation-based maintenance strategy that reduces unexpected downtime, avoids disastrous module failure, and engineers optimal workforce. In addition, it equates maintenance spending with the performance effect hence enhancing operational cost effectiveness.

17. Economic and Operational Impact

Replacement of sensor-based monitoring with sensorless vision-based diagnostics has far reaching economic consequences to photovoltaic operators. Conventional instrumentation infrastructures demand a significant amount of wiring, acquisition of sensors, calibration and occasional maintenance which adds to both high capital and operation costs. Monitoring systems based on images are important in eliminating these cost burdens, through the use of scalable optical sensing platforms. Hundreds of dispersed sensors can be replaced by a single UAV survey or fixed network of cameras, which also offers higher spatial resolution diagnostics. Operationally, automated defect detection will save manual inspection labor and will not reduce system downtime due to its quick ability to localize anomalies. Quickened maintenance reaction is directly proportional to better energy output and income retention. Predictive maintenance optimization further improves return on investment by avoiding the repetitive cleaning cycles, but does not cause a performance loss when intervention is delayed. Together, sensor-less vision systems create thinner operational models, better plant availability, as well as higher profitability in the lifecycle.

18. Standardization and Benchmarking Challenges

Although there is a fast-growing aspect of technology, photovoltaic imaging analytics field experiences high limitation of standardization and benchmarking. Among the most outstanding issues is lack of universally recognized PV image datasets, which cover a wide range of degradation conditions, climatic conditions, and typologies of different installations. Available data are usually specific to an institution, small in size, or taken in controlled settings, which limits the generalizability of the model. There are also no standardized annotation protocols and differences in granularity of labels, defect taxonomy and severity grading. Measurement of performance evaluation is also not consistent. Experiments use heterogeneous validation instruments, including pixel accuracy of segmentations, down to plant-level energy loss fidelity, and this renders cross study comparability challenging. The standardization differences are an impediment to reproducibility, slow algorithmic benchmarking, and regulatory approval of automated inspection systems. Research and industry place a high premium on the development of open-access datasets, unified annotation ontologies, and universal performance metrics.

19. Emerging Research Frontiers

A combination of artificial intelligence, optical sensing, and autonomous robotics convergent innovations are forming the frontier of photovoltaic image diagnostics. The use of self-supervised learning frameworks is becoming increasingly popular because it decreases the reliance on large annotated datasets, and therefore, it learns feature representations using unlabelled PV images. Domain adaptation methods are being formulated to provide algorithm consistency even between solar farms geographically dispersed and having different environmental as well as installation features. Hyperspectral defect analytics further evolves the sub-surface degradation sensor, which allows revealing the encapsulant discoloration, moisture intrusion, and material stress prior to its appearance. Another transformational direction is that of integration with robotic cleaning systems. Robots with vision-based cleaning can independently recognize the most soiled areas and perform specific cleaning tasks, which maximize the consumption of water and energy efficiency. Future research directions include quantum-enhanced optimization in inspection path planning, neuromorphic vision sensors in ultra-low-power monitoring, and federated learning as a privacy-sensitive multi-plant model training technique.

20. Conclusion

Senor-free diagnostics using images has been through an extensive transformation process as a novel academic research concept to an essential technological core being the base of intelligent photovoltaic-monitoring ecosystems. By utilizing advancements in computer vision, deep learning, optical imaging modalities, and the integration of cyber-physical energy systems, these frameworks can be used to accomplish high-resolution, scalable, and financially feasible solar asset management. The merging of edge computing, autonomous robotics, predictive analytics, and digital twin modelling is changing the fields of photovoltaic operations based on reactors to their fully autonomous performance optimization ecosystems. These capabilities are necessary with the growth of solar infrastructure on the global scale and its strategic value. Further interdisciplinary invention including materials science, artificial intelligence, aerospace robotics and energy informatics will be fundamental to optimizing the photovoltaic reliability, resilience and lifecycle productivity. Intelligent vision-guided diagnostics will be critical in the larger context of the global renewable transition, with the objective of maintaining a maximum level of efficiency within a solar energy system, which will in turn strengthen the sustainability of this type of energy source as a reliable power source in the future.

21. Acknowledgement

The authors highly appreciate the management of Thiagarajar College of engineering to have supported the research work financially through Thiagarajar Research Fellowship (TRF) scheme (File no.: **TCE/RD/TRF/July2024/07**) which was a major boost to the completion of the research work.

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