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Advanced Deep Neural Networks for Thermographic Pattern Analysis: Revolutionizing PV Module Fault Diagnostics.



Abstract: - Photovoltaic (PV) energy has emerged as one of the most important renewable energy sources, and it is now the fastest-growing energy technology. As the relevance of PV energy grows, it is crucial to examine faults and degradation of PV systems to develop the stability and implementation of electrical systems. The PV panels are the PV system element that is susceptible to rigorous working conditions, which leads to numerous probable problems impacting the system's operation and lifespan if not diagnosed or forecasted in a timely way. Fault analysis in solar PV arrays is required because it helps to stimulate reliability, efficiency, and safety in PV systems. If defects in a PV system are not identified promptly, not only is power generating capacity reduced but the problems are cascaded across the whole system. In this paper, the comparative analysis is done to find out the best classifier to identify the fault in the PV system so that it could be protected from degradation.

Keywords: PV, Thermographic Images, Image processing, Fault diagnosis, Classification and Deep learning.

I. INTRODUCTION

A PV system, frequently recognized as a PV system or a solar power system, is a kind of electric power system that employs PV to produce functioning solar energy (Parida et al. 2011). It consists of many elements, consist of solar panels that gather and convert sunlight into electricity, a solar inverter that transforms the output into direct to alternating current, and mounting, cabling, and other electrical accessories (Razykov et al. 2011). It might also include a combined battery solution and a solar tracking system to improve complete system performance since storage device prices are projected to reduce. A solar array is merely the noticeable element of a PV system; it does not include each of the accompanying equipment, which is frequently described as a balance of system (BOS). PV systems should not be puzzled by other solar heating and cooling technologies, for example, intense solar power or solar thermal (Hosenuzzaman et al. 2015). PV systems directly turn light into energy.

PV systems vary in size from small building-integrated systems or rooftop-mounted with a limited ten of kilowatts of capacity to large utility-scale power plants with hundreds of megawatts of capacity. The vast majority of PV systems are now grid-linked, with off-grid or stand-alone systems accounting for a negligible portion of the market (Lupangu et al. 2017).

PV systems have progressed from niche market applications to previous knowledge applied for mainstream energy generation (Charfi et al. 2018). They run silently, with no moving parts or contaminants in the environment. Over a 30-year service life, a rooftop system recoups the energy used on building and installation in 0.7 to 2 years and generates around 95 % net clean renewable energy (Siecker et al. 2017).

Photovoltaic (PV) technology and systems have grown rapidly during the last decade all over the globe (Sabbaghpur et al. 2016). Because of a huge and dependable energy supply, and continually refilled energy resource, PV is regarded as the highly capable and substantial renewable energy source (RES) since it provides clean energy at different power stages and many settings, including home (Madeti et al. 2016). It improves national wealth, power protection, public health, and environmental protection significantly. Solar energy has emerged as the extremely appealing and, in certain situations, the most cost-effective source of new energy production (Triki-Lahiani et al. 2018). Different issues may impact PV functioning, including maximum power point tracking inaccuracy, environmental impacts for example shadowing and snow or dust deposition on the PV surface, wire aging and losses, and failure in other PV elements such as the inverter and the power conditioner unit. Faults can reduce the power provided by a PV system by roughly 18.9% yearly, according to a monitoring study it was (Firth et al. 2010) published in 2010. As a result, adequate approaches for continually analysing current, voltage, and output power properties of PV systems, as well as detecting existing and growing defects were required. It is critical to have a

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detecting algorithm that promptly detects the existence of a defect in the PV system and determines the source of that issue to increase the complete system's operational performance and dependability.

A .Photovoltaic Array

The Solar PV Array, often known as a Solar Array, is a system consisting of a set of solar panels joined together (Firth et al. 2010). An array of photovoltaic solar panels, which are connected electrically to create a much bigger PV installation (PV system), produces more solar power the greater the surface area of the array. A solar array is the major cause of electrical power production in a full PV system. Photovoltaic panels and modules can't provide enough electricity to meet the needs of the general public. The standard output voltage of a solar panel is often 12 volts or 24 volts, depending on the manufacturer. The needed output may be achieved by linking a substantial number of single PV panels in series and parallel.

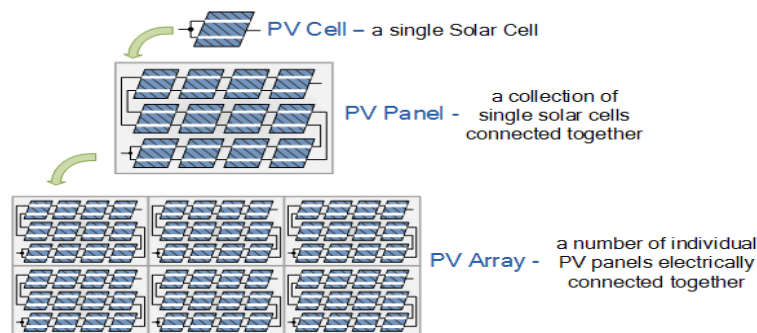


Fig. 1 A Photovoltaic Solar Array

When PV modules are linked to form a solar array, it is known as a solar array Yousri et al. (2018). Each PV module is comprised of various cells that are linked together. The cells convert solar energy into direct current power and PV modules are frequently described as "solar panels," while the term "solar panels" really refers to solar-thermal water or air heating panels. Comparing solar panels with traditional PV modules, these smaller-scaled units may be easily installed in a variety of settings, involving a home or office, a commercial building, or an industrial facility. The use and study of PV devices are known as photovoltaics (Yousri et al. 2020). The PV Solar Array is described in Figure 1. PV cells work by absorbing part of the Sun's energy and causing current to flow among 2 oppositely charged layers, which is known as the photovoltaic effect. Individual solar cells offer a little quantity of electricity, but when joined together, the electrical output may be enormous (Malathy et al. 2018). To achieve a desired peak voltage output, the cells, modules, and arrays may be associated in series or parallel, or a mix of both.

The solar cells of the PV are coupled in series to allow for output voltage control or in corresponding to allow for better output current control. The PV module's serial linking among solar cells has a disadvantage in that if one of the cells is destroyed, the PV panel's performance would suffer (Silva et al. 2014). Thermodynamics, reflectance, charge carrier division, and conductive proficiency are the four distinct efficiencies of solar cells. The total efficiency is the product of each of these efficiencies (Alsafasfeh et al. 2014). It is critical to notice a mistake, when possible to limit negative consequences and save energy and money. The most common kind of solar energy system is a PV system, as demonstrated in Fig. 1

Solar panel faults, often known as hot spots, may arise for many causes. Deficiencies in the bubbles in solar modules, delamination over cells, anti-reflective coating, interconnections, browning, and yellowing are only a few of the recognized causes (Zhaol et al. (2014). Over currents are often caused by defects in PV arrays, resulting in heat and damage to PV components. Open circuit faults, "Line-line faults (LLF)", and ground faults are the three kinds of faults that occur in PV arrays. An inadvertent connection among two sites in the solar panel causes an LLF (Alam et al. 2013). During an open fault or Arc fault, a current may be created owing to insulation failure in the "Current-Carrying Conductors (CCC)" (Alsafasfeh et al. 2013). An LLF might arise among two neighbouring strings or two spots on the same string. Cell damage, rodent damage, solder separation, and connection corrosion may all cause an open fault in a CCC. A low-impedance route among the ground and one of the CCCs is created by the ground fault (Matzik et al. 2016).

The reason to choose thermal images with climatic faults other than electric faults is given below:

electrocution of maintenance staff or a power loss. Electricians disturb the power supply and waste time and money by disconnecting the electricity or using heavy equipment to safely discover electrical issues. As a result, remote defect detection has become critical for long-term electrical facility maintenance. Machine diagnostic methods have developed from manual processes to vibration-based signal analysis as a result of technical advancements (Kim et al. 2021). Despite the positive findings of vibration-based prognostics, there are still certain limitations, such as the need for direct touch, the inability to detect heat degradation, noise signal contamination, and expensive calculation costs. An infrared thermal (IRT) image recognition technique is suggested in this paper for long-term and dependable operation. The IRT imaging technique is used for diagnostics in a variety of technical disciplines due to its non-contact, safe, and highly dependable heat sensing technology.

This paper is distributed into 4 sections, the 1st section contains the brief introduction of the paper, and 2nd section contains the related work of various authors. The 3rd section includes the comparative analysis, and the final section includes the conclusion and future scope.

II. TYPES OF FAULTS IN SOLAR PV SYSTEM.

Any damage or problem in a PV system component has the potential to significantly affect the plant's overall efficiency, energy yield, safety, and consistency if it is not promptly identified and fixed. Furthermore, some defects may increase the likelihood of burning if they persist. Systems for "fault detection and diagnostic (FDD)" are critical to the high-efficiency, dependable, and secure operation of photovoltaic facilities.

A PVM failure that happens in conditions that the module is used to typically has something to do with the system guarantee, claim Kato et al. (2019). Unexpected safety issues, decreased efficiency, accessibility to electricity, unstable system performance, and security are all brought on by any PVS problem. Different kinds of PVM faults are observed and examined in Pavan et al. (2013).

A. *Earth Fault*

The highly frequent fault in PV is an earth fault, which arises when the circuit generates an unintentional path to the ground. The first is system grounding the negative conductor is normally grounded through the PV inverter's Earth fault prevention device (GFPD). Equipment grounding requires that all revealed non-current-carrying metal components of electrical equipment, PV Bridging One or More Panels.

When a low resistance correlation is made among 2 sites of varying potential in a string of modules or cabling in a PV system, fault bridging arises. Bridging failures in PV arrays might be affected by cable insulation failure, water intrusion, mechanical damage, or corrosion (Ghosh et al. 2018).

B. *Open Circuit Fault*

An open circuit problem might arise if one of the current-carrying pathways in line with the load is damaged or accidentally opened. All of the above are examples of poor cell connections, connectors being plugged and unplugged at junction boxes, and wires breaking. When it comes to solar panels, series arc faults are more common because of the large number of connections they have, which makes them more dangerous than parallel bridging faults (Ghosh et al. 2018).

C. *Mismatch Fault*

Mismatch in PV modules occurs when an electrical characteristic of a cell or a group of cells changes, resulting in significant power loss. Mismatch defects are further divided into two types: transient and permanent faults. Temporary mismatch occurs when part of a panel is shadowed by trees or chimney cast, by overhead power wires or surrounding buildings, or by dust, dirt, snow, or other obstructions in the path (Ghosh et al. 2018).

D. Hotspot Fault

When certain cells in a PV array/string have distinct I-V curves (Forniés et al. 2018) owing to manufacturing procedures, differences in the properties of PVMs, extreme endurance, a hot spot (HS) might occur. Furthermore, soiling and dust deposition (Pavan et al. 2016), deprivation of the cells, insufficient edge isolation (Ndiaye et al. 2018) through visible component materials may all affect this feature. The partial shadow effect might be considered an example of the incompatibility issue. The HS phenomenon occurs when the shaded cells' bypass diode is damaged/disconnected, ensuing in a reduction in current and a decrease in voltage, causing the shaded cells to consume power by resting non-shaded cells rather than producing it, and if this process continues, the pretentious solar cells would be spoiled (Yang et al. 2010). Figure 6 describes several strategies for identifying HS, although many approaches for quickly detecting HS in a PVM rely on infrared data (Alzahrani et al. 2021).

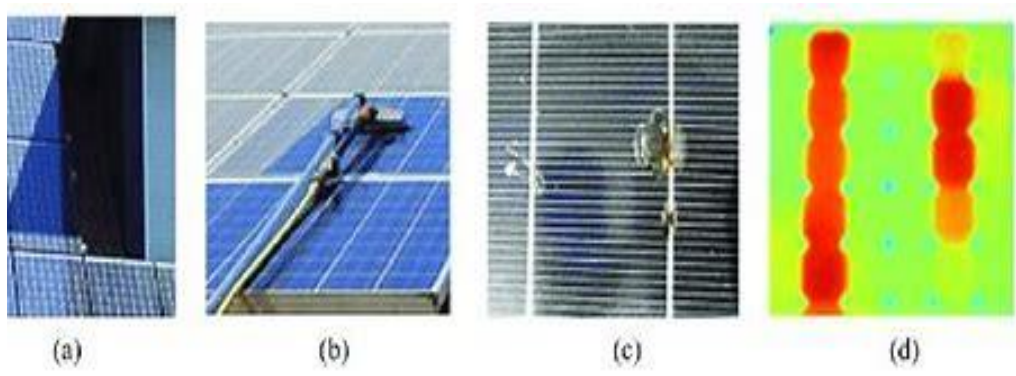


Fig. 2: HS fault: affects (a) shading, (b) Dust accumulation and soiling; (c) HS dented on solar cells Long-Dong et al. (2021). (d) Infrared imaging was used to identify HS events on a PVM.

Strategies for identifying HS, although many approaches for quickly detecting HS in a PVM rely on infrared data Simon et al. (2018). Table 1 below shows the types of faults and their reason for occurring.

Table 1: The types of faults and their reason for occurring

<i>S. no.</i>	<i>Type of fault</i>	<i>Reason for Occurring</i>
1	Earth Fault	Arises when the circuit generates an unintentional path to the ground.
2	Bridging One or More Panels	Bridging failures in PV arrays might be affected by cable insulation failure
3	Mismatch Fault	Mismatch in PV modules occurs when an electrical characteristic of a cell or a group of cells changes
4	Hot spot (HS) fault	When certain cells in a PV array/string have distinct I-V curves.

III. FAILURES DUE TO ENVIRONMENT FAULTS IN PV ARRAY.

Because photovoltaic cells require sunlight radiation to work, gloomy days tend to yield slightly lower productivity from solar panels than sunny ones [78]. The amount of cloud cover also affects the output of solar panels

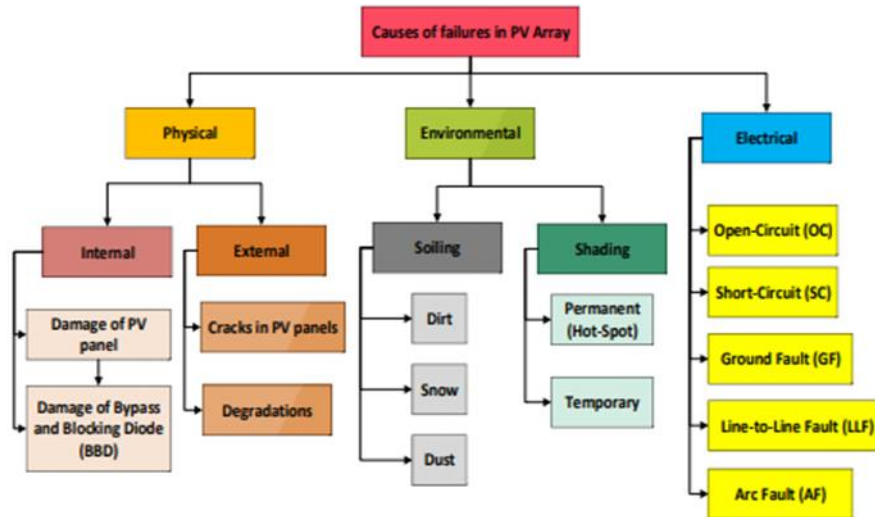


Fig. 3 Major causes of failures in PV array

on cloudy days. For example, solar panels may not be much affected by cirrocumulus or thin sheet-like clouds. In the meantime, even the greatest solar panels for gloomy days can see a 10% to 25% decrease in efficiency on partially cloudy days. Rainy days, though, are not as horrible as they might seem. Over time, dust accumulation on the panels may also have a detrimental effect on their performance. Rainwater can eliminate dirt, which reduces the need for some upkeep [79]

Physical faults are produced by internal (damage to PV panel or to blocking and by - passing diode (BBD)) or external (crashes in PV panels or degradation) failures (Jones et al. 2016). Environmental faults are caused by soiling (dirt, snow, dust) Jones et al. (2016), permanent shaded hot - spot (Guerriero et al. (2018), or temporary shade (Pierdicca et al. 2018). Electrical faults are open circuit (OC), short circuit (SC), ground fault (GF), LLF, and arc fault (AF) (Dkhichi et al. 2018), with their potentially dangerous consequences (fire risks and electrical shock) (Chouder et al. 2018).

IV. EFFECT OF ENVIRONMENTAL FAULTS ON THE PERFORMANCE OF SOLAR PANELS.

There is a various effect on the performance of solar panels some of them are given below: Environmental factors play a significant role in the performance of photovoltaic (PV) systems. In cloudy conditions, the accumulation of dust on solar panels over time can significantly decrease their energy output, necessitating regular cleaning maintenance. Snowy environments present their own challenges, as snow cover on PV cells can substantially impede their ability to capture sunlight and generate electricity. Temperature extremes, both hot and cold, can adversely affect the efficiency of solar panels, with excessive heat particularly detrimental to their power production capabilities. Windy conditions pose risks to the structural integrity of solar installations, potentially causing damage to the racking systems or the underlying roof structure if not properly secured. These diverse environmental factors underscore the importance of considering local climate conditions when designing and implementing solar energy systems to maximize their long-term effectiveness and durability. Table 2 describes the effect of environment on Solar PV panel and their outcomes.

Table 2: Environment Effects and their outcomes

S. no.	Effect	Outcomes
1	Dusky Environment	The panels getting dusty over time can also impact their output negatively.
2	Snow Environment	Affect the energy production of the PV cells.
3	Extreme Temperatures	Reduce the power output of the PV cells.
4	Windy Environment	Result in cracking system or the roof where the panels are mounted
5	Lightning	Result in voltage surges causing damage.

A. Summarization of Meteorological Fault in PV Module

Wind, which may cause blurring by disrupting the UAV's constancy, & the reflection of sun rays on module surfaces, which affects over-illuminated images, are two examples of environmental factors that affect the imaging process Aghaei, M., et al. (2016). Edge detection and other approaches that need low noise levels in the images are made more difficult by these components, making it more difficult to discover hot areas.

Dotenco et al. (2016) stated that for PV modules recognized in thermal images, 4 sets of characteristics are generated ("module medians, grid cell medians, histogram skewness, and vertical projections"). They identify the problematic modules established on temperature anomalies by doing a Dixon's Q test after a Grubbs' test.

Kim et al. (2017) stated that the Panel areas are recovered from UAV thermal images, and a technique for automated defect identification based on statistical values of thermal intensity for each solar panel is suggested. Another approach is presented that is centered on curve fitting of the histogram of grey thermal pictures. The histogram is mounted as a smooth curve using the least square approach, removing the blurring and local variations in the picture. Then, depending on the curve features, a threshold is chosen to separate the hot areas from the remainder of the picture.

Ghazi et al. (2018) stated that as the number of PV systems being installed in the UK increases, so does the need for further precise predictions of their functioning performance. This has encouraged researchers to investigate the relationship among output efficiency, weather conditions, and solid particles deposited on the panel surface. For example, field studies have shown that actual outputs can be concentrated by up to 60% without regular cleaning in dusty or polluted climates.

Kawamoto et al. (2011) stated that a technique for decreasing lunar dust has been developed using electrostatic traveling waves. During long-term lunar operations, this technology will be used for solar panels and optical components. The system comprises a particle conveyer and a power source that produces rectangular four-phase voltage. Table 3 gives the summary on effect of environmental condition in PV Array.

Table 3: Summarization of Meteorological condition in PV Array.

	Effect	Outcomes
Dotenco et al. (2016)	Extreme temperature	They identify the problematic modules established on temperature anomalies by doing a Dixon's Q test after a Grubbs' test.
Kim et al. (2017)	Extreme temperature	The histogram is mounted as a smooth curve using the least square approach, removing the blurring and local variations in the picture.
Ghazi et al. (2018)	Cloudy Environment	Actual outputs can be concentrated by up to 60% without regular cleaning in dusty or polluted climates.
Kawamoto et al. (2011)	Windy Environment	The system comprises a particle conveyer and a power source that produces rectangular four-phase voltage.
Dotenco et al. (2016)	Extreme temperature	They identify the problematic modules established on temperature anomalies by doing a Dixon's Q test after a Grubbs' test.

V. SOLAR PV IMAGING TECHNIQUES

There are various works given by the different authors which are given below:

Gauci et al. (2016) stated that the application of thermography has been proposed for a variety of medical applications that often need the removal of temperature data from particular sites of interest on the human body. Temperature extraction, on the other hand, is often done by hand, making the procedure both time-consuming and subjective. The author provides several approaches for autonomously segmenting and extracting temperature data from thermal pictures of human hands, shins, and feet that may be used in a variety of medical functions. Similarly, Faults in PV panel are analysed using various thermal imaging techniques and software. The comparison of imaging techniques is described in Table 4.

Table 4: Imaging Techniques Comparison

Sr. no.	Imaging	Technology	Faults
1	Thermography	Thermographic camera sensing infrared radiation	Shunt defect
2	Electroluminescence	Near-Infrared (NFIR) cameras	Fine cracks, broken gates, change in cell resistance
3	Thermal	IR Camera	interconnection failures, hot spots, and cracks
4	Ultrasonic	Ultrasonic transducer	cracks, voids, lamination

VI. ANALYSIS OF IMAGE PREPROCESSING TECHNIQUES.

In this, there are 3 techniques used for objection i.e., edge detection, discrete Fourier transform (DFT), and Convolutional Neural Networks.

A. *Edge detection*

The edge detection approach is highly helpful for object identification in images, or for distinguishing between multiple items in a given picture. Edge detection, in general, is heavily reliant on picture intensity, and the detection approach is a very important tool in machine vision, computer vision, and image processing.

Alawad et al. (2018) stated that in digital IP, edge detection is the initial stage in image recognition systems. Analyzing an image's edges is a good approach to resolve a lot of information from it, such as depth, curves, and its surface, since it may reveal these characteristics when colour, texture, shade, or light changes significantly. Because it is based on a flawed process, this might result in a distorted picture or vision.

Mohapatra and Narayan B. (2019) stated that nowadays, image edge detection is a hot topic of research. Exact detection will provide useful information, especially in medical picture analysis and processing. The edge detection approach can recognize the image's solid zones with solid contrasts. A high pass channel for identifying edges that concentrate on the image picture is used in the edge detection approach. Finger image authentication and identification are critical for biometric applications. For sudden changes in the intensity value of a visual image, the edge detection approach is highly useful. Corners, curves, and lines are crucial in an image and may be retrieved using an edge detection algorithm. Edge detection is important in image analysis since it reduces the size and substantial required data of an image.

Wang and Ruohui (2016) stated that the importance of edge detection in images for image processing cannot be overstated. It is utilized in a wide range of applications, including real-time video surveillance, traffic control, and medical imaging. There is presently no single edge detector that is both efficient and dependable. Traditional differential filter-centered algorithms are theoretically tight, but they need a lot of post-processing.

Shrivakshan et al. (2012) stated that edges define boundaries, they are a critical issue in image processing. Image Edge detection minimizes the quantity of data in a picture and filters away unnecessary information while maintaining the image's crucial structural qualities. Edge detection methods are critical because they are at the forefront of image processing for object identification.

B. *Discrete Fourier Transform (DFT)*

The DFT is a useful image processing method that is applied to break down a picture into its frequency response utilizing a starting image in the way of a spatial domain, for example, a conventional EL image.

Dhimish et al. (2019) stated that the creation of a unique approach for improving the recognition of tiny fractures in solar cells. The output picture of a traditional EL system is first established and recovered utilizing binary and DFT image processing methods. Using the geometric qualities of the EL picture, the binary image is utilized to improve the detection of fracture size, location, and orientation. The DFT, on the other hand, was utilized to analyze the EL picture in a 2-dimensional spectrum. The DFT output picture contains structures of all needed frequencies, which improves the identification of any faults in the solar cell. As a consequence, the new approach outperforms standard EL output pictures in detecting tiny fractures in solar cells.

C. *Convolutional Neural Networks*

The use of convolutional layers and subsampling layers to reduce computation time while enhancing invariance is common. However, to maintain specificity, a minor subsampling factor is preferred. It's not a new idea, but it's straightforward and effective (Lee et al. 2010). A fault detection system of PV module with CNN and joint learning method to detect the images was introduced in Su et al. (2021). It outperforms benchmarked approaches in terms of effectiveness and efficiency. However, performing with this type of classification and area location tasks in the regular model needs a lot of computation time. To overcome the drawbacks learning using traditional Algorithm, a deep CNN has emerged. Looking into deep dive analysis a wide literature and comparative analysis is studied in further sections.

ANALYSIS OF PV FAULT DETECTION USING DEEP LEARNING TECHNIQUES.

Amaral et al. (2020) stated that PV power plants currently play a significant part in the production of electricity from renewable sources. The PV modules of these power plants are mounted in trackers to achieve optimal efficiency. However, the trackers' movable construction is prone to failure, putting the required perpendicular position among the PV modules and the smartest moment in the sky in jeopardy. As a result, diagnosing a tracker

Table 5: Summarization of PV fault detection using Deep Learning Techniques

<i>S. no.</i>	Effect	Outcomes
Amaral et al. (2020)	PCA	Accordingly, an unsupervised technique centered on a novel IP system to predict PV slopes is presented to achieve the necessary defect diagnosis.
Pierdicca et al. (2020)	Deep Neural Network	A DL-centered AI system for identifying abnormal cells PV photographs collected from an unmanned aerial vehicle furnished with a thermal infrared sensor.
Kim et al. (2019)	RF regression	The RF regression approach likewise outperforms the others for this issue, with an R-squared value of 70.5 percent in the test data.
Pérez et al. (2019)	YOLO	When making precise choices that affect a particular proportion of the solar farms, monitoring, maintenance, and problem detection methods are critical.

Failure is critical to ensuring optimal energy output. Sensor-based and statistical-based approaches have been investigated; however, they are costly and inefficient. To deal with these issues, a unique technique based on machine learning is presented for defect diagnostics in PV trackers. The projected technique may be classed into two key groups in this sort of approach: supervised and unsupervised. Accordingly, an unsupervised technique centered on a novel IP system to predict PV slopes is presented to achieve the necessary defect diagnosis. A problem is detected by evaluating the slopes of various modules. This method is centered on principle component analysis (PCA), a recent image processing technique.

Pierdicca et al. (2020) stated that Renewable energy sources will be the sole option for reducing fossil fuel use and pollution. As a result, PV power plants are widely applied techniques for producing renewable energy. It is critical to keep track of a system's health. However, these approaches are time-consuming, induce interruptions in energy output, and often include laboratory apparatus, making them unsuitable for routine inspections. Furthermore, PV facilities are often located in distant areas, making any engagement unsafe. In this article, the author presents solAIr, a deep learning-centered artificial intelligence system for identifying abnormal cells in photovoltaic photographs collected from an unmanned aerial vehicle furnished with a thermal infrared sensor.

Kim et al. (2019) stated that PV systems have grown in popularity as RES. As solar power production is essentially determined on weather variations, anticipating power production by weather data offers a variety of financial benefits, such as more dependable proactive power and operation planning trading. Using meteorological data supplied by weather agencies, this research develops a model that forecasts the quantity of solar power output. This paper suggests a two-step modeling technique for connecting unexpected weather variables to weather predictions that have been made public. The empirical findings reveal that, regardless of the kinds of machine learning algorithms used, this strategy outperforms a baseline approach by a large margin. The RF regression approach likewise outperforms the others for this issue, with an R-squared value of 70.5 percent in the test data.

In the post-analysis, the average modeling process generates four variables, each of which is given a high priority. The model is capable of making credible one-day forecasts.

Pérez et al. (2019) stated that countries have made renewable energy, environmental practices, and carbon neutrality significant aims. Solar panels are an excellent way to generate electricity. When making precise choices that affect a particular proportion of the solar farms, monitoring, maintenance, and problem detection methods are critical.

The author offers a method that uses ML to identify the position of solar panels in this study. The main goal is to apply a machine learning model to assist solar panel farm managers in real-time finding solar panels in a real site. Author capable to fly above the solar farm and distinguish the panels using a camera and a drone. The YOLO (You Only Look Once) object identification model is utilized, with a data set of 280 photos utilized to test and train the neural network. The neural network was able to distinguish the panels in a variety of photos and movies in which the author put to the test, with high accuracy. Below Table 5 shows the summary of this work.

Table 5. Summarization of effect on problem detection techniques.

Author	Technique Used	Outcomes
Alawad et al. (2018)	Edge detection	As a result of the faulty procedure, this resulted in a distorted picture or vision.
Mohapatra and Narayan B. (2019)	Edge detection	Edge detection is important in image analysis since it reduces the size and substantial required data of an image. It is utilized in a wide range of applications, including real-time traffic control, video surveillance, and medical imaging.
Wang and Ruohui (2016)	Edge detection	Edge detection methods are critical because they are at the forefront of image processing for object identification. The DFT output picture contains structures of all needed frequencies, which improves the identification of any faults in the solar cell.
Shrivakshan et al. (2012)	Edge detection	Advanced and automated fault diagnosis is a procedure that provides immediate results and ensures a longer lifespan for a variety of important PVM components.
Dhimish et al. (2019)	DFT	The networks are trained using an infrared images dataset including infrared images of regular working and faulty modules.
Sridharan et al. (2021)	CNN	The CNN is used in this to assess the PV panel's surface and identify the existence of a fault.
Akram et al. (2020)	CNN	This research describes a unique method for estimating PV cell degradations using DCNNs.
Zyout et al. (2020)	CNN	
Pierdicca et al. (2018)	CNN	

VII. COMPARATIVE ANALYSIS OF PV FAULT CLASSIFICATION USING DEEP LEARNING TECHNIQUES.

This section of the paper contains the comparative analysis of PV fault classification using deep learning techniques are used to find out the best classifier. Table 7 shows the analysis based on various CNN Classifier. Sridharan et al. (2021) stated that traditional defect detection approaches need precise operating conditions, which take time, effort, and money. In today's fast-paced environment, innovative tactics and technology breakthroughs are expected to provide rapid results. Advanced and automated fault diagnosis is a procedure that provides immediate results and ensures a longer lifespan for a variety of important PVM components. Hypothesis: This research uses CNN to conduct autonomous fault identification in PVM, successfully classifying different errors based on photos taken by unmanned aerial vehicles (UAVs).

Akram et al. (2020) stated that with the increased usage of solar systems and the continued development of large-scale photovoltaic systems across the globe, automation of photovoltaic monitoring techniques is becoming more relevant since manual/visual inspection has limited applicability. This study uses isolated deep learning and improve model transfer deep learning algorithms to identify photovoltaic module flaws in infrared photos

automatically. The networks are trained using an infrared images dataset including infrared images of regular working and faulty modules.

Zyout, I., et al. (2020) stated that with the increased demand for creating and installing new solar energy systems throughout the globe, the necessity for autonomous solar panel flaw detection is becoming more critical. Deep CNN excel at handling picture classification tasks across a wide range of disciplines. The CNN is used in this article to assess the PV panel's surface and identify the existence of a fault. The use of transfer learning with AlexNet CNN produced highly favorable results, demonstrating the approach's potential for detecting numerous faults in the solar panel's surface.

Akram et al. (2019) stated that due to the restricted use of manual/visual assessment and increased manufacturing volumes of PV modules, automated flaw detection is gaining a lot of traction in the PV industry. The objective of this research is to discover a method to spontaneously identify PV module flaws in electroluminescence (EL) photos. The author introduced a new strategy for spotting faults in EL pictures that uses light CNN architecture and obtains state-of-the-art results of 93.02 percent on the solar cell dataset of EL images. It takes less time and processing power. It could run on a standard CPU machine and retain actual performance. One image prediction takes just 8.07 milliseconds. The author does considerable experiments on a variety of designs to suggest light architecture.

Pierdicca et al. (2018) stated that the utilization of RES, whose application is rising in necessity because of environmental and climatic concerns, as well as the global economy's recovery, will be a major challenge. Renewable energy sources will be the sole option for reducing fossil fuel use and pollution. The amount of allocated PV plants that generate energy has expanded dramatically, and the problem of checking and providing a PV plant has become critical, posing several issues such as efficiency, dependability, safety, and stability. This research describes a unique method for estimating PV cell degradations using DCNNs.

Ying et al. (2018) stated that many methods are prone to faults such as broken grids, open welds, and concealed cracks owing to the intricacy of PV module cell manufacture. Because the typical CNN approach of extracting visual features from a single channel is insufficient, this research provides a method of detecting flaws in PV module cells utilizing a “multi-channel convolutional neural network (MCCNN)”. Multi-channel can extract picture features from multiple scales since it has the scale of distinct image sizes. On the fully connected layer, the features are fused and then categorized with the Random Forest (RF) classifier, which enhances recognition accuracy. Table 7 describes the summarization of the work.

Table 7: Summarization on PV faults Classification using Deep Learning Technique

Author	Objectives	Technique Used	Obtained results	Future Scope	Performance Matrix (accuracy)
Akram et al. (2020)	To identify the computerized recognition of PV module defects	CNN	98.67%	Frameworks require low computation power and less time and can be implemented with ordinary hardware. They also maintained real-time prediction speed.	The develop-model transfer learning approach can also be used to achieve high performance for other imaging methods.
Ying et al. (2018)	To estimate the PV panel's surface and recognize the existence of a fault.	CNN	97.08%	Distinguish the PV module cells defect, and defect types quickly and correctly, and precisely label it on the original picture.	Enhancing the classification algorithm's generalization capabilities.
Akram et al. (2019)	To identify the Automatic detection of defects in electroluminescence (EL) images.	CNN	93.02%	Adopting just one or a few generalization techniques does not result in great accuracy.	By expanding the amount of the training data, the outcomes may be greatly enhanced. Because of the availability of massive datasets.
Kim et al. (2019)	To predict	CNN	70.50%	This strategy outperforms a basic	By expanding the amount of the

	power generation using weather information.			approach by a large margin, independent of the ML algorithms used.	training data, the outcomes may be greatly enhanced. Because of the availability of massive datasets.
Zyout et al. (2020)	To perform the automated assessment and defect discovery of the exterior of the solar panel.	CNN	95.50%	The promise of the CNN for developing computer vision functions is not limited to supplying high-quality and mass-production solar panels.	Real-world data is used to improve the classification algorithm's generalization capabilities.

A. Comparative study and Discussion on the existing data.

According to the above analysis the dataset and classifier which are used in the analysis are listed below:

Sridharan et al. (2021) used a photovoltaic module (PVM) dataset with the application of an SVM classifier and the accuracy of the model is 95.07%. Akram et al. (2020) used electroluminescence (EL) images dataset with the application of SVM classifier and the accuracy of the model is 97.67%. Ying et al. (2018) used the PV panels dataset with the application of an SVM classifier and the accuracy of the model is 97.08%. Akram et al. (2019) used an EL images dataset with the application of a random forest classifier and the accuracy of the model is 93.02%. Kim et al. (2019) used the PV panels dataset with the application of a random forest classifier and the accuracy of the model is 70.05%. Zyout et al. (2020) used the PV panels dataset with the application of SVM and the accuracy of the model is 95.5%. Akram et al. (2019) has the best accuracy which is 98.67 %

Table 8 illustrates the analysis of datasets and the classifier, and its graphical representation is described in Figure 8.

Table 8 Analysis of datasets and classifier

Authors	Dataset	Techniques	Accuracy
Sridhara et al. (2020)	PVM	SVM	95.07%
Akram et al. (2020)	EL images	SVM	98.67%
Ying et al. (2018)	PV panels	SVM	97.08%
Akram et al. (2019)	EL images	Random Forest	93.02%
Kim et al. (2019)	PV panels	Random Forest	70.05%

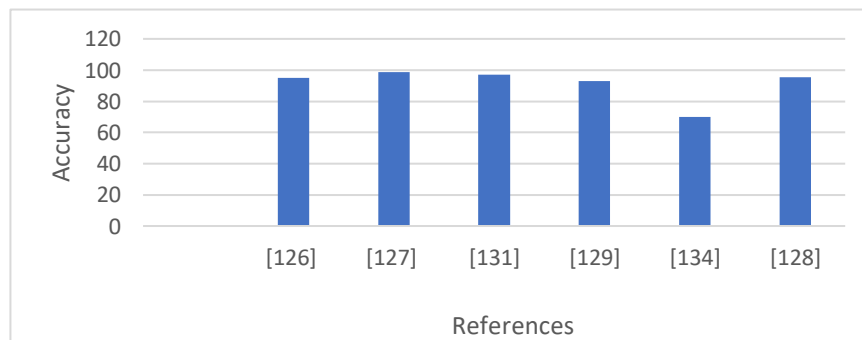


Figure 8 Performance parameter of PV Fault classification using Deep learning Techniques.

B. Analysis based on the type of loss function and accuracy

According to the analysis, Chowdhury et al. (2020) used the Cell to Module Loss function with the model accuracy of 92.2%. Kurukuru et al. (2020) used electrical function loss with a model accuracy of 97.52%. Gao et al. (2020) used a multi-class exponential loss function with a model accuracy of 98.61%. From these Gao et al. (2020) have the best accuracy of the model. Table 9 shows the summary of the analysis.

Table 9: Loss Function and Accuracy

S. no.	Author	Loss Function type	Accuracy
1	Chowdhury et al. (2020)	Cell to Module Loss	92.2%
2	Kurukuru et al. (2020)	Electrical function loss	97.52%
3	Gao et al. (2020)	Multi-class exponential loss function	98.61%

C. *Fault classification and Analysis based on the labeled dataset.*

In this work, A labelled dataset was split into a training set and a test set for this study. Each classifier will be trained using only the training set. Similarly, the test set is created at the start of the process and is used for all tests. The photos are divided into 70 percent training and 30 percent test photos in the dataset. The deep learning's performance Table 1 shows the models that were investigated for the fictitious dataset. The model's performance parameters have been studied in this comparative analysis. The accuracy scores for different transfer learning frameworks carried out for 10 epochs is presented in Table 10. It is observed that the ResNet-50 transfer learning architecture had the best performance. It can also be observed from Table 1 that ResNet-50 transfer learning framework trained faster than the VGG-16 transfer framework by about 31% on the thermal imagery dataset for fault detection Jeong et al(2022). Accuracy of data analysis techniques utilized by other relevant research work is summarised in table no. 10

Table 10: Evaluation metrics using pretrained model.

Pretrained Model	Accuracy	Precision	Recall	F1-score
Resnet 50	93.31	0.9770	0.5107	0.6708
Resnet 101	89.11	0.8367	0.4977	0.6242
VGG16	90.30	0.8495	0.4890	0.6207
VGG19	92.00	0.9694	0.5621	0.6534
Mobilenet	98.66	0.9843	0.5523	0.6910

Table 10 compares the evaluation results for each model, calculating performance measure using equations. According to the results of the network study, deep learning outperforms machine learning algorithms. This has been demonstrated that, in comparison to alternative deep learning models, the training time necessary to conduct the process takes longer. Table no. 10 shows that the parametric value illustrates the implementation study based on the thermal image input is taken from the FLIR camera from existing data set Ashwini et al(2022). From the analysis it is concluded that the Mobile Net model is the best model that can be included into the system.

XI. *CONCLUSION AND FUTURE SCOPE*

PV systems are susceptible to a variety of faults and failures, and early identification of such faults and failures is critical for PV system efficiency and safety. After installation and commissioning, the next step is to evaluate the performance deterioration of PV modules accurately and efficiently to get the most out of their effectiveness and prolong their lifespan. Various flaw detection techniques were covered in the study. Different kinds of camera sensors are used in the imaging techniques to detect deterioration or failure in the PV module. The technology of electroluminescence is used to identify flaws in produced modules. The suggested defect analysis method may be utilized to help plant operators rapidly detect and correct issues with the least effort and expense. Furthermore, the necessity for manual inspection will be minimized, lowering the total costs of PV module maintenance, and making solar energy an even more practical and appealing source of energy. In this paper various literature work based on various fault detection methods are discussed and further Classification analysis based on pretrained model using labelled dataset is studied in detail. Therefore, the analysis based on type of loss function with their

accuracy are performed. Future challenges and improvements to the work described here might include expanding the number of potential combinations in the Deep CNN base so that any issue type can be identified and diagnosed. Textured data of the image could be implemented in future work like temperature calculation, irradiance, emissivity, heat transfer etc.

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