International Journal of Emerging Trends in Science and Technology
10 (1) June 2024, 25-30
http://www.publishingindia.com/ijetst

A Literature Review on the Use of AI and Machine Learning for Fault Identification and Classification in PV Panels

R. Satheeshkumar[1], K. Jagatheesan[2*] and D. Boopathi[3]
[1]Assistant Professor, Department of Electrical and Electronics Engineering, Paavai Engineering College, Namakkal, Tamil Nadu, India. Email: satheesh2811@gmail.com
[2]Professor, Department of Electronics and Communication Engineering, M.Kumarasamy College of Engineering, Karur, Tamil Nadu, India. Email: jagatheesank.ece@mkce.ac.in
[3]Assistant Professor, Department of Electrical and Electronics Engineering, Paavai Engineering College, Namakkal, Tamil Nadu, India. Email: boopathime@gmail.com
[*]Corresponding Author

Abstract: In recent years, solar energy has drawn a lot of attention for the production of electricity. Also, owing of the advancements in technology in this area, photovoltaic (PV) systems are widely used throughout the world. To attain and maximize their effectiveness, solar PV systems do, however, require precise monitoring and routine follow-up. The PV systems are susceptible to a variety of defects, from transient to irreversible breakdowns. Determining the kind and location of faults in a PV system presents a substantial problem in order to promptly and economically maintains the system's essential performance without interfering with its regular operation. To minimize the harm a defective PV module does and protect the PV system from further losses, a suitable fault identification system should be turned on. Various PV fault classes and fault detection methods are provided in this paper. In particular, the advantages of Artificial intelligence (AI) a Machine learning (ML) techniques for categorizing and locating various fault types are discussed. Also provided is a summary of current approaches that combine thermography techniques with various artificial intelligence tools.

Keywords: Artificial intelligence, Defect detection system, Machine learning, Photovoltaic (PV) systems.

I. Introduction

There has been tremendous and continuous advancement in solar energy technologies worldwide. It is the most famous eco-friendly and renewable energy sources, safe for humans and other living things, and creates no noise when in use. Because solar energy requires no upkeep and produces no pollution, its production is continually increasing. According to International Renewable Energy Agency research [22], the installed photovoltaic capacity in that year was approximately 700,000 MW, and this figure is continually increasing.

Faults that have a significant impact on the systems efficiency are the primary cause of energy losses in solar systems. When a PV module fails, the systems production is affected, performance and reliability are affected [2], and there may eventually be a safety concern [3]. PV system malfunctions can put a building at risk for fire and result in large energy losses. Monitoring and fault diagnosis systems must be installed alongside solar installations in order to detect and promptly address issues, guaranteeing the installations safe and dependable functioning.

To address these issues, the literature has investigated a variety of problem diagnostic and monitoring strategies. These techniques vary in their demands for speed, complexity, number of sensors, and fault identification capacity. It is evident from the foregoing that PV systems are developing at this time. They require reliable and efficient systems for ongoing monitoring, diagnosis, and fault detection. As a result, using intelligent technique-based deep learning architectures is an appropriate strategy to attain better result in recognising the type and location of the issue.

The fastest, easiest to use, least expensive, and most appropriate methods rely on infrared (IR) thermography. Deep learning architectures, which are utilized in intelligent fault diagnosis and correction for photovoltaic systems and provide pertinent answers and actions at the right moment, are the key trend in the development of such intelligent systems.

Thus, monitoring the most recent AI architecture realizations for intelligent fault detection and diagnosis (FDD) of PV panels is the driving force behind our effort. A number of popular AI designs are explored, including generative adversarial networks (GAN), auto-encoder/decoders, stacked neural networks, Boltzmann machines (BM), and convolutional neural networks (CNN).

This paper's primary contributions are as follows:

- There is a thorough, methodical analysis of FDD techniques for solar systems offered.
- Intelligent FDD based thermography approaches are discussed, along with their advantages for categorizing and locating various fault kinds.
- Sufficient direction and suggestions for additional study in this field are given.

Below is the structure of this paper: Failure modes and faults classifications of PV systems are covered in Section II. Section III presents the different techniques for fault identification and diagnosis photovoltaic system. As one of the most promising techniques, thermography is one of the PV FDD approaches that are described in Section IV of the literature. Different AI approaches for PV system defect detection are covered in Section V. The Section VI, which concludes the study and offers a compelling summary of recent FDD, is devoted to future work.

II. PV Fault Classification

According to power losses experienced during operation, faults are divided into three primary kinds. These three kinds of failures are wear-out, midlife, and newborn [5]. When a PV system is first operated, infant failures happen. Infant failures are frequently the fault of the module installer or manufacturer; as a result, there is a significant loss when the power of the PV modules drops off quickly. Wear-out problems happen as PV modules reach the end of their lifespan. When the PV module's power drops to a specific point (80-70% of its starting power), it may terminate due to a safety issue.

Additionally, PV defects are categorized based on how serious they are. Acute PV faults are those that are more serious, and chronic PV faults are those that are less serious. When there is no output power, short and open-circuit failures have the potential to shut down the PV system. Hot spot, shaded, and bypass diode faults, on the other hand, are referred to as chronic defects since they are less severe. There are two types of faults: temporal (external cause) and permanent (internal cause) [23]. PV module performance can be evaluated by monitoring the amount of light received, as well as the state of the cells and their connections.

In order to guarantee production stability, availability, dependability, and security, photovoltaic plants need to be safeguarded against various problems such as illumination, overcurrent, and overvoltage. PV plants are protected by a number of standards. In National Electrical Code (NEC) [25] providing the safety standards for building PV facilities. For example, protective devices, overcurrent protection, circuit breakers, and ungrounded systems. Unfortunately, PV faults not all can be identified, and when they do, there is a significant risk of fires due to ground and line-to-line faults [6]. A defect tool is critical to the dependability and longevity of the PV panels since it allows for the constant identification of faults, which is important to secure the PV plant from different losses.

III. Methods for Detecting Faults

There are three basic methods to FDD procedures. Decision trees and conditional if-then rules are covered by the first method, which is qualitative data-based. The second method is based on quantitative data. Process history data is the basis for the final strategy. Based on models FDD creates mathematical models of the system by understanding its design principles in standard working conditions. Signal analysis uses the models' input-output data by utilizing the nonlinear equations of the PV panel model.

The differences between the measurements of the actual system and the model projections are used to determine whether a system flaw exists. The double-diode model, current-driven three-diode, and single-diode model [25] are well-known FDD models in PV systems. In addition to requiring a precise mathematical model, which can be difficult or even impossible to produce in the actual world, Model-based methods attain adequate precision at high irradiance but have reduced precision at low irradiance [30].

While the data-driven strategy concentrates on gathering a massive volume of data for analysis and interpretation, the model-based method necessitates previous understanding of the system, either quantitative or qualitative [6, 36]. Finding the connection between inputs and outputs signals is accomplished using FDD methods-based data-driven techniques, which make use of a significant amount of training data that reflects various operational settings with multiple defective scenarios [37]. In contrast to classification, which is the inclusion of a class label in the input data, regression is the prediction of a feature or sensor value.

IV. PV FDD Techniques

Electrical quantities, environmental data, or photos of solar panels are examples of the data types that are frequently employed in PV FDD systems. This kind enables for the classification of fault detection and categorisation methods used in solar systems into two groups: the non-electrical, which includes thermal and visual methods (VTMs), and the typical electrical class [33]. Electrical-based methods (EBMs) concentrate on statistical and signal processing techniques, or I–V characteristic curve analysis [8]. Further it can be discussed in following sections.

A. Electrical-Based Methods (EBMs)

i) Analysis of the I-V Curve

An I-V curve analysis's electrical measurement provide a standard FDD method for assessing open-circuit voltage, short-circuit current, and other metrics that might be used to pinpoint a system failure. Every time there is a change in the voltage or current across the module as a result of an external electronic load or power source, the current-voltage curve is tracked and measured [2]. As a reference, cells or modules with identical response characteristics are often compared to the module under test. Throughout standard operation, I-V characteristics follow a specific curve; however, fault time will change. The nature and sternness of a defect influence the degree of that shift in the curve [4].

Numerous faults can be found using a module's I-V curve. Sadly, pinpointing those failures accurately is not possible, thus other ways must be employed to find them. This makes the process more complicated overall because it requires a substantial time and money commitment [12, 14]. This is why adopting automatic and visual anomaly categorization can save more time, simplify system monitoring and maintenance, and save operating costs [12, 21].

ii) Statistical and Signal Processing Techniques

Time Domain Reflectometry (TDR), Earth Capacitance Measurement, and Speared Spectrumare examples of signal processing techniques that rely on waveform signal analysis [39]. Defective PV module arrays can be found and identified using the TDR approach. Regretfully, it could rely on installation factors like the wiring and materials used for PV components.

B. Visual and Thermal Method (VTM)

The techniques included in the VTMs include thermography, ultraviolet (UV) fluorescence (FL) imaging, and visual assessment.

i) Electroluminescence (EL) Method

Electroluminescence (EL) techniques [2] are a well-known VTM technology can be utilized to assess PV modules and diagnose failures [1, 7]. You can use EL images as a dataset. To induce radiative recombination within solar cells, DC current is utilized to power PV modules. A charged silicon camera (CCD), commercially available equipment, is used to measure electroluminescence emission.

ii) UV Fluorescence (UVFL) Method

By using the UVFL imaging technique of ethylene vinyl acetate (EVA) in PV cells, the degradation of photovoltaic modules may be examined [13, 31]. Even in low light outside also fault cell number and position in PV modules is identified, but not cracks on the cell's perimeter [2].

iii) Infrared (IR) Thermography

IR thermal imaging is a highly effective non-destructive and contact-free tool for detecting failures. In essence, the radiation process happens when an electrical component or the PV systems surface releases energy in the form of electromagnetic waves. Such that any item with a temperature greater than 0 kelvin or that receives external energy would emit infrared waves as a result of its moving atoms [9].

Thermography can be used to classify and locate failures in PV modules as well as other system components such junction boxes, cabling, diodes, DC box combiners, and connections. Because it delivers quick, affordable, dependable, precise, two-dimensional distributions, and dependable, precise of the distinctive characteristics of photovoltaic modules, infrared thermography (IRTG) is widely employed. Two distinct thermography methods passive IRTG and active IRTG for PV module failure.

a) The Active IRTG

Active thermal imaging raises an objects temperature by generating an internal heat flow inside it using an external heat source [9]. One sort of active infrared thermography that is quick and simple to use is pulsed thermography. A temperature addition from a heat source they are lamp or heating gun, is commonly used to warm the body [20]. PV modules of the long-pulse thermo gravimetric (TG) kind, where cooling is the primary goal, are continually heated using a low-power source [32]. Lock-in thermo gravimetric detection, which involves heating the object throughout an oscillating temperature domain, is used to find internal faults in wave change scenarios. Vibro-thermography, which uses mechanical vibrations to transform vibrations into thermal energy and produce hot spots in PV module defects such cracks and delamination, is based on vibrations [29].

b) The Passive IRTG

The passive IRTG technique is known as thermography, captures infrared radiation from PV modules under steady state circumstances without the need for additional heat sources. Passive TG only requires an infrared camera. It is the most used form because it is simpler and less expensive [7]. It is possible to detect faults without having to touch the thing, use hardware, or involve physical objects or people in any way.

The methodology is beneficial for the task of automated inspection since the authors in [28] present a method for PV fault identification using a deep learning (DL) method and a thermal image dataset to conduct cell recognition and instance segmentation. Additionally, the proper operation of those cameras requires operators who have received training and experience. To improve picture resolution, a pre-detection investigation is required to determine the appropriate altitude [9].

V. Techniques of Artificial Intelligence (AI) for FDD Systems

In recent decades, artificial intelligence (AI) approaches have found widespread use in a different of sectors, including natural language processing, speech recognition, astronomy, engineering, robotics, behavioral sciences, and medicine. This is a powerful and important instrument utilized in numerous PV system study domains, such as forecasting and prediction [13, 16]. Data-driven defect detection for PV systems can use a variety of approaches, including machine learning (ML it able tackle composite and nonlinear problems, as well as statistical methods. Artificial neural networks [7, 10], fuzzy logic [17], support vector machines [25], decision trees, and the k-nearest neighbor method [19] are a few examples of AI systems utilized in PV systems.

Machine learning techniques are a subdivision of AI methodologies that enable computers, such as databases, to automatically learn from past experience without explicit human programming. In the same way that ML and DL are components of AI technologies, deep learning (DL) is a particular sort of ML.

A method for fuzzy categorization is suggested by the authors of [17]. In order to identify EVA discoloration and delamination failures, this study uses the pixel counting technique for thermal picture to classify failures into three index values. But instead of diagnosing other kinds of errors, it concentrates on finding the hot spot.

For the purpose of detecting hot spots and classifying PV panels, a hybrid features-based support vector machine model is used in [25] to introduce a machine learning methodology. To increase efficiency a data fusion method is utilised to generate colour histogram, second-order co-occurrence matrix, and local binary pattern features. Compared to ML, DL is more potent. With numerous hidden layers and the ability to absorb and process vast amounts of data, it is regarded as a multi-computational neural network.

A. DL Frameworks

The convolutional NN, long short-term memory, generative adversarial network, recurrent neural network, Boltzmann machine, and auto-encoder/decoder are the most widely used DL frameworks for PV defect finding and cataloguing [3, 11].

i) Convolutional Neural Network (CNN)

CNN, a type of artificial neural network (ANN), processes input using convolution rather than standard matrix multiplication, which has a grid-like structure [20]. This is according to the writers in [21]. CNN is composed of several hidden layers, most of which are convolutional, pooling, and fully connected layers [22], in addition to the input and output layers. To detect the features of the image, max-pooling is utilized to select the maximum value and differentiate between the various pixel intensity levels.

ii) Long Short-Term Memory Networks (LSTM)

Recurrent NN contains LSTM, which addresses a problem in recurrent neural networks [24]. The LSTM network can manage longer dependencies, or connecting information as the interval between input and output data sequences expands. When modules are coupled to a LSTM RNN method and IEEE bus system described in [34] diagnoses a high-impedance problem with 91.21% accuracy.

iii) Generative Adversarial Network Networks (GANN)

GANN is made up of 2 networks [23], a discriminative network that evaluates the data for authentication and a generative network that creates new data instances. Each network is trained against a predetermined opponent. GAN reconstructs the input layer using administered learning [22]. In [33], GAN is used to discover DC series arc flaws, and a convolutional GAN is used for domain adaptation.

iv) Auto-Decoder/Encoder Networks (ADNN)

An ADNN is trained to encode the input data to a particular representation of the output in order to enable the reconstruction of the input from the output [25]. The auto-encoder's target output subsequently turns into the input of the auto-encoder. When the reconstruction error is as small as possible, the code denotes the learned feature [35]. Numerous hidden neural networks built from numerous ADNN each with an encoder and a decoder are referred to as stacked auto-encoder networks. To identify short-circuit problems in a PV system, the I-V curves are subjected to a stacked auto-encoder clustering technique [27].

v) Boltzmann Machine Networks (BM)

By learning to identify basic facts, BM, a stochastic unsupervised learning artificial neural network, may unravel complex issues. A unique form of BM is the deep belief network (DBN) [35]. The restricted Boltzmann machine (RBM) consists of layers that are visible and covered. In [26], the crack issue with the PV module is resolved by training the NN's initial values using the DBN. As supervised data, we use the rebuilt and training images.

vi) Ensemble Learning Algorithms

To provide the optimal prediction model, the ensemble learning technique incorporates many fundamental learner algorithm pattern schemes. The basic learning algorithms perform significantly worse than the ultimate perfect prediction model. [5, 15].

vii) Stacking (Stacked Generalization)

It has found widespread application in a variety of fields. During stacking, the results of the many base learner models are combined to create a new meta-learner model that represents the output outcome. Stacking is based on two algorithmic steps. The second stage includes the meta-learner algorithm, whereas the first includes a number of base learner algorithms. The authors of [18] employed three basis learners to diagnose

PV defects: deep neural networks, bi-directional LSTM, and LSTM.

VI. Conclusion

This research carried out a comprehensive review of the literature, which is necessary for PV systems to guard against a variety of losses like power, efficiency, and dependability. Numerous facets of PV failure analysis have been studied, including as classification, identification, and detection. The PV FDD approach emphasizes the use of thermal imaging as a straightforward, non-destructive tool for precisely locating and diagnosing flaws. The computer approaches for PV system failure analysis that were examined included artificial intelligence (AI) technologies and statistical methodologies.

References

[1] M. W. Akram, G. Lib, Y. Jina, X. Chenc, C. H. Zhua, and A. Ahmada, "Automatic detection of photovoltaic module defects in infrared images with isolated and develop-model transfer deep learning," *Sol Energy*, vol. 198, pp. 175-186, 2020, doi: https://doi.org/10.1016/j.sol ener.2020.01.055.

[2] M. U. Ali, H. F. Khan, M. Masud, K. D. Kallu, and A. Zafar, "A machine learning framework to identify the hotspot in photovoltaic module using infrared thermography," *Sol Energy*, vol. 208, pp. 643-651, 2020, doi: https://doi.org/10.1016/j.solener.2020.08.027.

[3] E. Alpaydin, *Machine Learning: The New AI*. Cambridge, MIT Press, 2016.

[4] G. Balasubramani, V. Thangavelu, M. Chinnusamy, U. Subramaniam, S. Padmanaban, and L. Mihet-Popa, "Infrared thermography based defects testing of solar photovoltaic panel with fuzzy rule-based evaluation," *Energies*, vol. 13, p. 1343, 2020, doi: https://doi.org/10.3390/ en13061343.

[5] J. D. De Guia, R. S. Concepcion, H. A. Calinao, S. C. Lauguico, E. P. Dadios, and R. R. P. Vicerra, "Application of ensemble learning with mean shift clustering for output profile classification and anomaly detection in energy production of grid-tied photovoltaic system," in *Proceedings of the 2020 12th International Conference on Information Technology and Electrical Engineering (ICITEE)*, Yogyakarta, Indonesia, Oct. 6-8, 2020, pp. 286-291.

[6] S. X. Ding, "Model-based fault diagnosis techniques design schemes, algorithms, and tools," Springer, Berlin, 2008. ISBN 978-3-540-76303-1 e-ISBN 978-3-540-76304-8. doi: https://doi.org/10.1007/978-3-540-76304-8.

[7] M. A. El-Rashidy, "An efficient and portable solar cell defect detection system," *Neural Comput. Appl.,* vol. 34, pp. 18497-18509, 2022, doi: https:// doi.org/10.1007/s00521-022-07464-2.

[8] S. Fadhel, C. Delpha, D. Diallo, I. Bahri, A. Migan, M. Trabelsi, and M. F. Mimouni, "PV shading fault detection and classification based on I–V curve using principal component analysis: Application to isolated PV system," *Sol Energy*, vol. 179, pp. 1-10, 2019.

[9] I. Goodfellow, J. Pouget-Abadie, M. Mirza, B. Xu, D. Warde-Farley, S. Ozair, and Y. Bengio, "Generative adversarial nets," *Advances in Neural Information Processing Systems*, pp. 2672-2680, 2014.

[10] A. H. Herraiz, A. P. Marugan, and F. P. G. Marquez, "Photovoltaic plant condition monitoring using thermal images analysis by convolutional neural network-based structure," *Renew Energy*, vol. 153, pp. 334-348, 2020, doi: https://doi.org/10.1016/j.renene.2020.01.148.

[11] Y.-Y. Hong, and R. A. Pula, "Methods of photovoltaic fault detection and classification: A review," *Energy Rep.,* vol. 8, pp. 5898-5929, 2022, doi: https://doi.org/10.1016/j.egyr.2022.04.043.

[12] A. W. Kandeal, M. R. Elkadeem, A. K. Thakur, G. B. Abdelaziz, R. Sathyamurthy, A. E. Kabeel, N. Yang, and S. W. Sharshir, "Infrared thermography-based condition monitoring of solar photovoltaic systems: A mini review of recent advances," *Sol Energy*, vol. 223, pp. 33-43, 2021, doi: https://doi.org/10.1016/j.solener.2021.05.032.

[13] M. Ko¨ntges, S. Kajari-Schro¨der, and I. Kunze, "Cell cracks measured by UV fluorescence in the field," in *Proceedings of the 27th EUPVSEC.* WIP, Frankfurth, 2012, pp. 3033-3040.

[14] D. Korkmaz, and H. Acikgoz, "An efficient fault classification method in solar photovoltaic modules using transfer learning and multi-scale convolutional neural network," *Eng Appl. ArtifIntell.,* vol. 113, p.104959, 2022, doi: https://doi.org/10.1016/j.engappai.2022.104959.

[15] M. Le, L. Van Su, N. Dang Khoa, V. D. Dao, V. Ngoc Hung, and V. H. Ha Thi, "Remote anomaly detection and classification of solar photovoltaic modules based on deep neural network," *Sustain Energy Technol Assess*, vol. 48, p. 101545, 2021, doi: https://doi.org/10.1016/j.seta.2021.101545.

[16] B. Li, C. Delpha, D. Diallo, and A. Migan-Dubois, "Application of artificial neural networks to photovoltaic fault detection and diagnosis: A review," *Renew Sustain Energy Rev.*, vol. 138, p. 110512, 2021, doi: https://doi.org/10.1016/j.rser.2020.110512.

[17] K.-C. Liao, and J.-H. Lu, "Using UAV to detect solar module fault conditions of a solar power farm with IR and visual image analysis," *Appl Sci*., vol. 11, no. 4, p. 1835, 2021, doi: https://doi.org/10.3390/app11041835.

[18] E. Lodhi, F. Yue Wang, G. Xiong, L. Zhu, T. Sinshaw, W. Ur-Rehman, and M. Adil Khan, “A novel deep stack-based ensemble learning approach for fault detection and classification in photovoltaic arrays,” *Remote Sens.,* vol. 15, p. 1277, 2023, doi: https://doi.org/10.3390/rs15051277.

[19] S. R. Madeti, and S. N. Singh, “Modeling of PV system based on experimental data for fault detection using kNN method,” *Sol Energy*, vol. 173, pp. 139-151, 2018.

[20] X. Maldague, F. Galmiche, and A. Ziadi, “Advances in pulsed phase thermography,” *Infrared Phys Technol.,* vol. 43, pp. 3-5, 175-181, 2002.

[21] D. Manno, G. Cipriani, G. Ciulla, V. Di Dio, S. Guarino, V. Lo Brano, “Deep learning strategies for automatic fault diagnosis in photovoltaic systems by thermographic images,” *Energy Convers Manag,* vol. 241, p. 114315, 2021, doi: https://doi.org/10.1016/j.enconman.2021.114315.

[22] C. Mantel, F. Villebro, G. A. dos Reis Benatto, H. R. Parikh, S. Wendlandt, K. Hossain, P. B. Poulsen, S. Spataru, S. Sera, and S. Forchhammer, “Machine learning prediction of defect types for electroluminescence images of photovoltaic panels,” *Appl Mach Learn.,* 2019, doi: https://doi.org/10.1117/12.2528440.

[23] A. Mellit, and S. Kalogirou, “Artificial intelligence and internet of things to improve efficacy of diagnosis and remote sensing of solar photovoltaic systems: Challenges, recommendations and future directions,” *Renew Sustain Energy Rev*, vol. 143, p. 110889, 2021, doi: https:// doi.org/10.1016/j.rser.2021.110889.

[24] A. Mellit, G. M. Tina, and S. A. Kalogirou, “Fault detection and diagnosis methods for photovoltaic systems: A review,” *Renew Sustain Energy Rev.,* vol. 91, pp. 1-17, 2018.

[25] NFPA 70, *National Electrical Code (NEC)*, 1st edn. 2020.

[26] B. Ni, P. Zou, Q. Li, and Y. Chen, “Intelligent defect detection method of photovoltaic modules based on deep learning,” in *2018 International Conference on Transportation and Logistics, Information and Communication, Smart City (TLICSC’18)*, 2018.

[27] N. O’Mahony, S. Campbell, A. Carvalho, S. Harapanahalli, G. V. Hernandez, L. Krpalkova, D. Riordan, and J. Walsh, “Deep learning vs. traditional computer vision,” in *Conference Paper,* 2019, doi: https://doi.org/10.1007/978-3-030-17795-9_10.

[28] R. Pierdicca, M. Paolanti, A. Felicetti, F. Piccinini, and P. Zingaretti, “Automatic faults detection of photovoltaic farms: solAIr, a deep learning-based system for thermal images,” *Energies*, vol. 13, p. 6496, 2020, doi: https://doi.org/10.3390/en13246496.

[29] J. Rantala, D. Wu, and G. Busse, “Amplitude-modulated lock-in vibrothermography for NDE of polymers and composites,” *Res Nondestr Eval.*, vol. 7, no. 4, pp. 215-228, 1996.

[30] S. Sairam, S. Seshadhri, G. Marafioti, S. Srinivasan, G. Mathisen, and K. Bekiroglu, “Edge-based explainable fault detection systems for photovoltaic panels on edge nodes,” *Renewable Energy*, vol. 185, pp. 1425-1440, 2022, doi: https://doi.org/10.1016/j.renene.2021.10.063.

[31] J. Schlothauer, S. Jungwirth, B. Ro¨der, and M. Ko¨hl, “Flourescence imaging - A powerful tool for the investigation of polymer degradation in PV modules,” *Photovolt Int.,* vol. 10, pp. 149-154, 2010.

[32] A. Sinha, O. S. Sastry, and R. Gupta, “Detection and characterisation of delamination in PV modules by active infrared thermography,” *Nondestruct Test Eval.,* vol. 31, no. 1, pp. 1-16, 2016.

[33] G. M. Tina, F. Cosentino, and C. Ventura, “Monitoring and diagnostics of photovoltaic power plants,” *Renewable Energy Serv Mank II,* pp. 505-516, 2015.

[34] V. Veerasamy et al., “LSTM recurrent neural network classifier for high impedance fault detection in solar PV integrated power system,” *IEEE Access*, vol. 9, pp. 32672-32687, 2021.

[35] A. Voulodimos, N. Doulamis, A. Doulamis, and E. Protopapadakis, “Deep learning for computer vision: A brief review,” *Comput Intell Neurosci.,* vol. 2018, pp. 1-13, 2018, doi: https://doi.org/10.1155/2018/ 7068349.

[36] J. Wang, J. Zhou, and X. Chen, “Data-driven fault detection and reasoning for industrial monitoring,” ISSN 2662-5458 (print); ISSN 2662-5466 (electronic). *Intelligent Control and Learning Systems,* 3rd edn. 2022. ISBN 978-981-16-8043-4; ISBN 978-981-16-8044-1 (eBook), doi: https://doi.org/10.1007/978-981-16-8044-1.

[37] D. Xuewu, and G. Zhiwei, “From model, signal to knowledge: A data driven perspective of fault detection and diagnosis,” *IEEE Trans Ind Inform.,* vol. 9, no. 4, pp. 2226-2238, 2013.