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Review article

Prognostics and health management of photovoltaic systems based on deep learning: A state-of-the-art review and future perspectives

Zhonghao Chang [a,b], Te Han [a,b,c,d,*]

[a] Center for Energy and Environmental Policy Research, Beijing Institute of Technology, Beijing 100081, China
[b] School of Management, Beijing Institute of Technology, Beijing 100081, China
[c] Beijing Laboratory for System Engineering of Carbon Neutrality, Beijing 100081, China
[d] Beijing Key Lab of Energy Economics and Environmental Management, Beijing 100081, China

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ABSTRACT

As global photovoltaic (PV) power generation capacity rapidly expands, efficient and effective health management of PV systems has emerged as a critical focal point. With the evolution of the Internet of Things (IoT), massive heterogeneous data has been generated in PV systems, enabling the widespread application of deep learning, a powerful data-driven modeling tool, in prognostics and health management (PHM) of PV systems. However, comprehensive reviews specifically focused on deep learning in PV system PHM are scarce. To bridge the gap, core concerns in PV system PHM, including condition monitoring, fault diagnosis, and prognostics, are emphasized. Through a summary of five hundred and six articles published from 2016 to September 2023, an overview of common PV signals, prevalent PV faults, and primary degradation patterns is given. Additionally, an abstract of eight open-source data resources on PV faults is further provided. Significantly, this work compiles cases of the application of deep learning models, led by CNN, in PHM of PV systems, discussing their characteristics and applicability to various types of PV signals. Extra attention has also been paid to the degree of adaptation of these deep models to specific PV PHM tasks. Additionally, this research addresses challenges faced by PV system PHM in the deep learning context, offering guidance for future research. In the future, deep learning will remain indispensable in PV system PHM, and this work aims to provide comprehensive information on deep learning methods, research, and engineering applications to researchers in the field.

Contents

* Corresponding author at: Beijing Laboratory for System Engineering of Carbon Neutrality, Beijing 100081, China.
E-mail address: hante@bit.edu.cn (T. Han).

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1. Introduction

Amidst the dual challenges of an environmental pollution and energy crisis, PV power generation has emerged as one of the most promising and sustainable solutions to address energy demands [1]. In the year 2022, the global PV capacity witnessed a remarkable surge, with a new installation capacity of 230 GW, signifying a year-on-year growth of 35.3%. This remarkable expansion has resulted in a cumulative installed capacity of approximately 1156 GW, demonstrating the sustained and robust global demand for PV systems. These systems have found extensive application across residential, commercial, transportation, agricultural, and industrial sectors [2]. In comparison to traditional fossil fuels, PV power generation offers a multitude of advantages [3]. Firstly, PV power generation processes are entirely devoid of pollutant emissions, thus ensuring minimal harm to the environment. Furthermore, PV power generation derives its strength from renewable energy sources, thereby evading the depletion concerns associated with fossil fuels. Additionally, the installation of PV systems is characterized by its simplicity and speed, resulting in significantly reduced installation costs. These inherent benefits have driven the widespread adoption of PV power generation. Presently, PV systems continue to experience robust development. The confluence of advanced hardware technologies and expanding application scenarios has led to several noteworthy trends: the iterative enhancement of PV components and system technologies is steadily propelling the attainment of comprehensive cost competitiveness in renewable energy generation. Application scenarios are witnessing diversification, including the development of large-scale energy hubs, distributed generation, and harmonious integration into household usage. Furthermore, the widespread adoption of energy storage solutions is facilitating the extended reach of PV systems. In light of these evolving trends, PV power generation systems are undergoing a broadening spectrum of applications.

The fundamental principle of PV system generation is to directly convert solar energy into electrical energy utilizing the photoelectric effect of semiconductor materials. This process directly converts solar energy into electricity without any intermediate conversion steps, resulting in high energy conversion efficiency and pollution-free operation. Furthermore, the flexibility and modularity of PV systems facilitate their widespread application in scenarios such as large-scale power stations, commercial rooftops, residential electricity usage, industrial electricity consumption, and urban electricity demand, as shown in Fig. 1. This system primarily comprises the following essential components: PV modules, controller, inverter and battery. PV modules constitute the fundamental component of a PV system, comprising multiple PV cells responsible for the direct conversion of incident sunlight into electricity. The controller functions as an automated control device responsible for managing the charging process of the battery through the coordination of multiple PV cell arrays. It also supplies power from the battery to the PV inverter for subsequent utilization by the load. The inverter plays a pivotal role in converting the variable DC voltage created the PV system into AC power at the utility frequency. The function of batteries is to store solar energy in order to provide continued power supply during nighttime or low-light conditions, thereby achieving stable energy provisioning and enhancing system reliability.

However, owing to the intricate design of PV systems, which are vulnerable to numerous elements like weather, temperature, and pollution, these components may face performance deterioration and malfunctions over time. The efficiency and operational lifespan of the PV system can be influenced to different extents by these components. PHM for PV systems can be used to track and examine these variables, identify issues quickly, and make necessary corrections. PHM for PV systems has gotten unheard-of attention as a result of the rising total installed capacity of PV systems [4]. PHM represents an emerging interdisciplinary technology that seamlessly integrates various fields, including electrical engineering, materials science, and data science. It assumes a pivotal role in the paradigm shift from preventive maintenance to predictive maintenance [5]. Through the application of PHM technology, engineers can detect anomalies during equipment operation, analyze performance indicators, ascertain degradation states, and estimate the remaining service life. The incorporation of PHM facilitates the formulation of more efficient maintenance strategies encompassing routine inspections, troubleshooting, and component replacements. Its implementation contributes to the reduction of maintenance costs and minimization of system downtime. Additionally, it enhances system reliability and availability, promptly identifies and mitigates safety hazards within the system, guarantees secure operation of PV system, and mitigates additional losses resulting from failures [6].

Traditional PHM methods mainly include physics-based and statistical-based approaches [7]. Physics-based methods typically require system modeling to predict the health condition of the system. However, this approach demands extensive domain knowledge and expertise, and for complex systems, the modeling process can be challenging [8]. Besides, statistical-based methods frequently depend on the assessment of past signals to forecast the health condition of PV system. However, this approach may be limited by data quality and quantity. Additionally, these methods typically can only detect known fault patterns and may not be able to identify unknown fault patterns.

With the continuous evolution of artificial intelligence (AI) technology, deep learning-based PHM methodologies have made significant strides, offering an effective approach for the management of the health of PV systems. The spectrum of deep learning approaches encompasses convolutional neural networks (CNN), recurrent neural networks (RNN), deep belief networks (DBN), deep autoencoders (DAE), generative adversarial networks (GAN), among others. The fundamental premise underlying these methods involves the utilization of multilayer neural networks to execute high-level abstraction and representation learning on data, thereby facilitating the identification and prediction of previously unknown faults. As a data-centric methodology, deep learning has found extensive application in the realm of PV system PHM, attributed to its prowess in handling intricate high-dimensional datasets, adaptive learning capabilities, scalability, and superior generalization performance. It excels in efficiently and precisely processing intricate data from PV systems, capturing intricate relationships and latent patterns within the system, which achieves elevated accuracy in fault prognosis and system health assessment.

To date, several review articles have been published concentrate on the application of machine learning in PHM within PV systems [1,9,10]. These review papers comprehensively examine various studies utilizing shallow machine learning techniques. However, considering the remarkable advancements and numerous successful applications of deep

Abbreviations

AI	Artificial Intelligence	b	Bias vector
ANN	Artificial Neural Network	D	Discriminator network
CNN	Convolutional Neural Networks	D_s	Source domain
DAE	Deep Autoencoders	D_t	Target domain
DBM	Deep Boltzmann Machine	f	Composition of the individual layers
DBN	Deep Belief Networks	G	Generator network
DNN	Deep Neural Network	L_{target}	Loss function of the target domain task
DT	Decision Tree	T_s	Learning task on source domain
EL	Electroluminescence	T_t	Learning task on target domain
GAN	Generative Adversarial Networks	W	Weight matrix
GRU	Gated Recurrent Unit	x	Input
IEC	International Electrotechnical Commission	z	Random noise input to the generator
IoT	Internet of Things	θ	Learnable parameters
LSTM	Long Short-Term Memory	σ	Activation function
PHM	Prognostics and Health Management		
PV	Photovoltaic		
RF	Random Forest		
RNN	Recurrent Neural Networks		
RBM	Restricted Boltzmann Machine		
SAE	Stacked Autoencoder		
SDAE	Stacking Denoised Autoencoders		
SVM	Support Vector Machine		
VAE	Variational Autoencoder		

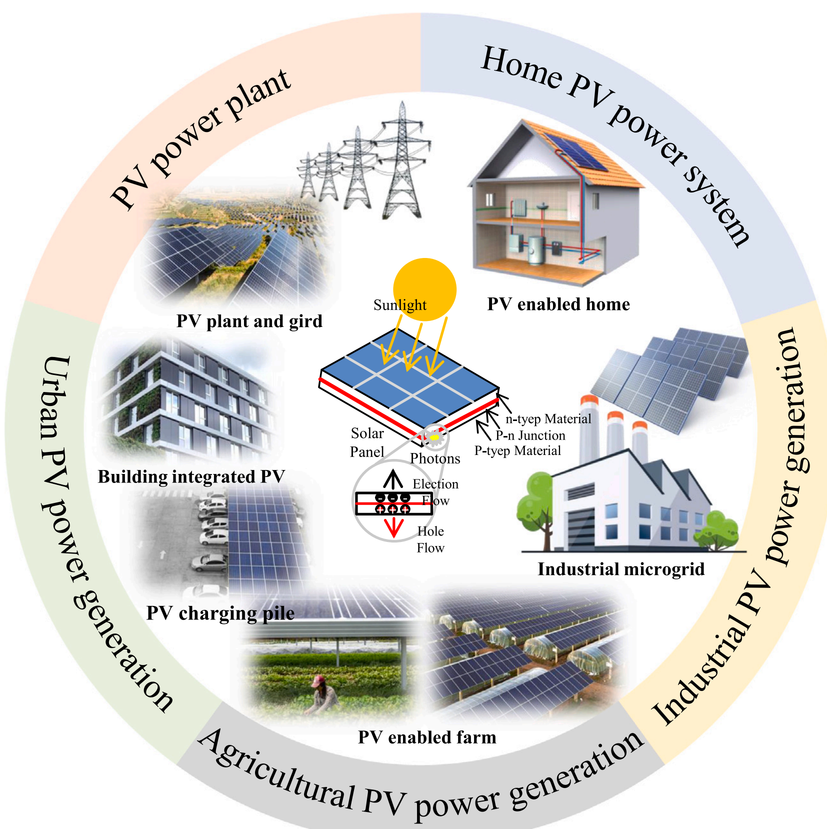

Fig. 1. Principle of PV power generation and its application scenarios.

learning in PV PHM, it is imperative to present a more focused review specifically centered around deep learning methods in PV system PHM. Such an approach would effectively encompass the latest advancements and solutions in this field. Furthermore, readers of review papers not only seek an understanding of the current development status of deep learning in conjunction with PV system PHM but also desire insights into future trends and research areas of interest. Regrettably, existing reviews lack a forward-looking viewpoint of the utilization of deep learning methods in PV system PHM. Therefore, this work addresses the current challenges and issues in this domain while providing a forward-looking outlook. Continuous research endeavors are anticipated to yield further breakthroughs and facilitate the broader application of deep

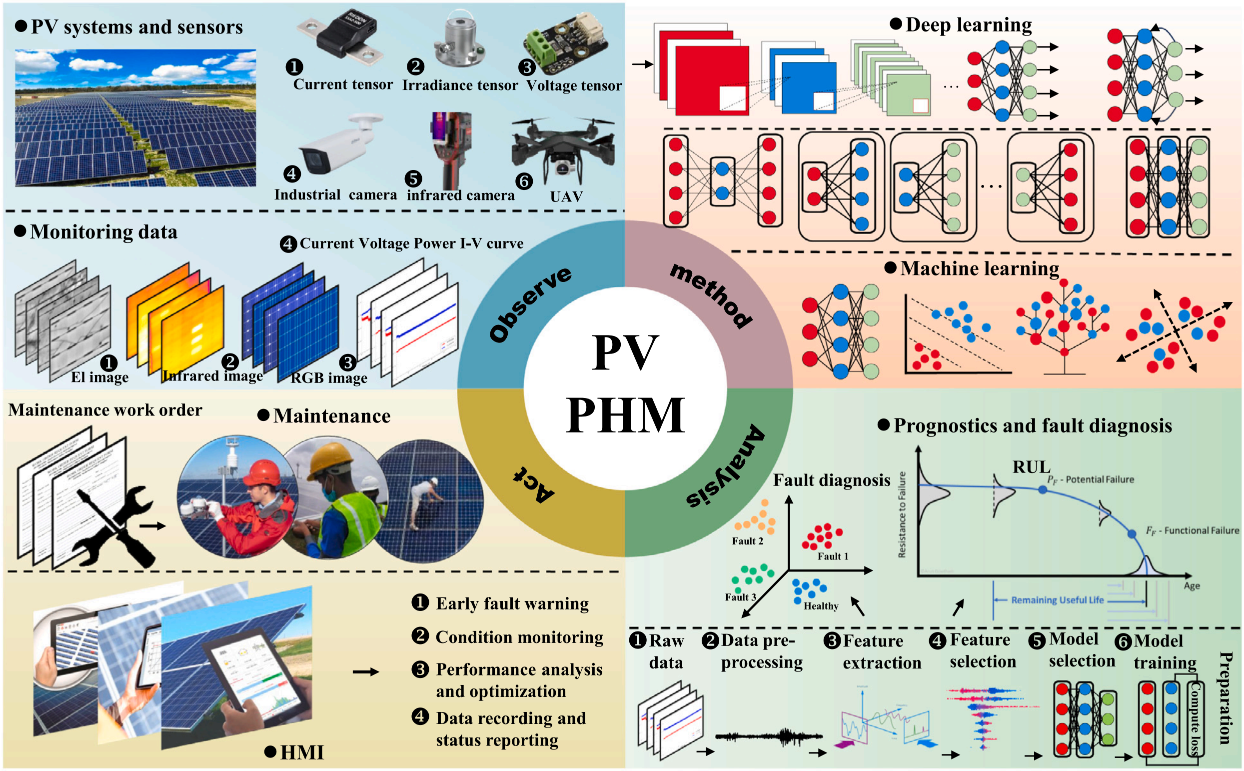

Fig. 2. Overview diagram of PHM for PV systems.

learning in PV PHM. Primary contributions of our research can be succinctly recapitulated as follows:

1. This research has compiled and briefly introduced the common types of monitoring data, fault types, and degradation patterns in PV system PHM. Additionally, this work has summarized an open-source dataset abstract to promote the development of this field.

2. This research particularly emphasizes the application of deep learning algorithms in PV system PHM. We explore the adaptability of deep learning, highlighting its capability of self-adjustment and extracting complex features from data when faced with the nonlinearity, complexity, and environmental variability characteristics of PV systems.

3. Additionally, this work addresses the challenges in PV system PHM, such as limited labeled samples and domain drift, and explore how to employ various deep learning models to mitigate and overcome these challenges, considering limited computational resources.

This research has reviewed the PV system's PHM tasks and various deep neural network (DNN) models that have been employed for PV PHM. Section 2 offers an introduction to the fundamental tasks of PHM, followed by a summary of deep learning frameworks for PV system PHM and a statistical analysis of relevant work in Section 3. Section 4 outlines utilizations of various deep learning architectures in PV system PHM. Finally, Section 5 concludes by providing a summary of the challenges addressed in this work and offering insights into potential avenues for future research.

2. Prognostics and health management of photovoltaic systems

The tasks of PHM in PV systems are vital for optimizing system performance and reliability. PV system PHM mainly focuses on the following aspects, including data observation, model construction, analysis and evaluation, as well as taking actions, as shown in Fig. 2. In the following discussion, this work will focus on the three most core parts of the PV system PHM task: condition monitoring, fault detection and diagnostics, degradation analysis and prognostics. These tasks collectively exert significant influence on comprehensive health management of PV systems.

2.1. Condition monitoring

To comprehensively evaluate the health status of solar PV systems, it is crucial to perform timely and efficient real-time monitoring of the signals emanating from the system [11]. Signal monitoring serves as the foundation for model construction, analysis and action by providing a wealth of real-time data, as shown in Fig. 2. Additionally, the quality of monitoring signals is highly correlated with effectiveness of the PV PHM's core focusing tasks, such as fault diagnosis, degradation analysis, and remaining life prediction.

With the rapid advancement of information technology, the trend of utilizing the IoT technology for equipment management has become increasingly prominent. Integration of IoT technology with sensor sensing, internet connectivity, and intelligent platform technology facilitates comprehensive data collection, real-time transmission, and intelligent processing [12–16]. This provides convenience for the collection of data signals. Monitoring signals frequently encountered in practical scenarios can be broadly classified into circuit signals, environmental signals, and image signals. Next, this research will list some of the more common types of signals:

- **Voltage:** PV system voltage data, essential for performance evaluation and fault diagnostics, captures dynamic variations linked to solar irradiance and temperature [17].
- **Current:** PV system current data, reflecting the rate of electric charge flow within the system, offers valuable operational insights influenced by factors like solar irradiance, temperature, and system configuration [18].
- **I–V curve:** I–V curve is depicted of a two-dimensional graph, with the x-axis representing current and the y-axis representing voltage. It conveys circuit data more densely than time-series current and voltage data, facilitating the extraction of multiple features for subsequent analysis [19].

- **Power:** PV system power data records the electrical output, representing energy generation, offering real-time insights into system efficiency and aiding in the identification of underperforming modules or potential faults [20].
- **Temperature:** PV system temperature data records the system's operating temperature, essential for assessing performance and health. It identifies hot spots or thermal anomalies indicating module issues [21].
- **Irradiance:** PV system irradiance data measures incident solar radiation on the system's surface [22], vital for assessing system performance and characteristics. It represents available solar energy for electricity conversion, varying with time, seasons, and location.
- **Humidity:** PV system humidity data measures moisture content in the ambient air, offering insights into atmospheric conditions affecting system performance [23]. It quantifies water vapor in the air as a percentage relative to saturation.
- **Infrared image:** Infrared imaging captures and represents the thermal distribution of objects via infrared radiation [24,25], utilizing infrared cameras or sensors to convert emitted infrared radiation into visual images. It reveals thermal energy, distinct from visible light, making it a valuable image signal type.
- **RGB image:** RGB images, a common image signal [26], capture red, green, and blue color channels from visible light sensors, forming color images. They offer detailed information for observing and analyzing features and faults on PV system surfaces, particularly in diagnosing surface contamination faults, often acquired via drones.
- **Electroluminescence image:** In the context of PV system PHM, electroluminescence (EL) imaging represents an efficient and rapid choice. It leverages the detection of luminescent characteristics in PV components under the influence of an electric field, facilitating the swift identification of potential faults such as circuit connectivity issues, localized hot spots, and crystalline defects.

For a clearer demonstration, this research has listed these common monitoring signals in Table 1. By monitoring signal parameters in PV systems, such as current, voltage, temperature, etc., it is possible to promptly detect fault phenomena such as circuit malfunctions and abnormal high temperatures. Through in-depth analysis of signal data, engineers can accurately determine the specific nature of the fault, precisely locate it, and assess its severity. Furthermore, real-time data regarding functionality in PV system can be acquired, thereby evaluating the system's health status.

Table 1
Classification of typical monitoring variables in PV systems.

Signal type	Categorization	Unit	Ref.
Voltage	One-dimensional time series data	V	Lu et al. [27] Seghiour et al. [28] Eskandari et al. [29] Lu et al. [30] Van et al. [31] Mustafa et al. [32] Aziz et al. [33] Harrou et al. [34]
Current	One-dimensional time series data	A	Lu et al. [27] Seghiour et al. [28] Lu et al. [35] Chen et al. [36] Eskandari et al. [29] Van et al. [31,37] Mustafa et al. [32] Gao et al. [38]
Power	One-dimensional time series data	kW	Seghiour et al. [28] Hong et al. [39] Guo et al. [40] Hong et al. [41] Aziz et al. [33] Harrou et al. [34]
Temperature	Environmental data	°C	Seghiour et al. [28] Chen et al. [42] Van et al. [37] Guo et al. [40] Mustafa et al. [32] Aziz et al. [33] Kapucu et al. [43]
Irradiance	Environmental data	W/m^2	Seghiour et al. [28] Chen et al. [42] Van et al. [37] Guo et al. [40] Mustafa et al. [32] Aziz et al. [33] Hajji et al. [44]
Humidity	Environmental data	g/m^3	Yu et al. [45] Guo et al. [40] Kapucu et al. [43]
I–V curve	Image data	NA	Yu et al. [45] Chen et al. [42] Liu et al. [46] He et al. [47] Van et al. [37] Ding et al. [48] Mellit et al. [49] Lin et al. [50] Akram et al. [51] Fadhel et al. [19]
Infrared image	Image data	NA	Manno et al. [24] Haidari et al. [25] Kellil et al. [52] Korkmaz et al. [53] Adel [54] Akram et al. [55]
RGB image	Image data	NA	Venkatesh et al. [26] Naveen et al. [56] Sizkouhi et al. [57] Espinosa et al. [58] Qian et al. [59]
EL image	Image data	NA	Et-taleby et al. [60] Sohail et al. [61] Akram et al. [62] Tang et al. [63] Zhang et al. [64]

2.2. Fault detection and diagnostics

Fault detection and diagnostics in PV systems are centered on identifying any anomalies that may occur within the system. This task entails real-time monitoring and data analysis to detect deviations from normal operation. Through timely diagnosis, engineers can effectively identify and address faults in PV systems, thereby mitigating potential economic losses associated with these faults.

The failures observed in PV systems can stem from a multitude of factors, encompassing physical, electrical, and environmental aspects [65–68]. The physical faults in PV systems encompass a range of issues pertaining to the physical integrity of PV cells, including internal damage, abnormal high temperature (hot spots), and module rupture or damage. Environmental conditions can also contribute to faults, such as shading and soiling caused by external factors or contamination. On the other hand, electrical faults arise from deviations in current flow along the predetermined path or circuit anomalies, such as open-circuit faults, line-to-line faults, grounding faults, arc faults, etc. In the forthcoming section, this research will present a comprehensive overview of the predominant fault categories commonly encountered in empirical investigations.

- **Hot spots:** Hot spot faults in PV cell arrays result from localized high-temperature regions within cells or modules, typically due to local current overload [69]. These anomalies can stem from various issues, including damage, cracks, or poor contacts within the PV module, leading to hot spot formation [70]. Elevated temperatures in these regions reduce power generation capacity, increasing power losses and impacting overall electricity output of the PV cell array [71]. Moreover, the high temperatures linked to hot spot faults can induce PV cell or module degradation and safety hazards, such as fire incidents [72].
- **Cells Crack:** Cracks in PV solar cells are a common type of physical failure, mainly due to the stress generated during welding and the collision between the manufacturing process. The presence of cracks results in a significant power loss, more than 2.5% of the solar cell's output power. In addition, evidence from Dolara et al. [73] indicates that the yearly deterioration rate of PV modules caused by PV microcracks is about 0.2%, so crack failures need to be detected and maintained in time.
- **Shading fault:** Shading faults in PV modules or solar panels result from environmental shadows, which fall into two categories [74]: solid object shadows (e.g., from buildings, dust, or trees) and atmospheric shadows (e.g., from smoke or clouds). Furthermore, certain

atmospheric pollutants, such as nitrogen dioxide, can also impact solar irradiance, subsequently resulting in shading effects [75]. These shaded areas significantly reduce sunlight-to-electricity conversion efficiency [76]. Shadow shading can disrupt PV array module operation, causing temperature variations and potential hot spot issues in components [74].

- **Soiling:** The soiling fault in PV modules refers to the influence exerted by various pollutants at exterior of PV panels, often induced by environmental factors. This common issue significantly impacts PV module performance and efficiency [76]. Dirt accumulation reduces power generation efficiency in the PV array, decreasing overall electricity output and affecting the economic viability and return on investment of PV projects [65]. Additionally, the presence of dirt can cause PV modules to overheat, potentially leading to hot spot faults [77].
- **Line–line fault:** Line–line failures in PV arrays are common electrical issues resulting from abnormal contact between PV cells or between cells and circuits. Such faults typically manifest either within the same string or across neighboring strings [78]. Short circuit faults in PV systems can stem from factors like cell damage, cable insulation failure, or unintended low-impedance current paths. These failures have a significant impact on PV cells, bypass diodes, and even entire components.
- **Open-circuit fault:** Open-circuit faults, categorized as electrical faults, involve the occurrence of an open circuit between PV cells or between cells and the circuit. These faults may arise from factors such as cell fracture, aging, high temperatures, fuse melting, or solder joint failure [79]. Open-circuit faults hinder energy transfer to the load or grid, leading to power losses in the system [51]. Furthermore, they can cause abnormal system voltages, impacting other components' operation and potentially compromising PV array safety and stability [80].
- **Arc fault:** Arc failures in PV systems refer to the unexpected flow of current through air or other media, and these failures can be caused by poor electrical connections between parallel modules of the battery. Persistent electric arcs can produce high-temperature plasma, which can cause significant damage to system components and pose a fire hazard [81].

The above list provides some commonly investigated fault types in research, which are more clearly shown in Table 2. Identifying fault types is one of the primary tasks in fault detection and diagnostics. In practical scenarios, PV systems may experience multiple faults simultaneously, and the same fault can exhibit varying degrees of severity (such as short circuit faults under different mismatch rates or shading faults at different levels). The exploration of the physical location where faults occur is also worthy of investigation. This imposes higher requirements on the fault diagnostic performance of PV systems.

By employing fault diagnosis techniques, operators can effectively oversee the condition of PV systems and promptly identify any faults or anomalies. This enables the implementation of proactive health management strategies for the PV system, thereby preventing significant damage resulting from failures, minimizing system downtime, and promptly addressing the economic losses associated with such failures.

2.3. Degradation analysis and prognostics

PV components or the entire PV array undergo gradual degradation over time as a result of prolonged usage and environmental factors. This degradation leads to a decline in performance and a reduction in economic benefits [87]. Furthermore, the degradation not only escalates the risk of faults but also significantly impairs the proper functioning of the PV system. To address this, it is crucial to conduct timely analysis of the degradation degree and pattern of the PV system, as well as predict its remaining useful life.

Degradation analysis primarily focuses on monitoring changes in performance indicators of the PV system, which helps identify the types and degrees of degradation in the system's components [88]. The results of degradation analysis exert significant influence on predicting remaining lifespan and prognostics of PV systems [89]. This prediction can be achieved through the utilization of data-driven models or PV models [90,91]. By conducting degradation analysis and prognostics, the health condition of the PV system will be assessed, facilitating informed decisions regarding maintenance or replacement strategies.

Through an analysis of the relevant works [88,92–94], this research has summarized some of the main degradation patterns, which include frame deformation, packaging material degradation, delamination, loss of adhesion, interconnect degradation, moisture intrusion, etc. These degradations can be caused by environmental causes such as wind, vibration, temperature fluctuations, oxidation, corrosion, collisions during installation, transportation, poor sealing, improper support, and aging of internal components over time, such as failure of sealing of packaging materials or connecting components, degradation of backpieces and other components.

Under different degradation modes, the extent and rate of degradation in PV systems often exhibit variations. By identifying the specific degradation mode, operators can undertake appropriate measures to enhance the maintenance of PV system's health status. The determination of degradation modes requires the analysis of specific indicators to ascertain the degradation mode, extent, and predict the remaining service life. By analyzing changes in performance indicators, degradation modes, degree of degradation, and predicted remaining service life can be determined. In accordance with the International Electrotechnical Commission (IEC) standard IEC 6172 [95], and in conjunction with other Refs. [88,96–98], the following performance indicators can be used: final power generation [99], reference irradiance [100], performance ratio [88], system efficiency [98], capacity factor [101], degradation rate [102]. Different indicators contain distinct information about the PV system. The selection of indicators should be based on the specific circumstances and issues at hand. Through the analysis of these indicators, engineers can determine the state of the PV system, determine the degree of degradation, and further predict the remaining useful life.

By conducting degradation analysis and prognostics, operators gain valuable in-sights into the factors influencing the decline in PV system performance. This knowledge allows for timely interventions to mitigate degradation, avoid the risk of faults, and ensure long-term performance sustainability.

3. Deep learning and prognostics and health management in photovoltaic systems

3.1. Conventional machine learning in PV systems' PHM

Modern PV systems are distinguished by their high complexity, encompassing numerous interconnected components and electronic elements. Consequently, the development of a robust and efficient framework for PHM becomes imperative. Such a framework should enable early fault detection, health status assessment, and facilitate decision-making and maintenance planning. The emergence of the Internet has brought forth a wealth of data and enhanced computational capabilities, thereby presenting novel opportunities for PHM in PV systems. Various machine learning techniques have been employed, including artificial neural network (ANN) [103], support vector machine (SVM) [104], random forest (RF) [105,106], etc. However, the utilization of these methods necessitates expert expertise and previous domain experience to manually identify pertinent characteristics [107]. Fadhel et al. [19] conducted various experimental tests on PV systems under healthy and faulty conditions to extract features and construct a database. Following this, principal component analysis is utilized for examination of these attributes. The proposed diagnosis approach is

Table 2
Classification of typical faults in PV systems.

Fault type	Categorization	Description/Caused	Ref.
Line–line fault	Electrical fault	The occurrence of damage or short-circuits in internal circuitry components within the inverter, or instances of short-circuiting or suboptimal electrical contact between two power lines.	Lu et al. [27] Seghiour et al.[28] Eskandari et al. [29] Lu et al. [30] Chen et al. [42] Liu et al. [46] Lu et al. [35] He et al. [47] Van et al. [37] Hong et al. [39] Ding et al. [48]
Open-circuit fault	Electrical fault	Degradation, wear, or loosening of cables or connectors, as well as damage to PV components like diodes and relays.	Yu et al. [45] Lu et al. [27] Eskandari et al. [29] Lu et al. [30] Chen et al. [42] Lu et al. [35] He et al. [47] Van et al. [37] Hong et al. [39] Ding et al. [48]
Arc fault	Electrical fault	The occurrence of elevated temperature and high-energy discharges within PV panels, cables, connectors, or other associated components.	Lu et al. [82] Chen et al. [36] Gao et al. [38] Jalli et al. [83] Fadhel et al. [19]
Hot spots	Environmental fault	Material non-uniformity, suboptimal electrical connections, and the deterioration of PV components in the course of the manufacturing procedure.	Manno et al. [24] Haidari et al. [25] Korkmaz et al. [53] Bakir et al. [84] Herraiz et al. [85]
Shading fault	Environmental fault	The shading effects produced by structures, vegetation, or other objects.	Yu et al. [45] Chen et al. [42] Liu et al. [46] Lu et al. [35] He et al. [47] Van et al. [37] Ding et al. [48]
Soiling	Environmental fault	Airborne contaminants encompassing dust, particulate matter, and naturally occurring environmental elements like tree leaves, pollen, and avian excreta.	Van et al. [37] Korkmaz et al. [53] Mellit et al. [49] Espinosa et al. [58] Solórzano et al. [74]
Cells crack	Physical fault	Mechanical stresses incurred during the processes of manufacturing, transportation, and installation, as well as external factors including severe weather conditions and collisions.	Venkatesh et al. [26] Korkmaz et al. [53] Sohail et al. [61] Akram et al. [62] Chen et al. [86] Zhang et al. [64] Espinosa et al. [58] Qian et al. [59]

characterized by its simplicity and speed, however, it still necessitates manual feature extraction.

Furthermore, with the continuous advancement of big data technology, traditional algorithms appear to be inadequate when dealing with massive multidimensional and heterogeneous data, making it difficult to meet the demand for efficient processing. Harrou et al. [34] utilized a model-driven approach on diagnosing temporary shading anomalies on DC circuitry of PV systems. Initially, a synthetic model was established utilizing a single diode approach to replicate attributes of monitored PV systems. The residual of the simulated model was then analyzed using a one-class SVM for fault detection. While the model exhibits high detection efficiency, it only focuses on the single dimension of power data. The omission of valuable information pertaining to the PHM of PV systems is a potential concern.

Moreover, the faults in PV systems typically involve intricate nonlinear relationships. Sampurna et al. [108] utilized the decision tree (DT) algorithm to input past power generation data from PV systems and uses error to assist fault diagnosis. The algorithm exhibits the capability to discern abnormalities or irregularities within the input data. Nevertheless, its capacity is limited to the detection of fault occurrences within the PV system, without distinguishing between various complex nonlinear fault patterns. Conventional machine learning approaches may struggle to capture these intricate relationships. Consequently, it is critical to develop advanced analytical tools at a higher level to measure potential features in the data stream in real time.

3.2. Framework of deep learning based PHM in PV systems

Deep learning constitutes a remarkable advancement in the realm of AI and has garnered widespread utilization in various engineering domains. Conversely to traditional machine learning methodologies, deep learning can notice deep, non-linear and complex relationships in data thereby reducing the dependence on domain-specific expertise and manual feature engineering. This not only enhances the spellbinding potential of deep learning but also streamlines the overall process by eliminating the need for laborious manual feature extraction [107]. Furthermore, traditional machine learning methods necessitate multiple stages of data preprocessing and feature engineering, thereby introducing complexity into the overall workflow. In contrast, deep learning models facilitate end-to-end learning and prediction, enabling the seamless transformation of raw input data into final output results within a single step. Owing to its remarkable advantages, deep learning has garnered widespread adoption in the domain of PHM for PV systems. Through an extensive review of the relevant works, as shown in Fig. 3, this research has synthesized a comprehensive framework for deep learning-based PHM in PV systems:

Data generation: The process of data generation could be conceptually subdivided into two core steps: data acquisition and subsequent analysis and processing, which are essential for obtaining inputs suitable for deep learning models. In Section 2.1, various types of raw data have been elucidated, encompassing measurements such as current, voltage, IV curves, power, temperature, humidity, and irradiance, which can be acquired through pertinent sensors. Additionally, inverters can provide access to current, voltage, IV curves, and power data [30,31]. Temperature, humidity, and irradiance data pertaining to the environment can be obtained from satellite data or environmental monitoring stations [37]. RGB images and infrared images can be captured using cameras and infrared cameras, respectively [26,55]. To enhance the performance of the models, it is often imperative to preprocess the raw data, employing techniques such as feature reconstruction, dimensionality reduction, time-domain and frequency-domain signal transformations, among others, to generate the requisite input data for the models.

Model development: The development of models is a critical aspect of the deep learning-based PHM framework for PV systems. The main process can be succinctly summarized as model selection and design, model training, and model evaluation and optimization. Model selection and design entail the careful selection of an appropriate deep learning model, such as CNN [45] or RNN [44], based on the specific tasks of PV system health management. This process also involves designing the network structure of the deep learning model, including determining the number of layers, neurons per layer, activation functions, loss functions, and optimizers. During the model training phase, the preprocessed data is partitioned into training and testing sets, with the training set utilized to train the deep learning model. Throughout the training process, the model parameters are

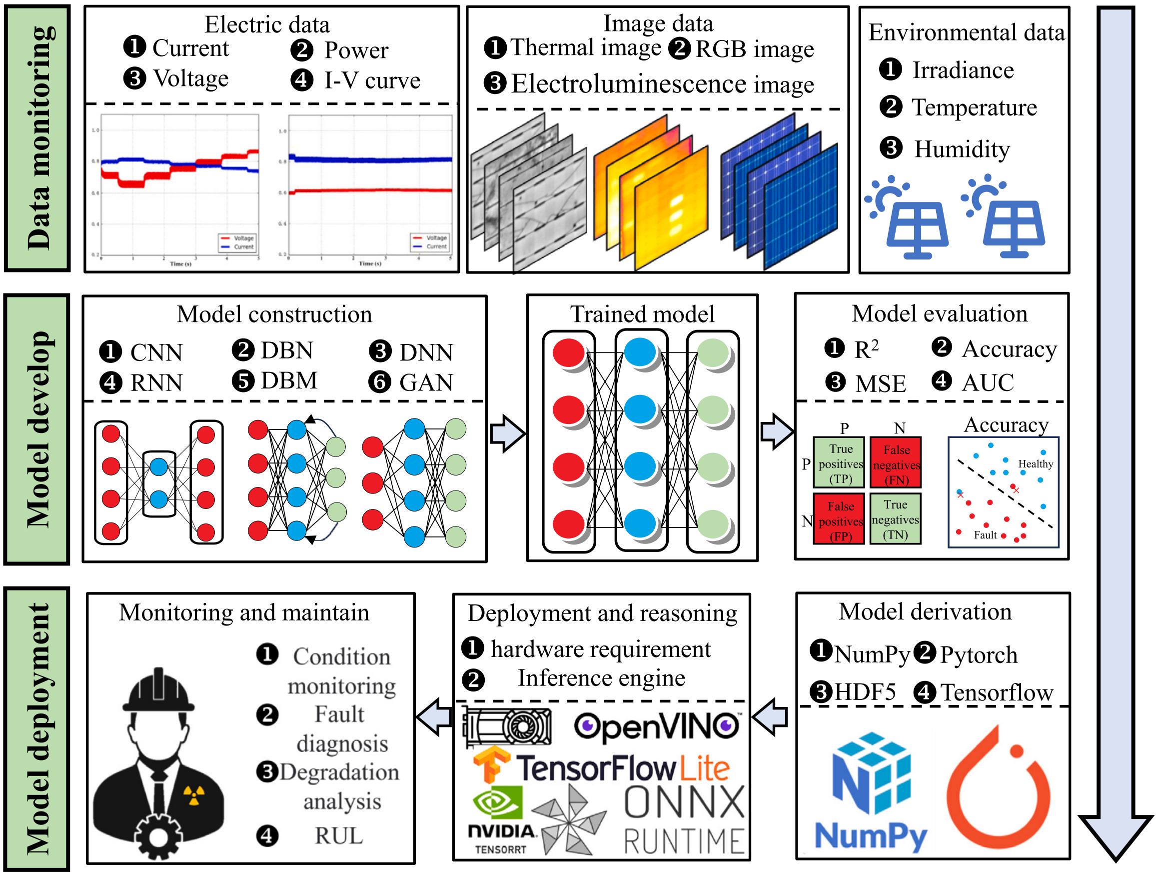

Fig. 3. PHM framework flow chart based on deep learning in photovoltaic system.

iteratively adjusted using the backpropagation algorithm to minimize the discrepancy between the predicted outputs and the true labels. Model evaluation and optimization encompass the assessment of the trained deep learning model's performance using the testing set. On the basis of the evaluation results, the model can be further optimized by fine-tuning hyperparameters, incorporating regularization techniques, and employing other strategies to enhance the model's generalization capability.

Model deployment: Model deployment is the intricate process of implementing a trained deep learning model in real-world production environments. This multifaceted process encompasses crucial steps such as model exporting and saving, deployment and inference, as well as monitoring and maintenance. Model exporting and saving entail the imperative task of exporting and preserving the trained deep learning model in a file format prior to deployment, thereby facilitating its seamless integration into production environments. Various deep learning frameworks offer dedicated functionalities for saving models, typically consolidating the model's architecture and parameters into a single file. Deployment and inference encompass the pivotal stages of loading the model into the designated environment and executing inference through forward computation. This entails feeding preprocessed data into the model and extracting the model's output results. Following deployment, it becomes indispensable to vigilantly monitor and maintain the model to ensure its unwavering stability and reliability. This encompasses the regular monitoring of the model's operational status, adeptly handling exceptional circumstances, and undertaking model updates and maintenance as necessary.

The performance of deep learning models in PV system health management heavily relies on the quality and richness of the training data. To facilitate readers' access to data, enabling them to develop new models with these datasets and thus advancing our research field, this research has compiled a freely accessible and downloadable (or available on-demand) dataset summary, including clear information on data acquisition methods, as presented in Table 3. These datasets are sourced from real-world industries or obtained through simulations. This research particularly recommends researchers to focus on the actual data generated in real industries. Actual data reflects the complexity and variability of the real world, resulting in models trained with greater realism and robustness. This authenticity is difficult to fully replicate with simulated data, which often rely on simplified assumptions and models. Furthermore, the actual data from the industry covers a wide range of operating conditions and failure modes, providing rich learning scenarios for the models and enhancing their generalization capabilities. In contrast, simulated data may not comprehensively simulate all possible situations and variations.

3.3. Bibliometric analysis

This research implemented comprehensive research by utilizing online search tools including Web of Science, and ScienceDirect, etc. The search was performed using keywords such as "photovoltaic system" OR "Prognostic and Health Management" OR "fault diagnosis" OR "remaining life prediction" and specific names of deep learning networks. This search retrieved a total of 506 articles published between 2016 and September 2023. A meticulous screening process was applied to eliminate duplicate studies. Following the application of the subsequent exclusion criteria, a cumulative of 465 studies were retained for analysis: (i) Excluding non-research papers such as books, patents, reports, and relevant work reviews; (ii) Publications failing to present performance outcomes have been excluded from consideration.

Table 3
Public dataset for PV health management.

Source	Description	Data type	Amount of data	Fault type	Link
Simulation	The dataset simulates 250 kW PV power station operations, providing 600-instance training set features 30 electrical parameters and a category column. The sampling rate for data collection is 750 Hz.	Tabular data	600 cases	• Line–line fault	https://github.com/amrrashed/Fault-Detection-Dataset-in-Photovoltaic-Farms
Industrial scenario	The dataset comprises 600 PV modules with hotspot faults, categorized into six types, featuring three electrical parameters per sample. The sampling rate for data collection is 1 Hz, which means sampling once per second.	Tabular data	600 samples	• Hotspot	https://github.com/ErikJhones/Self-Organizing-Map-SOM-with-KNN/tree/main/data
Industrial scenario	The dataset includes 36,543 near-infrared images with different defects and backgrounds, encompassing 1 normal and 12 abnormal image classes.	EL image	40 358 samples	• Finger • Crack • Blackcore • Thickline • Corner • Scratch • Etc.	https://github.com/binyisu/PVEL-AD
Simulation	The dataset covers 16 days of operational and fault data from a grid-connected PV station with two strings of 8 C6SU-330P PV modules each.	Tabular data	1 373 798 samples	• Short circuit • Degradation • Open circuit • Shadowing	https://github.com/clayton-h-costa/pv_fault_dataset
Industrial scenario	This dataset records electrical parameters and environmental information at different timestamps, reflecting actual operating conditions.	Tabular data	3000 samples	• Line–line fault • Open circuit	https://github.com/benjamin2044/PV_fault_Python
Simulation	The dataset is simulated under experimental conditions, and the current and point pressure information in the PV is recorded in each timestamp. The sampling rate for data collection is 1 Hz.	Tabular data	32 598 samples	• Hot spot • Short circuit • Vegetation • Shading • Crack	https://github.com/epri-dev/PV-Golden-Datasets/tree/main
Industrial scenario	The dataset, sourced from real industry, includes two EL image datasets for monocrystal and polycrystalline PV panels, each featuring three anomaly levels: mild, moderate, and complete.	EL image	2624 samples	• Anomaly	https://github.com/zae-bayern/elpv-dataset
Industrial scenario	The dataset comprises 1031 EL images of PV panels from industrial applications, exhibiting crack and corrosion anomalies.	EL image	1031 samples	• Crack • Corrosion	https://osf.io/v6pwe

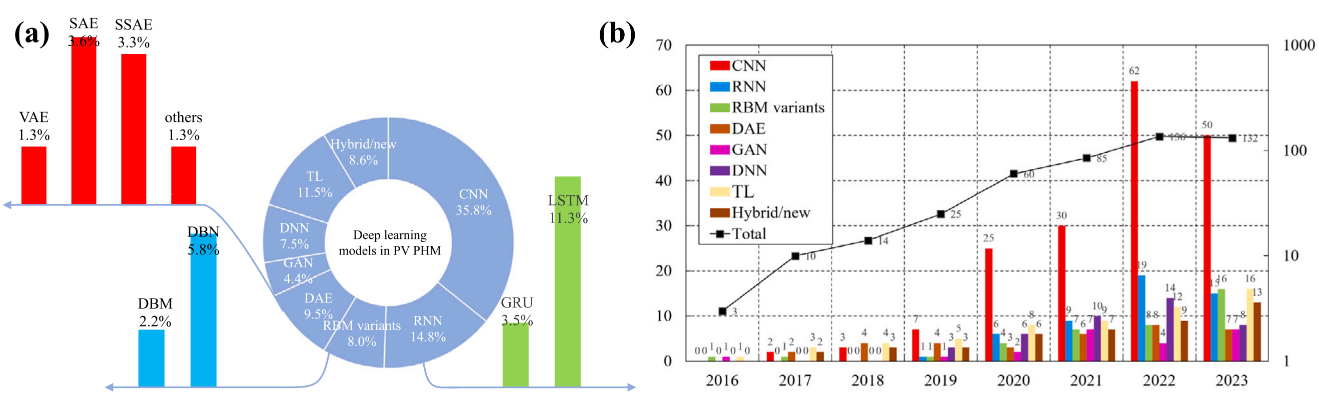

Fig. 4. (a) The proportion of models used in PV PHM from 2016 to September 2023 (b) The amount of individual model applications and total number of all model applications in each year from 2016 to September 2023.

(iii) Papers of insufficient length are excluded from consideration. (iv) Research that has not been validated or experimentally verified is not considered. Fig. 4 shows the number and percentage of PHM utilizations of each model in PV systems.

To acquire a more profound comprehension of the research's structure, a co-occurrence analysis was conducted on 465 selected research papers based on relevant keywords. The keywords encompass various aspects, including PV system health management tasks (fault diagnosis, remaining useful life, condition monitoring, etc.), deep learning models and related tasks (convolutional neural network, recurrent neural network, generative adversarial network, long short-term memory, deep autoencoder, deep neural network, feature extraction, feature selection, etc.), common signal types (I–V curve, infrared image, electroluminescence image, etc.), along with typical fault types (hot spots, open-circuit fault, etc.). Each keyword is depicted as a colored node, with the node's size reflecting the frequency of the term's occurrence in the scholarly studies. Additionally, the link weights between nodes signify the degree of co-occurrence between the associated keywords.

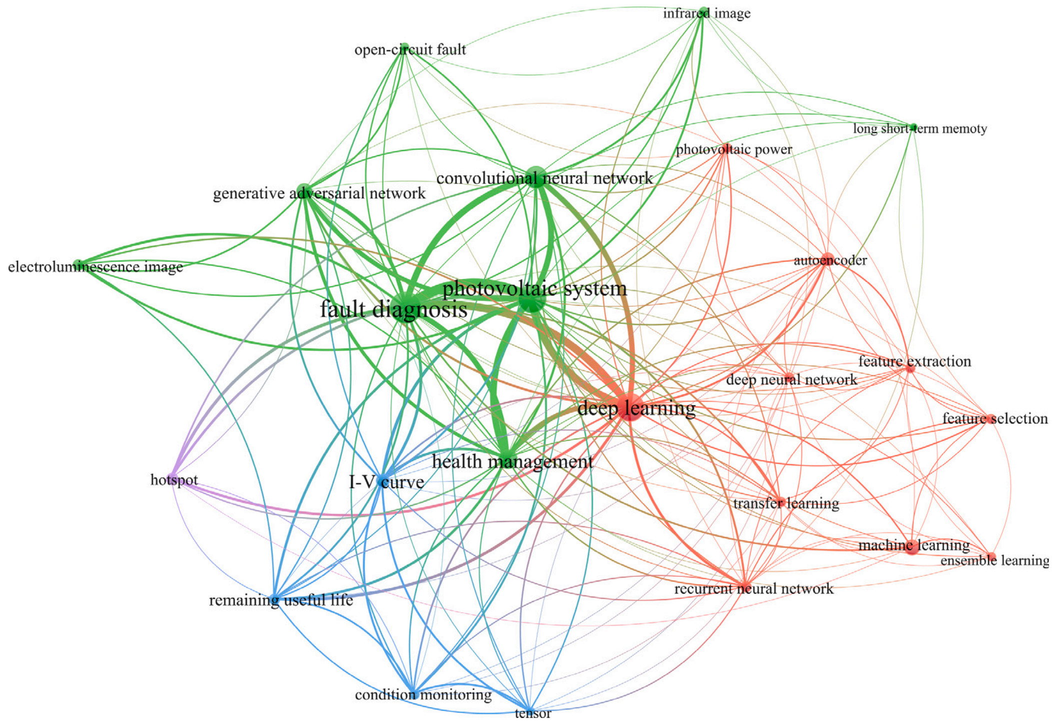

Fig. 5. A visualization of the keyword network connections showing co-occurrence.

VOSviewer employs modular clustering methods to categorize the highly frequent keywords into cohesive clusters. This research has combined keywords that express the same meaning, for instance, replacing "PV" and "PV module" and "PV array" with "PV system" and "fault detection" and "fault classification" with "fault diagnosis", with the aim of reducing superfluous intricacies. The ultimate map consists of three clusters (red, green, blue), where data points sharing identical hues are ascribed to their respective corresponding clusters. This research has assessed the centrality of each keyword to discern the foremost representative keywords within each cluster: condition monitoring (blue), deep learning (red), and fault diagnosis (green). An examination of these keywords and the terminology within each cluster enables an understanding of the interconnections between various tasks and DNNs. For example, "fault diagnosis" appears to be the primary task in PV system health management. The blue nodes represent the proximity of terms such as "condition monitoring", "remaining useful life", "i–v curve", and "sensors", suggesting that state monitoring primarily utilizes sensors to acquire i–v curve data, assess state of PV system, and predict remaining life. Detailed relationship between keywords is shown in Fig. 5, which presents a projection of co-occurrence connections among the top 24 frequently encountered keywords using the VOSviewer software tool. In the ensuing sections, this research shall furnish an detailed exposition of the utilization of different deep learning approaches in PV system PHM, based on the relevant work surveyed.

4. Deep learning models for prognostics and health management in photovoltaic systems

4.1. Deep neural networks

DNNs are a category of ANN which constructed from multiple hidden layers, enabling them to capture intricate data representations [109]. The fundamental principle behind DNNs involves employing successive layers of non-linear transformations to convert input data into an output suitable for classification, regression, or other tasks [110].

Formally, a DNN can be represented as a function $f(\mathbf{x};\theta)$, where $\mathbf{x}$ denotes the input, θ represents the learnable parameters (weights and biases), and f represents the composition of the individual layers. Each layer l in a DNN consists of a set of neurons. In each neuron's operation, the output is computed through the aggregation of weighted inputs originating from the preceding layer, subsequently undergoing a non-linear activation function $\sigma(\cdot)$:

$$\mathbf{h}^{(l)} = \sigma(\mathbf{W}^{(l)}\mathbf{h}^{(l-1)} + \mathbf{b}^{(l)}) \tag{1}$$

where, $\mathbf{h}^{(l)}$ denotes output of the lth layer, $\mathbf{W}^{(l)}$ denotes weight matrix, $\mathbf{b}^{(l)}$ represents the bias vector, and $\mathbf{h}^{(l-1)}$ denotes the input from previous layer.

Training DNNs typically involves the backpropagation algorithm, which involves iteratively adapting network parameters to minimize a loss function. This process mentioned above is accomplished through calculating the gradient of the loss concerning the parameters and updating them using optimization techniques such as stochastic gradient descent. DNNs find extensive application in the domain of PV system health management, facilitating precise tasks such as fault classification, anomaly detection, fault localization, and prediction. Detailed information on these applications is presented in Table 4. These networks contribute to enhancing the reliability and efficiency of PV systems while mitigating losses caused by faults [111–113]. Chen et al. [36] presents a DNN-based methodology to detect arc faults. By utilizing diverse data parameters and attaining high accuracy, the utilized approach effectively extracts features and detects series arc faults. Jalli et al. [83] utilized an anomaly detection strategy on the basis of deep fully connected networks, which introduced modal decomposition and achieved extremely high diagnostic precision. Venkatesh et al. [56] introduces an ensemble-based DNN approach using an image dataset captured by a unmanned aerial vehicle-mounted RGB camera. The utilized approach attains a commendable classification precision of 99.68% in the identification of visual anomalies on PV modules.

4.2. Deep belief network

DBN is a deep learning structure constructed from multiple layers, suitable for unsupervised learning and feature learning tasks [143].

Table 4
Summary of different deep learning models on PHM of PV systems.

Method	Ref.	Advantages	Disadvantages
DNN	Chen et al. [36] Jalli et al. [83] Venkatesh et al. [56]	Different layers are fully connected through parameters. This enables the preservation of more comprehensive information for the PHM of PV systems.	In the PHM calculation of PV systems, DNNs typically require a significant amount of computational resources for training and inference. This poses a significant burden on small-scale PV systems with limited resources.
DBN	Ding et al. [48] Li et al. [114] Massaoudi et al. [115] Wang et al. [116] Liu et al. [117] Tao [118]	In the process of PHM modeling, DBN considers the interaction information between layers, enabling the learning of higher-level abstract features in PV data.	Composed of multiple RBM components, the computational resource consumption of the system is significant, rendering it unsuitable for online PHM in PV systems.
DBM	Ding et al. [48] Nedaei et al. [119] Tao et al. [118] Ni et al. [120] Navarrete et al. [121] Bhuiyan et al. [122]	DBM is an unsupervised learning model that does not require annotated PV training data. This approach significantly saves time and costs while enhancing efficiency.	The training process of DBM is relatively complex and requires the utilization of specific training algorithms, such as contrastive divergence. The application of these algorithms can impact the stability of the model in the PV PHM domain.
DAE	Qian et al. [59] Edun et al. [123] Behrends et al. [124] Liu et al. [125] Gao et al. [126] Jalli et al. [83] Wang et al. [127] Rao et al. [128] Gaggero et al. [129] Chen et al. [130]	DAEs not only have the capability to map high-dimensional data to a lower-dimensional space, thereby enhancing the efficiency of PV PHM tasks, but they can also effectively remove noise from input data by training the model to reconstruct the original data, thereby improving the quality of PV data.	In the context of data dimensionality reduction, when the distribution of the PV PHM data to be compressed differs from the distribution of the training data, the resulting reduced-dimensional data may deviate from the desired outcome.
CNN	Akram et al. [62] Su et al. [131] Manno et al. [24] Sizkouhi et al. [57] Haidari et al. [25] Luo et al. [132] Chen et al. [36] Lu et al. [35] Yu et al. [45] Lu et al. [30] Hong et al. [39]	CNN are effective in processing image data such as thermal maps and EL images in PV systems, as they can capture local features in the input data and achieve local perception of images and spatial data.	Obtaining image data from PV systems is challenging as it requires specialized imaging equipment. This limitation can result in insufficient training data, causing a CNN to become highly sensitive to minor variations in the input data. Consequently, the CNN may fail to meet the stability requirements of PV system PHM tasks.
RNN	Van et al. [37] Guo et al. [40] Veerasamy et al. [133] Reda et al. [134] Fang et al. [135] Gao et al. [136] Zhou et al. [137]	The RNN model excels in handling time series data such as current, voltage, and other related variables in PV systems. It is capable of extracting rich contextual information from the raw data, thereby enhancing the effectiveness of PHM tasks in PV systems.	The training of RNNs is known to suffer from the issue of vanishing gradients, which hinders the capturing of long-term dependencies. While LSTM models have been introduced to overcome this problem, they come with increased computational complexity. On the other hand, GRU models offer improved computational efficiency compared to LSTM, but their simpler structure may limit their ability to handle complex PV PHM problems.
GAN	Lu et al. [138] [139] Lu et al. [82] Gao et al. [38] Lu et al. [27] Lu et al. [140] Bharathi et al. [141] Tang et al. [63] Li et al. [142] Lu et al. [27]	GANs have the ability to generate data, which greatly alleviates the challenge of data scarcity faced by PV system PHM.	The training of GANs is inherently challenging. It may encounter difficulties in converging to a Nash equilibrium, leading to a significant impact on the quality of generated PV data.

Its design draws inspiration from both probabilistic graphical models and neural networks, combining the advantages of probabilistic inference and hierarchical feature extraction. Through an unsupervised pre-training process, DBN can extract deep features from complex data generated by PV systems, such as voltage data, then they are utilized for health management purposes [117,144–146].

Ding et al. [48] utilized a PV system health status assessment method rooted in DBN and Hausdorff distance. This methodology attains satisfactory fault identification precision, and achieves good performance in classification of different fault types. Massaoudi et al. [115] propose an ensemble learning model and enhance the final output with DBN's metamodel layer. The lowest mean root error are achieved, which proves the stability of PV PHM application. Wang et al. [116] introduced a new hybrid diagnosis approach for power transformers, which utilizes a radio frequency identification devices and DBN for feature extraction to achieve reliable data acquisition and high diagnostic accuracy. Liu et al. [117] proposed a DBN based cluster modeling method for PV power plants. The dynamic equivalent modeling of PV cluster is carried out by using DBN algorithm. The model's validity and accuracy have been corroborated across three distinct perturbation scenarios. Although the research did not involve real-time fault diagnosis for PV systems, such efficient simulation techniques can expedite the evaluation of PV system performance and behavior, contributing to the timely detection and prediction of potential issues or faults.

DBN have demonstrated excellent performance in handling complex high dimensional data and possess strong feature extraction capabilities. With the advent of more advanced deep learning structures, such as CNN, the application of DBNs has gradually decreased in certain tasks. Nevertheless, the contribution of DBNs to the development of deep learning cannot be overlooked, and they still find wide application in the field of PV system health management. Table 4 presents a summary of applications of DBNs in PV PHM.

4.3. Deep Boltzmann machines

Deep Boltzmann machine (DBM), as an unsupervised learning model, has the capability to autonomously derive meaningful feature representations from unlabeled signals, which can be utilized in subsequent supervised learning tasks such as classification and regression [147]. Due to their excellent feature extraction capabilities, DBMs have also been applied in the domain of health management tasks for PV systems.

Ding et al. [48] extracts utility features from I–V features using feedforward neural networks with multiple stacked DBMs. The output results are then linked to conditions of PV system to assist the PHM. The obtained results show excellent performance. Nedaei et al. [119] applied restricted Boltzmann machine (RBM) for automatic feature extraction and combined a multi-class SVM classifier and RF algorithm at each layer. The simulation outcomes demonstrate a capability to achieve a 100% accuracy rate in fault identification and categorization of various short-circuit faults. Tao et al. [118] introduced a PHM approach based on DBM. In consideration of the network parameters, a genetic algorithm is employed for optimization. The results show that its accuracy is better than genetic algorithm, SVM and DBN optimized backpropagation algorithm. Ni et al. [120] used DBM to establish a correlation between healthy samples and training data, so as to identify faults. Simulation results confirmed satisfactory precision and high stability of the method. In [121], authors introduce a shadow detection framework for PV systems, using the contrast divergence method to train each pair of adjacent layers to RBM. The findings indicate the enhanced efficiency of the proposed methodology in comparison to conventional neural network approaches. Bhuiyan et al. [122] utilized deep learning algorithm on the basis of RBM to detect fault in PV inverters. The algorithm utilizes supervised and unsupervised hierarchical learning to extract features from a given data. The findings indicate that the diagnostic precision for 22 distinct inverter conditions attains a level of 99.78%. Research pertaining to the utilization of DBMs in PV PHM applications are documented in Table 4.

The examples discussed above illustrate the effectiveness of DBMs in the application of health management in PV systems. The training process of DBMs typically involves unsupervised greedy layer-wise pretraining, where each Boltzmann Machine is trained sequentially, followed by a global fine-tuning. This allows DBM to capture the high order correlation of PV current, voltage, power and other data, providing a future application opportunity in PV PHM.

4.4. Deep autoencoders

DAE is an unsupervised learning algorithm used for data dimensionality reduction and feature extraction [148]. It is constructed from an encoder and a decoder, as shown in Fig. 6, where the encoder is responsible for the transformation of input data into a lower-dimensional latent space, while the decoder is tasked with the reconstruction of the representation from the latent space back to the original data. The aim of an DAE is to minimize reconstruction error, enabling the decoder to accurately reproduce the original data [149].

The following represents the fundamental equations of an DAE:

Encoder:

$$\mathbf{h} = f(\mathbf{W}_e\mathbf{x} + \mathbf{b}_e) \tag{2}$$

Decoder:

$$\hat{\mathbf{x}} = f(\mathbf{W}_d\mathbf{h} + \mathbf{b}_d) \tag{3}$$

Reconstruction Error:

$$\text{Loss} = \frac{1}{N}\sum_{i=1}^{N}(\mathbf{x}_i - \hat{\mathbf{x}}_i)^2 \tag{4}$$

In the following equations, $\mathbf{x}$ represents the input data vector, $\mathbf{h}$ denotes the output of the encoder, $\hat{\mathbf{x}}$ signifies the output of the decoder, The symbols $\mathbf{W}_e$ and $\mathbf{W}_d$ denote the weight matrices pertaining to the encoder and decoder, respectively, whereas $\mathbf{b}_e$ and $\mathbf{b}_d$ signify the bias vectors associated with the encoder and decoder. The function $f(\cdot)$ denotes the activation function. Additionally, $\mathbf{x}_i$ represents ith sample of input data, $\hat{\mathbf{x}}_i$ corresponds with the reconstructed output of respective sample, and N denotes the number of samples.

Traditional deep learning structures often call for a significant quantity of annotated data to achieve satisfactory performance in the PHM of PV systems. However, obtaining a large volume of accurately labeled data in PV systems can be challenging and costly. In this context, DAEs offer a valuable advantage as they can be trained in an unsupervised manner, making them particularly favorable when data lacks labels or labeling is prohibitively expensive [28]. By employing DAEs, low-dimensional representations of the data can be learned automatically, facilitating feature learning. These learned representations can be effectively utilized for different missions, such as classification and prediction within the PV health management domain [144,150]. Compared to supervised learning paradigms used in conventional deep learning models, which heavily rely on labeled data, DAEs demonstrate clear advantages in scenarios with limited labeled data availability. As a result, DAEs have gained significant attention in the field of PV health management [59,83,125,127,128,130,151].

Qian et al. [59] improved the accuracy by combining short-term depth features obtained by stacking denoised autoencoders (SDAE) with long-term depth features extracted from the image dataset via CNNs. This combination produces better results compared to methods alone. Edun et al. [123] uses variational autoencoder (VAE) and spread spectrum time domain reflectometry to detect and locate anomalous data in PV arrays. VAE performs better for imbalanced data, and the method achieves an overall precision of 96% and 99% true positive rate for detecting anomalies. Behrends et al. [124] introduced a VAE algorithm to diagnose residual current anomalies in PV systems. It identifies faults in the presence of external influences. Liu et al. [125] proposes a anomaly monitoring approach for PV arrays on the basis of stacked autoencoder (SAE) and clustering algorithm, achieving high detection accuracy using limited labeled data samples. Gao et al. [126] adopted a multi-model combined fault diagnosis method that incorporates SAE. The method has a high accuracy (99.33%) and outperforms conventional approaches such as softmax, SVM and RF. The applications of DAE is summarized in Table 4.

4.5. Convolutional neural networks

A CNN represents a specific class of ANN commonly utilized in computer vision tasks [149]. The CNN employs convolutional layers to extract features from the input image and learn hierarchical representations of the input. Fig. 7(a) illustrates the fundamental architecture of a CNN. In a convolutional layer, a filter or kernel is convolved across input images to perform mathematical operation known as a convolution. This operation extracts local features from the input, which are then used to build higher-level features in subsequent layers. Through the stratification of multiple convolutional layers, a CNN can progressively acquire more intricate representations of the input data [152].

Mathematically, the convolution operation in a CNN can be represented as:

$$y[i,j] = \sum_m \sum_n x[i+m, j+n] \cdot w[m,n] \tag{5}$$

where x represents the input image, y represents the output feature map, and w represents the convolutional filter.

The pooling operation can be represented as:

$$y[i,j] = \max_{m,n} x[i \cdot s + m, j \cdot s + n] \tag{6}$$

where x is the input feature map, y is the output feature map, and s is the stride. Fig. 7(b) illustrates the convolution and pooling process mentioned above.

The fully connected layers in a CNN can be represented as:

$$y = \sigma(Wx + b) \tag{7}$$

where x represents the input feature vector, W denotes the weight matrix, b signifies the bias vector, and σ stands for the activation function.

Due to its exceptional image processing capabilities, CNNs have been widely employed in two-dimensional image classification and recognition tasks [62,131]. In the field of PHM, specific types of images have emerged, including EL images, infrared images, and RGB images.

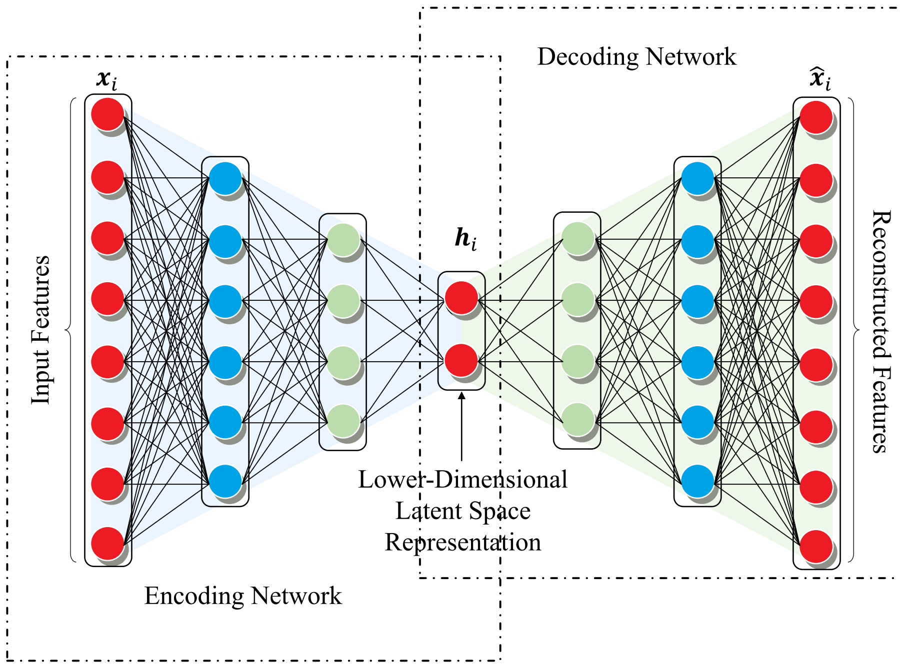

Fig. 6. Architecture of AE.

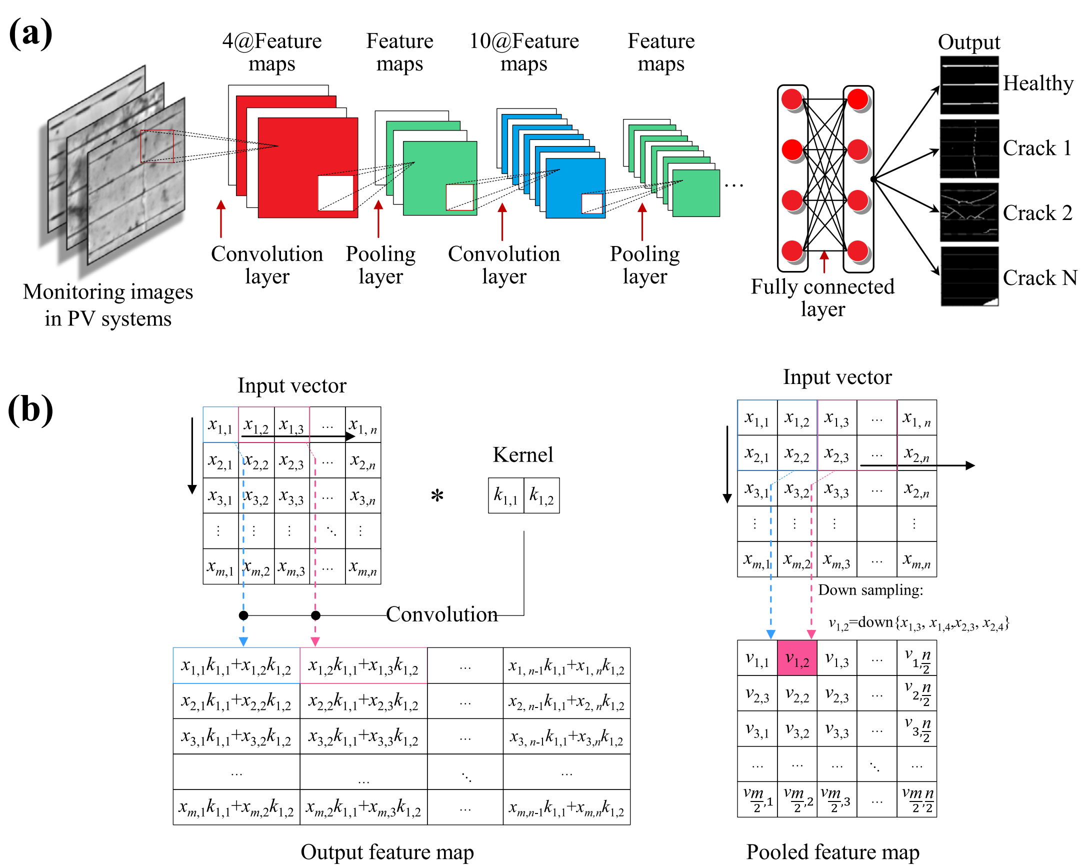

Fig. 7. Illustration of CNN: (a) Architecture, (b) Convolution and pooling process.

EL images are utilized for detecting internal defects and damages within PV panels, while infrared images are employed to identify thermal anomalies associated with these panels. Additionally, RGB images are used to document the general surface condition of the PV panels. CNNs possess a unique capability in extracting significative features from images, rendering them indispensable in the PHM of PV systems [153, 154]. Leveraging the hierarchical and adaptive characteristics of CNN architectures, these models effectively handle the aforementioned image types to accurately identify and address critical issues that may influence performance and dependability of PV systems.

Manno et al. [24] utilized deep learning techniques, including CNN and data augmentation, to perform automatic fault diagnosis on thermal images of PV systems. The proposed method achieved high accuracy in identifying various faults and demonstrated strong applicability in automatic fault diagnosis of PV systems. Sizkouhi et al. [57] utilizes a captured RGB image dataset as input to a CNN model, where the extracted image features are mapped to a decoder network. This mapping enables precise pixel-level prediction of the pixels covered by bird's drops on PV components. The attained average precision for both training and testing phases is 98% and 93%, respectively. Haidari et al. [25] introduced a investigation method on the basis of CNNs to detect hot spots fault of PV power stations. The processed thermal image is used as input. The results show that the structure can effectively distinguish the faulty module from the healthy module, and the overall accuracy reaches 98%. Luo et al. [132] used three selected CNN models to make certain adjustments to the enhanced PV image dataset, achieving an improvement in classification accuracy of up to 14%.

In addition to utilizing intuitive two-dimensional images, there is a wealth of readily available one-dimensional time series data in PV systems, such as current and voltage signals, among others. These signals carry valuable information about the system's health status and play a crucial role in understanding their overall condition. Therefore, many researchers have integrated these one-dimensional signals with CNN models to effectively extract the information of the health status of PV systems contained within these temporal signals.

Chen et al. [36] introduced an innovative detection approach employing a multi-input CNN. They provided the CNN model with training and testing input consisting of the filtered time-domain current signal and the current signal in the frequency domain following Fourier transformation. The achieved accuracy rate reached 97.48%. Lu et al. [35] introduced a dual-input CNN for open-circuit anomaly detection of PV systems. The important features and fine-grained features are extracted from the current and voltage timing diagrams respectively. These features were then weighted and used for fault classification, with an average detection precision of 99.6%.

In addition to directly inputting these one-dimensional signals, feature reconstruction methods can also be employed to transform them into multi-dimensional images, subsequently processed using CNNs. Yu et al. [45] reorganized multiple one-dimensional time series data, such as current, into two-dimensional time series plots. Subsequently, the CNN algorithm automatically extracted low-level graphical features from the two-dimensional image data for fault diagnosis, attaining an average precision of 97.95%. Based on the time series signals of current and voltage, Lu et al. [30] conducted data normalization and applied a sliding window technique to obtain a series of two-dimensional images. These images were then fed into a CNN model for fault diagnosis. By varying the sliding window size and the number of layers, the maximum accuracy achieved was 99.51%. Hong et al. [39] introduced a innovative approach to detect anomalies in PV systems, leveraging a 3D CNN. Their methodology involves preprocessing both the direct current and alternating current signals within the PV system. This preprocessing operation converts the signal into a three-dimensional image, subsequently employed as input for the CNN model in the context of condition monitoring. The outcomes reveal the superiority of the 3D CNN over conventional machine learning techniques, such as RF and DT, in effectively addressing the targeted problem. Publications related to the application of CNNs in PV PHM are presented in Table 4.

4.6. Recurrent neural networks

A RNN is a category of ANN commonly utilized in time-series analysis tasks. The principle of RNN lies in the introduction of recurrent connections within the network, enabling it to retain memory of previous inputs and propagate this memory to subsequent inputs. The architecture of RNNs is depicted as illustrated in Fig. 8(a).

A simple RNN consists of three layers: the input layer, the recurrent layer, and the output layer. The input layer contains N input units. This layer receives a vector sequence that varies with time t, such as $\{\ldots, \mathbf{x_{t-1}}, \mathbf{x_t}, \mathbf{x_{t+1}}, \ldots\}$, where $\mathbf{x_t} = (x_1, x_2, \ldots, x_N)$, In a fully RNN, the input units establish connections with the hidden units situated within the hidden layer, with the connectivity being determined by means of a weight matrix. The hidden layer consists of $\mathbf{W}_{IH}$ hidden units, denoted as $\mathbf{h_t} = (h_1, h_2, \ldots, h_M)$, which are interconnected over time through recurrent connections. The hidden layer defines the state space or "memory" of the system as:

$$\mathbf{h}_t = f_H\left(W_{IH}\mathbf{x}_t + \mathbf{W}_{HH}\mathbf{h}_{t-1} + \mathbf{b}_h\right) \tag{8}$$

where $f_H(\cdot)$ on behalf of the hidden layer activation function. $\mathbf{b}_h$ symbolize the bias vector of the hidden units. The hidden units are interconnected with the output layer through weighted connections, denoted as matrix $\mathbf{W}_{HO}$. The units $\mathbf{y}_t = (y_1, y_2, \ldots, y_P)$ of output layer P are represented as follows:

$$\mathbf{y}_t = f_O\left(\mathbf{W}_{HO}\mathbf{h}_t + \mathbf{b}_o\right) \tag{9}$$

where $f_O(\cdot)$ is denoted as activation function. While the $\mathbf{b}_o$ represents the bias vector of in the output layer. Due to the temporal continuity of input–target pairs, the aforementioned processes will be repeated with respect to time $t = (1, \ldots, T)$.

RNNs often encounter gradient explosion and gradient disappearance when processing long series data, so two RNN variants, gated recurrent unit (GRU) and Long short-term memory (LSTM), have been developed to improve the modeling ability of long-distance dependencies. The GRU and LSTM cell structures are illustrated in Fig. 8(b).

In current scenario, the applications of EL and infrared images for PV diagnostic and prognostic methods is prevalent. However, the high cost of specialized equipment required to acquire such images makes them economically impractical for small-scale PV systems. As a result, alternative approaches based on one-dimensional time series data analysis offer significant advantages for small-scale PV systems' PHM. One-dimensional electrical data, primarily presented as time series data within PV systems, holds the key to effective PHM. In this regard, RNNs have emerged as a superior choice for handling time series data compared to other deep learning models. Their ability to retain memory and capture temporal dependencies makes them well-suited for PV system health management applications. Therefore, RNNs have garnered extensive attention and adoption within the field of PV system health management, particularly for small-scale systems. Comprehensive application details are documented in Table 4, providing a detailed account of pertinent information. Their deployment allows cost-effective monitoring and predictive maintenance, ensuring optimal performance and longevity of small-scale PV installations.

Van et al. [37] proposed approach utilizes a RNN for PV system faults. The experiment consists of physical PV simulation to generate synthetic training data. By analyzing the balanced classification accuracy and severity estimation MAE, the model can be well generalized to climates other than those of the training data, and the model can also detect unknown faults. Guo et al. [40] introduced a novel quantitative diagnostic approach for detecting faults within PV systems is introduced. This method integrates a clustering algorithm with a transfer LSTM neural network, leveraging experimental data gathered from each individual PV module within the system. Veerasamy et al. [133] propose a novel LSTM-based approach for highly effective high-impedance anomaly detection in PV systems, achieving an outstanding overall detection precision of 91.21%, surpassing established classifiers such as k-nearest neighbors, SVMs, DTs, and naive bayes methods. Reda et al. [134] devised an RNN-based network that effectively identifies individual and combined faults in PV systems, demonstrating high-performance fault detection, precise fault duration estimation, and fault type identification within the PV system. Fang et al. [135] introduced a innovative anomaly detection approach that combines attention mechanisms with RNNs for accurate fault diagnosis

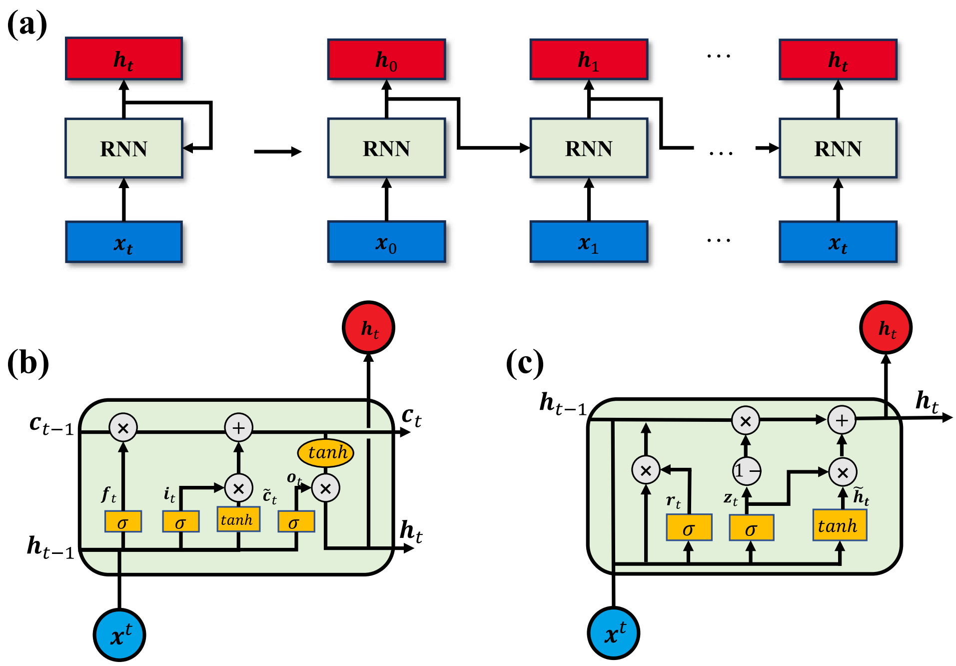

Fig. 8. Illustration of RNN and its variants: (a) RNN architecture, (b) LSTM unit, (c) GRU unit.

and localization, demonstrating both superior diagnostic performance and robustness in noisy PV environments. Gao et al. [136] proposed a residual gated cyclic cell model for fault identification of PV arrays. The model eliminates the need for artificial feature extraction and is unaffected by changes in irradiance. The approach achieved a detection precision of 98.61%, exceeding the performance of other well-known technologies. Zhou et al. [137] introduced an intelligent fault diagnosis method that utilizes RNNs to predict PV power prediction errors and construct fault features, achieving outstanding performance with a F1-score of 94%, showcasing the model's robust capabilities.

4.7. Generative adversarial networks

GAN is a framework composed of a generator network and a discriminator network [155], as shown in Fig. 9. The generator network learns the characteristics of the data distribution to generate samples that resemble real data, while the discriminator network learns to differentiate between generated samples and real samples. Through an iterative training process, the generator and discriminator compete with each other, ultimately enabling the generator to produce high-quality samples. The emergence of GAN has alleviated the issue of data scarcity to a certain extent [156,157].

The objective function for training a GAN can be formulated as:

$$\min_G \max_D V(D,G) = \mathbb{E}_{x\sim p_{\text{data}}(x)}[\log D(x)] + \mathbb{E}_{z\sim p_z(z)}[\log(1 - D(G(z)))] \quad (10)$$

where G represents the generator network, D represents the discriminator network, x represents real fault data, and z represents random noise input to the generator.

The field of PV system fault diagnostics and prognostics has seen a surge in deep learning-based methods. However, a significant challenge arises from the limited availability of fault data in PV systems. This scarcity often leads to deep learning models being prone to overfitting and struggling to generalize well, which hinders their widespread adoption in PV system health management. To address this issue, researchers have turned to GANs. By leveraging GANs, it becomes possible to generate synthetic samples that closely resemble real fault data. This approach enables data augmentation and expansion of the training dataset, enhancing the model's ability to generalize and improve robustness. Consequently, an increasing number of studies are now integrating machine learning models with GANs to effectively apply them in PV system health management [27,63,142]. This innovative combination allows for a more comprehensive and accurate diagnosis and prediction of faults, contributing to the advancement and practicality of deep learning methods in this domain.

Lu et al. [138] introduced an anomaly detection model based on GANs, where the generator network learns the data distribution of a normal PV panel dataset. By comparing anomalous PV panel data with the learned distribution, faults can be identified. Comparative analysis against leading-edge semi-supervised and unsupervised approaches revealed a significant improvement in the area under the curve. Romero et al. [139] employed deep GANs to generate a synthetic dataset comprising 10,000 PV cell EL images. The evaluation resulted in an inception score of 2.3 and a fréchet inception distance of 15.8 when compared to authentic images. These findings indicate the potential utility of this dataset for enhancing machine learning algorithms and analyzing solar cell defect patterns. Lu et al. [82] presented a novel framework for detecting cross-domain DC series arc faults, utilizing adversarial data augmentation. The framework's effectiveness was validated through rigorous experimentation with four diverse datasets, featuring different power sources, inverters, and operating conditions, thereby confirming its robustness across varying amounts of fault data. Gao et al. [38] converted transient current data from PV systems into two-dimensional images, employing GAN-based image augmentation to alleviate the scarcity of fault diagnosis samples. They subsequently trained a CNN to classify fault types and introduced a fusion sample training approach that incorporated normal samples from diverse PV systems to enhance the model's generalization capacity. Lu et al. [27] leveraged a small dataset to create an efficient fault diagnosis model and devised a fault diagnosis approach that combines wasserstein GAN and CNN. The results demonstrate that the designed fault diagnosis model accurately identifies line faults and open circuit faults, outperforming traditional GAN approaches. Lu et al. [140] introduced a method that integrates domain adaptation with GANs. It involved learning an intelligent transformation from normal vectors to arc vectors using source domain data, followed by generating synthetic arc data from target domain normal data. Domain adaptation techniques were applied to facilitate accurate fault diagnosis in the target domain. Bharathi et al. [141] utilized GAN to generate 45,000 infrared images

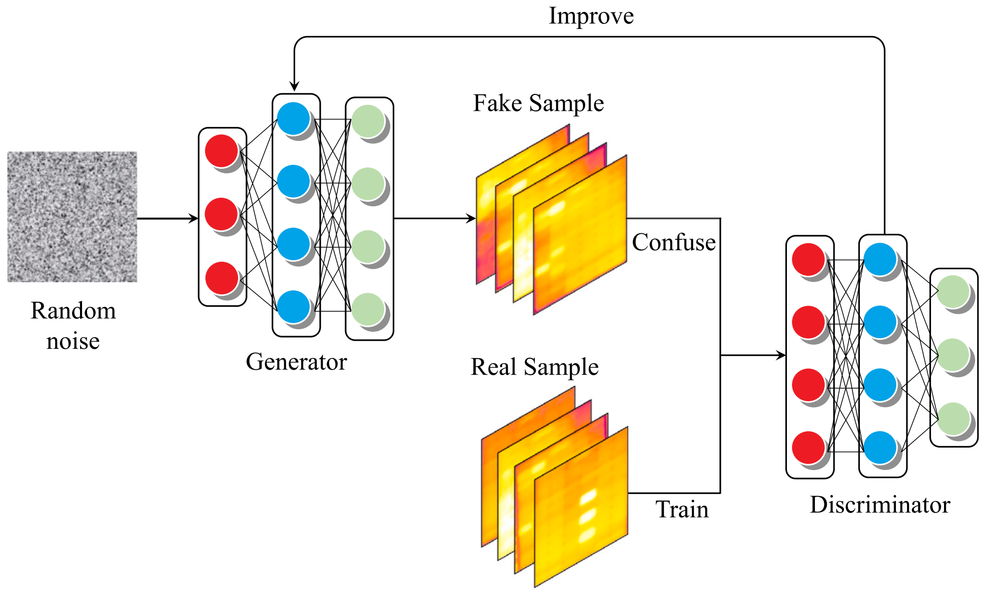

Fig. 9. Architecture of GAN.

corresponding to various fault types, which were subsequently employed to train and evaluate a CNN. This data augmentation approach led to a classification accuracy of 91.7% for eight fault categories. The utilization of RNNs in PV PHM is summarized in Table 4.

4.8. Hybrid and emergent models

Deep learning is a rapidly advancing field, wherein researchers have been continuously endeavoring to devise novel architectures. Numerous hybrid models constitute amalgamations of foundational structures such as CNNs, RNNs, and DAEs. Analogously, within PV PHM domain, proactive endeavors are being made towards the development of more efficient hybrid models. For instance, due to the superior classification performance of SVM under limited training sample conditions, certain studies have orchestrated a fusion between SVMs and deep learning models, yielding favorable outcomes. Abdelilah et al. [60] presented an innovative PV panel EL image fault detection and classification model that combines CNN and SVM, outperforming similar methods with classification accuracies of 99.49% and 99.46% on two separate databases. Furthermore, Zhou et al. [137] synergistically combined an RNN model with SVMs for predictive analysis of post-processed PV outputs, enabling the extraction of fault features and enhancing the diagnosis of shading faults in PV systems.

Within the framework of PV PHM, the processing of multidimensional sensory data with inherent interdependencies presents a pivotal challenge. For instance, interdependencies exist between temperature and irradiance, as well as between current and voltage. Understanding these internal dependencies is crucial for effective PHM in PV systems. Several research endeavors have amalgamated CNNs and RNNs within a cohesive model, with the aim of capturing both spatial and temporal information inherent in multidimensional time series data. This integration enhances feature extraction accuracy and thereby improves the efficacy of PHM in PV systems. Gao et al. [136] introduced a fusion model which integrates CNNs and GRUs to identify faults within PV arrays. The model comprises a four-layer one-dimensional CNN module and a GRU module. This approach achieved a classification accuracy of 98.61%, surpassing methods like ANNs and extreme learning machines. Hichri et al. [158] devised a hybrid anomaly detection approach for PV arrays utilizing a integration of CNNs and LSTM networks. Results demonstrated the efficacy of this method in accurately diagnosing faults across various operational conditions.

The integration of attention mechanisms in machine learning has the potential to enhance the feature extraction capabilities of deep learning models. Several works have incorporated these mechanisms into their models and achieved remarkable performance in the PHM domain of PV systems. Gao et al. [38] introduced a squeeze-excitation attention module into GAN networks, which improved the generalization ability of CNNs, particularly in scenarios involving disturbances such as MPPT adjustment and irradiance mutation. Fang et al. [135] incorporated attention mechanisms into LSTM networks, addressing the limitations of RNNs in focusing on important features and thereby improving the anomaly detection performance of PV arrays. Lin et al. [50] utilized a fault diagnosis scheme for PV systems on the basis of a multi-scale ResNet network. By introducing attention modules into ResNet, the quantity of network parameters and computational intricacy were diminished. Fu et al. [159] introduced SE-ResNet, a fault diagnosis algorithm for PV arrays that combines ResNet with a squeeze-and-excitation network. Experimental results showcased the model's exceptional performance.

Currently, some high-performance models require a significant amount of resources, while resources are often limited in some deployment scenarios, such as edge computing. To address this issue, researchers have developed lightweight and efficient deep learning models that can guarantee performance in resource-constrained deployment scenarios [160]. Compared to traditional deep learning, lightweight deep learning offer faster inference speed, lower resource consumption, and stronger transferability. Although they may slightly underperform standard deep learning models in some complex tasks, they have proven to be effective and practical in many real-world applications [161]. Akram et al. [55] utilized a lightweight CNN trained on infrared images of laboratory PV components, achieving a fault diagnosis accuracy of 98.67% with efficient computational resource utilization and reduced processing time. Lu et al. [82] proposed a framework for cross-domain DC series arc fault detection based on an adversarial data augmentation lightweight transfer CNN. The framework achieved an accuracy of 97.95% on the target domain.

In the face of the challenge of insufficient model generalization in PV systems' PHM, several studies have adopted novel emergent ensemble learning methods to train models by integrating different types of models. The trained ensemble models incorporate the characteristics of different models and exhibit good generalization performance. Eskandari et al. [29] employed ensemble learning algorithms, utilizing a weighted voting approach to detect different faults in PV systems.

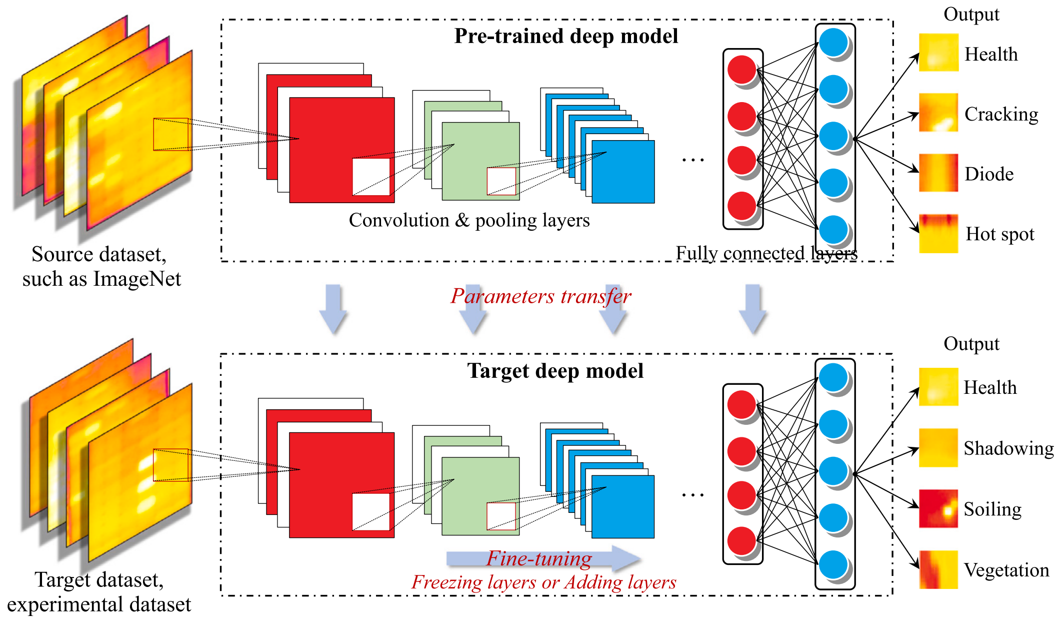

Fig. 10. Illustrations of transfer learning approaches.

Experimental results substantiate the model's high effectiveness and reliability, achieving a diagnostic accuracy of 99% for diagnosing faults in PV arrays. Sohail et al. [61] trained, evaluated, and compared deep learning models on an online PV system EL image dataset. Through ensemble learning techniques, they demonstrated that the ensemble outperformed individual models in terms of performance.

4.9. Transfer learning

When constructing numerous models, they are often tailored to fit the specific environment of a certain plant and trained solely on datasets from that plant. Nevertheless, a notable drawback of this approach lies in the fact that although the model is validated on datasets from a specific plant, its generalization capability cannot be guaranteed when confronted with data from different sources [53]. Consequently, whenever adaptation to a new plant environment is required, the model must undergo retraining using data from the new plant, which not only consumes considerable human and material resources but also poses a significant impediment to the scalability of the model. In this specific scenario, the advantages of transfer learning are fully demonstrated. After training with knowledge from the source domain (i.e., the original plant environment), the model has learned some general feature representations that possess good generalization performance for different tasks. In this case, only a small number of target domain (i.e., the new plant environment) samples are required to fine-tune the model structure and parameters, enabling the model to quickly adapt to the data generated in the new plant environment. This eliminates the need to retrain the model entirely in the new plant setting, thereby significantly improving the scalability of the model. Furthermore, the model's performance on new tasks is usually superior to that of a model trained from scratch because it has already acquired a certain amount of prior knowledge [149].

TL predominantly centers on scenarios involving a source domain D_s and a target domain D_t, denoted as $D_s = (x_i, y_i)_i^{N_s}$, where x_i and y_i represent data samples and their corresponding class labels. Additionally, $D_t = (x_i, y_i)i^{N_t}$ represents the target domain. Consequently, the definition of transfer learning can be articulated as follows: Given a source domain D_s, a learning task T_s, a target domain D_t, and a learning task T_t, the objective is to extract knowledge from the source domain D_s and learning task T_s to enhance the learning performance of the prediction function $f\mathrm{t}\,(x;\theta)$ in the target domain, where $D_s \neq D_t$ or $T_s \neq T_t$. Fine-tuning serves as the primary approach to TL in the context of PV system PHM. Fig. 10 illustrates the key steps involved in the fine-tuning process. Initially, the model $f(x,\theta)$ is pre-trained on D_s and subsequently fine-tuned on the specific task or domain to enhance the model's performance and generalization capabilities for the target task, achieved by minimizing the loss function. The fine-tuning process can be mathematically expressed as follows:

$$\theta^* = \arg\min_\theta L_\mathrm{t}\ \left(f_\mathrm{t}\ (x;\theta), y_\mathrm{t}\ \right) \tag{11}$$

where θ^* represents the model parameters after fine-tuning. L_{target} on behalf of the loss function of the target domain task. $f_{\mathrm{target}}(x;\theta)$ symbolizes the fine-tuned model that is adjusted on the target domain, where x represents the input data from the target domain. y_{target} is the target labels of the target domain. During the fine-tuning process, the model parameters θ are adjusted on the target domain to minimize the loss function L_{target} of the target domain task.

TL typically employs previously trained deep structures, such as ResNet, AlexNet, and VGG, which are extensively trained on large-scale datasets like ImageNet, COCO, and Open Images. Their rich feature representations, learned from extensive training, make them an ideal launching point for TL in PV health management. Initially, these models may not be suitable for specific PV system health management tasks, yet transfer learning offers an approach to enhance their adaptability and scalability. Korkmaz et al. [53] employed the pre-trained AlexNet model for anomaly detection in PV components, fine-tuning it on an extensive dataset of 20,000 infrared images. Their approach achieved an average fault detection accuracy of 97.32% and identified 11 types of anomalies with an accuracy of 93.51%. Hou et al. [162] utilized the pre-trained Xception model on grayscale EL images from ImageNet, achieving superior accuracy in PV panel defect recognition through fine-tuning on publicly available EL images, while demonstrating the time-saving advantages of TL. Similarly, Zyout et al. [163] employed AlexNet for classifying normal and defective PV panel surface images. They achieved impressive results in detecting various surface defects on solar panels. Ding et al. [164] utilized the GoogLeNet pre-trained model to classify different fault categories with an average accuracy of 98.125%. They used RGB images from ImageNet for pre-training and drone-captured RGB images of PV systems for target domain data. Liu et al. [165] introduced an anomaly detection approach on the basis of ResNet-50, initially trained on the COCO dataset and fine-tuned using 631 RGB images of PV surfaces. Experiments show that

Table 5
Summary of transfer learning techniques applied to different deep learning models for PHM of PV systems.

Literature	Pretrained model	Pre-trained datasets	Transfer data	Strategy of transfer	Evaluation
Korkmaz et al. [53]	AlexNet	A publicly available infrared solar module dataset from Raptor Maps, 123,668 infrared images	23,100 infrared PV panel images	The first four convolution layers and three fully connected layers in the five convolution layers of the pre-trained model were migrated.	The average accuracy of fault detection was 97.32%, and the average accuracy of 11 abnormal detection was 93.51%.
Hou et al. [162]	Xception	2624 8-bit grayscale PV EL images in imagenet	PV panel EL images from the public dataset	Migrate and fine-tune all layers of the pre-trained model.	The average accuracy was 79%. Calculation time: 664 s.
Zyout et al. [163]	AlexNet	PV array RGB image data on the imagenet platform	PV RGB images obtained from online resources	The last three layers of AlexNet were reconstructed into a fully connected layer with two output neurons, a softmax layer and a classification layer.	The best verification accuracy is about 93.3%.
Ding et al. [164]	GoogLeNet	PV array RGB image data on the imagenet platform	RGB image of PV system taken by drone	Removes the old fully connected layer, softmax classifier and initializes a new fully connected layer.	The average accuracy of fault classification in 8 categories is 98.125%.
Liu et al. [165]	ResNet-50	RGB images of PV panels in the public dataset COCO	631 RGB images of PV surfaces were used in the lightweight dataset	Freeze migration of some shallow network layers and fine-tune migration of other layers.	
Wei et al. [166]	VGG-16	Infrared image of PV panel in imagenet	Infrared image of PV panel obtained in laboratory	Migrate and fine-tune all layers of the pre-trained model.	The accuracy of fault identification reaches 95.15%.
Xie et al. [167]	ResNet-50	Pv single crystal panel RGB picture	PV polycrystalline panel RGB picture	The attention mechanism is introduced in the last three blocks of ResNet-50, and the others are frozen and fine-tuned.	The F1-score in the polycrystalline RGB image target domain improved by 0.2631, achieving a recall of 84.70% and an accuracy of 90.15%.
Lin et al. [50]	SE-ResNet	I–V curve data obtained in PV array	I–V curve data obtained in PV array	The feature extraction layer is frozen and migrated, and the classifier is retrained for fine tuning.	The accuracy of classification of different dust faults on the test set reaches 99.12%.
Sung et al. [168]	CNN	Current time series signal obtained by PV array	Current time series signal obtained by PV array	The trained CNN model is frozen and migrated to an LSTM layer as a feature extractor.	The accuracy of low energy arc fault detection reaches 95.8%.
Ahmed et al. [169]	DCNN	Infrared image dataset of solar PV panel	Infrared image dataset of solar PV panel	Migrate the pre-trained model and fine-tune it.	The fault detection accuracy reaches 97.62%.
Guo et al. [40]	LSTM	The power data of the PV system under normal condition	The power data of PV system obtained by fault experiment	Migrate the pre-trained model and fine-tune it.	It is superior to other fault detection methods in different weather scenarios.
Akram et al. [55]	CNN	EL images	A dataset of infrared images of PV panels obtained in the laboratory	The convolution layer and the fully connected layer of the pre-trained model are frozen and migrated, and the pooling layer is fine-tuned.	The detection of PV module faults reached an averageaccuracy of 99.23%.

the performance of the ResNet-50 model has been significantly improved after adopting transfer learning strategy, which illustrates the promising prospect of transfer learning in expanding the scalability of the model. Wei et al. [166] utilized a VGG-16 previously trained with ImageNet infrared images, fine-tuning it to create a faster CNN model that achieved a 95.15% accuracy on a laboratory PV system's infrared image test set. These findings collectively emphasize the significant utility and effectiveness of TL in enhancing PV system health management performance.

Custom models, tailored to specific task requirements and pre-trained on large-scale datasets, are another effective method in TL. These models can be optimized according to task characteristics, making them more adaptive to target tasks. By leveraging a small amount of data for fine-tuning, these custom models can swiftly adapt to novel tasks, exhibiting remarkable scalability and efficiency. Lin et al. [50] introduced a multi-scale SE-ResNet network for PV system fault detection. The model, pre-trained on I–V curve data from PV systems, displayed accuracy rates of 99.12% and 84.96% for various dust fault classifications. During the fine-tuning process, solely the classifier undergoes individual retraining, which facilitates the model's rapid and efficient adaptation to specific target tasks. Sung et al. [168] adopted a TL-based arc fault detection network utilizing a lightweight 2D-CNN network pre-trained on current time-domain and frequency-domain signals. The trained CNN model, combined with an LSTM layer, diagnosed PV system states with an accuracy of 95.8% for detecting low-energy arc faults. In another work, Ahmed et al. [169] pre-trained a 7-layer CNN model on an infrared image dataset. The model, fine-tuned on a new dataset, achieved a 97.62% accuracy rate in classifying PV panel defects, outperforming other pre-trained networks and standalone CNNs. Guo et al. [40] employed a 3-layer, 60-neuron LSTM model, pre-trained on power data from a faultless PV system, for shade fault diagnosis. By transferring the parameters to the target domain model, superior performance in varying weather scenarios was attained after fine-tuning on power data from fault experiments.

Domain adaptation, a specific type of TL, is of considerable importance in scenarios where the source and target data distributions diverge significantly. This is of particular significance within the domain of PV systems, where environmental factors lead to distinct variations in operational data across different locales. The central concept behind domain adaptation is to minimize the domain divergence by aligning the feature distributions of the source and target domains in a shared feature space, thereby allowing the model to generalize berrter on the target domain. Xie et al. [167] proposed a domain-adaptive

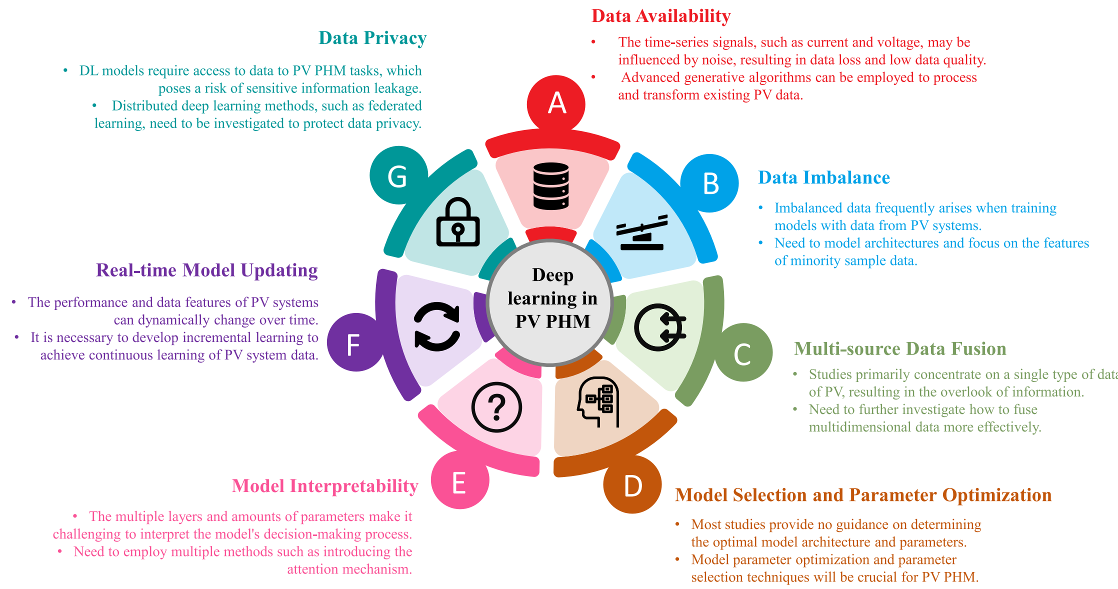

Fig. 11. Challenges and opportunities in deep learning of PV PHM.

solar cell image defect detection method. The ResNet-50 network was pre-trained using labeled monocrystalline RGB image data from an auxiliary domain, and a domain adaptation layer was introduced to minimize the differences between the source domain (monocrystalline images) and the target domain (polycrystalline images). Ultimately, this crack detection model achieved a 0.2631 improvement in F1-score on the polycrystalline RGB image target domain, with a recall rate of 84.70% and precision rate of 90.15%. Some typical transfer learning application cases are listed in detail in Table 5.

5. Discussions and prospect

In our research, a comprehensive review of various aspects pertaining to the application of deep learning in PV system PHM is presented. It is evident that deep learning has achieved significant success in handling large volumes of data, addressing complex nonlinear relationships, automatically extracting features, and enhancing model performance in PV system PHM. However, in order to fully replace established PHM technologies in industries, further exploration of its potential is required. To summarize future directions, the key challenges faced by researchers today are outlined. Fig. 11 provides an overview of these challenges, each of which is described below.

1. Data Availability: Deep learning typically relies on abundant data; however, constructing PV system PHM models often encounters the issue of limited availability of high-quality training data. The operational context of PV systems is intricate and variable, and the acquired time-series signals, such as current and voltage, may be heavily influenced by noise. Additionally, system monitoring data often encounters problems such as sensor failures and transmission failures, resulting in data loss or low data quality. Moreover, labeling fault data requires substantial human and material resources. To address these issues, advanced generative algorithms can be employed to process and transform existing PV data, eliminating noise while generating additional training samples.

2. Data Imbalance: Imbalanced data frequently arises when training models with data from PV systems. For instance, there may be an imbalance in the quantity of thermal images under normal and hot spots conditions. This can cause the model to focus on features of the class with a larger sample size while selectively ignoring the class with fewer samples, resulting in weak recognition capabilities for PV fault samples and significantly reducing the performance of PV PHM. Future research needs to further investigate how to design deep model architectures and adjust the weights of different classes to focus on the features of minority sample data.

3. Multi-source Data Fusion: Many studies in PV system PHM primarily concentrate on a single type of data, such as electrical data (current, voltage, power), or a specific type of image (EL image, RGB image, thermal image) for fault diagnosis. This inevitably overlooks a substantial amount of valuable information for PV system PHM. Exploring efficient methods to integrate multidimensional information to optimize the effectiveness of deep learning models in PV system PHM has become a challenge. Future research needs to further investigate how to fuse multidimensional data more effectively, such as employing a multi-input model to simultaneously input EL images and RGB images for panel fault diagnosis, or inputting thermal images and electrical data, such as current, for anomaly screening, to enhance the comprehensiveness and accuracy of PV system PHM.

4. Model Selection and Parameter Optimization: Selecting the optimal network structure and parameters is a crucial issue. However, most studies fail to provide guidance on determining the optimal model architecture and parameters for specific PV PHM problems. Up to this point, the majority of models have been crafted through manual design by domain experts, a process susceptible to errors and time inefficiency. Additionally, although some deep learning models offer high performance and automation, they heavily rely on a wide range of hyperparameter choices. In the future, in-depth research on model parameter optimization and the utilization of automated techniques for optimal model architecture and parameter selection will be crucial for PV system PHM.

5. Model Interpretability: Deep learning models contain a large number of connection layers and parameters. This complex structure makes it challenging to understand and interpret the model's decision-making process. To address the issue of poor interpretability in deep learning models, future efforts can focus on the following aspects: Firstly, analyzing the importance of the model's attention to PV system input features can provide insights into the model's focus on predicting results. For example, feature importance evaluation methods can be employed to determine which features in the PV system exert significant influence on the model's predictions. Secondly, introducing attention mechanisms to weight input data or internal features can explicitly indicate which parts of the input data exercise significant impact on the network's decision-making, thereby increasing interpretability.

6. Real-time Model Updating: Due to the variability of outdoor environments, the performance and status of PV systems, as well as

the data features, can dynamically change over time. This leads to data and feature distribution drift that reduces performance of deep learning models in diagnostic prediction for PV systems. Additionally, during the training process, learning new information may result in the complete loss of previously acquired knowledge. Therefore, it is necessary to develop and improve new algorithms, such as incremental learning, to achieve continuous learning of PV system data while retaining previously acquired knowledge in the PV domain.

7. Data Privacy: Detection data in PV systems often contains sensitive information, such as equipment parameters and operation records. The leakage of this data may lead to the disclosure of trade secrets or damage to a company's reputation. However, deep learning models require access to and analysis of this data to achieve fault diagnosis, performance prediction, and other tasks, which poses a risk of sensitive information leakage. Protecting data privacy when using deep learning models has become an important challenge. To address these challenges, distributed deep learning methods and data encryption techniques can be employed. For example, federated learning can be applied to push model training to edge devices where the data resides, reducing the risks and costs associated with data transmission while protecting data privacy.

6. Conclusion

Regarding the hot research topic of PV system PHM under deep learning, this research gives a systematic review through the summary of 506 articles published from 2016 to September 2023. The types of monitoring data, prevalent fault types, and typical degradation patterns within the PHM of PV systems are compiled. It is observed that the data utilized for PV fault diagnosis frequently relates to specific fault categories. For instance, image data is typically employed for diagnosing faults such as cracks and hotspots, whereas electrical data, including current and voltage, is required to assist in the diagnosis of line-to-line faults and open circuits. Furthermore, to foster the advancement of the entire field, this research provides 8 open-source datasets containing various faults. Subsequently, the advantages of deep learning, such as automatic feature learning, the capacity to process enormous volumes of data, and its remarkable performance, are emphasized. Common deep learning models, including SAE, CNN, RNN, GAN, and more, are systematically analyzed, emphasizing their unique traits and applications in the realm of PV system PHM. Among them, CNN is considered the most popular model in this field. In specific applications, it has been discovered that CNNs are not only utilized for processing PV image data but can also handle various types of data, including current, voltage, and I–V curves.

Moreover, this research delves into some challenges facing the development of this field, with the most common constraints reflected at the data level, including data imbalance, scarcity, and privacy. To more thoroughly address these problems, studies are recommended to conduct more in-depth research on data-generating models, unsupervised and semi-supervised learning algorithms, and federated learning. Finally, opportunities for future research are also discussed. On the one hand, with the rapid development of the IoT technology, it is worthwhile for researchers to explore the use of multimodal data for the health management of PV systems. On the other hand, the research of advanced models for high-performance real-time detection of PV system status also holds great research prospects. Overall, this research provides a comprehensive review on deep learning methods and applications in PV system PHM, offering researchers a clear framework and an understanding of the current state of the field, thereby advancing its development.

CRediT authorship contribution statement

Zhonghao Chang: Investigation, Methodology, Software, Formal analysis, Writing – original draft. **Te Han:** Supervision, Conceptualization, Methodology, Validation, Funding acquisition, Writing – review & editing.

Declaration of competing interest

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

Data availability

Data will be made available on request.

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