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Comparative investigation of imaging techniques, pre-processing and visual fault diagnosis using artificial intelligence models for solar photovoltaic system – A comprehensive review

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ABSTRACT

Photovoltaic systems provide an eco-friendly key to meet our increasing energy demand while mitigating the adverse impacts of conventional fossil fuel-based energy generation. The effective power generation from PV systems can be obtained from fault-free systems. Detecting and correcting faults in solar photovoltaic (PV) systems is vital to ensure their best performance, safety and durability. In the existing literature, some have concentrated only on possible faults in PV, some on inspection techniques for monitoring, and some on Machine learning models applied in fault detection. In this work, a combined review of the types of possible PV system failures, image acquisition methodologies, preprocessing techniques, and artificial intelligence (AI) models could accurately localise and distinguish the faults in PV systems that are presented. This work discusses different literature on automatic fault detection methodologies. This enables readers to focus on critical aspects while developing a practical fault detection technique for Solar PV systems.

1. Introduction

The world is experiencing an extraordinary challenge at the intersection of rising population growth and surging energy demand. As global population statistics continue to increase, the stress on conventional energy sources and the environment strengthens. The authors [1] have stated that an increase of 1 % in the population density surges the electricity demand by 0.77 % and fuel consumption by 0.25 %. Meeting this swelling energy demand while mitigating the adverse effects of fossil fuels on our planet has become a chief concern. In response, the implementation and improvements of renewable technologies have been evolving as a promising solution to address these crucial issues.

Sustainable development seeks clean and accessible energy entirely, which can only be achieved with renewable energy as they are distributed largely across the globe [2]. Solar power remains a principal candidate as the finest among renewables for a brighter, cleaner, and more sustainable energy future. [3]It would support the energy prices to get balanced and provide abundant environmental and socio-economic profits. This could be indicated by the contribution of solar energy in accomplishing sustainable development by fulfilling energy demands and then protecting the environment [4]. Solar energy, being the most significant energy source, presently experiences noteworthy evolution with a capacity of more than 940 GW installed globally in 2021, whereas the capacity of 70 GW only in 2011, which is represented in Fig. 1. Solar technology has experienced noteworthy evolution through innovations in materials and manufacturing processes.These technological progressions have not only expanded the range and applicability of solar energy but also have some complexities that require vigilant maintenance. Various faults and performance issues can be caused by the lack of maintenance that is in accordance with the effectiveness of solar systems.

Every year, solar panels struggle from the efficiency loss of 0.5 % – 1 % which results in the reduction of power generation. This loss arises from electrical and environmental faults [5]. [6] has analysed the mismatch faults of the PV system by considering the electrical parameters of voltage, resistance and temperature. Arduino controller is used for the analysis. Regardless of the material technology or its type, modules are also subjected to varied environmental conditions related to

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Nomenclature

PV	Photovoltaics	DT	Decision Tree
AI	Artificial Intelligence	RF	Random Forest
I-V curve	Current-Voltage Curve	LSTM	Long Short-term Memory
VI	Visual Inspection	RGB	Red Green Blue
IR-T	Infrared thermography	AC	Alternative Current
UV-F	Ultra-violet Fluorescence	DC	Direct current
EL	Electroluminescence	LLF	Line-Line Fault
PL	Photoluminescence	GF	Ground Fault
FDD	Fault Detection and Diagnosis	RCAG-Net	Residual channel wise attention gate network
MLT	Machine Learning Techniques	GAN	Generative Adversarial Network
CNN	Convolutional Neural Network	CCD	Charge coupled device
PID	Potential Induced Degradation	ReLU	Rectified Linear Units
LID	Light Induced Degradation	PPV	Positive Predictive Value
DCNN	Deep Convolutional Neural Network	FDR	False Discovery Rate
DC	Discriminant Classifier	ROC	Receiver-Operating Characteristic
ANN	Artificial Neural Network	TP	True Positive
SVM	Support Vector Machine	TN	True Negative
FL	Fuzzy Logic	FP	False Positive
kNN	k-nearest neighbours	FN	False Negative

the outdoor arrangement [7]. Those outdoor environmental conditions are harsh for modules, leading them to extreme photochemical or thermo-mechanical stress. In addition to the manufacturing defects, the environmental surroundings pay immensely to the PV's ageing rate, degradation and defects. Environmental faults include shading, soiling, snowing and varying climatic conditions like temperature increase incline to cause substantial loss of power in the PV panels[8]. Physical causes like partial shading, glass breakage, soiling, corrosion, hotspots, junction box failure, bypass diode failure and short circuits, which reduce the reliability, performance and lifetime of PV Modules, make it mandatory for the detection of faults at the correct instant. D. P. Winston, 2020 has analysed the modification of string connections with the junction boxes in the solar panel during faulty and hotspot conditions.

Various characterisation methodologies have developed along with different capabilities for identifying PV defects and have experienced different complexities in execution. To select a suitable diagnostic method, the existing number of defects needs to be examined first. Typical diagnosis strategies for PV faults can be broadly divided into two categories: visual inspection and automatic fault analysis.

The most popular methodologies for automatic analysis include data-driven methods and model-based residual analysis. For the data-driven methods, Electrical measurements, environmental data or Panel images are used. These analyses can be accomplished by using different techniques like statistical methods or by using ML technology. The electrical properties can be monitored by recording its current–voltage (I–V) characteristics [9]. While a single panel's I–V curve can reflect the performance largely and it is highly time-consuming to measure each module or panel in the PV plant. A novel fault detection scheme using

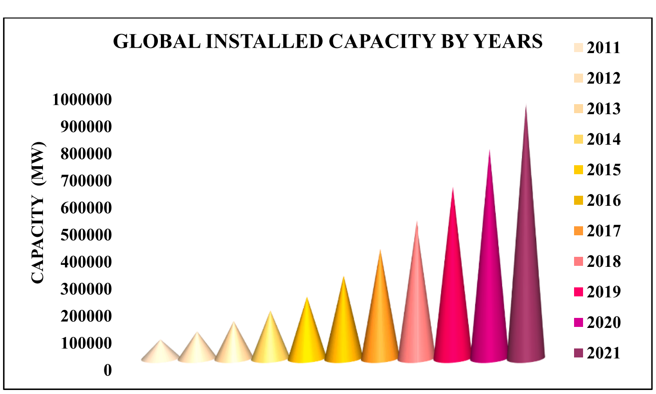


Fig. 1. Adapted from [44], Evolution of photovoltaic installations globally over past decade.

honeycomb and bridge configurations, proposed by Ganesan et al., 2023, is capable of detecting line-to-line and open-circuit faults. Imaging methods serve as faster diagnostic tools for defect detection in comparison. Fig. 2 indicates the number of literatures, identified defects through five different imaging techniques, including visual inspection (VI), infrared thermography (IR-T), electroluminescence (EL), photoluminescence (PL) and ultraviolet fluorescence (UV-F). The images are acquired using Unmanned aerial vehicles, hand-held cameras, and visual inspection using manpower or electrical characterisation. After the Image acquisition, The images undergo preprocessing techniques, which include feature selection, Data cleansing, Labelling, and Normalization techniques [10]. Machine learning techniques (MLT) are capable to work with complex, non-linear problems. MLTs are applied in Fault Detection and Diagnosis (FDD) which consist of methods with certain principles and distinct architectures. The common methods include Convolutional neural network (CNN) [11]and Artificial Neural Network (ANN) from deep learning, Fuzzy Logic (FL) [12], Support Vector Machine (SVM), k-Nearest Neighbor (kNN), Decision Tree (DT) and random forest (RF) based machine learning techniques. There are different optimisations involved in the CNNs to enhance the efficiency of the system in defect classification. The techniques based on Artificial intelligence (AI), including neural networks, are exceptional optimisers for non-linear functions. However, there are some common challenges involved, like configuration of the model, database collection, or availability to increase the model's efficiency and scalability in detecting different kinds of faults. Sakthivel et al., 2023 have analysed different AI techniques, including wavelet, Fuzzy inference, SVM, and k-NN, to enhance fault detection accuracy. Fig. 3 shows the number of literatures that have employed various types of images. Fig. 4 showcases the number of literatures that used the different types of AI models.

2. Organization of the review

The paper is interested in carrying out the review of previous studies majorly to explain the following topics:

- The inspection techniques involved in fault diagnosis
- Different types of imaging techniques
- The causes and effects of faults involved in the solar PV
- Image preprocessing techniques
- Different types and configurations of AI and ML models
- Common challenges and prospects of the models employed

The remaining sections of the article explain the Inspection systems in the section 2; Identification of solar faults in section 3; Review on

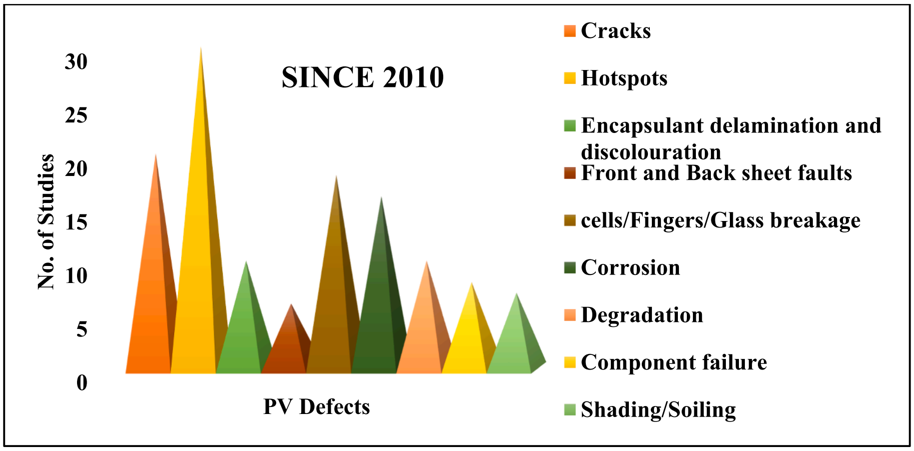


Fig. 2. Number of studies included different types of faults calculated since 2010.

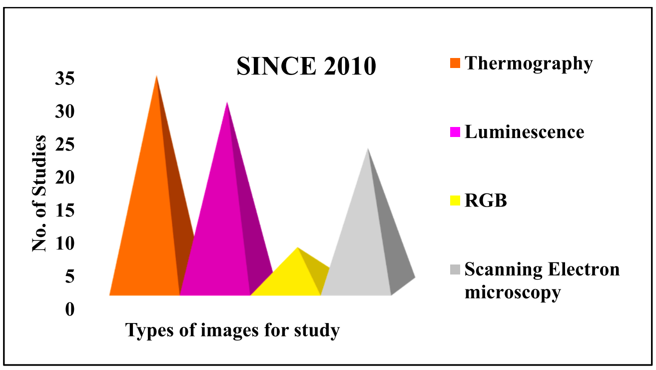


Fig. 3. Number of studies employed different types of imaging technology since 2010.

images required for the study in Section 4; Preprocessing techniques involved in the section 5; AI models contribution in fault diagnosis of PV in section 6; Finally, the validation metrics for the models in the last section. Fig. 5 represents the organization or layout of the article.

3. Stage 1: Inspection techniques in solar PV

Visual inspections become the first option for detecting PV modules' failure modes and signatures that can be observed through human eyes. Visual inspection of PV modules should be conducted before and after the modules have been subjected to the environmental or electrical factors. Table 3 presents the literature works reviewed majorly the types of faults and their inspection techniques. Fig. 6 represents the various types of Inspection techniques employed for the detection of faults in Solar PV.

Visual inspection easily allows to detect failures during installation or due to environmental influences and ageing. It majorly focuses on symptoms due to the failures such as texture changes, damage to back sheets, discoloration, haziness, bubbles, breakages, etc., than "diagnosis" (e.g., PID, hotspots, etc.). [13]discussed relation between the visual inspection and the result of electrical test from 608 degraded-modules when operated in dry and hot climates in Algeria. Likewise, authors like [14] has utilised visual inspection for diagnosis of various failure signatures that consist of the colour change in cells or browning, snail trails and failure in junction box while outdoor installation of silicon modules. Results from Visual inspection are experimental in nature. So, they cannot give qualitative explanations about the module failure reasons since they can only expose the apparent damages.

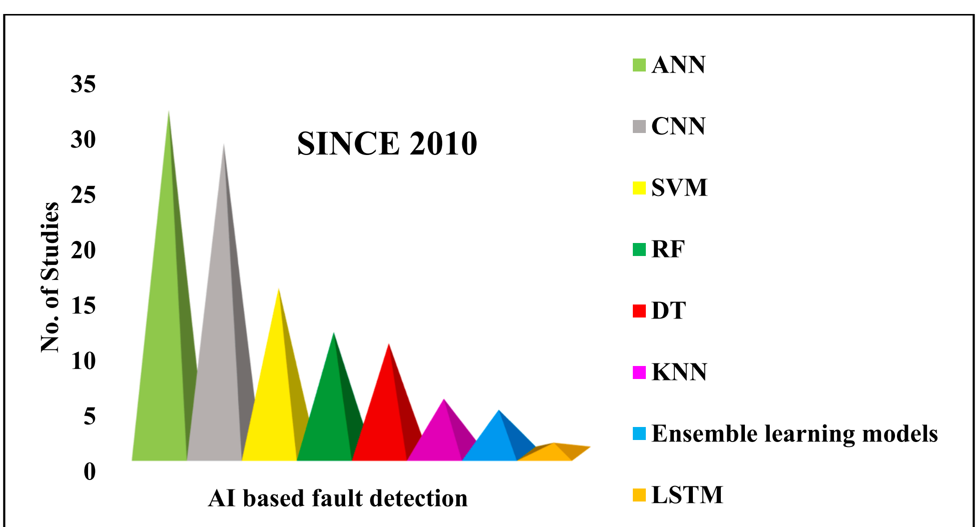


Fig. 4. Number of studies employed different AI models since 2010.

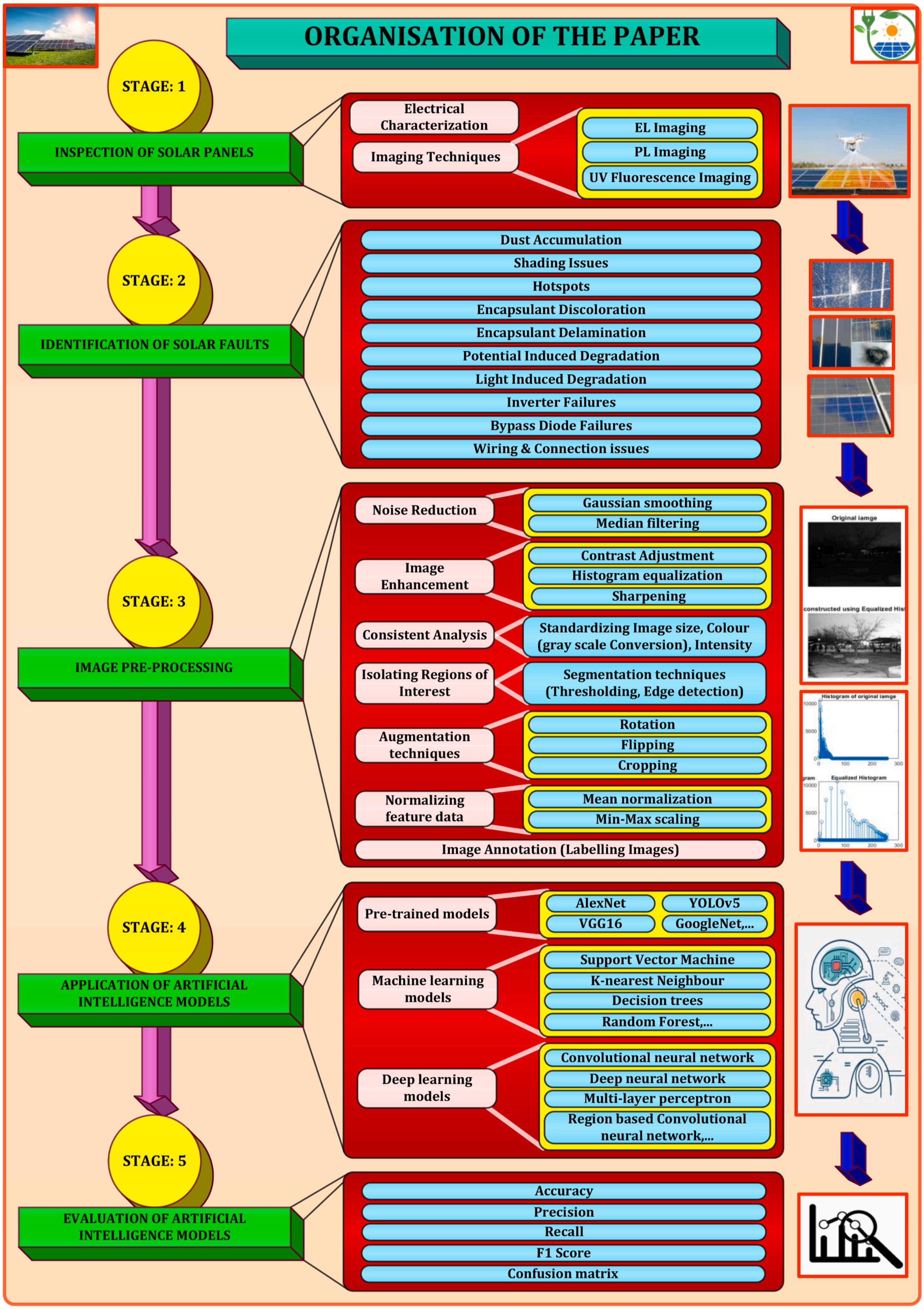


Fig. 5. Organization of the Article.

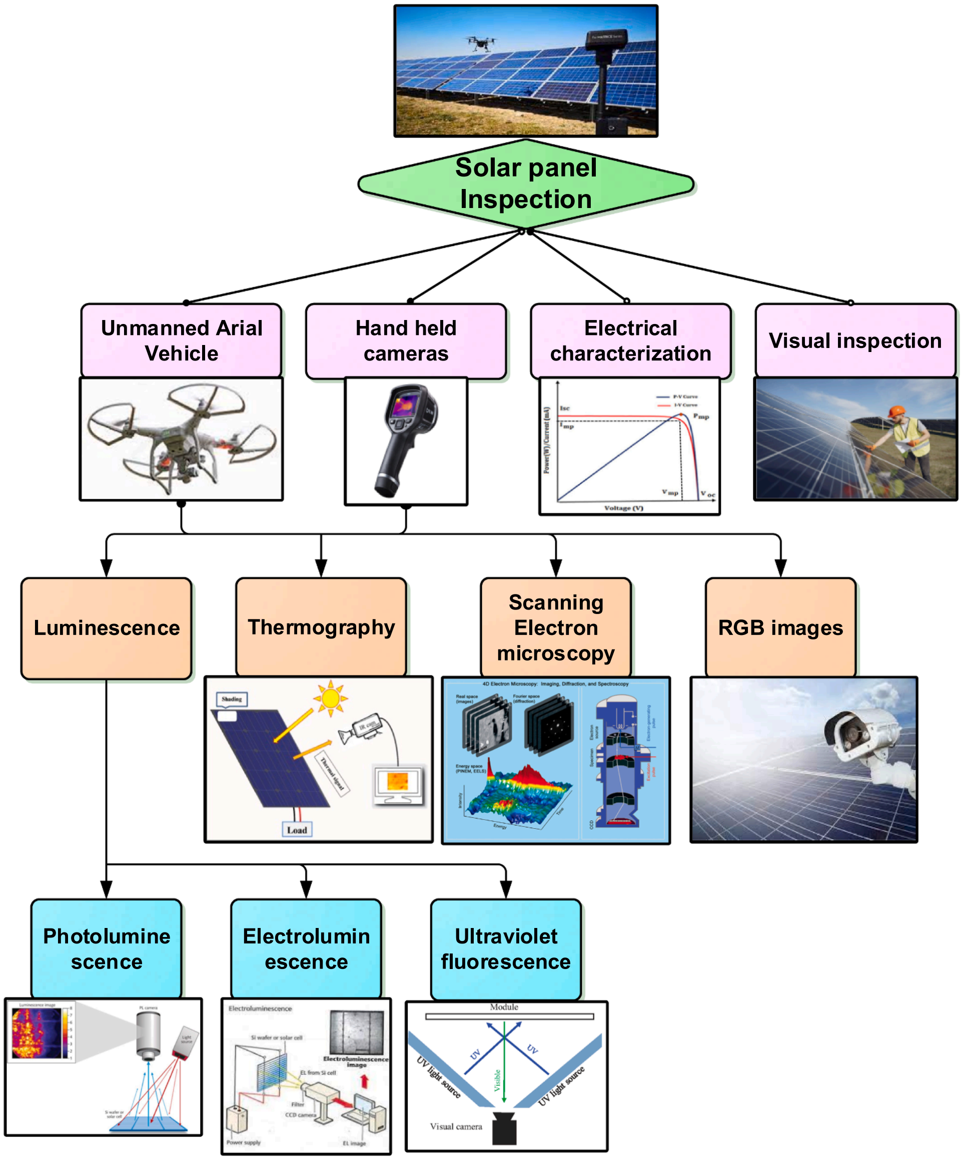


Fig. 6. Inspection techniques for fault detection in solar PV.

3.1. Electrical characterisation

The electrical (I-V) characteristics comprise a large amount of information about the health condition of panels. V-I curve analysis for different operating conditions involves plotting the characteristics of output current and voltage from the PV module or PV array. Deviations from the typical V-I curve can indicate damages like shading, soiling, cell damage, or electrical component faults. Abnormalities in the curve, like the reduction in open-circuit voltage (Voc) or the reduction in short-circuit current (Isc), can generate problems within the PV system. The Table 2 showcases the electrical characterisation for different types of faults observed from reviewed literature.

3.2. Imaging techniques

Imaging techniques of PV arrays are sensible to the degradation modes and defects while manufacturing and installation, and even based on ageing from the deployment of panels in the field. Various defect modes could be solved if they are identified and distinguished promptly. In the current works of literature, imaging methodologies like photoluminescence (PL), electroluminescence (EL), and ultraviolet (UV) fluorescence techniques are popular characterisation techniques that are employed for the PV fault detection analysis. Those techniques are capable of identifying various defect modes that cannot be detected by visual inspections, thereby leading to a severe reduction in PV module performance and also creating safety problems.

3.2.1. EL imaging

Electroluminescence is the process in which a material emits light when an electric current is passed through it. In the context of PV, EL imaging relies on the principle that defects or imperfections within the solar cells can emit light when subjected to an electrical bias. A solar cell or module is subjected to a reverse-bias voltage whether it has some defects. It causes to emit light from defects and areas with reduced electron-hole recombination efficiency.

When a forward bias current is applied, the infrared light is emitted as a result of radiative recombination. It is obtained using the camera with the sensor features of a silicon Charge-coupled Device (CCD). The sensor records every pixel individually and denotes the spatially resolvable datapoint of photon emission. The captured images are in grayscale. The defective areas are represented as the darkened parts as the faulted parts do not irradiate and are disconnected electrically, which in turn reduces the power production.

3.2.2. PL imaging

PL imaging is a contactless characterisation technique similar to EL imaging, for analysing PV panel conditions by giving information for determining the performance, spatially resolved quality and defects. The both techniques EL and PL depends on the acquisition of luminescence signal released by the material of solar cell but the only difference is the way that the signal generated[9]. EL could detect several failures like PID, cell cracks, electrical mismatch etc., but the PL is able to detect the series resistance and the minority carrier lifetime.

PL could be efficiently carried out without the electrical connections to the cells. It does not need any modifications in wiring. When the charge carriers recombine with those excited by solar irradiation, the solar cell emits radiative signals that PL can capture. The bright portions of the images indicate the healthy cells, and the darker portions of weak light emission indicate the defective areas of the solar panel [15]. In current literatures, authors have employed PL as an imaging tool for analysing various failure modes.

3.2.3. UV fluorescence imaging

UV fluorescence imaging is a non-destructive option and is capable of the examination of PV faults, especially the discoloration of the encapsulant of the panel. The UV fluorescence (FL) of EVA was utilised for the first time to analyse the discolouration of PV modules in 1997. UV-FL imaging could be utilised as the alternative technique for EL and PL imaging.

UV fluorescence spectroscopy works on the principle of fluorescence, which occurs when molecules absorb photons of light and subsequently emit photons of lower energy (longer wavelength) in response.[16]In UV fluorescence spectroscopy, the sample is exposed to UV or visible light of a specific wavelength (excitation wavelength), causing molecules in the sample to become excited. When the excited molecules return to their ground state, they release fluorescent light at longer wavelengths (emission wavelength). Then, the emitted fluorescence is measured. It is analysed to obtain information about the sample's composition, concentration, and characteristics.

4. Stage 2: Identification of solar PV faults

The power generated from every photovoltaic (PV) module should be summed up to get the whole array power. And the power of the array should be very much nearer to the power predicted for the normal operation of PV. Though, in practical conditions, there are several factors which lead to the reduced power output from the PV array[17]. Faults occur in PV systems due to various factors, including environmental conditions, manufacturing defects, installation issues and equipment wear and tear. Detecting and addressing these faults promptly is essential to maintain the reliability of a solar installation. Fig. 7 gives the complete chart for the types of faults based on three aspects: factors inducing the faults; DC/AC side of PV; the array level, module level, conditioning unit and cable faults. Here are the common fault classifications occurring in PV systems explained in this section. Table 1 shows the different literature papers in which various ML models applied for specific fault detection, their preprocessing techniques and the evaluation criteria are discussed.

4.1. Dust Accumulation

The settlement of dust, pollen, and debris on the solar panel's surface could block the sunlight and diminish the efficiency of the panel. Temperature, irradiation, air pressure, polluted air, Wind speed, direction of wind, dust storm and humidity are the environmental factors of dust accumulation[18]. The daily average energy reduction is about 4.4 % due to the dust settlement on PV panels for 1 year. It may also raise up to 20 % on without rainfall condition for long time[19].

Solar panel temperature from 1 − 10 degrees Celsius could be credited to the external factors like soiling or dust. Actually, dust is a thin layer which covers the solar array's surface. The particles of the dust would have less than 10 mm in diameter.[20]. However, it also depends upon location and the environment. The dust can be settled from various sources such as pollution by wind, vehicular movements and pedestrian volcanic eruptions. The dust accumulation over time heightens the effect of soiling[21]. The amount of dust accumulated on the PV surface badly disturbs the overall power generated from the PV on a daily, monthly, annual and seasonal basis. This fault is one of the most commonly occurring types which can be addressed through cleaning and maintaining periodically.

4.2. Shading Issues

The shading effect is caused by impediments like buildings, clouds, trees or nearby erections, which can cast shadows on solar panels and lead to uneven energy generation. It causes the shaded cells to work as load and bypass diode to conduct[22]. It results the internal temperature to increase for both shaded cell and the bypass diode. If some portion of the PV array is shaded and the remaining regions are entirely exposed to the irradiance, the output current considerably decreases. The impact of Shading Faults on the PV system increases when the number of panels in a row of an array increases.

The partial shading causes a reduction in solar irradiance, which thereby reduces the performance of the panel because output current is the function of irradiance. The system is disturbed with the non-linearity between voltage and current under partial shaded conditions. According to [21], the losses of power can vary from 10 % − 70 % due to shading. Effective planning and designing of the panels by implementing bypass diodes in solar panels can mitigate shading issues.

4.3. Hotspots

The major cause for the occurrence of hotspots is instability of the solar irradiance and ambient temperature. [23] have experimented and showcased the ambient temperature while the experimentation is found to be 26.1 °C. The highest temperature observed in the hotspot area is found to be 29.3 °C and the difference in temperature is 3.2 °C for one module. Hotspots occur when a specific cell or portion of a solar panel becomes extremely hot due to mismatched cells, partial shading, or electrical faults. Hotspots are also caused due to degradation, cracks, contamination, broken diodes, etc.…

While reverse bias happens in abundance because of shading or any other kind of faults, high power is dissipated in the unhealthy cell, which leads to overheating or hotspot. The hotspot then creates cracks, breakage, melting of solder, degradation of the solar cells, or even other destructions. (M. M. [24]Prolonged hotspots can cause cell damage or even fires, making their detection and mitigation critical.

4.4. Encapsulant Discoloration

The change in color or appearance of the encapsulant material causes the encapsulant discoloration where the encapsulant material is used to protect and insulate the electronic components or photovoltaic cells. This encapsulant material is often a polymer or resin [25]. Continued exposure to UV radiation from the sun can cause degradation and change in color of encapsulant material to degrade. Then, the color will be changed. The molecular structure of the material will be broken by the UV radiation. High temperatures can accelerate the ageing of encapsulant materials and that would lead to discoloration [26]. Exposure to severe chemicals or environmental pollutants can react with the encapsulant, affecting appearance. Discoloration may lead to loss of functionality and reduce performance characteristics of encapsulated components.

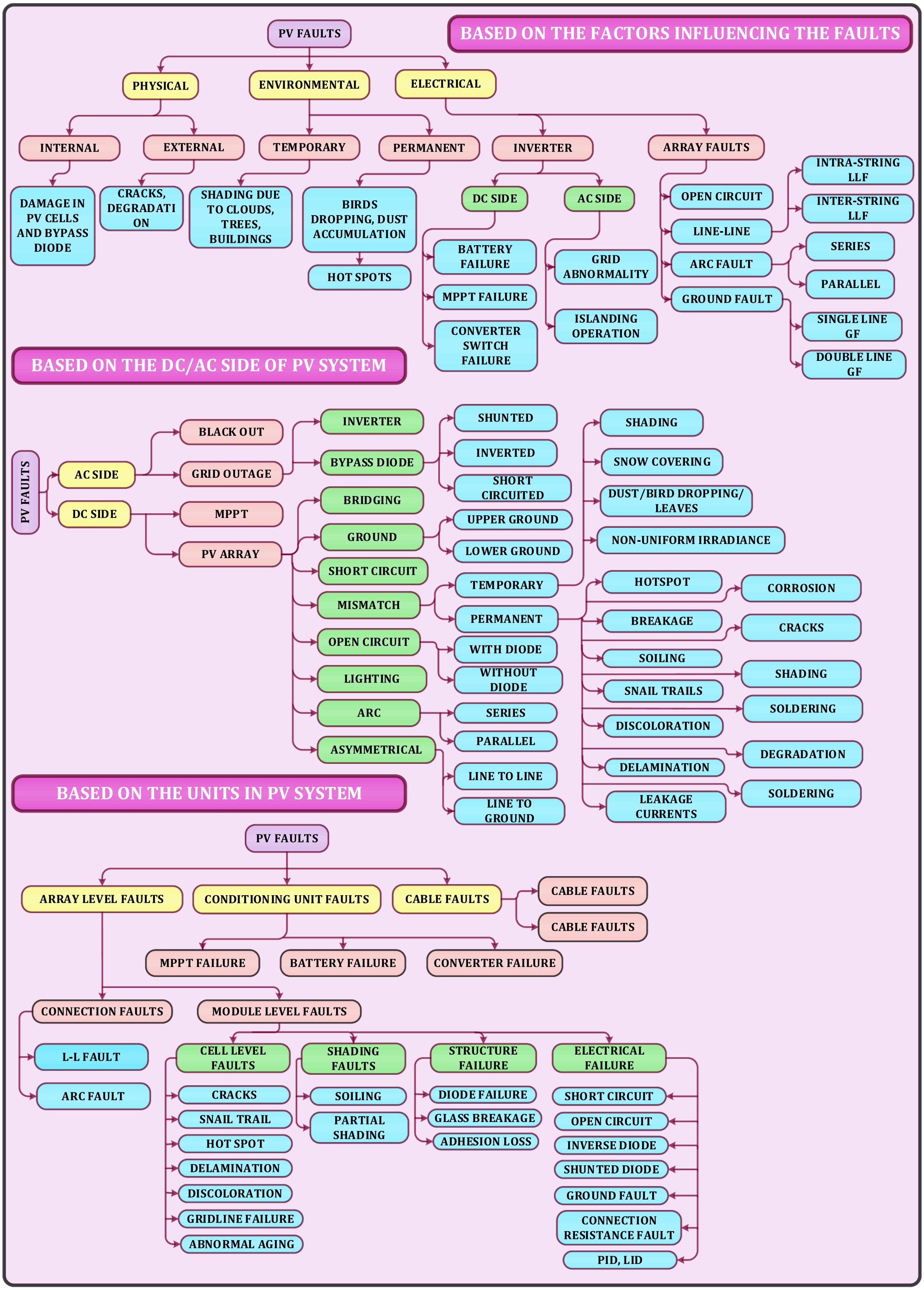


Fig. 7. The chart for different types of possible solar PV faults.

Table 1
Inference from different literature papers reviewed.

Author details	Type of work	Proposed technique	Dataset	Inference	Evaluation techniques
[37]	Early diagnosis of the hot-spots	• SVM • KNN • Decision tree • Discriminant classifiers (DC)	Not mentioned	DC performed well with accuracy = 98 %	• Confusion matrix • ROC
[35]	Automatic fault diagnosis by thermographic images tool	• Normalization • Homogenization • Discrete wavelet transforms • Grey scaling • Thresholding • Box blur filtering, • Sobel Feldman	• UAVs • ground-based operators – Dataset of 1000 images	• 1000 images set CNN 99 % accuracy • computational time- 30 min using Low Mid-Range CPU – • 200 images set 90 % accuracy using MLP, • 100 % accuracy using CNN	Not mentioned
[45]	Surface damage detection	Deep learning-based inspection image analysis methods.	Four specific image sets	accuracy = 0.79 from high- to low-resolution images from thermal images to visual images from PV panels to wind turbines	Not mentioned
[32]	Electroluminescence (EL) images	Channel attention, spatial attention into Multi attention U-net	Not mentioned	Mean intersection over-union (m-IOU) = 0.699, F-measure = 0.799.	5-fold cross validation
[40]	IR thermographic images	gamma correction function (preprocess) improved + (CNN); CNN model using IR temperatures; eXtreme Gradient Boosting (XGBoost) algorithm replaced with CNN.	Not mentioned	High detection accuracy and low time consumption	Confusion matrix
[46]	PV modules with micro-cracks, hotspots	Feed Forward and Back Propagation technique and SVM	Not mentioned	• average accuracy – 87 % for feed-forward back propagation neural network • 99 % for SVM	%Accuracy
[47]	Multiple large-scale images transformed to detect the overheated region precisely.	Deep joint learning model	Not mentioned	• Outperforms the benchmarked approaches by its effectiveness and efficiency	Precision Recall
[48]	Kirsch Operator Based Image Segmentation – multiple visible defects (Encapsulant delamination, Dust shading, Glass breakage, Gridline Corrosion, Yellowing and Snail trails) – RGB colour images from UAV	Deep convolutional neural network-three-phase ML approach.	Comprehensive dataset collected from real-world solar PV plants	• Compared with conventional pattern recognition algorithm, • Pretrained Vgg16 • Standard CNN-Based solution	Three-Fold Cross Validation
[39]	IR camera mounted on UAV	RCAG-Net	• 700 defect-free images • 312 defective images	• Performance improved to 92.61 % of F-measure, and recall for the hot spot defect to 97.06 %	• precision • recall • F-measure
[49]	Planetary gearbox, gear, and bearing-gear mixture, including the fault diagnosis of bearing.	Fault diagnosis method based on time–frequency representation (TFR) and deep reinforcement learning (DRL)	First 1000 samples for training and last 1000 samples for testing where each sample with 1280 data points	Accuracy = 99.5 % for single-speed load cases, also outperforms in multi-work conditions	99.5 %. Accuracy of the model-Planetary gearbox
[50]	IR camera mounted on UAV	rgSIFT descriptor with k-NN	• 300 images (80 % of total 375) for training. • Remaining 20 % images (75 images for testing	• Naive Bayes • decision tree • Stochastic gradient descent, • Random forest • k-NN	Accuracy = 98.7 %
[51]	Not mentioned	• Review on • GAN • Deep CNN • Deep convolutional GAN	9732 images with different rotation angles of 90∘, 180∘ and 270∘ for training.	Not mentioned	The average accuracy ranged between 95 % and 98.4 %

4.5. Encapsulant Delamination

Encapsulant delamination is a significant and one of the common field failures. When the layers of encapsulant material detach or peel away from each other or from the substrate they meant to protect, it becomes encapsulant delamination. When the bonding between the encapsulant layers or between the encapsulant and the substrate is inadequate, it can lead to delamination [27]. Frequent temperature fluctuations can cause differential expansion and contraction that leads to delamination over time. Moisture can infiltrate the encapsulant and weaken the adhesion that causes delamination. Excessive mechanical stress can also result in delamination. Delamination can expose sensitive electronic components or the PV cells to environmental factors which cause damage and reduce performance. Voids and air gaps can be created because of the delamination, which dissipates heat and affects the overall system integrity (M. C. C. [28].

Addressing discoloration and delamination of encapsulant material is essential for making the system reliable, and that leads to the long life of various encapsulated systems, from electronic devices to solar panels. Selecting proper materials, manufacturing processes, and environmental controls are essential for preventing these issues. Consistent inspection and maintenance could help one to identify and address the problems as they arise.

4.6. PID (Potential-Induced Degradation)

PID arises when leakage currents are produced due to the voltage potential between the frame and the solar cell, which reduces the performance efficiency of the solar panels. Ground fault protection systems and PID-resistant modules can aid in avoiding the degradation problem. PID is the phenomenon that has the potential to negatively impact solar PV panel performance and, over time, reduce power output. When various parts of a solar PV system establish an unexpected electrical potential, often by voltage difference, it causes the solar cells to degrade.

These solar complications must be found and solved through regular inspections, monitoring systems, and timely maintenance. A positive approach to problem management ensures that a solar installation runs effectively, maintains its durability, and maximises the return on investment and contributing to sustainable energy production.

4.7. Light-Induced degradation (LID)

LID is a phenomenon that occurs particularly in monocrystalline silicon, where performance efficiency temporarily reduces, immediately after installation. LID can lead to efficiency reduction in the PV panel by up to 2–3 % during the initial hours or days of exposure. This effect leads to defects in the wafer itself, which is produced by continued exposure to light [29]. This can be mitigated with specific materials and manufacturing processes. LID is a phenomenon that can disturb the panels' initial performance shortly after they are exposed to sunlight. LID generally occurs in the initial hours or days of sunlight exposure by the panel and can lead to a temporary reduction in solar cell efficiency [30]. LID is chiefly associated with the interaction between boron and oxygen within the silicon material utilised in solar cells. When the solar cells are exposed to sunlight, this defect is activated, which leads to a reduction in the efficiency of cells.

4.8. Inverter Failures

Inverters are fundamental components of PV systems which convert DC power produced from the panels into usable AC power. Inverter faults or failures can upset the entire system and may result from issues such as component wear, overheating, or electrical faults. Inverter failure is a common issue in solar power systems, which can significantly influence the efficiency of solar PV installation. The efficiency of the inverters declines at a minimal rate once it attains the peak level with incident energy of around 400–700 W/m^2. It happens because of the temperature rise within the inverter while it supplies a heavy load[29]. Inverters are essential as they convert DC power from solar PV to AC power that can be used in homes and also fed into the grid.

4.9. Bypass diode Failures

Bypass diodes are employed in solar panels in order to prevent power loss from the shaded or malfunctioning cells. When bypass diodes fail, it can cause a drop in overall panel efficacy, which might need replacement. Bypass diodes are one of the important components in PV panels and arrays, exclusively in situations where multiple solar cells are connected in series[22]. Bypass diodes are used to prevent power losses due to shading, soiling, or cell mismatch. When solar cells in the panels are partially shaded or even not functioning appropriately, the bypass diode permits the current to bypass the shaded or faulty cell, ensuring that the other cells produce electricity.

4.10. Wiring and connection Problems

Faults in the wiring, loose connections, or corroded terminals could cause electrical losses, increase resistance, and cause overheating.[31] Periodical inspection and maintenance are vital to make sure that all electrical connections and components are safe and functional. Proper wiring and connections are essential to guarantee the effectual and secure operation of a PV system. Fig. 8 presents the types of faults that occur in the solar panel components.

5. Stage 3: image preprocessing techniques

Image preprocessing is a critical step in developing an automatic fault detection system using AI algorithms. Table 4 shows the papers that reviewed the detailed procedure of automatic fault detection, including image acquisition, preprocessing, AI models deployed, and their evaluation metrics.

5.1. Noise Reduction

As real-world environments often contain noise, preprocessing techniques are employed on raw solar panel images to improve quality, reduce noise, and prepare them for effective analysis by AI algorithms.

[32] Noise Reduction includes techniques like Gaussian smoothing and Median Filtering. Applying a Gaussian filter helps to reduce high-frequency noise and smoothens the image. Median filtering is an effective technique that removes the salt-and-pepper noise which can occur in images captured under difficult conditions [33].

5.2. Image Enhancement

Image enhancement techniques, such as contrast adjustment, histogram equalization, and sharpening, can be implemented to improve image quality. These techniques help make images visually appealing and help to highlight some special features. If multiple images are employed, they might need to be registered to ensure that they align correctly.

Solar panel images are obtained using cameras or other imaging devices placed within or near the solar PV installation. The images contain information about the complete solar array or may even focus on individual solar panels or sections. Contrast adjustment and brightness correction are involved to enhance the Images acquired. They help improve the visibility of information and potential faults.

Techniques like histogram equalization or contrast stretching can be applied to images [34]. Adjusting the brightness levels warrants the image is well-exposed, and that avoids underexposure or overexposure issues.

5.3. Standardization

Standardizing image size, color, or intensity can be important for consistency analysis. While training the machine learning model, fixed-size images are needed for the essential training of ML models, which could improve the computational efficiency during processing.

If necessary, color conversion can be done, where Solar panel images are often in RGB colors, but for fault detection, they may be converted to

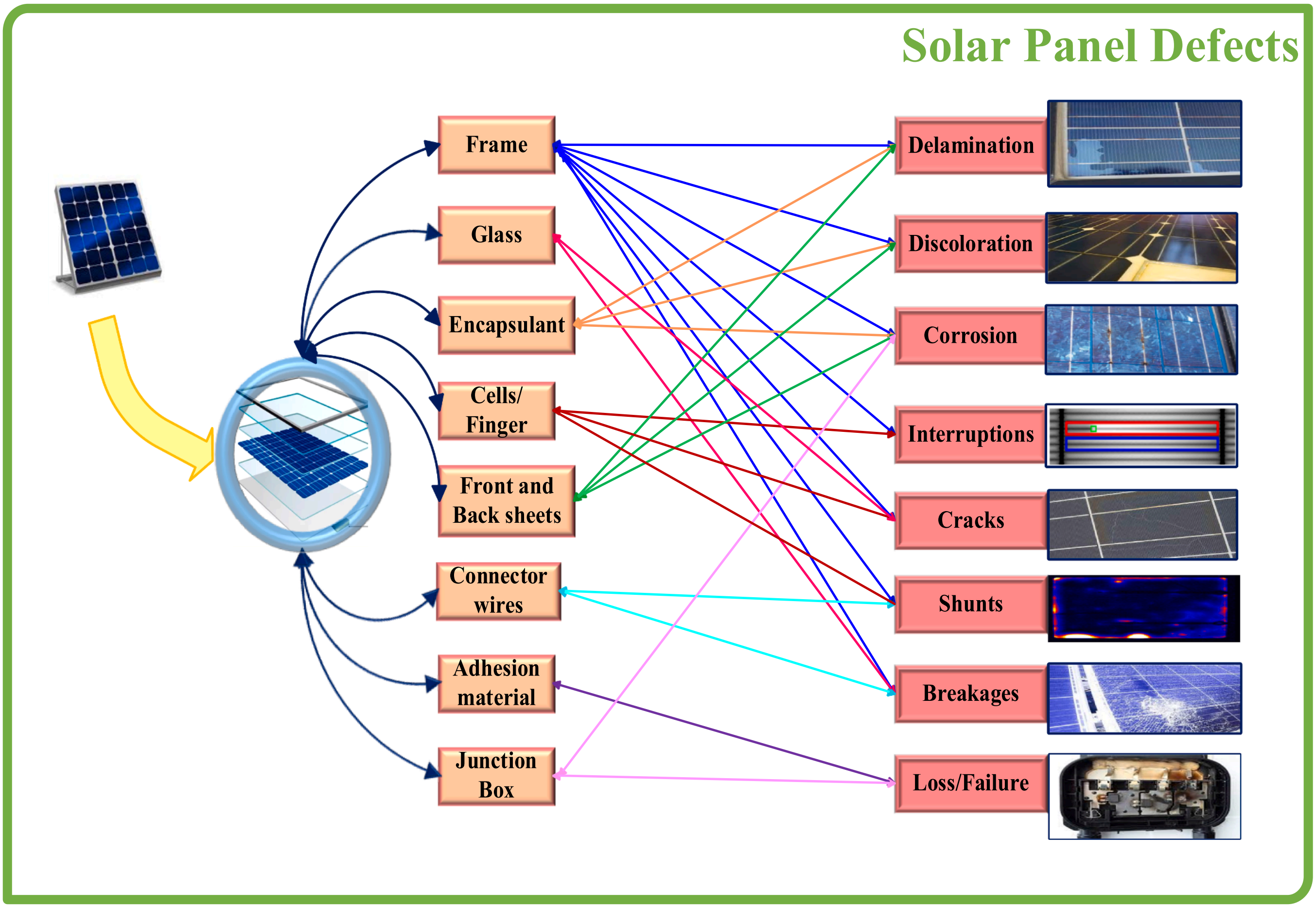


Fig. 8. Faults that occur in the panel components.

grayscale to simplify processing and reduce computational load. Resizing the image to a standard size can also help guarantee reliable input for AI algorithms. It can also reduce computational complexity.

5.4. Isolating regions of Interest

[33]Segmentation techniques can be used to isolate regions of interest (ROI) within the images and make it easier to focus on the objects or areas where defects might occur.

Identifying the region of interest within the image, which actually includes the solar panels and surrounding areas. This step reduces the computational complexity and focuses the analysis on the appropriate portions of the image. Image Segmentation is the vital part that includes Thresholding and Edge detection. [35] Thresholding techniques can be employed to separate the solar panels and their surroundings from the background. Edge detection algorithms like Canny or Sobel can be employed to outline the panels and distinguish them from rest of the image. Morphological operations, such as dilation and erosion, can be applied to clean up the segmented image and remove minor artifacts or gaps in the panels.

5.5. Augmentation Techniques

To improve the robustness of an AI model, augmentation techniques like rotation, flipping, and cropping can be employed to generate additional training samples, which are optional in the process [35].

5.6. Normalizing feature Data

Extracting relevant features from the preprocessed image is essential for fault detection. These features may include texture, shape, and intensity information. Then, Normalizing the feature data to ensure that all features have the same scale. Common normalization techniques include mean normalization and min–max scaling. Then, the preprocessed image dataset will be separated into training, validation, and test sets for training and then for evaluating the efficiency of AI model.

5.7. Image Annotation

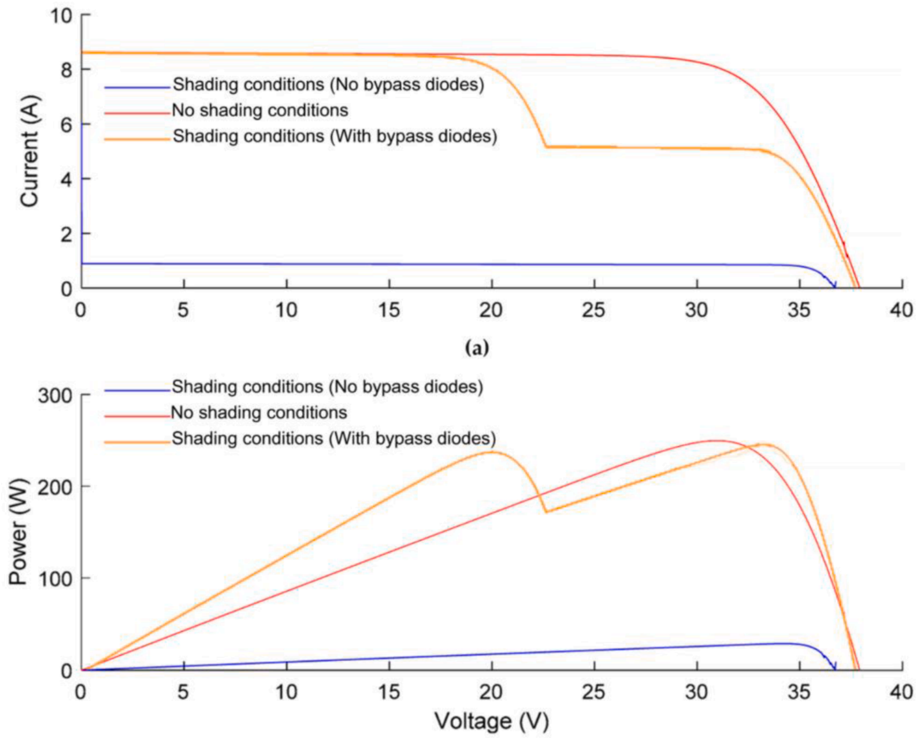
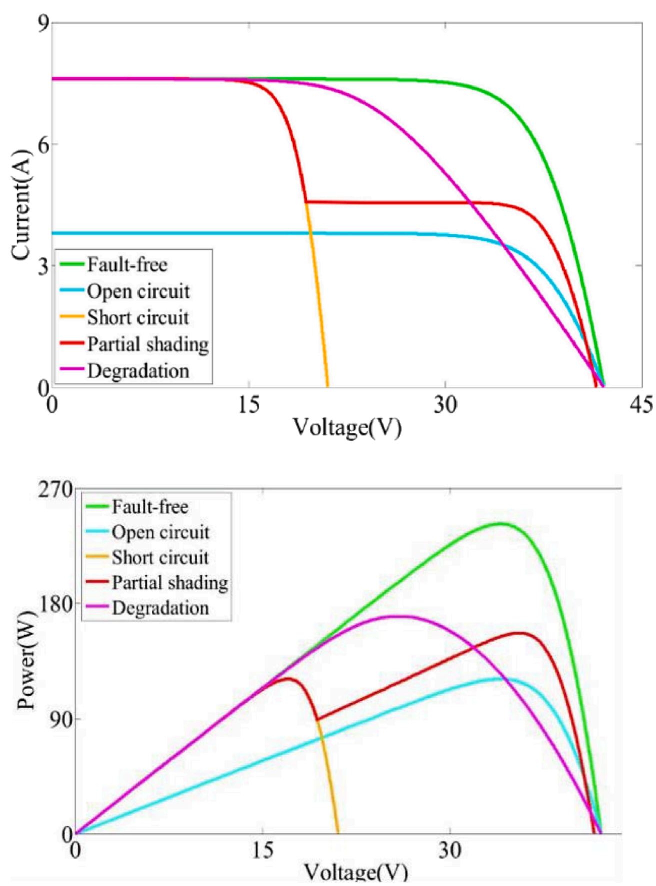
The preprocessed data is then saved along with labels which indicates the presence and absence of the faults and then used for training and testing AI algorithms. The process of labelling or adding metadata to images is to provide additional information about the objects or regions within the image.

The preprocessed images are then fed into AI algorithms for training and detection of panel faults. Proper image preprocessing is critical as it helps the AI model focus on relevant information, reduce noise, and enhance its ability to detect faults precisely and proficiently.

6. Stage: 4 Artificial intelligence models

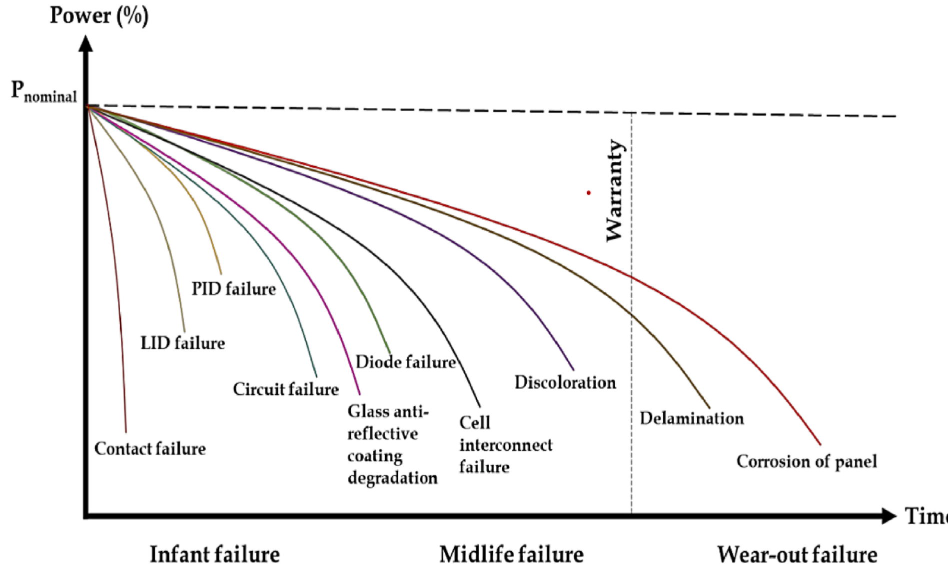
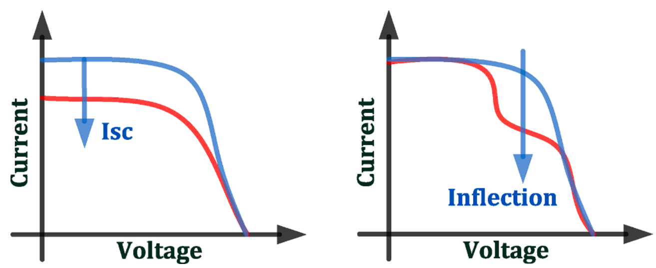
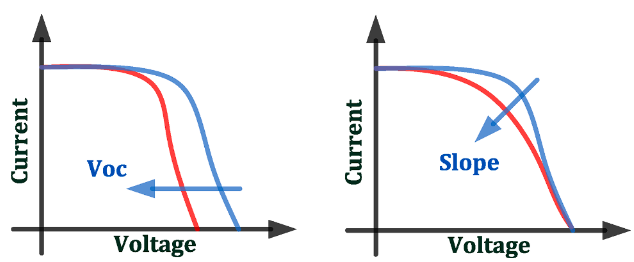
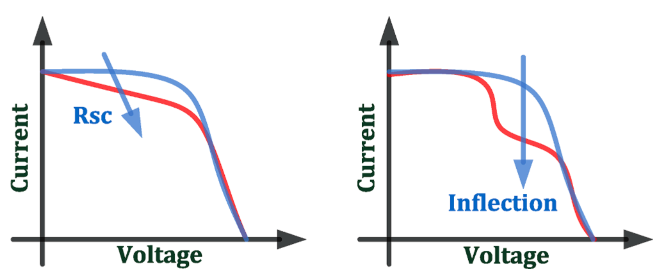
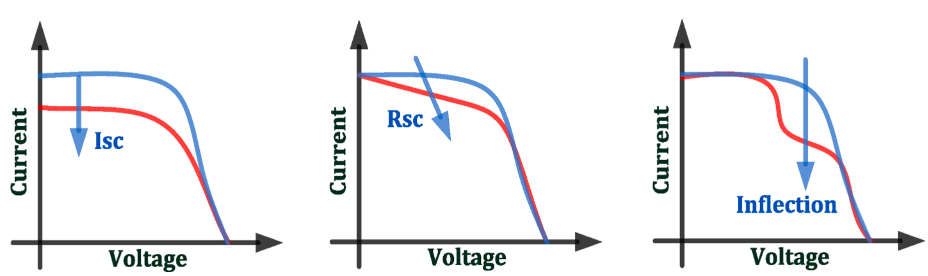
ML is the subsection from AI. ML is the one of fresh divisions which has arisen recently in engineering after the IInd World War to learn and develop intelligent units. ML flourishes on mining the meaningful details from plenty amount of data. Hence, ML discusses technology that answers questions by using the current availability of data. Artificial

Table 2
Electrical characterisation of corresponding types of fault.

Fault condition	Corresponding electrical characterization
Shading condition with and without bypass diode	
Degradation, partial shading, open circuit and short circuit.	

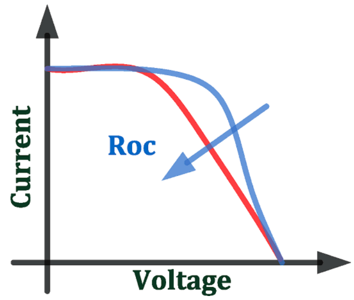
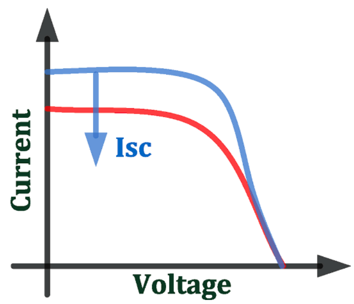
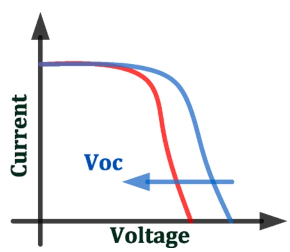
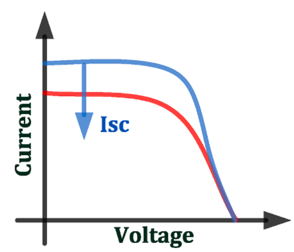
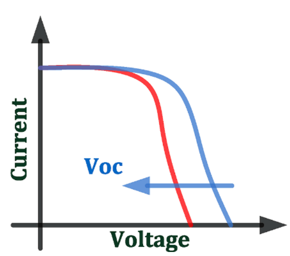
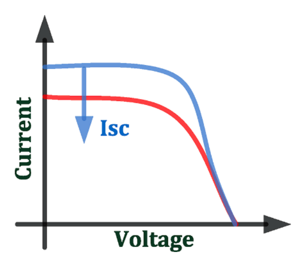
(continued on next page)

Table 2 (*continued*)

Fault condition	Corresponding electrical characterization
• CONTACT FAILURE • LID FAILURE • PID FAILURE • CIRCUIT FAILURE • GLASS ANTI REFLECTIVE COATING DEGRADATION • DIODE FAILURE • CELL INTERCONNECT FAILURE • DISCOLORATION • DELAMINATIONCORROSION OF PANEL	
FRACTURED SOLAR CELL	
POTENTIAL-INDUCED DEGRADATION (PID)	
QUICK CONNECTOR FAILURE	
DELAMINATION	

(*continued on next page*)

Table 2 (*continued*)

Fault condition	Corresponding electrical characterization	
INTERNAL CIRCUITRY DISCOLORATION		
ENCAPSULANT DISCOLORATION		
JUNCTION BOX/BYPASS DIODE		
LID/LeTID		

intelligence, Statistical analysis, Information theory, computational complexity, biology, control theory, Philosophy and cognitive science are some fields from which ML attracts on theories and proceedings.

ML and AI can be seen in our day-to-day activities taking from transportation-self-driving and self-parking cars, banking-fraud detection and in finance sector, google searches, social media applications, image recognition, recommendation systems, prescription and in the medical field also. In Solar PV applications, it is used in tracking the duration of sunshine and its clearness index, the solar irradiation, mean temperature, diffusion fractions and the insolation. In addition to that, they are employed for modelling, simulation, sizing, configuring and control of systems, forecasting of output power obtained from standalone PV systems and grid-connected PV systems and in fault diagnosis. Table 5 shows the literature papers that reviewed different artificial intelligence models for different classifications of solar faults.

The paper [36] has proposed the CNN architecture which has 5 convolution layers and 3 fully connected (FC) layers. By employing different kernels, Convolution layers are there to extract the features from EL images. The extracted features are then sent to FC layers. Finally, the output of FC layer is made available to 4-way classifier. The classifier adopted non-linear ReLU, and the features are classified as 4 defect labels. In order to minimise the computational complexity, the 2nd and 5th convolution layers are followed by the max-pooling layer. Training parameters used are given by Batch size, Momentum, Learning rate, Weight decay and epochs. High accuracy is obtained with the model in classifying the fault types.

In the work of [34], for classifying thermal images of PV, The Comparative analysis is conducted using different ML algorithms based on their performance in training the features. Using 3 different datasets (dataset I, dataset II, and dataset III), three experiments are conducted on training those datasets and proposed a hybrid feature dataset III for study. For the first dataset, the optimised SVM hyperparameters for D and γ are found to be 1 and 0.004. For second dataset, D and γ obtained are as 0.46 and 0.1. For third dataset, 0.2 and 0.46 are obtained for D and γ. The SVM model proposed, predicts 305 out of 315 thermal images. Confusion matrix, positive predictive value (PPV), false discovery rate (FDR), receiver-operating characteristic (ROC), F-Measures, and training time for all 3 training datasets are discussed. The model trained has shown the highest accuracy of 92 % while testing with the new dataset.

The contribution of M. R. U. [32] is towards Multi attention U-net (MAU-net). The proposed model contains two layers namely channel

Table 3
Papers which reviewed about the classification of faults and their inspection techniques.

Ref	Inspection/Diagnosis	Fault types
[52]	• Scanning electron microscopic images of dust	• Behaviour of dust: deposition, rebound, and resuspension
[53]	• EL imaging camera – microcracked cell • FLIR thermal imaging camera – Hotspot Solar cell	• Yellowing/browning of encapsulants and back sheets • Bubble formation • Delamination of encapsulants and back sheet • Discoloration of busbars • Oxidation formation • Hotspots • Corrosion of connection • Cracks in back sheet • Cell breakage • Microcracks
[54]	• IR – imaging • Main aspect – Authors – Year – Citation • IR-images showing thermal anomalies • Thermal signature category – Description – Reason	• Whole-cell part • Part of hot cell • Single hot point = hot spot • Uniform hot substring patchwork pattern of hot cells • Hot junction box
[9]	• I-V Curve • Visual Inspection • Ultraviolet fluorescence • Infrared thermography • Luminescence techniques • Electroluminescence • Daylight Photoluminescence • Infrared thermography • Electroluminescence	• Cell cracks • Hotspots • Delamination • Internal circuitry discolouration • Potential induced degradation • Light and elevated temperature-induced degradation • Light-induced degradation • Failures in bypass diode, junction box, quick connector
[55]	• Visual Inspection • Electrical Parameter measurement • Imaging • EL Imaging • PL Imaging • UV Fluorescence Imaging	• Typical degradation modes with moisture ingress: • Encapsulant discolouration • Cracks and breakages • PID • LID • LeTID • Adhesion loss • Corrosion • Delamination
[56]	NA	• Shading • Soiling • Dust Accumulation • Weather • Delamination • Discolouration
[57]	NA	• Manufacturing process induced: • Finger Interruptions • Finger cracks • Finger shunts • Cell and Interconnect warpage • Thermo-mechanical fatigue induced degradation: • Solder joint breakages • Intermetallic compound cracks • Finger breakages • Interconnect breakages • Chemical modes of degradation: • Silver oxide depositions • Glass frit corrosion and finger delamination • Solder material corrosion • Snail trails • Interconnect corrosion • System voltage assisted degradation: • PID assisted delamination at fingers • Interconnect burnouts
[27]	• Scanning electron microscope (SEM) • Energy-dispersive X-ray spectroscopy (EDS) • Images – silver fingers at delaminated areas	• Failure modes discussed in this review: • Electromigration • Delamination • Corrosion
[58]	NA	• Potential Induced Degradation • Frame defects • Junction box defects • Milky pattern • Darkening • Cell cracks • Hot spots • Front grid and AR layer oxidation • Bubbles • Back-sheet delamination
[18]	• Thermal imaging	• Dust properties • Bird droppings • Fig. – Hail storm affected PV module • Multiple direction breakages
[23]	• NA	• Failures in: • Cell gridlines • Wires/Connectors • Back sheet • Delamination • Frames • Between cell gaps • Metallization • Interconnect Ribbons • Junction Box • Cell crack • Front Glass • Resistive solder bonds • Bypass diode
[59]	• Thermography images • EL images • Visual, Imaging, Data analytic using IV curve, Signal analysis, …	• Hot spot • PID • Crack at cells (snail track)
[60]	• Photobleaching effect	• Browned cell • Edges and through cracks • Delamination of front encapsulant • Bubbles • Burn marks • Discoloration • Back-sheet delamination • Corrosion • PID • Snail trails
[44]	• Infrared thermography • Thermography	• Resistive solder bonds hotspots • Types of defects and IR pattern
(M. C. C. [28]	NA	• Discolouration of EVA encapsulant • Corrosion in metallic contact • Delamination • Bubbles
[61]	NA	• Classification of faults • Arc faults • Shade faults • Other faults
[62]	NA	• Encapsulation failures • Backsheet adhesion loss • Cell cracking • Broken interconnection • Shading and soiling • Hotspots • Module corrosion • PID • LID • Inverter failure modes and other failure modes (Junction box, Bypass diode, mismatch faults, Ground fault, LL fault, Arc faults)

(continued on next page)

Table 3 (*continued*)

Ref	Inspection/Diagnosis	Fault types
[31]	• Infrared equipment	• Fires • Hotspot • Diode fault • Shading • Soiling • Dust accumulation • Oxidation and discoloration • Broken glass • delamination and bubbles
[29]	NA	• Dust accumulation • Shading • Soiling of PV panels • Degradation-Glass breakage, Hotspots
[22]	• Electroluminescence test in dark room • detection of faults (IV by capacitor method,	• Extreme Dirt and cell cracks • Failures in bypass diodes
[63]	• c-Si based technologies • Thin film technologies • Test methods for PID susceptibility: • PID testing on module level • PID testing on cell level	• PID mechanisms in PV • Module level: Glass material, Encapsulation
[17]	• Fault detection methodology: • IV characteristics • Visual inspection • IR thermal imaging • Ultrasonic inspection • EL imaging • Lock in thermography	• Classification of faults • Side (AC/DC) – Type of fault-Description-Ref.
[21]	NA	• Shading by soiling on PV performance • Dust accumulating
[64]	NA	• Hot spot • Glass breakage • Ribbon discoloration • Encapsulant discoloration • PID • Cell breakage • Corrosion in cells
[30]	NA	• Boron-oxygen degradation • Copper related degradation • Quasi-mono and multi-crystalline silicon
[65]	• I-V pattern • Infrared thermography diagnosis • Thermal image processing • Thermal orthophotoplan technique	• Optical degradation (glass breakage and delamination) • Electrical mismatch and degradation • PID, Defective bypass diode • Cell cracks, consequent snail trails • Degraded soldering • Broken interconnecting ribbons (disconnected cells)
[66]	• Crack Statistics • Monte Carlo Simulations of Cracked Modules	• Crack types: • Dentritic • Several directions • +45 degrees • −45 degrees • Parallel busbars • Perpendicular busbars • Crosscrack
[67]	NA	• Catastrophe faults: • Ground faults • LL faults • arc faults
[68]	NA	• Degradation in terrestrial PV • Statistical analysis • Degradation rates due to accelerated aging • Indoor PID testing and Outdoor PID testing
[26]	• Electrical characterization • Visual inspection • Electroluminescence imaging (EL imaging) • Ultrasonic inspection • Infrared imaging (IR imaging)	• Degradation • Broken cell • Broken interconnect • Junction box failure • Solder Bond Failures • Open circuits leading to Arcing • Delamination of encapsulant • Corrosion • Encapsulant loss of adhesion and elasticity • Hot spots • Encapsulant discoloration • Shunts at the scribe lines • Ground fault • Electrochemical corrosion of TCO • Bypass diode failures
[69]	NA	• Dust on glass • Transmissive degradation – Transparent materials
[70]	NA	• Degradation of PV: • Discoloration • Corrosion • Delamination • Breakage and cracks in cells • PID • Hot spots • Bubbles
[14]	• Visual Inspection, Measurements: • Dark I-V measurements • Individual cell shunt resistance measurements • Light Intensity measurements • Worst-Case Cell Determination • Determination of Temperature Coefficients • Monitoring Isc and Voc	• Degradation modes: • Optical degradation • Front surface soiling • Cell degradation • LID • Temperature-Induced Degradation • Mismatched cells

attention layer and spatial attention network to highlight defective area especially. The model proposed is evaluated using 5-fold cross-validation while implemented on the real PV – EL image datasets. The results have shown the network which is able to segment and identify complex defects exactly. The mean intersection over-union (m-IOU) obtained as 0.699 and F-measure as 0.799 that performs well when compared with previous models.

The quadratic discriminant classifier is studied for fault detection in the study of[37]. MATLAB is used for the analysis. The minimum accuracy, 25 % is obtained using DT for 1st dataset, and 98 % of maximum accuracy obtained using 3rd dataset. The classifications considered in the study are healthy PV module, one hot-spotted solar cell, two hot-spotted solar cells, and three or more hot-spotted solar cells. Thus, the ML tool's accuracy helps predict early-stage hotspots.

The paper[38]has used ensemble-based DNN and RF classifier to classify glass breakage, snail trail, delamination, discoloration, burn marks and healthy panels. The performance of ensemble-based DNN model is evaluated by comparing it with the pre-trained models. Transfer learning is also used where trained weights of other networks are shifted to designed model with less changes in final layers. In the field of computer vision, various pre-trained models are applied for the classification tasks.

The study by [33] employs encoder–decoder neural network. These networks are built of contraction part and symmetric expansion part. The former compresses the information of high-dimensional image into feature sets. Then the latter gradually updates the encoded features back to original resolution. Encoders and decoders combination provides the segmentation networks. There are tuning parameters which allow to generate multiple segmentation models. For encoder part, Mobile-net, ResNet, VGG-net, and U-net are used. For decoder part, U-net, FCN-net, PSP-net, and SegNet are used.

[39] have proposed a residual channel-wise attention gate network

Table 4
Papers which reviewed about the detailed procedure of automatic fault detection.

Ref	Inspection	Fault types	Preprocessing	Model developed	Performance indices
[71]	• Infrared module dataset class	• Damage in diode • Damaged cells due to Shading or severe soiling • Shadowing • Hot-Spot Cracking • Soiling • Vegetation • No-Anomaly	• Data augmentation	• CNN • Non-linear activation functions: RelU and Softmax	• K-fold cross validation • Z-score normalization • Loss function • Confusion matrix
[72]	• EL images • CDCR images • RGB images	• Cracking orientation: • Parallel to busbar • Dendritic/Branched • Deep cracks isolate the cell parts • Perpendicular to busbar • −45 degrees • +45 degrees • Other faults are: • Contact forming failure • Finger failure along cracks • Silicon material • Finger failure	• Data augmentation	• Deep learning approach	NA
[10]	• External quantum efficiency plans • X-ray photos – normal and unhealthy condition of bypass diode	• PV System failures: • Shading • Degradation Open-circuit • Bypass Diode • Line-to-Line • Bridging • Illustration of Common degradation types: • Hotspots • Ribbon discolouration • Glass breakage • Encapsulant discoloration • Delamination • Bubbles	NA	• Classification of ML Approaches • Conventional ML methods for Condition monitoring • Advanced DL methods for Condition monitoring. • Knowledge-guided methods for Condition monitoring.	NA
[73]	• Electrical parameters taken at Standard Test Conditions (STC)	• degradation assessment on ground mount PV plants and rooftop PV plants.	NA	NA	• Final Yield • Reference yield • Performance ratio (PR) • Levelized cost of electricity (LCOE) • Capacity Utilization Factor (CUF) • PV System efficiency • Annual Degradation rate
[74]	NA	NA	NA	• ANN • FUZZY LOGIC • Genetic Algorithm (GA) • Hybrid models: • ANN + GA and FL + GA • Adaptive neuro-fuzzy interface system (ANFIS)	• RMSE, MBE, MAE, R2
[75]	NA	• Line to line faults	• K-fold cross validation K = 10 • Feature extraction • Data normalization • Feature Selection algorithm	• Ensemble technique voting based probability • Classifier – (NB, SVM, KNN)	• Confusion matrix
[76]	• Visual inspection • Thermography • Electroluminescence • Photoluminescence • Microplasma luminescence	• Faults due to exte Ensemble technique voting based rnal causes • Snail trails • Defective bypass diode • Broken interconnects • PID	NA	• Wavelet – Multi layer Perceptron neural network (MLPNN)	• Computational time • Accuracy (%) • Confidence intervals

(RCAG-Net) to attain a fusion of multiscale features to suppress the complex and unwanted backgrounds and then highlight the major features of defects mainly to identify small hot spot defects. In this paper by [11], Different CNN architectures are used for semantic segmentation of background elimination and segmenting the faults from the panels. Then, classification is also done using CNN architecture for fault identification.

Three different analyses are done in this paper [40]. Improved gamma correction function is combined with CNN for preprocessing in the first method. IR images of PV modules are employed for the study. Secondly, Threshold function is used as preprocessing tool and given to CNN model for classification. Then, XGBoost is used for classification

Table 5
Papers which reviewed only the different types of models and the fault inspection.

Ref	Inspection	Model Reviewed
[77]	• Endogenous data • Meteorological measurements • Numerical weather prediction • Satellite data • Sky images • Spatio-correlated hierarchical information	• Recursive autoregressive and moving average (RARMA) • Coupled autoregressive and dynamical system (CARDS) • ANN with only the past irradiance data in global horizontal irradiance forecasting • AI based forecasting • KNN-based forecasting • ANN-based solar forecasting • DL-based solar forecasting • Ensemble learning-based solar forecasting
(M. M. [24]	• Visual Inspection • I-V Characteristics • EL Imaging • IR Imaging • UV–FL Imaging • SEM Images • EBIC Imaging	• Clustering based computation
(B. [78]	• Visual images • Electroluminescence images • Infrared images	• Shallow neural network (SNN) • DNN models • Hybrid ANN for Fault detection • 3 scenarios of ANN (SNN, DNN, Hybrid application)
[79]	NA	• Artificial Intelligence and Machine Learning types • Distribution of AI-based fault detection methods for PV systems found in the available literature. • Neural network-based methods in existing literature • Regression-based methods in existing literature: • Decision tree-based methods in existing literature: • SVM-based methods in existing literature: • Neuro-fuzzy-based methods in existing literature: • Wavelet-based methods in existing literature: • Other methods in existing literature
[80]	NA	• DL-based methods for fault diagnosis of PV systems
[81]	• Infrared Thermography (IRT)	• VLAD and CNN • Convolutional feature maps • Deep feature pooling
[82]	NA	• Physical analysis • Fast Fourier transform • Time Domain analysis • Wavelet analysis • AI method
[83]	NA	• Genetic algorithm and its variants • Particle Swarm Optimization • Chaos Optimization algorithm • Artificial Bee Swarm Algorithm Optimization • Artificial Bee Colony Optimization • Biogeography Based Optimization (BBO) • Flower Pollination Algorithm (FPA) • Bacterial Foraging Algorithm (BFA) • Bird Mating Optimization Algorithm (BMO) Simulated Annealing Algorithm (SA) • Harmony Search Algorithm (HS) • Pattern Search algorithm (PS) • Teaching Learning Based Optimization (TLBO)

Table 6
Papers which reviewed only different types of field inspection techniques for fault classification.

Ref	Inspection
[84]	• Infrared thermography (IRT) • Aerial Infrared Thermography • Unmanned Aerial Vehicles (UAV)
[85]	• Thermographic cameras for PV inspection • Thermographic images captured and RGB image captured • Thermographic image and Light weight aerial thermographic camera image captured • Aerial thermographic inspection
[86]	• Electroluminescence • Photoluminescence • Electron beam induced current • Laser beam induced current • High critical temperature superconductor superconducting quantum interference device (HTS-SQUID) • Scanning electron acoustic microscopy • Lamb wave air coupled ultrasonic testing (LAC-UT) • Resonance ultrasonic vibration • Visible optical NDT • Dark lock in thermography • Induction thermography • Illuminated lock-in thermography • Quantitative lock-in carrierographic (LIC) • Machine vision • Spectral and spatially resolved photoluminescence • Mechanical test

Table 7
Papers which reviewed about the influence of economics in the Solar panel.

Ref	Faults considered	Inference
[9]	• Cell cracks • PID • Short circuit bypass diode	• Ranked based on Cost Priority Number calculations • Strongest financial impact lead by Cell cracks, PID short-circuited Bypass Diodes • PID are the energy losses • Cell cracks constitute fixing costs
[87]	• Failure or degradation of components and subcomponents of PV module	• Ranked based on risk priority number • In first place the inverter, grounding/ lightning protection system. • In a second position, the modules, cells and contacts.
[88]	• Mono-string mono-module fault • Multi-string multi-module fault • Mono-string multi-module fault	• Influence of normal interest rate on NPV and payback period • Influence of energy selling price on NPV and payback period
[25]	• Broken cells • Encapsulant discolouration • Encapsulant delamination • Backsheet warping or detaching • Metallization or Busbar discoloration • Burn through backsheet • Solder bond failure • Diode failure • Hotspots	• Summarized based on risk priority number • Using 3 factors: Occurrence rating, Detection rating, Severity rating
[89]	• Aging of components	• Cash flow analysis of two locations (Northern and southern regions of Italy)

instead of CNN in the third analysis. To conclude, Hybrid models perform well when compared to single models.

Statistical assessment and AI detection of defects in PV only allow some things to be evaluated as their occurrence and appearance. Then, evaluating the time frames of repairing or its downtime, it is not enough for the economical assessments because of their impact. Different methodologies are applied for the economic analysis. Table 7 shows the various works that conducted the research on the economical influence in solar photovoltaics.

7. Stage: 5 evaluation methodology

The models employed for detection of the faults are employed using metrics. They are accuracy, precision, recall, F1 score and the confusion matrix. The metrics are helpful in calculating errors between the actual and the predicted values by the machine learning models[41].

Confusion matrices are precious tools for understanding the performance of classification models, especially when dealing with imbalanced datasets or when different types of errors have different consequences in applications. It helps the readers and machine learning experts to make informed decisions about the model selection and fine-tuning. A confusion matrix is a basic tool in field of ML and statistics specifically while evaluating performance of classification models. It provides a clear and brief way of understanding the model's performance by comparing the predictions with the actual results [42].

A confusion matrix is classically used for binary classification problems where there are two possible classes or outcomes: positive and negative. However, it can also be adapted for multi-class classification problems by extending it to cover various multiple classes.

Confusion matrix helps one to make well-versed decisions about the improvements of model employed. It provides detailed perceptions about the strengths and weaknesses of numerous models. This allows one to gain better decision on which particular model is the best fit for the corresponding task. The behaviour of the model can be interpreted clearly by understanding the confusion matrix. This provides more information about the misclassifications, which require further concentration or feature engineering.

Confusion matrix is a square matrix that consists of 4 main elements:

1. True Positives (TP): When the model predicts the positive class correctly, then it becomes true positive. In other words, the model predicts the positive result where actual outcome is positive.
2. True Negatives (TN): When the model predicts the negative class correctly, where the actual class is also negative, it becomes true negative.
3. False Positives (FP): When the model wrongly predicts the positive class as negative, then it becomes false positive.
4. False Negatives (FN): When the model wrongly predicts the negative class as positive, then it becomes false negative.

Once these components are obtained, Various performance metrics can be evaluated, including Accuracy, Precision, Recall and F1 score [43]. Accuracy can be calculated by the proportion of right predictions (TP + TN) out of the total predictions. Proportion of the true positives out of all positive predictions (TP / (TP + FP)) is precision. Precision measures how good the model performs when it predicts a positive outcome. Recall is defined as the proportion of true positives out of all actual positives (TP / (TP + FN)). Recall measures how well the model captures all the positive cases. The F1 Score is harmonic mean to the precision and recall, which strengthens the trade-off between the two metrics. The prediction or computational time by the models employed can also be calculated, and the computational memory usage is calculated for the models and can be compared.

8. Discussion

The digest of the topics, which involved the techniques for acquisition of images, preprocessing and the AI explained in the literature, is discussed in brief in the below section.

8.1. Summary of inspection techniques and preprocessing

Visual fault detection typically starts with acquiring images of objects or products. These images can come from various sources, such as cameras, sensors, or specialised imaging equipment. It's essential to set up cameras with appropriate parameters like resolution, focus, exposure time, and lighting conditions to capture high-quality images. Controlled and consistent lighting is crucial to ensure uniform image quality. The different techniques in the detection of faults and their diagnosis are explained in this literature. The inspection techniques use unmanned aerial vehicles, Infrared thermography, electroluminescence, photoluminescence, and Lock-in thermography. Table 6 shows the papers that only discussed the inspection techniques for fault diagnosis.

8.2. Summary of AI techniques

Artificial techniques include Deep learning models, object detection techniques, Classification models, Transfer learning models, and ML models like SVM, DT, RF, etc.… for anomaly detection of different faults. CNN is generally employed for visual fault detection tasks. It is particularly well-suited for image-based classification and object detection.

For identifying and locating defects on objects, models like Faster R-CNN, YOLO or SSD are used. If Goal is to classify the entire object as either faulty or not, CNN-based image classification models can be used. Pre-trained models (e.g., from ImageNet) can be fine-tuned on the specific defect detection dataset to leverage the knowledge learned from a broader range of images.

Unsupervised techniques like autoencoders or one-class SVMs can be used for anomaly or defect detection when there are no labelled examples of defects. Then, Training process is carried out for a dataset of labelled images including both defective and non-defective items which is crucial. To enhance the ability of the model to generalise, Augmentation techniques like rotation, flipping, cropping are often implemented to rise the diversity of the training samples. The general metrics for evaluating visual fault detection models include accuracy, precision, recall, F1-score, and area under the receiver operating characteristic curve (AUC-ROC).

8.3. Summary of evaluation methodologies

To assess model generalisation, techniques like k-fold cross-validation can be used to divide the dataset to train and validation subsets. Depending on the specific application, it may need to set a decision threshold to balance precision and recall based on the cost related with the false positives and false negatives. Analysing the confusion matrix provides insights into model performance, especially in terms of false positives and false negatives.

Table 8 presents the summary of literatures conducted based on all the reviewed aspects including inspection techniques, types of solar faults taken under research, Image processing techniques, AI models employed and their evaluation metrics.

9. Recommendations and insights

A comprehensive review on imaging techniques, preprocessing methods, and visual fault diagnosis utilizing artificial intelligence (AI) models in solar PV systems is conducted. In this review, various Imaging technologies includes Infrared thermography, electroluminescence imaging, and visible light imaging are assessed for the applicability in detecting diverse types of Solar PV faults. It is also explored that the advancements in imaging technologies, such as high-resolution cameras, drones, and satellite imagery, create an impact on fault detection. While getting into the preprocessing domain, this review examines different techniques such as noise reduction, contrast enhancement, and image normalization for enhancing the quality of PV images.

The fault diagnosis accuracy can be further improved by exploring the integration of external data sources using weather data and historical performance data. This visual fault diagnosis is conducted with the help of AI models like CNNs and RNNs that effectively classify faults based on visual information. The review will also investigate

Table 8
Summary table of the papers which are reviewed based on the five aspects: (PV inspection, PV Faults, Image processing techniques, AI models and Evaluation metrics).

Reference	Panel Inspection	Faults analysed	Image processing techniques	AI model employed	Evaluation metrics
[48]	UAV-based: Visible and thermal images	Dust-shading, Encapsulant delamination, Glass breakage, Gridline corrosion, Snail trails and Yellowing	Kirsch operation-based Image Segmentation (Edge detection, Background elimination, Interference Elimination), Deep defect Feature Extraction	Multiple classification support vector machine (MC-SVM) algorithm	Three-fold cross validation, Accuracy
[38]	UAV equipped with a high-resolution digital camera	Snail trail, Glass breakage, Delamination, Discoloration and Burn marks	Discrete wavelet transform (DWT), fast Fourier transform (FFT), texture, grey level co-occurrence matrix (GLCM) and grey level difference method (GLDM).	Ensemble-based Deep neural network with Random Forest classifier	5-fold cross validation, Accuracy, Receiver operating characteristic curve
[32]	Real industrial dataset: Electroluminescence images	Crack defect, Finger interruption and defect-free	Multi attention network with spatial and channel attention	Multi attention U-net architecture	5-fold cross validation, mean intersection over-union (m-IOU), F-measure, accuracy, recall, precision.
[43]	Infrared Imaging camera and images collected from internet	Normal and defective panels	Data augmentation: cropped, resized, rotation and flipping operations	Isolated learning from scratch and Develop-model transfer learning	5-fold cross validation, confusion matrix, Computational cost
[36]	Obtained from public domain and private dataset provided by JinkoPower Company (China) Electroluminescence images	Micro-crack, Break, Finger-interruption and Defect-free	GAN based augmentation (Generative adversarial network)	CNN architecture	Accuracy, loss function and computational time.
[35]	UAV-based and ground-based operators: Thermographic images	Normal and Hotspot	Homogenization of pixels, Normalization, Thresholding, Grayscaling, Discrete wavelet transform, Box blur filtering and Sobel Feldman filtering.	CNN architecture	Confusion matrix, Accuracy, loss function, Receiver operating characteristic curve
[37]	Not mentioned	Early-stage PV hotspots: 1 hot-spotted solar cells, 2 hot-spotted solar cells, more than 3 hot-spotted solar cells	Normalization of data	Discriminant classifiers	Accuracy, Confusion matrix, Receiver operating characteristics curve
[90]	FLIR thermal camera	Defective, Non-defective without hotspots, Non-defective with hotspots	Grayscale conversion, Histogram equalization, Gray Level Co-Occurrence Matrix (GLCM), Histogram of gradient, Principal component analysis	nBayes-based multi-class density-based classifier	Accuracy
[42]	FLIR A310 IR camera: eddy current lock-in thermography (ECLT) and eddy current pulsed thermography (ECPT)	Broken edge, Surface impurity, scratch crack, Hotspot and Large area damage	Independent Component Analysis (ICA), Principal Component Analysis (PCA) and Non-negative Matrix Factorization (NMF)	LeNet-5, VGG-16, GoogleNet	Accuracy
[11]	Obtained from different internet search engines	Defect-free, cracks, shadows and Dusty	Semantic segmentation using CNN architecture	CNN architecture for classification	Accuracy

explainable AI techniques to boost interpretability. Prominence will be placed on a thorough literature review, finding research gaps and discussions on real-time applications, challenges, and potential future directions, ensuring the exploration of the present state and future possibilities in the field of AI-based fault diagnosis for solar PV systems.

10. Conclusion

In this paper, several articles have been reviewed, and research has been made based on 5 aspects: (i) Inspection of the PV panels for faults, (ii) The possible faults that can occur in PV panels, (iii) Different types of imaging techniques used for the research, (iv) Role of artificial intelligence in fault detection of the PV panels and (v) Evaluation metrics for the AI techniques used.

Various possible visual faults and their causes, such as degradation, corrosion, delamination, partial shading fault, interruptions, cracks and delamination, faults occur in the bypass diodes and blocking diodes are elaborated. Images acquired from the solar panels are processed before being given to the models. The various types of images, which include electroluminescence, photoluminescence, thermal imaging and ultraviolet fluorescence imaging techniques, are discussed in detail. The preprocessing techniques are discussed and summarised from different literatures. From the fault detection methodologies reviewed from the literature studies, AI models are evolving in the domain. The neural networks and machine learning models used in fault detection are reviewed. The neural networks are performing well when compared with conventional transfer learning models and ML models like SVM and DT. The evaluation techniques, like the Classification report metrics and Confusion matrix for the models, are discussed elaborately. Finally, this review of fault detection in solar and diagnosis methodologies utilising ML models and imaging techniques could provide essential insights into optimising the maintenance and reliability of PV systems, eventually contributing to the advancement of solar energy technology and its widespread adoption.

CRediT authorship contribution statement

Gurukarthik Babu Balachandran: Supervision, Methodology, Conceptualization. **M. Devisridhivyadharshini:** Validation, Methodology, Investigation, Formal analysis, Conceptualization, Visualization, Writing – original draft. **Muthu Eshwaran Ramachandran:** Conceptualization, Methodology. **R. Santhiya:** Formal analysis, Methodology, Validation.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

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