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Artificial intelligence and internet of things to improve efficacy of diagnosis and remote sensing of solar photovoltaic systems: Challenges, recommendations and future directions

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A R T I C L E I N F O

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A B S T R A C T

Currently, a huge number of photovoltaic plants have been installed worldwide and these plants should be carefully protected and supervised continually in order to be safe and reliable during their working lifetime. Photovoltaic plants are subject to different types of faults and failures, while available fault detection equipment are mainly used to protect and isolate the photovoltaic plants from some faults (such as arc fault, line-to-line, line-to-ground and ground faults). Although a good number of international standards (IEC, NEC, and UL) exists, undetectable faults continue to create serious problems in photovoltaic plants. Thus, designing smart equipment, including artificial intelligence and internet of things for remote sensing and fault detection and diagnosis of photovoltaic plants, will considerably solve the shortcomings of existing methods and commercialized equipment. This paper presents an overview of artificial intelligence and internet of things applications in photovoltaic plants. This research presents also the most advanced algorithms such as machine and deep learning, in terms of cost implementation, complexity, accuracy, software suitability, and feasibility of real-time applications. The embedding of artificial intelligence and internet of things techniques for fault detection and diagnosis into simple hardware, such as low-cost chips, may be economical and technically feasible for photovoltaic plants located in remote areas, with costly and challenging accessibility for maintenance. Challenging issues, recommendations, and trends of these techniques will also be presented in this paper.

1. Introduction

The photovoltaic (PV) market has seen remarkable growth over the past two decades, mostly because of the reduced cost of PV modules, support schemes and renewable national energy targets. According to the International Energy Agency [1], solar PV development reached record growth of 115 GW in 2019, and a trend for robust growth is expected in the years ahead. Following this trend, fault detection and diagnosis (FDD) algorithms are becoming a critical part of PV park (also called farms or arrays) operations for security and reliability. More recently, web-based monitoring is being used at isolated and inaccessible solar PV parks to reduce operational and maintenance cost. Keeping PV plants at high levels of reliability without in-loco monitoring and maintenance is a challenging task, considering that around 2% of PV modules fail after 11–12 years of operation. PV modules go through a wear-out failure scenario at the end of their working lifetime [2]. In general, PV plant underperformance is usually caused by failures on the arrays and inverters. Deterioration in PV array performance is mainly caused by dust, sand accumulation, mismatch, crack, and aging of the PV modules [2], while inverter faults are mainly due to overvoltage, overheating, and electrical damage.

Faults detection, identification and localization in PV farms can be classified into three main methods:

a) *Manual methods*, including visual inspection, time domain reflectometry, earth capacitance measurement, speared spectrum. These methods are very suitable for small-scale PV plants at string level.
b) *Semi-automatic methods*, utilize thermal cameras, infrared or electroluminescence imaging to analyse and localize the fault. This is often employed for large-scale PV plants.

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List of abbreviations

ANN	Artificial Neural Network
AFCI	Arc Fault Circuit Interrupter
AI	Artificial Intelligence
ASIC	Application for Specific Integrated Circuit
BBN	Bayesian Belief Network
BkDi	Blocking Diode
BPNN	Back-Propagation NN
ByDi	Bypass Diode
DBN	Deep Belief Networks
DCGAN	Deep Convolutional GAN
DCNN	Deep Convolutional NN
DL	Deep Learning
DT	Decisions Trees
EL	Electro-Luminescence
EL	Extreme Learning
ENN	Extension NN
FD	Fault detection
FDD	Fault detection and diagnosis
FF	Fill Factor
FL	Fuzzy logic
GAN	Generative adversarial network
GFDI	Ground fault detection and interrupt
GPRS	Global Positioning Radio Service
HSp	Hot Spot
IoT	Internet of Things
IR	Infrared
k-NN	k-Nearest Neighbours
LG	Line-to Ground
LL	Line-to-Line
T_a	Air temperature
T_m	Module Temperature
I_{pv}	PV Current
I_{grid}	Current Grid
I_{bat}	Battery Current
V_{bat}	Battery Voltage
Rh	Relative Humidity
Ws	Wind Speed
Il	Load Current
LoR	Logistic Regression
LR	Linear Regression
LSTM	Long Short-Term Memory
MCTS	Monte-Carlo tree search
MD	Markov Decision
ML	Machine Learning
MPPT	Maximum Power Point Tracking
MLP	Multilayer Perceptron
MS	Monitoring System
NB	Naïve Bayes
NNs	Neural networks
NF	Neuro-Fuzzy
OC	Open circuit
OCPD	Over Current Protection Device
PCA	Principal Component Analysis
PSh	Partial Shading
PV	Photovoltaic
PVP	PV Plant
PVS	PV System
QL	Q-Learning
ReLU	Rectified Linear Unit
RF	Random Forest
SAPVS	Stand-Alone PVS
SC	Short circuit
SMD	Smart Monitoring Devices
SMS	Smart-Monitoring Systems
SSPVP	Small-Scale PV Plant
SVM	Support Vector Machine
TD	Temporal Difference
V_l	Load voltage
V_{ac}	AC voltage
I_{ac}	AC current
I_{mpp}	Current at maximum power
V_{mpp}	Voltage at maximum power
Rs	Series resistance
V_{nom}	Normalized Voltage
I_{norm}	Normalized Current

c) *Automatic methods* use data loggers and monitoring systems to collect data and implement fault detection algorithms to check performance. These methods are often used for PV generators with a rated power ranging from a few kWs to hundreds of MWs.

The manual methods employ offline procedures, where the PV module or PV string is disconnected from the system to assess faults. The semi-automatic and automatic methods are run online in real-time. In addition, automatic methods can be categorized broadly into two approaches. The first approach aims to design a simple algorithm to detect, identify and possibly localize faults based on mathematical analyses. The second approach is based on the application of artificial intelligence (AI) techniques in more complex settings to proactively response to faults and self-heal and or to plan maintenance. However, a large dataset is used (measured currents, voltages, images, solar irradiance, infrared or electro-luminance images) in order to identify, classify and localize faults.

The application of AI techniques in solar PV farms has been available for the last two decades in order to improve modelling, control optimization, and output power forecasting efficacy of the sizeable datasets [3,4]. Other AI, approaches use machine learning and deep learning, again to handle the large datasets and hasten control and decision-making [5–9].

The internet of things (IoT) enables communication and data sharing among a wide variety of devices, systems, and services. Over the last few years, IoT approaches have also been investigated in PV system monitoring and remote sensing in response to an industry need to effect better fault diagnostics and prognostics [10,11]. These investigations have shown that there are many benefits to employing IoT in the field, such as improved accuracy and efficiency, less human intervention, and thus a reduction of costs.

To date, commercial equipment has not been able to diagnose and localize all faults types. In addition, they are also not able to make a clear diagnosis to prompt autonomous decisions. For example, if the fault is dangerous or not, and if it needs a quick intervention, particularly in the case of multiple faults, fault recognition, nature and localization in large scale-PV arrays. A few prototypes have been developed and tested in laboratories. However, the large-scale deployment of such technology needs technology transfer from laboratories to industrial sectors, in order to realise if this prototype is cost-effective or not.

Currently, there are a number of research articles on FDD [3,5–9, 13–15], which are summarized in Table 1. Many of these report that localization remains a challenging issue (like the cost, time required and complexity of implementation) particularly for large scale PV arrays, and that existing FDD methods focus mainly on the major fault identification, such as line-to-line, ground faults, arc faults and hot spot. In

Table 1
Available review papers on fault detection, protection, identification, and localization in solar PV systems.

Ref	Year	Comments
[3]	2008	It was the first attempt to review the future of expert system application in FDD, the authors showed the use of artificial neural network and Adaptive neuro-fuzzy inference system in PV systems diagnostic. It was shown that ANFIS could be used and have a great potential in the detection of fault based-expert system.
[7]	2017	The authors discussed various fault detection techniques in both DC and AC sides of PVSs. Electrical methods (I–V curves, TDR, ECM) and nonelectrical methods (Visual inspection, thermal camera, image, etc.) have been presented. Some recommendations are presented in this paper. However, FDD-based AI techniques have been briefly presented.
[15]	2017	A part of the review paper is devoted on the recent advancement (last five years), of monitoring and diagnosis systems at different levels, module, string, and array. The authors have focused more on the application of drones and cameras in aerial inspections of faulty PVPs.
[6]	2018	The authors presented an extensive review on FDD methods. They focused mainly on electrical methods and only faults in DC side of the systems were discussed. Presented methods were discussed from the points of view of cost, complexity implementation, and generalization capability in large scale-PV plants. They concluded that FDD-based AI would continue to progress in the near future. They proposed some application of AI in this area, but they don't focus deeply on methods based on aerial detection-based infrared or electro-luminance images.
[5]	2018	A short review on fault detection methods and MSs has been presented. The authors discussed different faults in DC and AC side of PV systems. They showed some application of NNs in fault detection, but these are also not deeply discussed.
[13]	2018	The authors presented a complete review on the most challenging issue on the protection of PV system and fault diagnosis. Presented methods were analysed in terms of sensor requirements, ability to diagnose and localize faults, integration complexity and accuracy, applicability and cost. Some ML techniques and certain recommendations have been reported in this paper on the protection, diagnosis, etc.
[13]	2018	This is a comprehensive review of the-state-of-art techniques for DC arc faults detection in PV systems. Several DC arc fault models have been reviewed and compared. The pros and cons of different detection methods were discussed and compared in detail.
[15]	2019	A comparative evaluation of available advanced techniques is reported. The authors focused mainly on the protection against line-to-line, line-to-ground, and arc faults. They recommended that fault detection techniques could be installed as a supplementary protection scheme along with the conventional protection device. They also concluded that some faults such as arc fault are not well studied. The authors presented the application of machine learning in a general way.
[8]	2019	Four major PV array faults: ground fault, arc fault, hot spot and line-to-line have been reviewed. The authors presented also conventional and advanced FDD techniques for managing these faults. The presented methods are also evaluated based on a metric score.
[9]	2020	An extended review on fault detection in PV arrays is presented in detail. The authors focused more on the fault detection process. They concluded that the investigated faults can be detected from several techniques and algorithms but differ from detection efficiency, complexity, accurate detection and reliability.

addition, these articles do not focus on the application of advanced AI techniques for fault detection, identification and localization. The review of the state of the art of the published literature on solar PV systems has identified that there is a significant knowledge gap in the academic research and in the field of embedded AI and IoT techniques for intelligent FDD. Furthermore, most of the AI methods developed, are generally verified in laboratory simulation, and few of them have been really verified experimentally. This is because it is difficult to get accurate results that mimic real-world environments, equipment limits, and implementation cost.

The state of the art review of solar PV systems differs from the existing body of published review articles because it provides a critical review of the application of AI techniques for FDD, and also shows that the application of IoT techniques is very suitable in developing smart remote sensing. The differences are:

a) It offers a comprehensive comparison of the most relevant AI techniques based on machine learning, deep learning and the IoT. These are compared in terms of cost implementation, complexity and accuracy, software, and feasibility in real-time applications and experimental verification.
b) This review critically appraises the implementation of such AI techniques into embedded systems, which has not been addressed previously, in order to design a smart miniature device, for use in inverters and/or PV modules to enhance communication between the different component elements.

This review, will comprehensively address five key questions to hopefully direct better technology transfer in the field. Why should machine learning and deep learning be used in solar PV system FDD? When should machine learning or deep learning be used? What are the user needs to develop effective FDD methods based on machine learning or deep learning? What parameters are needed to select an appropriate machine learning or deep learning algorithm for FDD? How can emerging technologies and embedded systems contribute to advancing FDD in solar PV systems?

This paper is organized into seven sections. Section 1 provides a brief high-level introduction. Section 2 examines AI techniques in the context of solar PV systems FDD. Section 3 overviews faults and protections techniques in solar PV systems. Section 4 provides a concise description of IoT and smart monitoring of solar PV systems, and a succinct assessment of existing solar PV monitoring systems that employ IoT approaches. Section 5 discusses the most widely used FDD methods in solar PV, and focuses particularly on AI techniques. Section 6 studies recent applications of deep learning and machine learning for FDD and localization. Finally, Section 7 concludes and summarises the key challenges, recommendations, and recommends future directions.

2. Artificial intelligence techniques

A multitude of intelligent computing technologies are on the verge of becoming the prevalent alternative to conventional data processing techniques [16]. As shown in Fig. 1 machine learning is a subset of AI; similarly deep learning is a subset of machine learning, so it can be inferred that both machine learning and deep learning are tools of AI.

According to the literature, machine leaning can be used in the case of very complex problems for which traditional techniques are not able to find a solution, or it is difficult to be applied and it is suitable for non-stable environments as it can adopt easily to new data. In machine learning there is no or complex relationship between inputs and outputs so it is suitable for problems that require many long lists of rules.

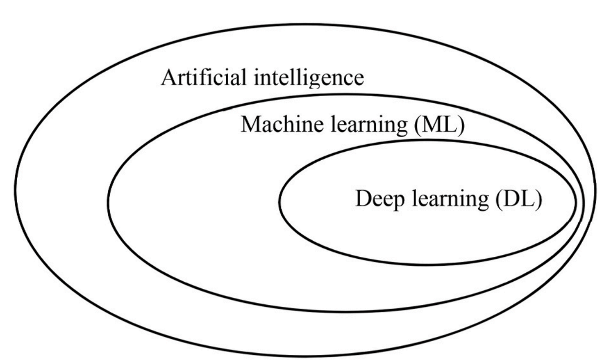

Fig. 1. A Venn-diagram of artificial intelligence: link between artificial intelligence, machine learning and deep learning.

In some cases, deep learning is used to improve the results of machine leaning, which implies that models based on deep learning are more accurate. Recently, deep learning is gaining popularity due to its accuracy in classification and prediction when trained with huge amount of data and thus it is applied in complex problems that machine learning is not able to solve. It should be noted that when a small amount of data is available machine leaning algorithms are more suitable than the deep leaning ones. In addition, deep leaning algorithms can use directly raw data and extract automatically the relevant features from them.

Generally, there are no specific rules to select the most suitable algorithm for a given application, as each algorithm has its strengths and weaknesses and the selection of the suitable algorithm depends mainly on factors such as the nature of the problem, the amount of available data, the algorithm implementation and complexity, and finally the expected accuracy and generalization capability.

2.1. Machine learning

According to Samuel [17], machine leaning refers to techniques that are able to give computers the ability to learn automatically from experience (i.e., from data included in a database) without being explicitly programmed by human beings. Fig. 2 shows the different steps of machine leaning implementation, starting from the raw data, features extraction and pre-processing, training and evaluation, and model deployment.

Machine leaning is broadly classified into four major classes of algorithms [18] as shown in Fig. 3: a) supervised learning, b) unsupervised learning, c) semi-supervised and d) reinforcement learning.

Machine learning algorithms belonging to the first class are the support vector machine, k-nearest neighbours, linear regression, logistic regression, decisions trees, naïve Bayes, neural networks, and random forest. The second class includes algorithms such as k-means, fuzzy c-means, and hierarchical clustering. The third class of machine learning regroups generative models, graph-based models and other. The fourth class includes, Q-learning, deep q network, Markov decision methods, and others.

In supervised learning (see Fig. 4a) an algorithm tries to create some relationships and dependencies between the input and output features, such that to be able to estimate the output values for new data. In this kind of learning, the data are labelled and can be used to solve both regression and classification problems. In the unsupervised learning (see Fig. 4b), there is no labelled output and the algorithm searches for rules and patterns in the available dataset in order to describe the data better. This type of algorithm has no idea about the expected results and the machine is trained with unlabelled data and can mainly be used to solve problems related to clustering and association. The third class is called semi-supervised algorithm and in this type of learning the database comprises both labelled and unlabelled data, but most data are not labelled due the cost and the required skills to label the data. The algorithm is trained in order to find a model and the main types of problems solved with this kind of learning are classification and clustering.

The last class is reinforcement learning (see Fig. 4c). This type is mainly used to produce high dimensionality into lower dimensional data for visualization or analysis purposes. There are no training data sets, but an agent continuously learns from the environment in an iterative fashion. This type of learning can be used for solving classification and control problems.

2.2. Deep learning

A simplified process of deep leaning is shown in Fig. 5. As can be seen the feature extraction step is removed, as it is not needed in this kind of learning, because deep learning algorithms are able to learn and automatically extract features from raw (original) input data.

Deep learning is a relatively new improvement in NN and represents a way to train deep neural networks, and as traditional NN-based methods, might be affected by problems such as over-fitting and diminishing gradients [19]. Basically, any NN with more than two layers is called deep. On the other hand, deep learning is a semi-supervised training approach, suitable for deep NN training [16]. The main deep learning methods are the deep convolutional neural network, long short-term memory, deep belief networks, generative adversarial networks, deep convolutional and other hybrid combinations [20]. As shown in Fig. 6 a key advantage of deep leaning networks is that they often continue to improve as the size of the data increases [21].

In the following subsections only the most used types of deep learning in fault detection and diagnosis of PV systems are briefly described. These include the convolutional neural networks (CNN), long short-term memory (LSTM) and generative adversarial network (GAN). More details about the rest of deep learning algorithms can be found in Ref. [18].

2.2.1. Convolutional neural networks (CNN)

Convolutional Neural Networks are a specialized kind of NN for processing data that has a known grid-like topology. These are simply NNs that use convolution in place of general matrix multiplication in at least one of their layers [20]. Like other NNs, a CNN is composed of an input layer, an output layer, and many hidden layers in which mainly convolution and pooling layers are used. Fig. 7 shows the structure of a deep CNN. The most popular activation function is the Rectified Linear Unit (ReLU), which help to accelerate convergence speed, and the SoftMax function used before the output layer.

2.2.2. Long short-term memory (LSTM)

Long Short-Term Memory is a kind of recurrent NN. The main drawback of recurrent NNs is that they practically fail to handle long-term dependencies. As the gap between the output data in the output sequence and the input data in the input sequence increases, recurrent NNs fail in connecting the information between the two [22]. The LSTM network however, is capable to handle these long-term dependencies. Fig. 8 displays a simplified architecture for a LSTM neural network. An LSTM block typically has a memory cell, an input gate, an output gate,

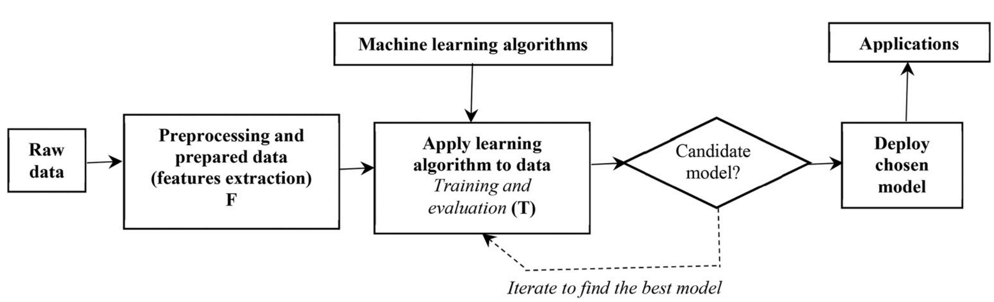

Fig. 2. Machine learning workflow.

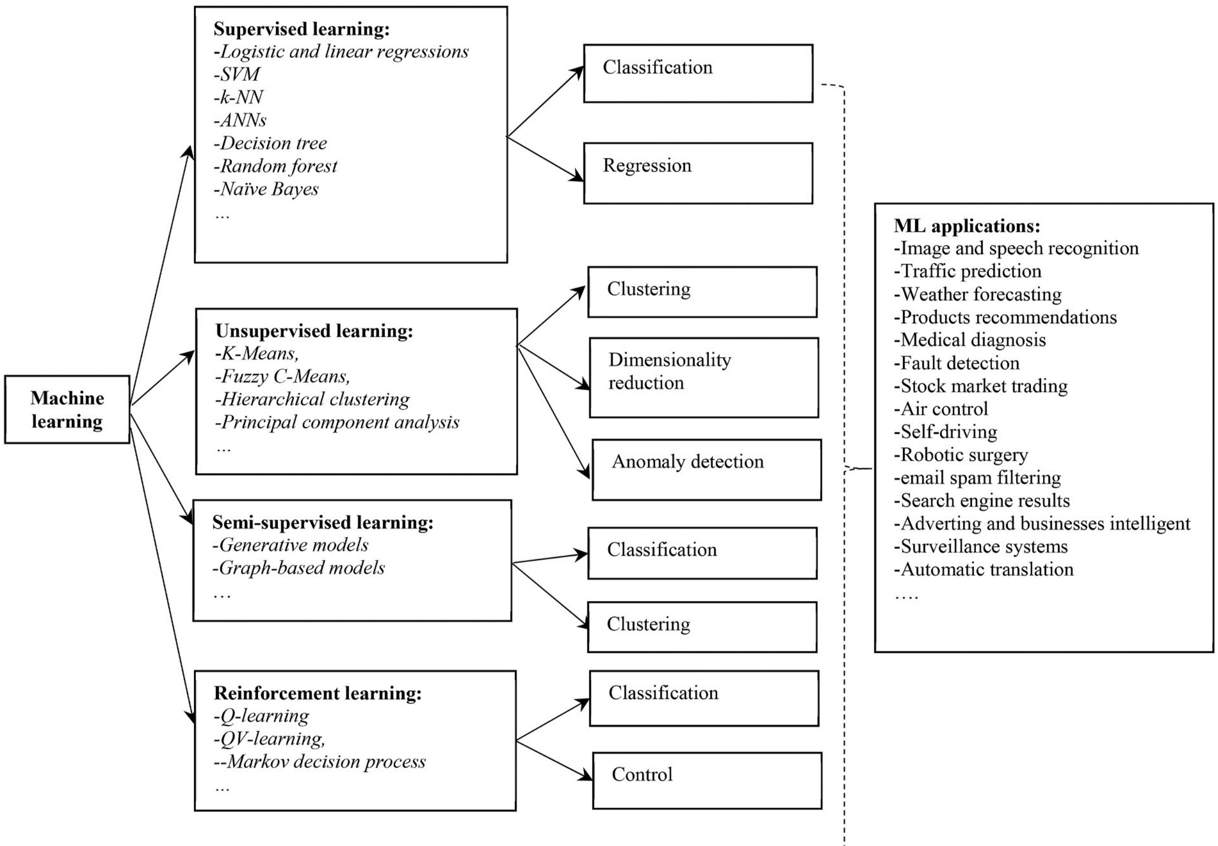

Fig. 3. Major ML algorithms and their applications.

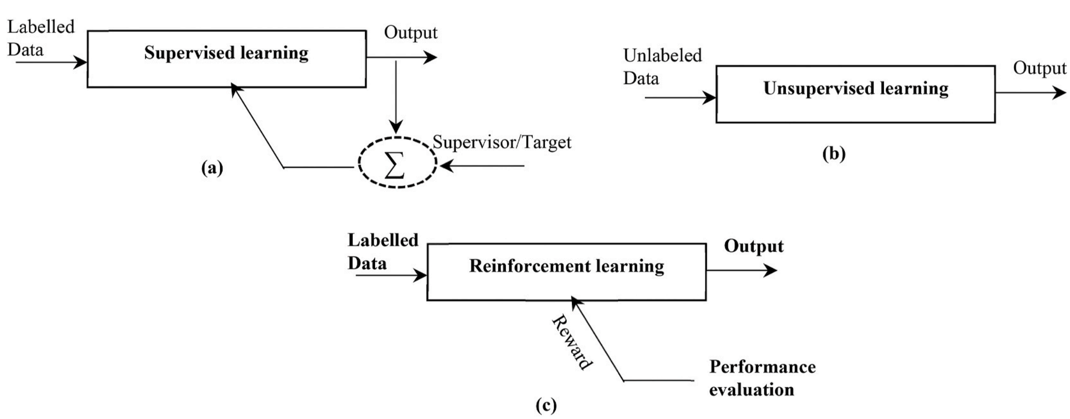

Fig. 4. Learning: a) Supervised learning, b) Unsupervised learning, c) Reinforcement learning.

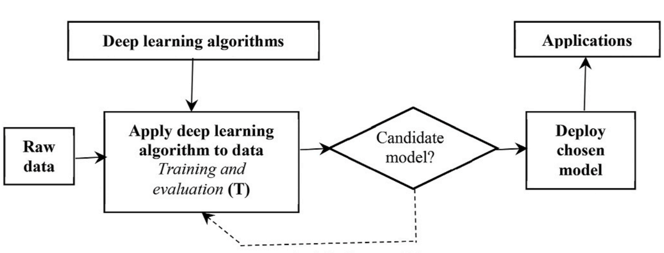

Fig. 5. Deep learning workflow.

and a forget gate in addition to the hidden state used in traditional recurrent NNs [22].

2.2.3. Generative adversarial network (GAN)

A general structure of Generative Adversarial Network is shown in Fig. 9 [23]. It consists of two networks a generative and a discriminative. The first one is used to generate new data instances, whereas the second to evaluate the data for authenticity. Each should be trained against a static adversary. GAN use supervised learning in order to reconstruct the input layer.

3. Photovoltaic systems, fault types and protection devices

This section intends to provide a short description of different PV

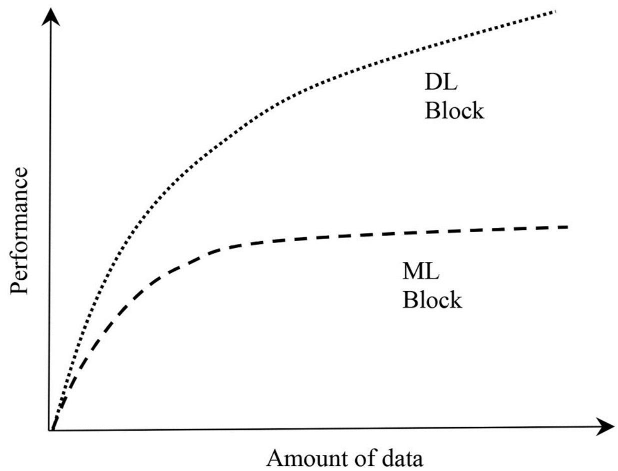

Fig. 6. Performance comparison between DL (….) and ML (——) with respect to the amount of data (adapted from Ref. [18]).

configurations, the major faults that can occur on PV plants, particularly in DC side which refers to the PV arrays, and a brief presentation of available protection devices.

3.1. Photovoltaic plants

PV systems consist mainly of PV arrays, batteries, converters and inverters. They are globally classified into three types of systems:

a) stand-alone alone PV systems - in this type batteries are always used, and it can be employed particularly in remote areas, with no access to the main grid (see Fig. 10a).
b) hybrid PV systems, - in this type more than one renewable source can be integrated, e.g. a wind generator, or fossil fuel source like a diesel engine generator (see Fig. 10b).
c) grid-connected PV systems – this is the most used type in medium- and large-scale PV plants, such as residences, commercial facilities and utility companies (see Fig. 10c).

From the point of view of capacity, PV systems can be classified as small-scale, residential systems, up to a few kW; medium scale, commercial systems, up to hundreds of kW; and large-scale utility grid, with tens of MW capacity [24].

3.2. Faults in photovoltaic plants

Faults in PV arrays can be classified as permanent or temporal. Permanent faults comprise delamination, bubbles, yellowing, scratches and burnt cells. Therefore, this category of faults can be removed simply by replacing the faulty modules. Temporal faults are basically due to partial shading effects, dust accumulation (soiling or any other kind of dirt), and snow that can be removed by operators without replacing PV modules [25]. Furthermore, the cause of the fault could be external or internal, and both lead to a decrease in the output power, efficiency and reliability of the overall system [2].

3.3. Protection of photovoltaic plants

To ensure stable production, availability, reliability, and security, PV plants should be carefully protected from the different kinds of faults (lighting, surge, anti-islanding, overcurrent, and overvoltage) [26]. There are various standards that aim to protect and mitigate fault in PV plants [27–31]. For example, the National Electrical Code [31] addresses safety standards for the installation of PV plants (grounding equipment, protection devises, overcurrent protection, circuit breaker, and ungrounded systems). However, some faults stay undetectable and can create serious problems including risk of fires [32], for example line-to-line, ground faults and blind spots which occur in cases where an undetected ground fault exists in the grounded current-carrying conductor [13,32–34].

Thus, the existing codes and standards need to be considered carefully [35]. Fig. 11 shows a simplified schematic of a grid-connected PV plant which included the main protection devices like, the over current protection device, ground fault detection and interrupt and arc fault circuit interrupter.

A ground fault detection and interrupt (GFDI) is used to protect the PV array during grounding faults, the over current protection devise (OCPD) is used to protect the PV array from line-to-line faults, and the arc fault circuit interrupter (AFCI) is a standard protection device generally used against the series arc fault. Different commercial mitigation techniques are developed to prevent fire in grounded and ungrounded PV arrays.

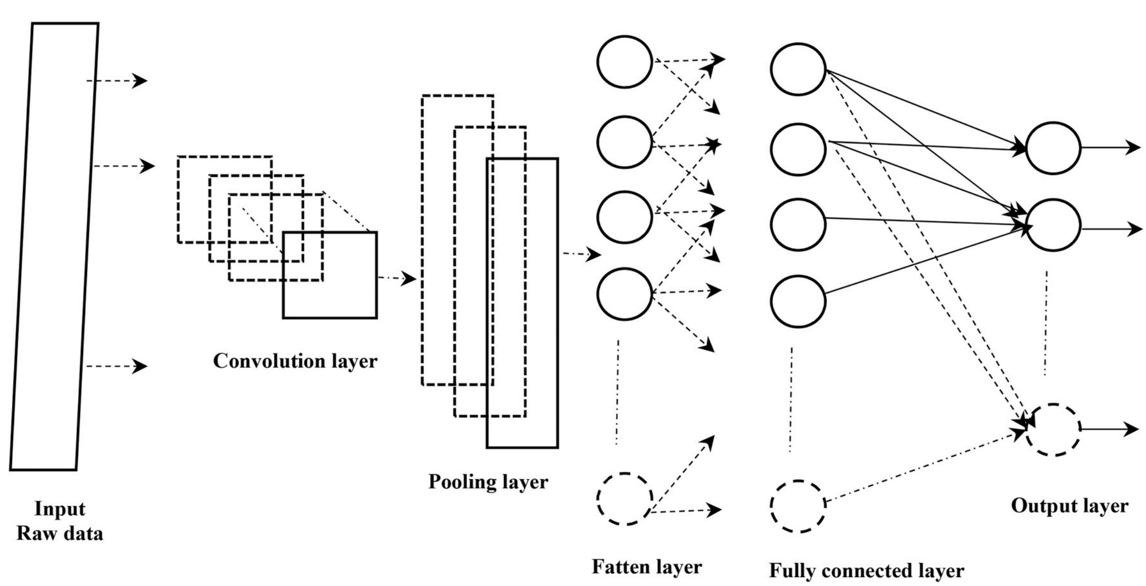

Fig. 7. Deep NN structure (adapted from Ref. [20]).

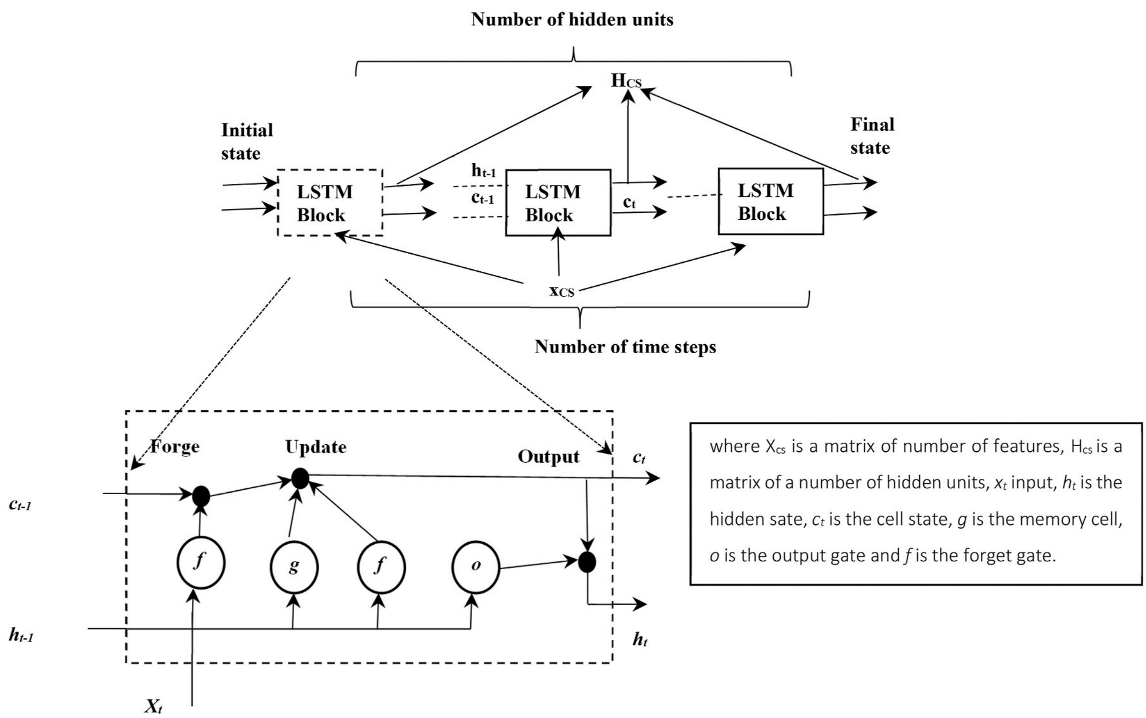

Fig. 8. LSTM NN structure (adapted from Ref. [22]).

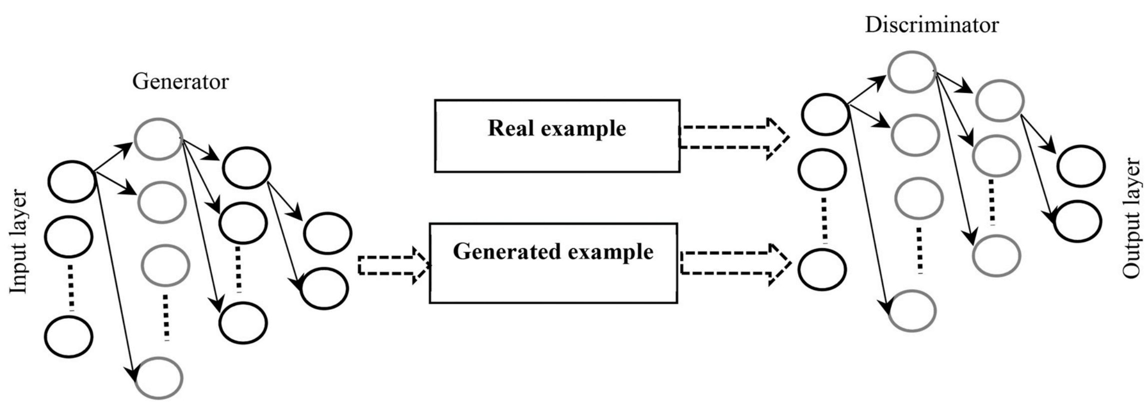

Fig. 9. GAN structure (adapted from Ref. [23]).

4. Smart- PV monitoring systems based on internet of things techniques

4.1. Monitoring of PV systems

Monitoring systems can be classified basically into two categories, centralized and decentralized. The main task of both configurations includes the monitoring of the meteorological and electrical data, in order to control and supervise the installation [36]. Normally, monitoring activities of the plant performance are carried out through the monitoring system integrated into the array inverter. Generally, all large PV installations are typically monitored for efficiency and availability, enabling detection of fault conditions or low efficiency. However, for small residential systems a cost-effective solution for monitoring and fault detection is not available [24].

There are numerous kinds of commercial monitoring systems that can be used mainly in small- and large-scale PV plants. Usually, this equipment is equipped with some options in order to provide a good service to the users such as easy graphical software, webpage display, error notifications, and others. However, they present also some drawbacks, like the high cost, the fact that there is no way to implement a new procedure (firmware), they consume energy and usually require storage [10,11].

4.2. Internet of things (IoT)

Recently the IoT embedded networks [37] have drawn tremendous interest due to their flexibility, various advantages, the provision of a network of connected devices in which real time information can be shared and used in order to enhance life quality, and generally improve the industrial processes, the energy efficiency, and level of services. The IoT is defined as a network that can connect any object with the internet, based on a protocol for exchanging information and communication among various smart devices. As reported in Ref. [38], a smart IoT system employs AI techniques to achieve automation and adaptation. The IoT consists mainly of three layers, the perception or object layer, the network layer and the application layer [38].

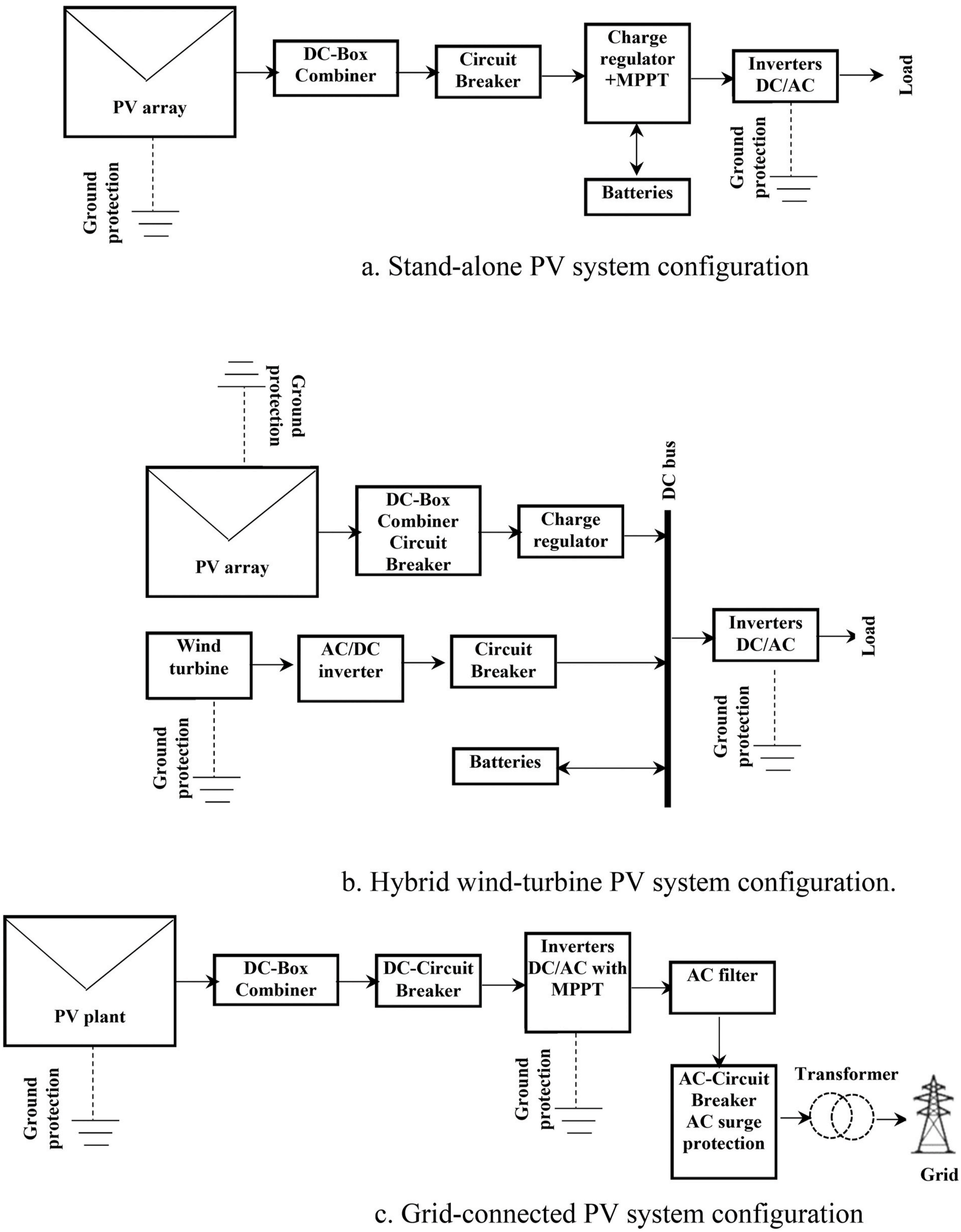

Fig. 10. a. Stand-alone PV system configuration. b. Hybrid wind-turbine PV system configuration. c. Grid-connected PV system configuration.

4.3. The IoT-based smart monitoring of PV systems

A modern monitoring system's workflow can be divided into three stages [10], an acquisition layer, a record layer and storage, and a supervision and access layer. The first generation of smart monitoring devices has been built in Japan [39]. The designed smart monitoring system consists of a microcontroller, a network radio, relays for reconnecting or bypassing panels, and sensors. With the smart monitoring systems, PV modules are seen and managed as IoT nodes [39].

In large-scale PV plants with many inverters, sensors and protection devices, it is cost-effective to embed all communication functions into a single hardware, instead of using multiple individual communication devices [40]. Thus, the real-time monitoring and control enabled by high-speed communication technologies, become essential to handle the

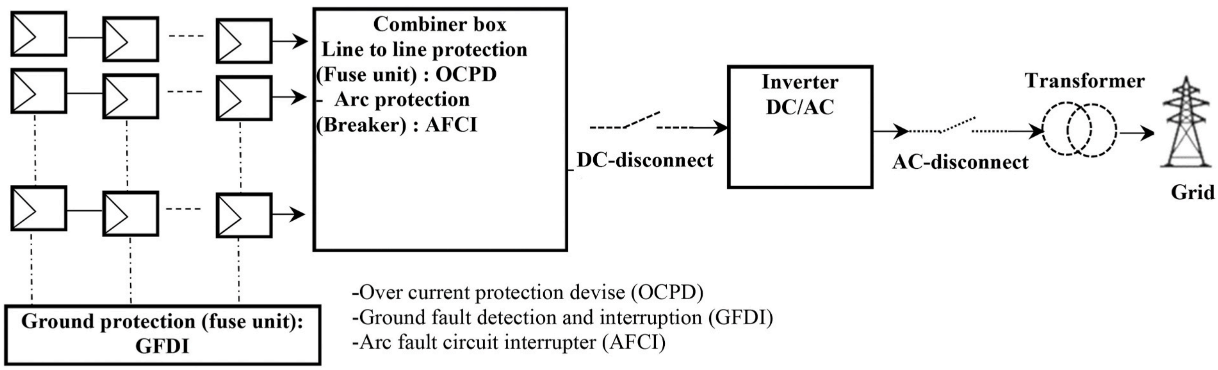

Fig. 11. Grid-connected PV system with protection devices.

distributed renewable generation systems [40]. In addition, the new IoT connection concept allows the development of an easily operated data collection system which includes wireless sensors [10]. So, advanced monitoring systems should integrate the IoT technique, to check the performance and the system evolution in real time and advice users periodically about the health of the system. Moreover, the use of the IoT enhances the understanding over the real time operating parameters. This helps in accessing the control of PV systems installed at remote areas, their effective and fast fault diagnosis, maintenance, and recording of the power generation and other performance data for analysis [41]. Fig. 12 shows a detailed schematic of a PV monitoring system based on the IoT technique.

The system consists of different sensors used for measuring different quantities such as DC-current and voltage from PV strings and arrays, solar irradiance, AC-current and DC-voltage from inverters, air temperature, cell or module temperature, and other parameters such as wind speed, relative humidity and cloud cover. For this purpose, quality and accurate measurements are needed, so sensors should be well calibrated and conditioned according to international standards.

A data-acquisition unit is used for collecting different data, for example a low-cost embedded microcontroller, including a Wi-Fi module used for sending the collected data to the server. For this purpose, a different protocol is used so as this unit system is efficient. In the monitoring and supervision unit the stored data could be visualized and analysed through a graphical Webpage, so the users can be notified about the status of their system operation, indicating the type of faults and the localization (or the faulty element in the installation). This can be, for example, achieved by integrating one of the advanced machine learning or deep learning algorithms.

4.4. Applications of the internet of things in PV monitoring systems

Recent applications of smart PV monitoring systems based on IoT are summarized in Table 2. In Ref. [42] an effective implementation of an intelligent remote monitoring system for solar PV power conditioning units (PCU) is presented. The system can be installed in solar PV-PCU to provide support for management and maintenance operations. The authors showed that the system can monitor, store, and manipulate data from solar PV-power conditioning unit, and the remote monitoring functions can be realized in real time. In this application, a GPRS (Global Positioning Radio Service) module is employed to send data to the remote server.

A low–cost IoT-based embedded monitoring system for solar PV systems is discussed in Ref. [43], where a GPRS module and a low–cost microcontroller were used. The authors present a procedure for remote monitoring for solar PV power conditioning unit, but experimental verification is not presented. A GSM module is used for a PV monitoring system as presented in Ref. [44]; the system is able to collect current, voltage and air temperature. A small smart off-grid solar photovoltaic system design is presented in Ref. [45]. The designed system can provide

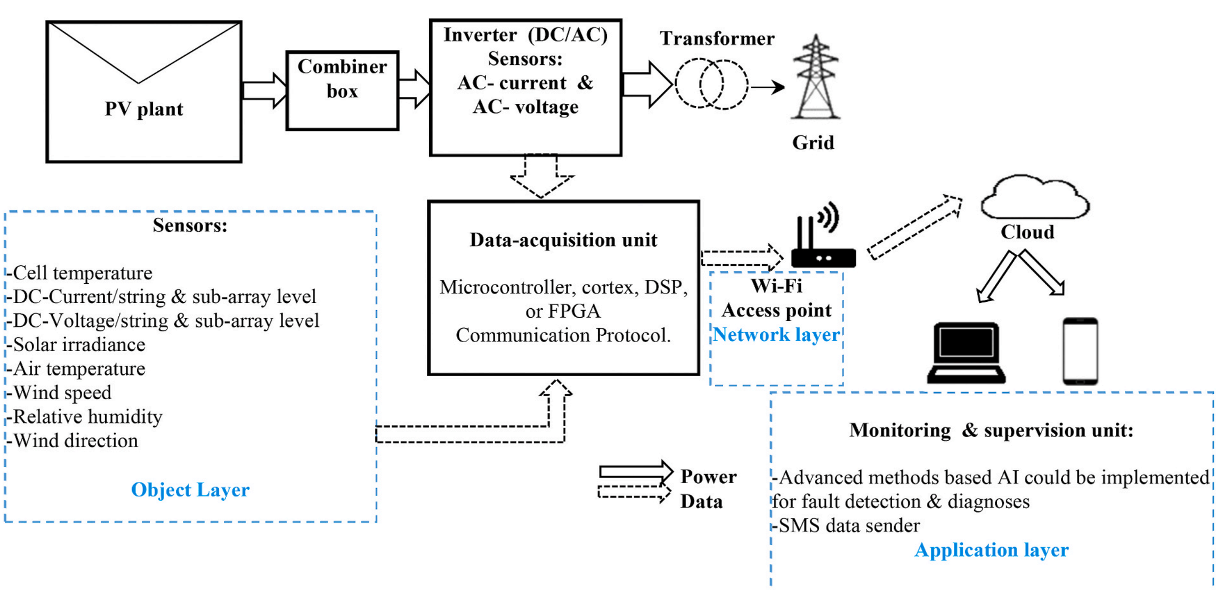

Fig. 12. Schematic of a smart PV monitoring system based IoT technique.

Table 2
Smart monitoring PV systems based on the IoT technique.

Ref	Year	Monitored data	Fault detection	Devices	Complexity &Cost	Software/ Visualization	Sensor types	PV system capacity
[42]	2016	T_a, V_{pv}, V_{pv}, I_{grid}, & V_{grid},	No	PIC18F46K22 SIM900A GPRS module	Easy Low-cost	Web hosting service	LM35, current and voltage sensors	PV array level
[43]	2016	I_{pv}, V_{pv}, I_{bat} &V_{bat}	No	GPRS module	Easy Low cost	Web hosting service	–	PV module level
[44]	2017	I_{pv} & V_{pv}	No	Arduino Uno SIM 900 A GSM Module	Medium Low cost	–	LM35, Voltage transducer, Hall Effect current sensor	PV string level
[45]	2017	I_{pv} & V_{pv}	No	ESP8266, Node MCU	Easy Low cost	Blynk App supported by Android	Voltage and current sensors	PV module level
[46]	2017	G, T, V_{pv}, & I_{pv}	Yes	TMS320F28335 ZigBee, GPS module, Raspberry PI3	Relatively complex Medium cost	Private webpage	FZD-V1-2000 DS18B20 Hall voltage and current sensors	PV array level
[47]	2017	I_{pv}, V_{pv} & T_a	No	Arduino UNO Raspberry PI 3	Easy Low-cost	ThinkSpeak	ACS712 DHT11	PV module level
[48]	2018	Ws, T_a, T_m, I_{pv}, V_{pv}, Rh, & Ws	No	3G Arduino Uno Ethernet Shield W5100	Easy Low-cost 140.71 euro	ThinkSpeak	DS18B20, DhT22, current sensor, voltage sensor and other	PV module level
[49]	2018	I_{pv}, V_{pv}, V_l, V_l, G & T_a	No	Arduino, Ethernet Shield, 3G modem	Relatively easy Low cost	ThinkSpeak ThingView,	ADCs Current sensors	PV module level
[50]	2018	I_{pv}, V_{pv}, I_{ac}, V_{ac}, G & T_a	No	Raspberry Pi Arduino, RFM69CW	Relatively easy low-cost 99 euro	Webpage application	DTH22, CMP21 LM35, STC-013-000 hall effect sensor	PV module level
[51]	2018	I_{pv}, V_{pv}, T_a, & G	No	Arduino, Mega 2560, ESP01,	Easy Low cost 75 euros	Webpage locally hosted	ACS712, LM35, Reference solar cell	PV module array
[11]	2019	I_{pv}, V_{pv}, T_a, & G	Yes	Arduino, Mega 2560, ESP01.	Easy Low cost 72 euros	Webpage application	ACS712, LM35, reference solar cell	PV string level
[52]	2019	I_{mpp} & V_{mpp}	No	Arduino Uno ESP8266 Wi-Fi module	Easy Low-cost	ThinkSpeak	Current: ACS712 Voltage:	PV module level/PV simulator
[53]	2019	G, T_a & T_m	Yes	Raspberry PI	Easy Low-cost 55.87 euros	Dashboard home page	DS12820, ADS1115 LP02 Pyranometer	Small PV array
[54]	2019	T_a, T_m, I_{pv} & V_{pv}	No	Raspberry PI Arduino, RFM95 LoRa Breakout	Easy Low-cost 39.26 euros	–	DS12820, DHT, Voltage transducer, Hall Effect	PV module level

an alternative electrical supply for a mushroom farm. The measured voltage charging (PV to battery) data can be visualized in real time by a smart phone, to check the status of the system using the Blynk App which is an application supported by Android and IOS. Users could also receive comma separated value files containing the measured data.

An IoT-based remote monitoring system and a control unit for PV plants have been developed in Ref. [46]. The system facilitates preventive maintenance, historical analysis of the PV plant, as well as real time monitoring and fault diagnosis based on the extreme learning technique. A PV monitoring centre webpage can also send warning information to the users via E-mail once a PV array fault occurs.

Another IoT-based monitoring solar energy system is presented in Ref. [47] in which the authors used a low-cost Arduino and Raspberry Pi3 to collect and transmit data to the cloud via ThinkSpeak. The system is implemented and verified experimentally, but the transmission procedure, the solar energy system and the PV module employed, are not well presented. In Ref. [48] a novel data-logger for the monitoring of PV systems via website and mobile applications was designed. As indicated by the authors the cost of the monitoring system is considerably lower than the available commercial devices and allows high accurate remote monitoring. A 3G connectivity system was used in this application.

A smart data logger based IoT system is developed and validated for real-time monitoring for a small stand-alone PV plant [49]. To improve the accuracy of measurement two externals analog digital converters (ADC) with 18 bits resolution were used. The monitored data can be visualized on a smartphone using the free Android applications ThingView and ThinkSpeak. In Ref. [50] an alternative monitoring system for PV installations is described and assessed. The sensors employed were calibrated according to IEC-61724 standard minimum-accuracy values in terms of current, voltage, and power. According to the authors, the cost of designing the monitoring system is lower than the commercialized one. In Ref. [51] the authors designed a smart system for monitoring PV arrays using the IoT. The system was checked for online PV module current, voltage, irradiance and temperature. The data were then sent to the cloud via IoT using Wi-Fi module and Arduino Mega 2560.

A smart PV remote sensing system for fault detection and identification was developed in Ref. [11]. The prototype designed, which was based on a simple identification algorithm, was verified experimentally and shown its capability to identify the type of some faults such as short-circuit, open-circuit, dust accumulation, and shading effects [55]. At the moment, this solution of integrating the fault detection system into PV modules is not cost-effective, particularly for large scale PV plants. In Ref. [52] a remote monitoring PV system based the IoT was developed in which the monitored data (I_{mpp} and V_{mpp}) were compared with the ones obtained with a local PV simulator. The authors used ThingSpeak and a free webpage for IoT objects, to visualize data; a low-cost microcontroller and a Wi-Fi module were also used. In Ref. [53], the authors proposed a monitoring system for a grid-connected PV system. The novelty in this monitoring system is that it can identify the non-ideal operating conditions of the system. In addition, results showed that after the calibration and noise reduction process, the developed architecture achieves the precision requirements established by the IEC61724 guidelines. A wireless low-cost solution based on long-range (LoRa) technology for monitoring PV power plants has been proposed in Ref. [54]. The designed system can cover long distances with minimum power consumption. From the overview of the systems presented in Table 2, the following points can be outlined:

- ✓ Overall, IoT-based remote monitoring PV systems have been used for domestic applications (small-scale PV plants) and they are typically of lower cost than the commercialized equipment, but with some limits in performance. In addition, commercialized monitoring systems are much more expensive and they globally cannot respond to all user's requirements.
- ✓ Most of the designed smart-monitoring systems are developed and tested at PV module level. However, few of the monitoring systems comply with the international standard (IEC61724) reported in Ref. [56], including class B and class C that are the most appropriate for small-scale PV plants, which decrease significantly the quality of the designed monitoring system.
- ✓ Free open sources and tools (such as IoT platforms ThinkSpeak and Blynk, and hardware platforms Raspberry and Android) are used, as they provide a rapid development and a cost-effective solution for smart monitoring systems. However, accuracy, efficiency, and security should be addressed carefully.
- ✓ The mostly used communications technology are the Wi-Fi, Zegbee and GPS. Each of them has a different performance in power consumption, distance covering, and cost. For example Wi-Fi (based on IEEE standard 802.11) is a mature networking technology and much appropriate for medium distance (100 m - few km) with medium power consumption, while Zegbee (based on IEEE standard 802.15.4) has low power consumption and cost, but it is suitable only for small distances (up to 100 m); LoRa network is much appropriate for large distance up to 15 km with low power consumption.
- ✓ The application of the IoT in this area will rapidly continue to progress, and more data will be stored and will be available. The biggest drawback of the IoT is to ensure the security of application in its large database. In addition, a non-smart IoT system will have limited capability and will be unable to evolve with big data [38]. The IoT is a good platform for the development of a cost-effective smart monitoring system, if the final application succeeds to comply with the relevant technical standards.

5. Fault detection and diagnosis methods

Any fault occurring in PV plants can decrease significantly the performance as well as the security of the plants. To address these issues, numerous FDD methods have been recently proposed in the literature. A FDD method should first detect the fault and should act rapidly, because if the fault is not detected on time it can create serious problems, such as fire. Secondly, the FDD should be able to identify the nature or the type of the faults. Faults classification process should be integrated in order to make a clear decision, i.e., permanent faults should be treated in a different way than the temporally faults. Thirdly, it should be capable to isolate the fault to avoid the risk of fire. This can be done by the system protection against overcurrent, lighting, and grounding. Finally, it should be able to localize faults, which is a challenging issue in large scale PV plants particularly with multiple faults that can occur simultaneously. Advanced FDD should be able to predict the fault, which is a very big challenging issue to date.

Overall fault detection and diagnosis methods as shown in Fig. 13 comprise three major steps:

a) **Step 1** *Detection*: this is a crucial step, in which data are measured and then compared with reference values produced from models to detect any anomalies. Here an accurate threshold value should be defined in order to avoid false alarms. This step is not influenced by the nature of the fault, if the fault is defined, even if several faults occurred at the same time. However, these are affected by the quality of the measured data (noisy data), and the reference models (physical model, and data-driven model). It should be noted that the method based on driven data can also be used to detect faults.

b) **Step 2** *Identification*: in this step an algorithm is executed to identify the nature and the cause of the faults, which is a hard task, particularly if several faults occur at the same time, i.e., faults with the same signatures. In this step, advanced algorithm-based AI techniques, including machine learning and deep learning are the most suitable.

c) **Step 3** *Localization and isolation*: this is the last step in which the system localises the position of the fault and then isolates this fault quickly. This step is very challenging and requires more information and expert knowledge.

To the best of author's knowledge, to date there is no applications of embedded FDD devices employed and commercialized for photovoltaic systems. Most commercialized equipment are not able to diagnose and localize all faults and make clear and prompt decision, i.e., if the fault is dangerous or not, and if it needs a quick intervention or not. Particularly in the case of multiple faults, the system should be able to perform fault recognition in which the nature of the faults is identified, the fault is located in large-scale PV plants, and must have the ability to predict possible failures before the fault happens.

Available FDD methods can be broadly classified into two classes the visual and thermal methods and the electrical methods. The first class is a semi-automatic and the second class is an automatic method.

5.1. Visual and thermal methods for detection of fault and diagnosis

These methods can be used to detect both type of faults, permanent and temporary, as for example discoloration, browning, surface soiling, hot spot, breaking, and delamination. Aerial drones are used to collect images (infrared and electroluminescence) and then used to localize and identify faults based on some advanced image processing algorithms; recently deep learning algorithms are used for this purpose. These methods can identify and localize the faults, nevertheless sophisticate equipment or instruments are needed, such as thermal cameras and drones. Visual supervision by Operation and Maintenance (O&M) services is more expensive and time consuming and thus it is not recommended for large-scale PV plants. In addition, even in small-scale PV plants this method is not able to detect invisible faults such as hotspots. With reference to IEC-61215 [57] standard, several defects can be detected based on visual supervision, such as bubbles discoloration, browning, delamination, burning marks, cracked glass or cells, dirt points, lose or exposed damaged wiring, interconnections rust or corrosion, snail tails, and damaged or broken pieces [58,59].

A simplified semi-automatic FDD-based thermal imaging simplified diagram is shown in Fig. 14. This method is mainly used to localize faults and detect faults on PV modules such as, hot spots, snail trails, back sheet delamination, glass breakage in thin film modules, thin films module delamination, bubbles, delamination, burn marks on back sheet and laminated cell fragments. Recently, this type of method is gaining more interest due to the successful application of deep leaning in image processing and pattern recognition.

However, the distance between the cameras from the PV array, drones, and image resolution should be taken into consideration in order to collect good quality images, which can help the accurate diagnosis based on images.

5.2. Electrical methods for detection of fault and diagnosis

The electrical methods can be used for the detection and diagnosis of faulty PV modules, strings and arrays, inverter switches, batteries, arc fault, grounding fault, diodes fault and hot spots. Major electrical-based FDD methods rely on some type of PV plants model to detect various types of faults. Electrical methods can be also globally classified into three groups, as follows.

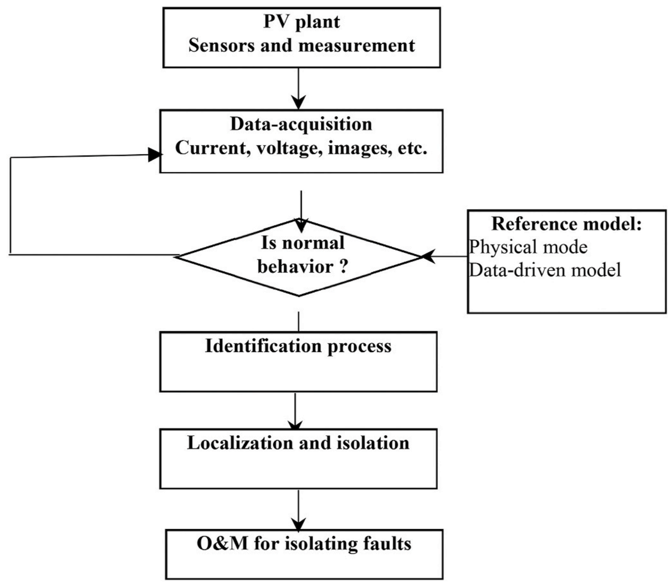

Fig. 13. Flowchart of a fault detection, identification and localization process.

5.2.1. Statistical and signal processing approaches

Statistical and signal processing methods are mainly based on the analysis of the signal's waveform (see Fig. 15). Offline techniques such as time domain reflectometry (TDR) [60], spread spectrum time-domain reflectometry (SSTDR) [61] and earth capacitance measurement (ECM) [62] are employed. These methods can be used to detect and localize faults, however, an external generator function is required and during the diagnosis (see Fig. 15) the system should be off (offline system). These techniques are not automatic and are used generally in small-scale PV plants. In addition, these techniques are not able to identify the type or the origin of faults. However, an automatic and online fault diagnosis methods are highly recommended in modern monitoring and supervision techniques [6].

5.2.2. Methods-based I–V characteristics analysis

These methods are based on the analysis of the I–V curves of the PV arrays. A data-acquisition system is essential in order to collect and store the I–V curves, and then based on the measured values of solar irradiance and solar cell temperature the simulated I–V curves can be plotted based for example on one diode, two diodes, Sandia model or other improved versions of models.

These methods compare some significant points from the I–V curve to get an idea on the type of fault (see Fig. 16). In some cases however, these methods are not able to identify faults that have the same signatures or symptoms [61] and they can localize the fault but for small-scale PV plants only.

5.2.3. Methods based on artificial intelligence techniques

These methods include the application of machine learning and recently deep learning. Machine learning is mainly used for methods based on the measured I–V curves, currents, voltages and other parameters, while deep learning is basically used in fault diagnosis based on infrared and electroluminescent images. In these methods, a large database is compulsory to train and test the classification and the recognition models. Fig. 17 shows the working principle of these methods. Methods based on AI are mainly used to detect, classify and identify the nature of the faults, and they can solve the problem that creates the faults that have the same signatures or symptoms.

Methods based on infrared (IR) thermography images can use also the machine learning technique, however, deep learning is the most suitable if a large database is available. In addition, the classification accuracy depends on the amount of data, data quality and the algorithms used. Raw data without pre-treatment (noise removal) can seriously reduce the performances of FDD methods.

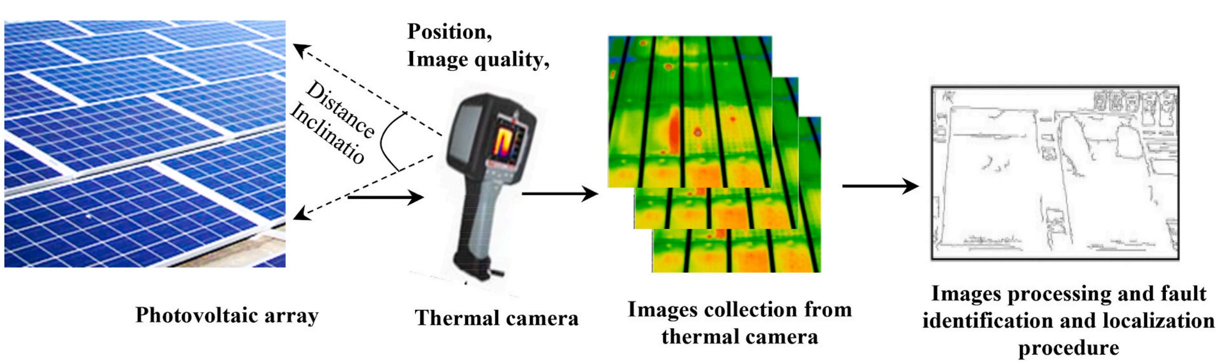

Fig. 14. Simplified diagram of fault diagnosis based thermal image processing.

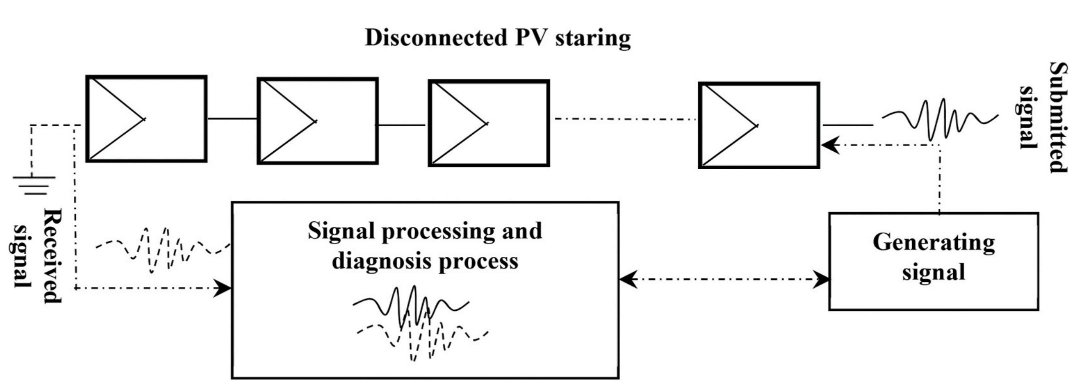

Fig. 15. TDR-based method for FD in a disconnected PV string.

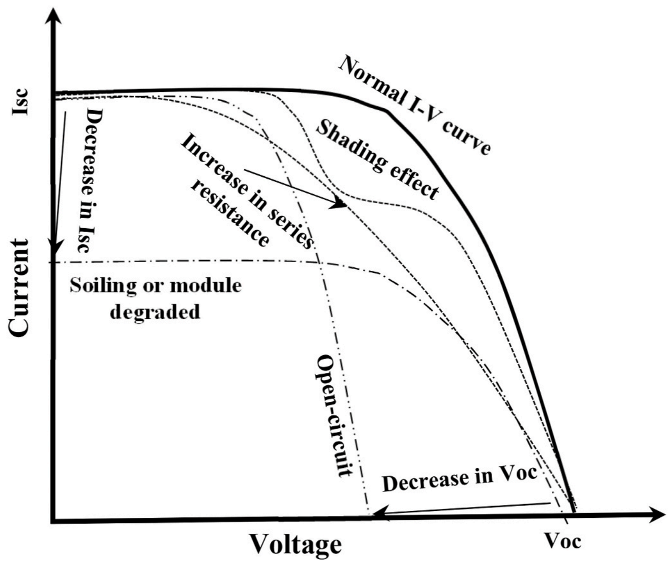

Fig. 16. Example of I–V curves (Normal: solid line, faulty: dotted line).

6. AI-based fault detection and diagnosis methods

The next subsections review the literature available on the application of machine learning and deep learning in fault detection and diagnosis systems for PV plants. A suggested smart monitoring embedded configuration based on the AI and IoT is presented in the last subsection.

6.1. Application of machine learning

In recent years, various machine learning algorithms have been applied for FDD of PV plants. As an example, Fig. 18 shows a simplified application of ANN (supervised learning) for fault classification and identification [63]. Table 3 reports the most popular machine learning algorithms used for the FDD of PV plants. Papers reviewed are compared in terms of the ability to detect, identify and localize faults, complexity, cost, prototype implementation, real time verification, investigated faults, capacity of the PV plants and the type of the machine learning used.

One of the earliest publications in which the authors developed an expert system-based learning method to diagnose a PV system appeared in 2003 [64]. The designed technique is used to diagnose the shading effect. The method was simulated and validated experimentally. From the point of view of complexity, the method is simple and effective but verified only in the case of shading effect. A very simple coding procedure based on back propagation NN (BPNN) was introduced in Ref. [65], generally the method provides good accuracy, unfortunately, the method was not tested with real data. In Ref. [66] a modified ANN is used to build an intelligent fault diagnosis method for a domestic PV system (3.15 kWp). Solar Pro simulation software was used to obtain the maximum power. According to the simulation, the proposed method can identify faulty PV modules (shaded PV modules) accurately and quickly. The system is not verified experimentally but verified offline. A set of 1995 samples were used to train the network. Among the first applications of NN to localize faults in a small-PV array is the one presented in Ref. [67]. While the method was promising, its implementation for real-time application is more difficult, as many sensors are needed to measure the voltage in each PV module.

A kind of NNs named Bayesian belief network is developed to detect temporal and permanent faults in a grid connected PV system [68]. The method was simulated for offline applications. The method is focused more on the data-collection and at this stage, the method is not able to diagnose the fault. An expensive instrument is required to apply this method, while DC and AC faults are investigated in the paper. A fuzzy logic (FL) based fault detection method is designed to detect faults in a PV array. The investigated faults are broken diodes, water infiltration and shading. Preliminary results have shown that the system is able to

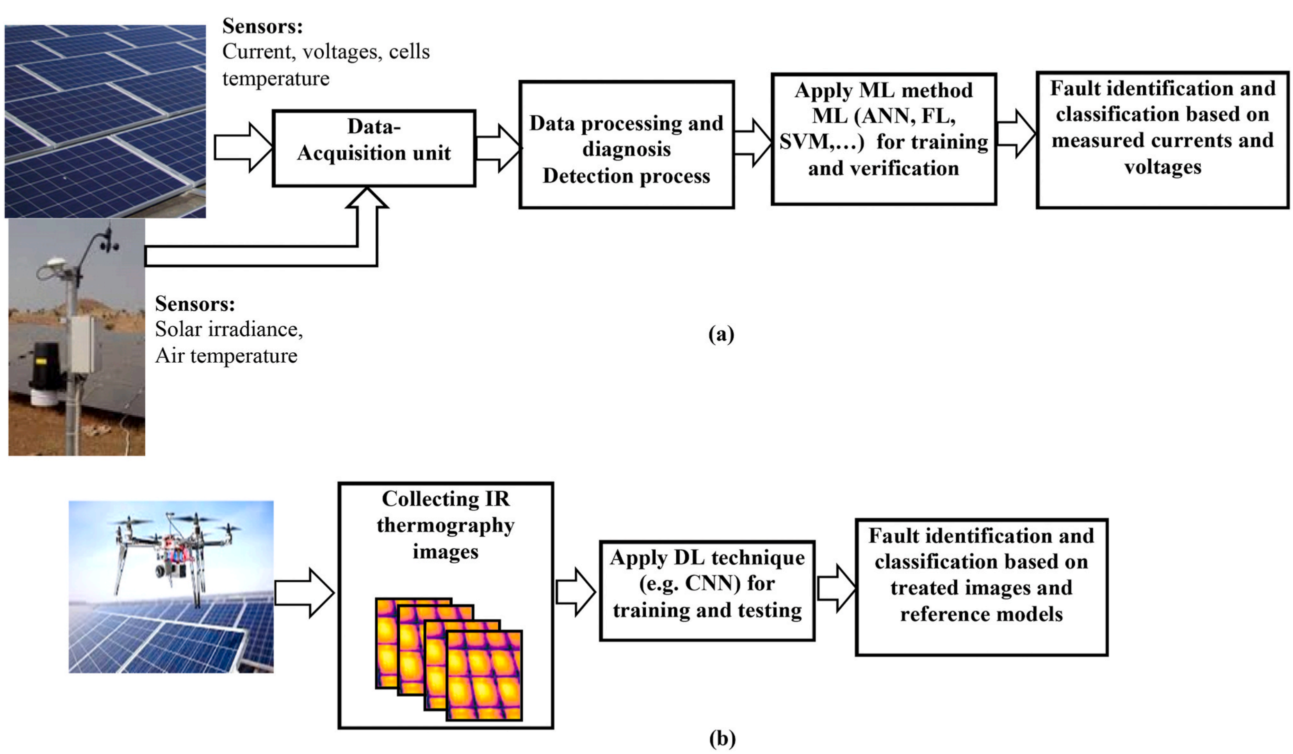

Fig. 17. Simplified framework of fault identification and classification based on AI-techniques: a) I–V based machine learning approach and b) thermography based deep learning approach.

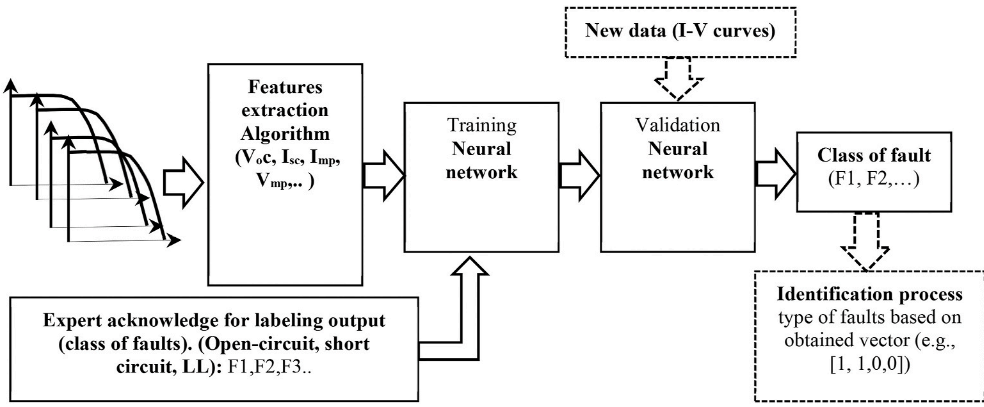

Fig. 18. Example of an ANN application for fault identification and classification based on I–V curves.

recognize more than 90% of faults, even in the presence of noisy data [69]. The first application of decision trees (DT) based classification for faults in a PV array was introduced in Ref. [70]. Three common faults, line-to-line, shading, and open-circuit were evaluated, and the classification rate was 98.9%. In Ref. [71] the authors built an intelligent tool based multilayer perceptron (MLP) for fault detection in PV arrays. An expert system (ES) was also used to analyse the cause of the faults.

A simplified method based on ANN is introduced in Ref. [72], the input of the MLP are the T, I_{mpp} and V_{mpp}. They can detect some faults such as short circuit, degradation and shading on a PV array. The method was implemented and simulated under Matlab/Simulink and the results were satisfactory. The first application of fuzzy logic to detect the increase in series resistance (Rs) of PV modules was developed in Ref. [73]. Four parameters are used as input, while the output provides a binary result (yes/no), which indicates the increase of Rs or not. The method was evaluated using experimental measurements, and it shows good detection rate. A wavelet with MLP was designed to identify faults in a PV array (open-circuit, short-circuit, shading and degradation). A set of 500 samples was used and the simulation results showed that the model provides more accuracy with correlation $r = 96\%$ than a simple MLP [74].

In [75] the authors combined a support vector machine (SVM) and k-nearest neighbours (k-NN) in order to improve the classification rate of short circuit faults in a PV array. Results showed that the hybrid model provides better results in terms of accuracy compared with SVM, and k-NN when used alone. In Ref. [76] the authors developed an extension neural network (ENN) algorithm to detect the shading effect on the PV array. Reported results indicate a high recognition rate, with only a minimal learning data requirement. The algorithm is implemented in a low-cost microcontroller for real-time validation. In Ref. [77] the authors developed a simple ANN to predict the PV string output power and the predicted power was used to detect a possible fault. The investigated faults are the short-circuit, open-circuit, partial shading and MPPT problem. Simulation results show that the method suggested can detect accurately the fault. A BPNN-based on genetic algorithms (GA) was designed to detect, partial shading, short-circuit and abnormal aging. Results demonstrated that the method could detect the investigated common faults with high precision. Nevertheless, no experimental validation was proposed [78].

A cost-effective solution to detect arc fault in PV systems based on FL is proposed in Ref. [79]. Matlab-based simulation results proved the accuracy of the method with a detection rate of 95.8%. The method is cost-effective because it could be simply implemented into a low-cost analog circuit. The detection process is mainly based on frequency analysis, peak detection and observation of the operating point. In Ref. [80] the authors introduced a new method based on the ANN-FL for fault identification at PV module level. The technique was verified, and the highest probability of detection was 86%, so it can be used for temporal fault detection. It was pointed out that the algorithm can quickly learn from the PV performance data collected and provide accurate fault detection results. Under low solar irradiance, short circuit faults, including line-to-line and line-to-grid become hard to detected. To solve this problem a method based on multi-resolution signal decomposition and fuzzy logic was built [81]. More than 3000 samples were used to design the method, and the identification rate is close to 98%. The method was also validated experimentally to identify line-to-line and line-to-grid faults.

In [82] the authors classified the blocking diode, bypass diode and increase in series resistance faults using a simple neuro-fuzzy (NF) classifier. A dataset of 5670 samples, generated by a PV emulator, was used and classification rate accuracy is between 90% and 98%. The first implementation of the fault diagnosis based on an embedded system, using reconfigurable circuit Field Programmable Gate Array (FPGA), is described in Ref. [83]. A simple feed-forward NN (FFNN) was developed to identify eight faults including shading, open-circuit and short-circuit, and the classification rate was 90.3%. The designed model was implemented into an FPGA-based system generator. The method was simulated and validated experimentally for online applications. In Ref. [84] the authors suggested a simplified method based on MLP to detect the shading effect in a PV string. The method is able to detect different patterns of shading that can occur on a PV array. A dataset of approximately 3000 samples was used to construct the model, and the results indicate that it can easily detect a faulty module. The method can be effortlessly implemented into a low-cost monitoring system.

In [85] the authors applied a radial basis function-extreme learning machine (RBF-ELM) network to classify short-circuit, shadow and aging in a PV system. Results showed that the average classification rate is 93.55%. Only simulation results were provided in this study. A method based on theoretical I–V curves and fuzzy classifier was designed for PV array fault classification [86]. The developed fault detection method depends on the variations of the voltage and the power of the system. Evaluated faults include short circuit and shading effects, although the method is able to evaluate also a hot spot based on the theoretical I–V curves with a classification rate of about 95.3%. A Multi-class least square support vector machine (LSSVM) model in Bayesian theory was built to classify open-circuit, short-circuit and abnormal aging faults in a PV array, and the results are simulated in Matlab and verified experimentally [87]. The classification accuracy was 97.5% which outperforms other classifiers examined like, SVM and LLSVM. In Ref. [88] the authors developed a Kernel extreme learning machine (KELM) approach to diagnose PV plant faults. A set of I–V curves was used to build the model, which was used to detect and classify four common faults in a PV array, i.e., short-circuit, open-circuit, partial shading and degradation. Simulation carried out under Matlab/Simulink demonstrated the capability of the method to detect and classify the investigated faults. However, the model is not validated experimentally.

Table 3
Application of machine learning in fault detection and diagnosis of PV plants from 2009 to 2019.

Ref.	Year	ML-based method & type of learning	Identification, detection & localization	PV system & Capacity	Complexity and integration & Software	Type of faults	Prototype development & dataset	Real time verification	Accuracy & cost
[65]	2009	BPNN Supervised	Identification	GCPV –	Medium Matlab	Anomalies	No –	Offline	99% –
[66]	2010	Modified MLP Supervised	Identification	PV array 3.15 kW	Easy in point of view simulation –	Faulty module in array (shading)	No –	Offline	100% –
[67]	2011	ANN Supervised	Localization	PV array –	Medium –	SC	No –	Offline	–
[68]	2011	BBN Supervised	Detection	GGPV array –	Easy Netica API	DC & AC faults	No –	Offline	–
[69]	2011	FL Unsupervised	Identification	PV array level 3 kW	Relatively easy –	Broken cells& shading	No –	Offline	90% –
[70]	2012	DT	Detection & Classification	PV array level –	Medium –	OC, PSh & LL	No 764,529 samples	Offline	99.8%
[71]	2012	MLP Supervised	Detection & diagnosis	PV array –	Medium –	Anomalies	No –	Offline	–
[72]	2012	ANN Supervised	Detection	PV array level –	Easy Matlab/Simulink	SC, degradation and shading	No –	Offline	–
[73]	2012	FL Unsupervised	Detection	PV module level	Medium –	Power loss	No –	Offline	96%
[74]	2014	ANN Supervised	Identification	PV array	Medium Matlab	SC,OC, PSh abnormal degradation	No 500	Offline	96%
[75]	2014	SVM-kNN Supervised	Classification	PV module level –	Medium Matlab	SC	No –	Offline	75.8%
[76]	2014	ELM Supervised	Classification	PV array 3.5 kW	Easy –	Shading	Yes –	Online	100%
[77]	2015	ANN Supervised	Detection	PV string level –	Easy Matlab	SC,OC, PSh and MPPT	No –	Offline	–
[78]	2015	BPNN-GA Supervised	Detection	PV module level –	Easy Matlab	SC, PS & abnormal aging	No 1600 samples	Offline	–
[79]	2015	FL Knowledge-based	Detection	PV array level	Medium –	Arc	No –	Offline	95.8 –
[80]	2015	ANN-FL Supervised	Detection	PV module level 3.7 kW	Medium –	decrease in output power	No	Offline	86% –
[81]	2016	FL Knowledge-based	Detection & identification	PV array level	Relative easy PSCAD/EMTDC & Matlab	LL LG & OC	Yes –	Online	94%–96% –
[82]	2016	NF Supervised	Classification	PV module level	Medium Matlab/Simulink	Increase on RS, ByDi, BkDi	No 5670 samples	Offline	90%–98% –
[83]	2016	MLP &RBF Supervised	Detection & classification	PV string level 480 W	Medium Matlab & VHDL	SC, OC, & shading,..	Yes 775	Online	90.3% –
[84]	2016	MLPNN Supervised	Detection	PV string level 2.3 kW	Medium Matlab	PSh effect	No 3000 samples	Offline	90% –
[85]	2017	RBF-ELM Supervised	Classification	PV array level	Medium Matlab	SC, PSh & aging	No –	Offline	93.55% –
[86]	2017	FL Knowledge-based	Classification	PV array 1.1 kW	Medium –	SC, PSh & HSp	No, –	Offline	95.27% –
[87]	2017	LLSVM & Bayesian Supervised	Classification	PV module level 3.5 kW	Medium Matlab	OC,SC & abnormal-aging	No, 320 × 140	Online	97.5% Medium cost
[88]	2017	KELM Supervised	Detection & classification	PV array level 1.8 kW	Matlab/Simulink	OC, SC, PSh, degradation	No. 4800 samples	Offline	–
[89]	2017	Multi-class SVM Supervised	Identification & classification	PV module level 415 W	Relatively easy to be implemented Matlab/Simulink	LL, Degradation	No	Offline	97.98% –
[90]	2017	Probabilistic NN Supervised	Detection & classification	PV-array 9.54 kW	Relatively easy to be implemented Matlab and Psim	LL, SC and disconnected string	No	Offline	100% –
[91]	2018	Fuzzy C-Means Unsupervised	Detection & classification	PV array 3 kW	Medium Matlab	SC,OC & PSh	No 175	Offline	96%
[92]	2018	DT (C4.5) Supervised	Detection & classification	PV array	Easy Matlab/Simulink		No	Offline	99% –

(*continued on next page*)

Table 3 (*continued*)

Ref.	Year	ML-based method & type of learning	Identification, detection & localization	PV system & Capacity	Complexity and integration & Software	Type of faults	Prototype development & dataset	Real time verification	Accuracy & cost
						LL, SC & disconnected string			
[93]	2018	Improved GA –	Identification & localization	PV string	Easy Matlab/Simulink	SC & OC	No	Offline	95% Cost-effective
[94]	2018	RF Supervised	Detection & classification	PV array 2 kW	Matlab/Simulink	SC, OC, degradation PSh	Verified experimentally No	Online	99.13%–99.22% –
[95]	2018	k-NN Supervised	Detection & classification	PV string level	Matlab/Simulink	SC, LL, PSp & OC	No	Offline	98.7% –
[96]	2018	ANN-FL Supervised	Detection	PV string level 1.1 kW	Medium Matlab/Simulink	Shading effect	No 6480 samples	Offline	92.1% –
[97]	2018	MC-NF Supervised	Classification	PV module	Relatively easy Matlab/simulink	RS, ByDi BkDi	No 2860	Online	–
[98]	2019	Fuzzy C-Means Unsupervised	Classification & identification	PV array level	Relatively easy –	SC & OC	No 977 samples	Online	–
[99]	2019	FL Knowledge-based	Identification	PV module level	Medium Matlab/Simulink	HSp	No 8000 samples	Offline	97.7%
[100]	2019	One class SVM Supervised	Detection	GCPV 9.54 kW	Easy Matlab & Psim	SC, OC and PSh	No 1440	Offline	99.3%
[101]	2019	MLPNN Supervised	Classification	PV module level 169.92 kW	Medium –	HSp	No 1568 samples	Offline	92.8%
[102]	2019	SVM Supervised	Detection	PV array	Easy –	–	No	Offline	92%–94%
[103]	2019	FL Knowledge-based	Classification	PV module level	Medium Matlab	Delamination & discoloration	No	Offline	–
[104]	2019	kNN Supervised	Detection	PV array 3.18 kW	Easy Matlab/Simulink Labview	OC, SC & and PSh	No 1440 samples	Offline	94% –
[105]	2019	FL Knowledge-based	Detection	PV array	Easy Matlab/Simulink	OC, SC & and PSh	No	Offline	–
[106]	2019	NB Supervised	Classification	PV module level 42.24 kW	Medium Matlab	HSp	No –	Offline	94.1% –
[107]	2019	SVM & RF Supervised	Classification	PV module level	Medium –	Cracks	No –	Offline	99.75 Expensive

In [89] the authors designed a multiclass SVM used to diagnose faults at PV module level. The faults investigated are the line-to-line and abnormal degradation. To characterize the fault features, two parameters were used fill factor (FF) and KF ($KF=I_m/(V_{oc}-V_m)$). Simulation results indicate that the classification rate is about 98%, although the dataset used included only 144 sets. In Ref. [90] two probabilistic NN classifiers were used for detection and classification of faults in a 9.54 kW grid connected PV system. The investigated faults are short-circuited modules and one disconnected PV string. The effectiveness of the procedure was assessed by using experimental data with good accuracy, although the method was not able to detect which PV module is short-circuited. Overall, the method presents promising results with respect to detection and classification. In addition, noiseless and noisy data are also considered in this study, and a dataset of 11,840 readings was used to train the NN.

In [91] the authors proposed a method based on Fuzzy-C-Means and fuzzy logic to detect and classify short-circuit, open-circuit, and partial shading in a 3 kW PV plan. The method was simulated and it was shown that a small amount of data is adequate to implement the method, with a good accuracy of 96%, however, this cannot by implemented in real-time. In Ref. [92] the authors used a C4.5 DT algorithm to detect and classify faults in a grid-connected PV system. Sandia model is employed to model the output power of the system, and the line-to-line, short circuited module and string faults are examined. Results indicated that this kind of supervised learning can classify the faults with an accuracy up to 99%. In Ref. [93] a GA is used to identify and locate faults in a PV system under non-uniform irradiance. Additionally, the method can distinguish between open-circuited and short-circuited PV modules in the array. As a small number of sensors are required on the DC-side, and the method can decrease the overall cost of the system. This method could be implemented for online diagnosis, but only two kinds of faults are considered. The performance of the method in terms of faults identification is about 95%.

In [94] the authors used a Random forest ensemble learning algorithm to detect and diagnose faults, including open-circuit, line-to-line, degradation and partial shading in PV arrays. In this method, the PV-array voltage and the PV-string currents are used. The method was verified experimentally with very good detection and classification accuracy of 99.2% and 99.1% respectively. However, the method is not able to localize other faults. To avoid local optimum when dealing with large and complex data the authors in Ref. [95] investigated the use of k-NN ML algorithm to detect and classify faults in a PV system such as open-circuit, short-circuit, line-to-line and partial shading. Matlab/Simulink SimPowerSystem was used to design, simulate and classify different faults, which are then verified using measured data from the I–V curves (I_m, G, V_m, T and P_m) with an average fault classification of 98.7%. This method was not implemented in real-time applications. In Ref. [96] the authors carried out a comparative study between ANN and FL and the results conducted proved that both methods are able to detect possible faults in a PV string (1.1 kW). In the case of the ANN, detection accuracy is 92.1%. Most faults investigated were about shading effects on PV modules, and the size of the recorded dataset included 6480 samples. Two parameters are defined voltage ratio and power ratio which were used as inputs to the machine learning algorithm.

A multiclass FL model implemented in Matlab/Simulink is designed to classify some permanent faults [97]. The method was tested using a

PV emulator system. The results showed that the model is able to classify the faults investigated with good accuracy. To identify short-circuit and open circuit faults in a PV array a Gaussian Kernel Fuzzy C-Means clustering method was used by the authors in Ref. [98]. Measurements of V_{nom}, I_{norm} and FF were utilized as feature parameters to design the fault classification procedure. A total of 799 samples were used and the simulation results proved that the procedure works correctly with good accuracy. In Ref. [99] six categories of hotspots on various PV modules were identified based on FL. A thermal camera was used, and a total of 2580 PV modules that were affected are examined. The designed fault detection based on FL to identify the category of the hotspot requires as inputs three parameters the percentage power losses, short-circuit and open circuit. Results indicated that the average detection accuracy is about 97.7%, while the main drawback of the method is that it is not able to identify hot spot in high partial shading conditions.

One class of support vector machine was developed to detect possible anomalies in a grid connected PV system [100]. Simulation results showed that the developed method performs better than K-means, Birch, mean-shift, expectation–maximization, and agglomerative clustering. A simple MLP classifier was designed to classify faulty modules based on thermography images in Ref. [101]. A total of 1568 samples were used to construct the classifier. The results showed that the classification accuracy is 92.8% which is better than others investigated based on support vector machine and k-NN. The authors in Ref. [102] used a minimum amount of collected data from a PV array to develop a SVM-based abnormal fault detection system. The average accuracy is between 92% and 94%. The method is very simple and does not require a large amount of data and can be developed at low-cost. As reported in Ref. [103], the detection and classification of progressive defects such as ethylene-vinyl acetate (EVA) discolouring and delamination through thermal imaging techniques is challenging because of the atmospheric temperature variations and camera signals noise. A method based on FL was used to automate classification process, however the method was verified offline only.

In [104] the authors developed a fault detection method based on k-NN, Shewhart, which is a graphical tool for quality control, and exponentially weighted moving average (EWMA). Parameters such as I_{mpp}, V_{mpp}, P_{mpp}, G and T are used as input to the k-NN. It was demonstrated that the k-NN based on EWMA and Shewhart with parametric threshold is able to detect open-circuit, short-circuit and temporarily shading. Several faults have been investigated in Ref. [105], including short-circuit, open circuit, shading effect, and snow falling on a PV array. Three parameters obtained from the I–V cures were defined and calculated. These parameters were used to identify the type of the fault occurred. A total of 720 I–V curves were collected in order to develop the FL-based model, although the method provides good results it was not validated in real-time. In Ref. [106] Naïve Bayes machine learning technique is used for classification of hot spots in a PV array. A total of 374 samples of thermal images were used to classify the faults into three categories, defective module, non-defective with hot spot and non-defective without hot spot. Matlab was employed to extract the features with grey level co-occurrence matrix for naïve Bayes development. Principal component analysis algorithm is also used to reduce the dimensionality of a dataset consisting of a large number of interrelated variables and the classification rate was accurate within 94.1%. Support vector machine and random forest (RF) classifiers are applied by the authors in Ref. [107] using electroluminescence images to detect and differentiate between three classes of cracks in PV modules. A total of 735 images of PV modules were used to investigate and evaluate the machine learning methods. It was shown that the accuracy is high, but the dataset is very imbalanced. It was pointed out that both classifiers provide quite similar results.

Fig. 19 shows the number of applications of machine learning applications per year, and an estimate trend for the next years.

With reference to Table 3 and Fig. 19 the following points can be observed:

✓ Among the 30 papers reviewed which are published in conferences and journals only five of them are focused on the experimental testing, i.e., applied real-time verification. In addition, very limited papers are focused on the AC side which refer to the inverters, as the major faults can occur on the PV array side, including strings and modules.

✓ Methods based on infrared thermography and electroluminescence images are relatively expensive, as sophisticated equipment is needed, which is not always available in many laboratories. In addition, expert-based knowledge is necessity in order to extract the appropriate features from raw data. Nevertheless, these methods are very promising when deep learning is used to localize and identify different defects in PV modules.

✓ Supervised and un-supervised learning are the most utilized in this area, while semi-supervised and reinforcement learning are rarely used. The ANN and FL have demonstrated their abilities to identity and classify most faults that appear in PV arrays with good accuracy.

✓ As a smaller amount of equipment and sensors is required, methods-based I–V curves are cost-effective. However, the reliability of these methods depends mainly on the accuracy of the PV model, including the precision of the instruments and the sensors employed.

✓ Even though these methods provide good results, the overfitting problem and generalization capability of some techniques based on machine learning such as NNs should be carefully considered.

✓ The Matlab/Simulink is the most investigated software to implement machine learning-based fault detection and diagnosis, due to its flexibility. However, a very limited number of prototypes was designed and verified for real time application based on Matlab.

✓ The examined machine learning applications showed a good accuracy ranged between 90% and 99%, however, the accuracy of the designed FDD based on machine learning in real-time depends mainly on the quality and the size of the database. Therefore, data should be carefully pre-treated with an effective extracting features process.

There is not strong evidence that unsupervised learning (e.g. fuzzy C-means), is better than supervised learning (e.g. SVM), as it depends on the type of data (labelled or unlabelled), features and the size of database. The feature dimension is also an important factor in case of constraints like computational cost, simplicity and implementation. Few machine learning-based methods require a small amount of data (fault data) to develop their FDD model, like K-means. Therefore, it can be concluded that it is not easy to generalize as most applications presented are carried out in different regions employing different PV modules technologies.

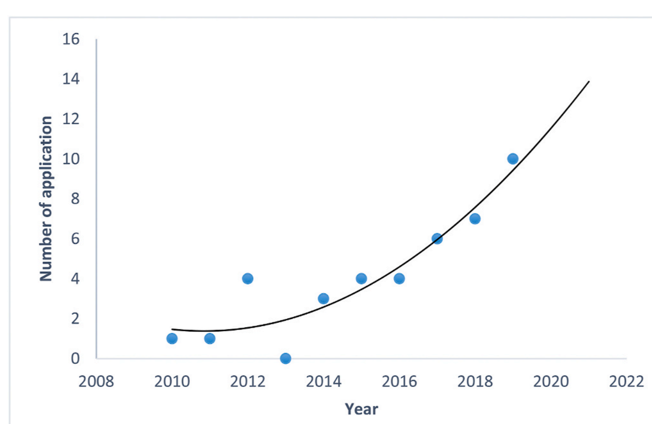

Fig. 19. Trend of ML application in fault detection and diagnosis of PV systems for the next years.

6.2. Applications of deep learning

Deep learning is used to address some issues of conventional ANNs for the FDD of PV plants, such as shallow ANNs, with one hidden layer and low performance, overfitting problems, manual features extraction, and others. In most cases, expert knowledge is mandatory to diagnose correctly the faults, and usually they cannot support the huge amount of collected data, particularly thermal or electroluminescence images for the design of automatic FDD systems. Deep learning algorithms such as deep convolutional NN (DCNN), generative adversarial network (GAN) and deep convolutional GAN, have demonstrated their capability in images pattern recognition, and classification. Recently researchers, particularly the ones using infrared and electro-luminescence images, are very motivated by the application of deep learning and this is a hot research area. Fig. 20 shows a basic workflow of using DCNN for detection and classification of faults in PV modules.

The application of deep learning in fault detection, localization and classification of PV plants, is presented for the first time in 2018. Table 4 reports the recent applications of deep learning in FDD for PV plants. In Ref. [108] the authors used DCNN and SVM to detect, localize, and classify faults of large-scale PV plants using unmanned aerial vehicles. Around 7560 PV images were used to build the method. Results proved the capability of the method to locate and classify common defects in PV array including delamination, dust-shading, snail trails, gridline corrosion, and yellowing, with good accuracy. However, the method is very expensive, as it requires drones and supercomputers. In Ref. [109] the authors used VGG-16 (Visual Geometry Group) net, which is a kind of CNN consists of 16 layers, to detect anomalies in PV modules from collected thermal images using drone. A set of 9732 images in different rotation angles of 90°, 180° and 270° were used to train the network. Results indicate that the method provides good precision based on the calculated statistical tests such as recall and F1-score. Although an open-source code was used, the method remains costly in terms of collecting images and instruments employed. An attempt to address multi-defects in PV modules based on deep learning, was proposed in Ref. [110]. The authors used DCNN to extract defect features from images and then used multi-class SVM for classification purposes. A set of 126 multi-defects images were used to validate the effectiveness of the proposed method. The average accuracy for different defects ranged between 95% and 98.4%.

In [111] the authors combined deep convolutional GAN and CNN to identify arc faults in a PV string. A PV emulator was used to generate different arc faults in building the datasets of 25,000 normal and 5000 arcing samples of current signal. Three parameters were used to evaluate the method sensitivity and safety and the results are very promising. The authors in Ref. [112] used another kind of deep learning which is long short-term memory (LSTM) to extract features from simulated normal and faulty I–V and P–V curves of a PV array under noisy and noiseless data. A SoftMax classifier was used to classify the investigated faults like line-to-line and hot spot. The classification accuracy is about 98%, however, the method was not assessed under experimental data. The authors in Ref. [113] also applied a DCNN for the automatic detection of cell defects in electro-luminescent images of different PV modules. A total of 1000 images were used from a public solar dataset to train and evaluate the method. An average accuracy of 93% was achieved by using only a few data, but the method accuracy could be improved by increasing the size of the dataset. However, the method demands expensive equipment such as an electroluminescence camera.

A 2D representation of PV current and voltage was used to build a dataset, in order to feed a DCNN for line-to-line and open circuit fault identification [114]. Features are automatically extracted from the time series graphs (I and V). The method exhibits good accuracy in terms of classification rate which is equal to 99.5%. In Ref. [115] the authors used a CNN with 2D ResNet (residual CNNs) structure of I–V curves to design a method for fault detection and diagnosis. The investigated faults are open circuit, short circuit, degradation and partial shading. Although the ResNet method presents more accurate results with an accuracy of 99.9%, it requires complex computation. The same authors proposed a transfer learning method based on CNN. This consists of two steps, the first to train a DCNN based on electro-luminescence images and the second uses the trained model for identification of possible defects in infrared images (Thermography) [116]. The results showed that a good accuracy is obtained with both methods (isolated CNN based infrared image and transfer learning based electro-luminescence), and an average accuracy is 98.7% for isolated CNN and 99.2% for the second method developed.

With regard to the reviewed papers presented in Table 4 the following points can be highlighted:

- ✓ Generally, hybrid methods which include machine leaning and DCNN can improve the performance of the fault-detection and classification of PV plants using images. Therefore, this emerging technology could provide more accurate results but increases the system complexity.
- ✓ Designing an automatic and online fault diagnosis method for simultaneously multi-defect/faults detection remains a challenging issue.
- ✓ Although the localization problem can be solved by using methods based on unmanned aerial vehicles, this technique is relatively expensive and mainly focused on faults in PV modules, and an

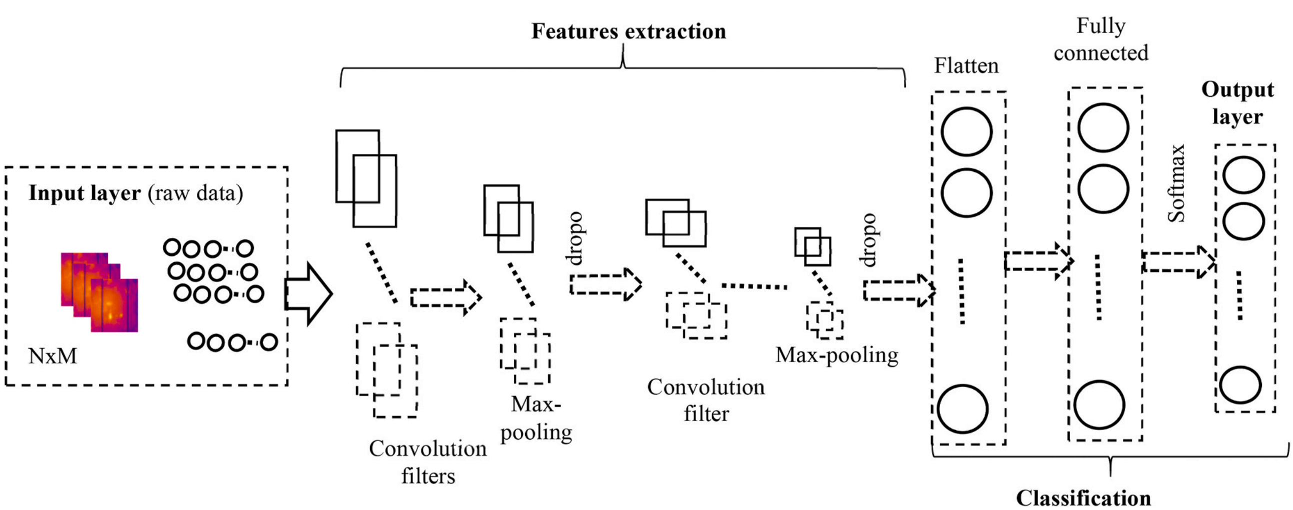

Fig. 20. Example of DCNN for fault diagnosis based on thermography image.

Table 4
Application of deep learning in fault detection and diagnosis of PV plants, from 2018 to 2020.

Ref	Year	DL-based method	Identification, detection & localization	PV system	Complexity, integration & Software	Type of faults	Prototype development& datasets	Real time verification	Accuracy & cost
[108]	2018	DCNN	Localization & classification	LSPV farm	Relatively complex Open source (Python)	Delamination, dust-shading, snail trails, yellowing	No 7560 images	Yes Online	96%–100% High cost
[109]	2018	CNN (VGG-16)	Detection	LSPVP	Complex and strict testing environment Open source code	Anomalies	No 9732 images	No Offline	– High cost
[110]	2019	DCNN-MC-SVM	Detection & Identification	LSPVP	Complex operation Open source code	Delamination, dust-shading, snail trails, yellowing	No –	Yes Online	95.03%–98.42% High cost
[111]	2019	DCGAN &CNN	Identification	PV string level	Relatively complex Open source (Python)	Arc faults	No 30,000 samples	No Offline	97.68% High cost
[112]	2019	LSTM	Classification	PV array	Medium Open source	LL HSp	No 6067 samples	No Offline	98% Low-cost
[113]	2019	DCNN	Detection	PV module	Simple Open source (Python)	Defect on solar cells	No 1000 EL images	Yes Online	93.02% Medium cost
[114]	2019	DCNN	Classification	PV string	Medium Open source (Python)	LL & OC	No 2D current and voltage signal	No Online	99.51% –
[115]	2019	RestNet	Detection & identification	PV module level	Relatively complex Matlab/Simulink	SC, OC, PSh & degradation	No I–V curves	No Offline	99.94% Low-cost
[116]	2020	DCNN	Detection	PV module	Medium Open source (Python)	Defect on solar cells	No IR images	Yes Online	99.23% Medium

extensive study should be carried out for other PV system components such as inverters.

✓ So far, no FDD methods based on deep learning is embedded into electronic devices for real time application, while few prototypes based on machine learning for fault detection and diagnosis have been developed in laboratories, and no commercialized devices are available until now.
✓ Deep CNN is the most used deep learning structure rather than the LSTM which is more suitable for time series prediction, but an overall different form of DCNN including VGG16 and RestNet, is mainly used to extract features and detecting common defects on PV modules like, delamination, yellowing, glass breaking, snail trails, and others.
✓ Deep learning-based methods are applied for large-scale PV plants or farms, including utility grid, and it has been shown that Python is the most used programming language, as is an open-source language which contains many libraries and a platform, such as Scikit-learn, Keras, and Tensorflow suitable to develop machine learning and deep learning applications.
✓ From the cost implementation point of view, methods based on infrared and fuzzy logic images are expensive, even though they proved their effectiveness in fault detection, identification, localization, and classification.
✓ Although transforming measured I–V curves to 2D images of current, voltage and power for faulty images identification provided good results, the method become complex and there is no comparison with the old method based on I–V curves to justify the process. It is believed that efforts should be focused on real problems such as automatic and fast diagnosis of faults based on thermal images.

6.3. Embedded configuration based on internet of things and artificial intelligence techniques

Fig. 21 shows a suggestion of a smart configuration based on IoT with embedded intelligent FDD into a low-cost device for remote sensing of PV plants. It consists of sensors for measuring currents, voltages, and cell temperature in each PV string, and an irradiance sensor.

An embedded FDD method based, for example, on online NNs for fault recognition and classification can be used. A reconfigurable FPGA can be used to generate a Bitstream of the code, and then the generated file can be implemented into a low-cost circuit, for example an application for specific integrated circuit.

Subsequently, a data-acquisition circuit and a Wi-Fi module can be used for transmitting data to the cloud via the IoT technique. The transferred data which can comprise the current, voltage, cell temperature and solar irradiance, including the state of the PV system can be displayed through a webpage, so as the information can be given on the type of the fault and the faulty module or string. In addition, the operators could be notified by a simple SMS if any problem is occurring.

7. Challenges, recommendations and future directions

7.1. Challenges

The most challenging issues in this area can be summarized as follows:

✓ For fault localization, particularly in large-scale PV plants, only few attempts have been done using aerial inspection (e.g. drones) to localize hot spot faults in PV arrays and other defects. So, more attempts are required.
✓ For multiple fault detection, the most available FDD are for one or two faults, so this needs to include all possible faults that could happen.
✓ Cost effective based–embedded system including IoT and AI techniques, seems to be an important technology that needs to be further developed.
✓ Fault prediction is a very huge challenging issue, existing methods are not able to predict faults before happening.
✓ Technology transfer from laboratories to industrial sectors is necessary. The prototypes designed in laboratories should be in compliance with standards and be cost-competitive for commercialization.

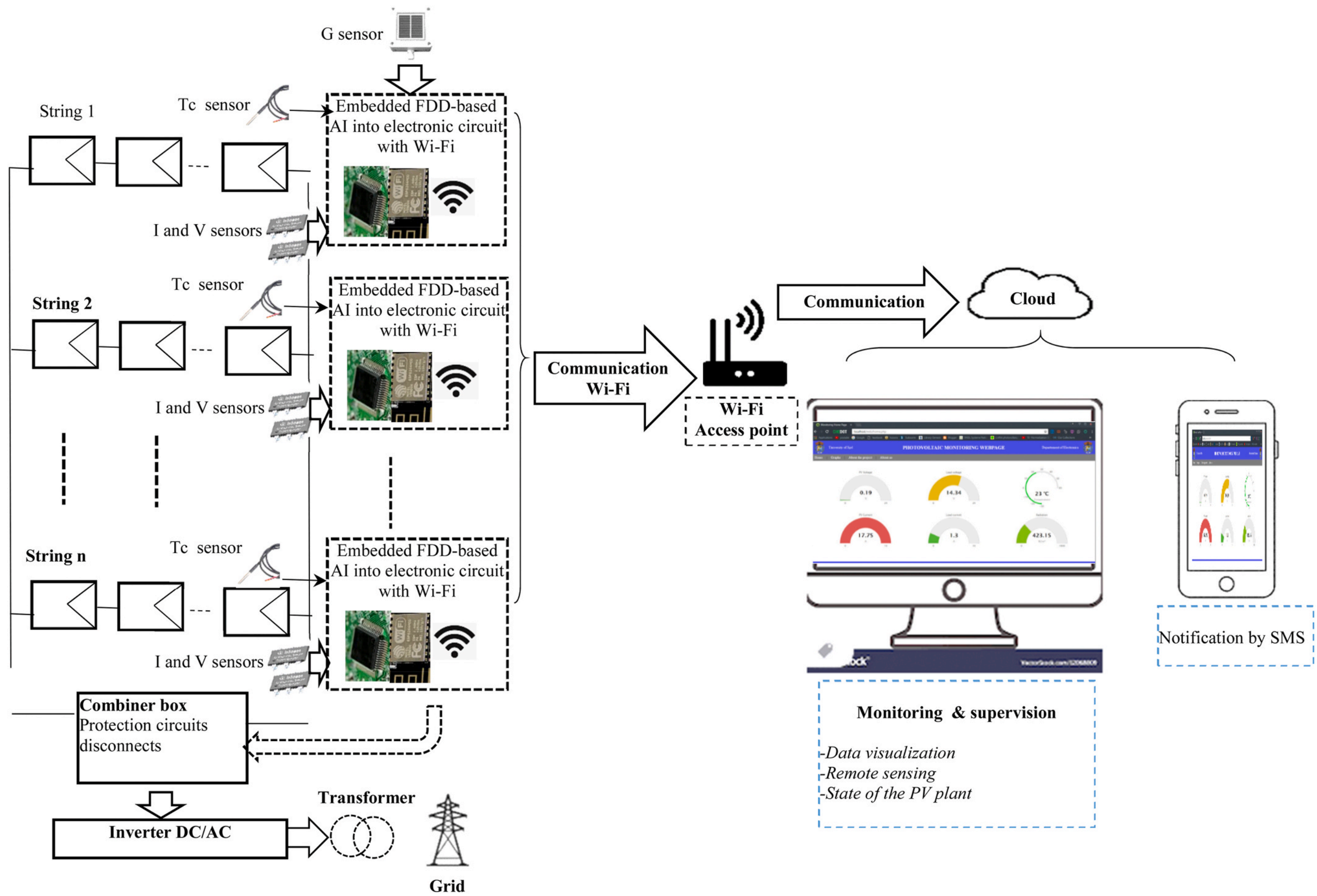

Fig. 21. Suggested smart-embedded FDD based IoT and AI techniques for remote sensing of PV plants.

7.2. Recommendations

The following recommendations can be given as derived from this study:

✓ Various international norms (IEC, NEC, and UL) should be respected when designing a machine learning-method including measurement and precaution, to obtain reliable results that consider real-world disturbances caused by environmental factors and signal noise originating from the measurement devices.

✓ In order to design a miniature circuit with a competitive cost, the implementation of such technique into embedded reprogrammable devices is recommended. Furthermore, focusing the efforts on the development of reliable, affordable and scalable FDD techniques is highly recommended.

✓ Combining methods based on infrared thermography and I–V curves–based AI can contribute to solve the shortcomings of each method. Thus, emerging methods can help to develop a complete tool able to identify, detect, and localize the major faults in PV plants. However, a large database with good quality images and measurements is required, particularly with the deep learning-based method.

✓ The IoT technology is strongly recommended in designing smart monitoring systems with FDD techniques and for remote sensing of PV plants. Furthermore, a smart scheme is highly recommended for the fast isolation and immediate protection of the plants.

✓ Integration of FDD based on AI technique into a low-cost chip is also recommended and this will contribute to the advancement of this area and show experimentally the effectiveness of these techniques.

7.3. Future directions

There are several areas in which further research is needed for making the deployment of the applications of AI and IoT techniques to become easy, efficient and affordable. The following tasks are suggested:

✓ Experimental implementation, including online verification of machine learning, deep learning and IoT techniques is very limited, and they should run in real-time in order to show their effectiveness.

✓ Using hybrid AI-based techniques is encouraged to improve fault classification and identification of the nature of faults. In addition, different configurations of deep learning could also contribute to the progress of fault diagnosis based on images.

✓ Emerging technologies such as the IoT and AI-based embedded systems is also encouraged, and they will significantly contribute to advance this subject by implementing advanced FDD techniques in the near future.

✓ The IoT technology will continue to play a major role in increasing the quality of the monitoring and diagnosis of PV plants installed in remote locations. This can help users to check their PV systems online, predict possible faults, visualize the evolution of different parameters and analyses the data.

✓ With the availability of large amount of collected data, called big data, and the development of advanced deep learning algorithms, fault prediction will be possible, and this will be a very promising area in the near future.

8. Conclusions

The motivation behind this review paper is to show to the readers a systematic and comprehensive review on recent applications of machine learning and deep learning in fault detection and diagnosis, the integration of the internet of things, as well as possible embedded technologies based on artificial intelligence techniques.

Deep learning is a subset of machine learning. Machine learning uses mathematical algorithms that allow machines to learn automatically and algorithms can learn from data with features extraction. Deep learning uses neural networks and can learn from raw data without features extraction, which is the main difference between machine learning and deep learning.

Artificial intelligence techniques including deep learning and machine learning have recently gained popularity in this field and attracted many researchers to design and implement new effective fault detection and diagnosis methods. Currently, with the large amount of data collected and the availability of supercomputers, a fast progress can be expected in the near future for the application of machine learning and deep learning in this area. Therefore, designing smart-fault diagnosis systems based on artificial intelligence and internet of things will become more and more indispensable.

Machine learning and deep learning have great potential to increase the accuracy and performance of monitoring systems to detect, identify, classify and localize different types of faults. In addition to the existing protection and detection devices, the most effective way to protect and mitigate faults from a photovoltaic plant is to integrate an embedded fault detection method based on advanced tools.

Finally, detailed challenges, recommendations, and future directions are given to readers in order to make a clear vision on the future trends in this area, including subjects that should be developed.

This review can help researchers in academic institutions and industrial sectors to get a clear idea about the actual application of machine learning, deep learning and internet of things techniques, and their distinct challenges in this highly important and promising field of research.

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.

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