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Review article

Deep learning approaches for visual faults diagnosis of photovoltaic systems: State-of-the-Art review

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ABSTRACT

PV systems are prone to external environmental conditions that affect PV system operations. Visual inspection of the impacts of faults on PV system is considered a better practice rather than onsite fault detection mechanisms. Faults such as hotspot, dark area, cracks, glass break, wavy lines, snail tracks, corrosion, discoloration, junction box failure and delamination faults have different visual symptoms. EL technology, infrared thermography, and photoluminescence approaches are used to extract and visualize the impact of faults on PV modules. DL based algorithms such as, CNN, ANN, RNN, AE, DBN, TL and hybrid algorithms have shown promising results in domain of visual PV fault detection. This article critically overviews working mechanism of DL algorithms in terms of their limitations, complexity, interpretability, training dataset requirements and capability to work with another DL algorithms. This research article also reviews, critically analyzes, and systematically presents different clustering algorithms based on their clustering mechanism, distance metrics, convergence criteria. Additionally, their performance is also evaluated in terms of DI, CHI, DBI, S-score, and homogeneity. Moreover, this research work explicitly identifies and explains the limitations and contributions of recent and older techniques employed for features extraction, data preprocessing, and decision making by performing SWOT analysis. This research work also recommends future research directions for industry and academia.

List of Acronyms

AP- Affinity propagation	GRU- Gated recurrent unit
ANN- Artificial neural network	HOG- Histogram of oriented gradients
AE- Autoencoders	HN- Histogram normalization
ARI- Adjusted rand index	HC- Hierarchical clustering
AGA- Adaptive genetic algorithm	IRT- Infrared technology
CP- Cluster purity	LSTM- Long short-term memory
CNN- Convolution neural network	LBP- Local binary patterns
CH- Colour histogram	MSC- Mean shift clustering
CHI- Calinski harabasz index	PV- Photovoltaic
DL- Deep Learning	PCA- Principal component analysis
DBI- Davies bouldin index	PL- Photoluminescence
DBSC- Density based spatial clustering	RF- Random Forest
DT- Decision tree	RI- Rand Index
DBN- Deep belief network	RNN- Recurrent neural network
DBM- Deep Boltzmann machine	RBM- Restricted Boltzmann machine
DI- Dunn index	SAE- Sparce autoencoders
EL- Electroluminescence	SC- Spectral clustering
ENN- Elman neural network	SVM- Support vector machine

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EMI- Entropy and mutual information	SSDAE- Sparse stacked denoising autoencoders
FCM- Fuzzy C-mean	STC- Standard testing conditions
FDD- Frequency division duplexing	SURF- Speed up robust features
FCM- Fuzzy mean clustering	SIFT- Scale invariant feature transform
FPN- Fuzzy petri nets	TL- Transfer learning
GAN- Generative adversarial network	UAVs- Unmanned air vehicles
GMM- Gaussian mixture model	VAE- Variational autoencoders

1. Introduction

Due to rising energy demand and costs, PV systems have gained significant attention worldwide. International renewable energy agency (IRENA) projects that the global installed capacity of grid-connected PV systems will reach 2156 GW (GW) by 2030, which is approximately 14.7 % of compound annual growth [1]. In recent years, the primary

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focus has been achieving high reliability and efficiency in PV systems [2]. Faults in the PV system is a major threat to its reliability, that can be avoided by regular monitoring and an intelligent fault detection mechanism. According to the national renewable energy lab (NREL), 17.4 % power losses were recorded, in year 2022, due to different faults in the PV systems [3]. In the existing literature, three fundamental PV fault detection approaches are proposed, that are, vision-based detection, image-based detection with classification, and data analytics-based detection [4–7]. Vision- and imaging-based techniques have been widely used to detect visual PV faults [8]. Visual inspection of PV modules is usually conducted under standard testing conditions (STC) from multiple angles to ensure that all faults are visible to the naked eye [9]. Detection based on data analytics classifies faults by considering multiple observable parameters [10]. In recent years, PV systems are photographed by UAVs equipped with onboard sensors and digital cameras [11]. The visible faults that may occur in a PV system and their symptoms are summarized in Table 1, which includes glass breakage [12], partial shading [13], soiling [14], snail trails [14], discoloration [15], delamination [16], corrosion [17], hotspots [18], cell cracks [19], bypass diode breakage [20], junction box failure [21], and short circuits [22], as shown in Fig. 1. Visual inspection usually is conducted through IRT, EL, and PL [23]. IRT uses the thermal emission of a PV to identify areas of high or low temperature. These areas can indicate the presence of faults, such as hot spots or cell cracks [24]. EL uses the light emitted by a PV to visualize the electrical activity within the module, which can identify faults, such as delamination or cell cracks [25]. PL uses the light that PV emits when exposed to ultraviolet light that can also locate faults, such as impurities, in the semiconductor material [26]. Visual fault detection approach has several advantages over traditional fault detection methods, such as remote monitoring, high accuracy due to high-definition images, and non-destructive testing.

DL approach, utilizing CNN, has demonstrated exceptional efficacy in the field of visual fault detection, mainly when implemented in the context of extensive PV plants [27]. It usually uses image data collected by UAVs [28]. DL techniques have shown promising results in terms of fault detection speed and accuracy. While on contrary, DL's immediate real-time viability is constrained by the need for large datasets, specialized hardware, and skilled personnel. PV fault detection using DL enables the algorithms to identify and classify specific anomalies based on the characteristics of the given dataset [29]. In addition, it is possible to modify a particular algorithm's learning parameters for the specific fault detection. Small dataset or sample size issue arises when analysis is required based on short time duration [30]. It sometimes negatively impacts the detection technique but at the same time establishing large dataset is a challenging task. Data preprocessing is also a challenging task due to the noise and outliers that effects features learning capability of DL [31]. Moreover, modification in DL architecture for achieving higher accuracy is a complex task that requires domain knowledge and experience.

Table 1
Visual faults and their symptoms.

Fault	Visual Symptoms	Ref
Short circuit	Dark area or spot on PV module	[45]
Junction box failure	Dark spot on the PV module	[46]
Glass breakage	Crack, hole, or missing glass piece	[47]
Partial Shading/ Hotspot	Dark color of the area with blackish sharp boundaries	[48]
Soiling	Hazy appearances	[49]
Snail trails	Dark wavy lines on PV module	[50]
Discoloration	Brown or yellow tint due to exposer to acidic liquid	[51]
Delamination	Separation between glass and backing of the module due to bubbles and blisters on the surface of PV module	[52]
Corrosion	Rusty and corroded appearances	[53]
Cell cracks	Small and darks lines on modules	[54]

Three strategies are usually followed for the steps involved in DL based fault detection and classification process, that are data preprocessing, features extraction and selection, and classification. These strategies depend upon the requirements and computational resources availability [32]. First strategy is utilization of signal analysis, statistical analysis models for preprocessing and features extraction and deep learning-based model for classification [33]. This strategy reduces complexity and increases classification accuracy. The second strategy is adaptation of classical statistical analysis techniques for preprocessing and DL model for features selection and classification. This approach does not require manual intervention because classification is based on unsupervised extracted features. Third strategy is utilization of DL models from raw data to final classification, which is end-to-end approach, computing output directly from the input [34]. Working principles of all three strategies are shown in Figs. 1–3. Exemplary of third approach in Fig. 3, is based on CNN [35] (see Fig. 4).

The optimization techniques used in solar PV systems have been extensively studied and improved over the years. These techniques have been further enhanced with the integration of deep learning algorithms for visual fault detection. Recent studies have shown promising results in improving the efficiency and reliability of solar PV systems [36–44].

The contribution of this review article study is critical analysis, review on advancement, SWOT analysis of DL based algorithms, and comparison of working principle of the various DL-based fault detection and diagnosis algorithms for PV systems. This article critically overviews working mechanism of DL algorithms in terms of their limitations, complexity, interpretability, training dataset requirements and capability to work with another DL algorithms. This research article also reviews, critically analyzes, and systematically presents different clustering algorithms based on their clustering mechanism, distance metrics, convergence criteria. Additionally, their performance is also evaluated in terms of DI, CHI, DBI, S-score, and homogeneity. Moreover, this research work explicitly identifies and explains the limitations and contributions of recent and older techniques employed for features extraction, data preprocessing, and decision making by performing SWOT analysis. This review article identifies new features of comparison and analysis, which help researchers to identify proper research gap in the realm of DL based fault detection. This research work also recommends future research directions for industry and academia. This article also reviews the applications of DL algorithms in the context of visual fault detection, such as anomaly detection, targeted defect detection, concurrent identification of multiple faults, and defect type clustering.

This review article consists of five sections; first section introduces the area of research and its importance. Section part of the article consists of applications of deep learning in the context of visual fault detection. Third section reviews and analyzes different DL algorithms, whereas forth section discusses the importance of data augmentation and also critically compares different augmentation techniques. Last section concludes the article with recommendations and research gap.

2. Application of deep learning in context of visual fault detection

Deep learning algorithms are utilized for multiple purposes in different domains. Detection of visual faults as an application of DL algorithms contains anomaly detection [56], targeted defect/fault detection [57], concurrent identification of multiple faults [58], and fault type based clustering [59]. These applications are for detecting and classifying faults, such as line cracks, cell cracks, scratches, broken glass, paste spots, dirty cells, fingers interruptions, contact failures, cell busbar corrosion, soiling, snail tracks, discoloration, delamination, broken edges, large area damages, hotspots, surface impurities, unsoldered connections, burned cells, black cores, and dislocation patterns. Brief review and analysis of different applications are as follows.

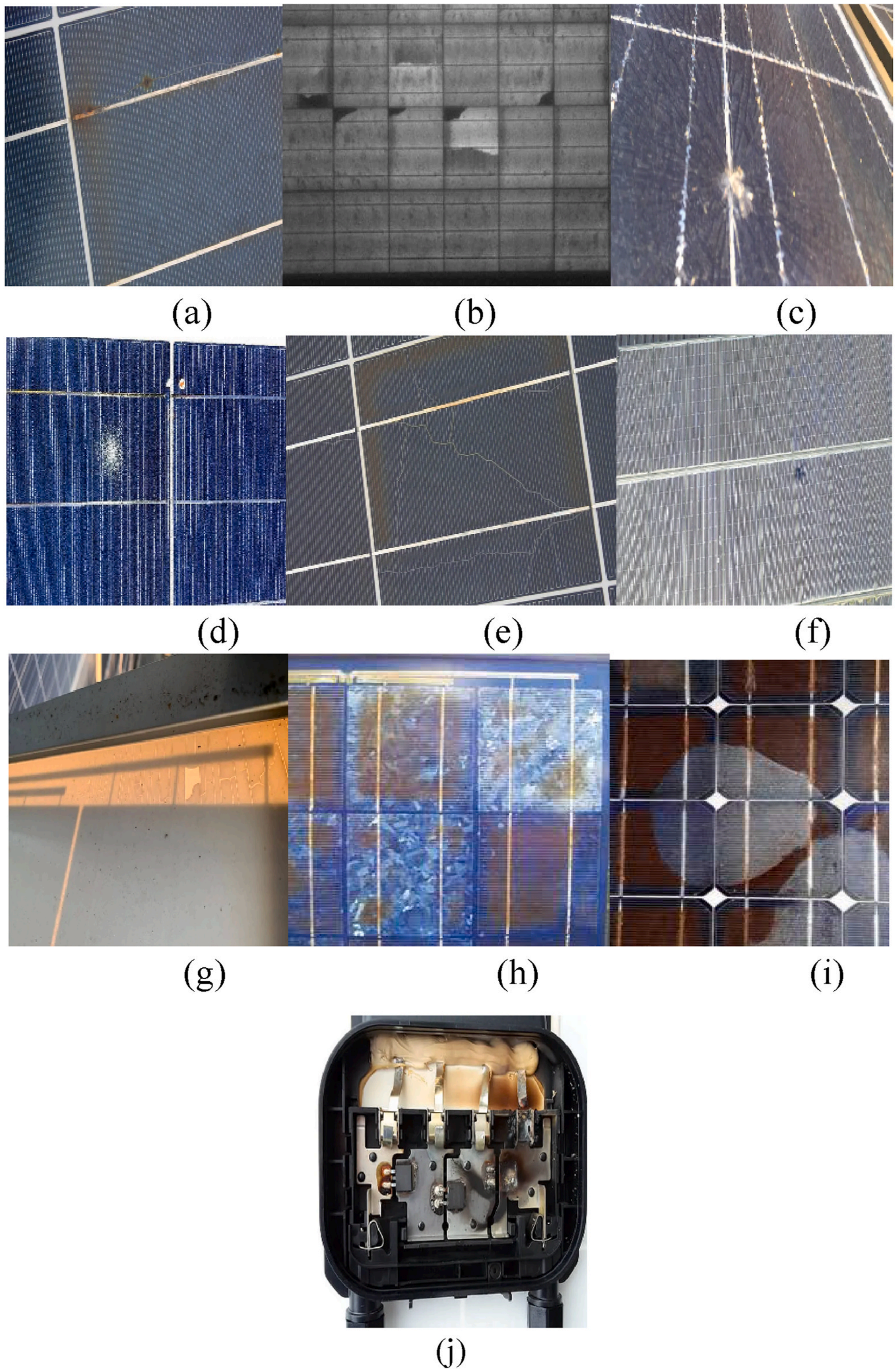

Fig. 1. Visual PV faults (a) Hotspot (b) micro cracks (c) glass breakage (d) chipped solar cell (e) snail trails (f) uneven color (g) cracked back sheet (h) corrosion (i) delamination (j) junction box failure [55].

2.1. Anomaly detection

Anomalies in PV cells or modules are abrupt variations in the voltage, current, or overall performance of the cell caused by environmental factors [60]. Anomalies at the module level are irregularities that arise in individual solar modules, such as cell hot spots, manufacturing flaws, cell degradation, shading, and bypass diode activation [61]. These anomalies result in a decrease in overall power output. Additionally, anomalies like soiling, which reduces the incident sunlight reaching the solar cells effects output voltage even more [62]. Anomalies at the string level, such as open circuits, short circuits, and high resistance, can occur due to various circumstances, including but not limited to damaged connectors and manufacturing faults [63]. Detecting abnormalities is critical for assuring the long-term reliability of solar PV

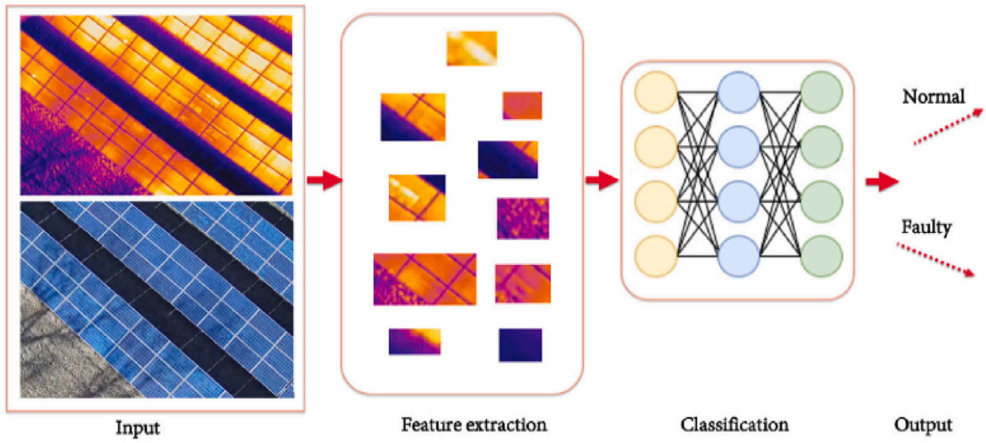

Fig. 2. PV faults detection-first strategy (feature extraction using single processing or other traditional technique, detection and classification using DL [35].

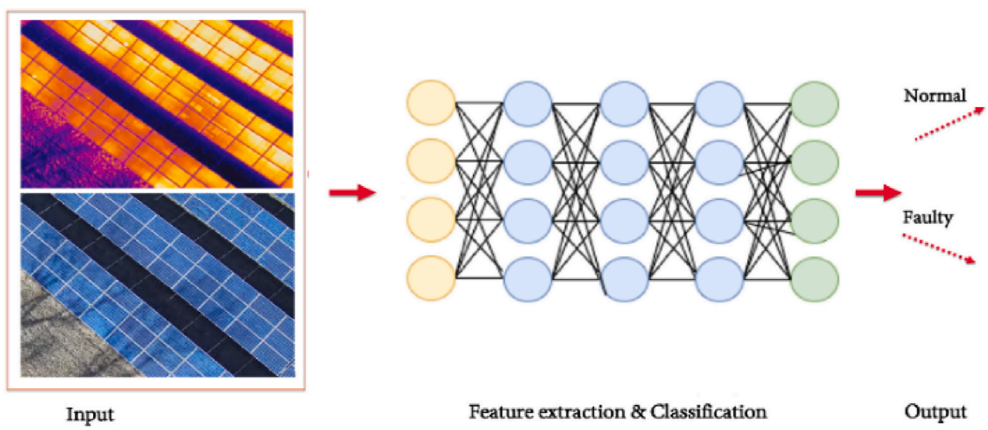

Fig. 3. Classical statistical analysis for Pre-processing, DL for feature extraction and fault detection [35].

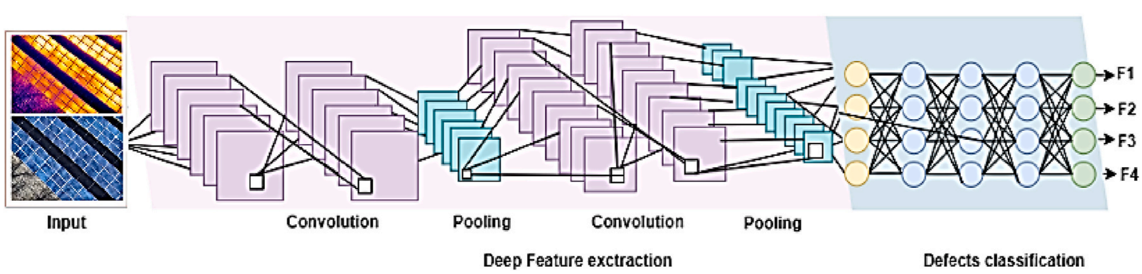

Fig. 4. End-to-end DL based approach for fault detection (A CNN architecture example) [35].

systems, reducing significant failures and costly maintenance. Continuous monitoring for anomaly detection helps in improving system efficiency and increasing return on investment (ROI).

2.2. Similar type fault clustering

Clustering is a popular unsupervised machine learning paradigm used in various fields, including fault detection and visual inspection in the PV industry. Unsupervised DL approach uses clustering algorithms to classify similar visual faults, removing the need for tagged training data. Initially, anomalies on the PV module surface are recognized without classifying the specific type of fault. A DL, such as CNN or autoencoders, is then used to assess defective surface samples and identify analogous faults autonomously [64]. The unsupervised DL model learns important surface faults parameters such as shape, size, color, and other characteristics in the first step [65]. Following that, the model clusters the various faults and presents them to the user as type 1, type 2, and so on until all fault categories have been classified. One significant advantage of this approach is that it eliminates the need for prior knowledge of fault categories or manual labelling of faulty samples because the entire process is unsupervised. The following major step or stages need special attention while performing unsupervised visual defect clustering in deep learning:

1) Extraction of characteristics/features: The first stage entails extracting relevant features from faulty images. These features can be extracted using various methods, including CNNs, LBP [66], Gabor Filters [67], HOG [68], CH [69], Histogram normalization [70], SIFT [71], SURF [72], autoencoders [73], and PCA [74]. Table 2 shows the potential benefits of each feature extraction

Table 2
Review and comparison of clustering techniques against several parameters.

Ref	Clustering Algorithm	Clustering Mechanism	Distance Metric	Convergence Criteria	Number of Clusters (K)
[66]	K-mean	Classifies faults into K using mean centroid	Euclidean	Until centroids stabilize	User-define
[67]	Hierarchical	Tree of nested clusters	Linkage	Until dendrogram converges	User-define
[68]	DBSC	Classifies faults based on density and connectivity	Various distance	Not applicable	Automatic
[69]	AP	Classifies faults by determining exemplars	Negative Euclidean	Until message stabilize	Automatic
[70]	MSC	Assign local density peaks to each fault	Euclidean	Until cluster converges	Automatic
[71]	GMM	Represent faults as combination of Gaussians	Mahalanhobis	Until parameters stabilize	User-define
[72]	SC	Classifies fault by projecting data into low dimension space	Graph-based	Not applicable	User-define
[73]	FCM	Assign fuzzy membership values to faults	Euclidean	Until memberships stabilize	User-define

Table 3
Summary of the review of working mechanism and performance classification algorithms.

Ref.	Features extraction techniques	Limitations	Advantages	Complexity	Interpretability	Training data required	Capability of integration with different algorithms	Comparative analysis
[108]	CNN	For limited data it is ineffective tool	learn intricate patterns, adapt well, High accuracy	Very high	Learned features are not easily interpretable	Large	Yes	Better results for hidden faults, cracks classification and segmentation
[57]	LBP	Cannot capture irregular patterns and intricate cracks	Implementation in real environment with different light conditions	Low	Provides easy and basic information of cracks	Any dataset	Yes	It is preferred to be used as complementary technique, not stand alone
[62]	SIFT	Not specifically optimized for PV cracks detection.	Scaling and rotation. Robust in different lights and affine transformations.	Moderate	Provides distinct feature	Any labeled dataset	Less	It is used for comparison and matching of faulty/un-faulty solar cell images.
[58]	Gabor filters	Need optimal scale, orientation data, and parameters tuning	Provides frequency analysis. Highly accurate in capturing features variations.	Moderate	Interpretable frequency and multi orientation representation	Labeled dataset with sufficient samples	Medium capability. Depends upon problem and scenario	It is effective in detecting repetitive and directional patters/cracks
[59]	HOG	Cannot detect fine details of cracks	Detect edges and gradients with accuracy. Robust to image rotation	Low	Interpretable representation of PV cell images	Large, labeled dataset is required	Can be used with other techniques for enhanced accuracy	Used for PV thermal images for detecting contours of hotspot faults. It is best for edge-based patterns.
[60]	CH	Detects only anomalies based on colour variations.	Simple, easy to implement and gives high accuracy in PV cell image segmentation	Low	Provides simple representation based on colour information	Does not required large, labeled dataset	Can be used with multimodal feature extraction techniques	It is preferred where colour distribution shows anomalies. Suitable for resource constrained environment
[63]	SURF	Not specialized for cracks. Influenced by the key points on image	Robust to scale, rotation, and affine changes.	Moderate	Provides easy key points matching	Data for training key point descriptors	Often used as a complementary technique.	It is used for comparison and matching of faulty/un-faulty solar cell images.
[61]	HN	Amplifies noise and artifacts	It enhances PV cell image contrast.	Low	Provide simple and efficient contrast information	Works on any dataset	Can be used with other techniques for enhanced accuracy	Best for PV images of different contrast levels.

technique in the context of PV fault classification. The unique properties of the images influence the selection of an algorithm, the level of complexity of the cracks, and the computational needs of the application (see Table 3).

2) Similarity Measurement: After feature extraction, a similarity metric is used to assess the degree of similarity between diverse defect images. The metric determines the degree of distance or similarity between feature vectors and is critical in clustering faults with commonalities. Clustering methods commonly employed are K-means [75], HC [76], DBSC [77], AP [78], MSC [79], GMM [80], Fuzzy C-means FCM [81], and Spectral clustering [82]. Each of these clustering algorithms has limitations and strengths. Their effectiveness depends upon characteristics of images and size of dataset [83]. In the context of PV visual faults, various parameters of these algorithms can be compared and analyzed to determine their suitability and effectiveness for any specific task. Some working or operational parameters are distance metric, number of clusters, clustering evaluation metrics, density threshold, linkage criteria, bandwidth, fuzziness parameter, graph connectivity, convergence criteria, etc. Table 2 compares reviews of different clustering algorithms for above mentioned parameters. Whereas performance evaluating parameters are DBI [84], S-score) [85], DI [86], CHI [87], RI [88], Adjusted rand index [89], homogeneity [90], Cluster Purity (CP) [91], Entropy and Mutual Information (EMI) [92]. DBSC, AP, MS, and GMM exhibit promising performance in PV solar cell image-based categorization according to the assessment metrics, as they gain higher S-Scores, suggesting more excellent clustering quality [93]. The best algorithm to use, nevertheless, will depend on the dataset, the required number of clusters, and how easily its results can be understood. It is crucial to experiment with various clustering algorithms and parameter settings and confirm the findings using domain expertise to select the optimum PV image-based fault classification strategy. DBSC, MS, and GMM, lower DBI values classify fault more distinctly [94]. The higher DI values for DBSC and hierarchical clustering indicate better cluster separation. A higher CHI for GMM stands out, indicating excellent clustering

performance. FCM also displays higher homogeneity, completeness, and V-measure scores, indicating better agreement with genuine class labels when available. Table 4 reviews and analyses different clustering algorithms.

3) Assessment: The effectiveness of the unsupervised visual defect clustering algorithm may be measured using many measures such as accuracy, precision, and recall. These criteria are used to assess the usefulness and dependability of clustering results.

There are several advantages of unsupervised visual fault detection and identification using classification algorithms. Following conclusions can be drawn, such as:

- Classifying PV faults does not require labeled data unnecessarily. Unsupervised techniques do not relay on labeled data for training, that makes it easy and robust.
- Automatic clustering techniques classify similar PV faults without prior knowledge or manual involvement.
- Deep learning-based classification algorithms are scalable. They utilize efficient processing of big datasets containing fault images, making them suited for real-world applications with large data volumes.

Advances in feature extraction have substantially increased the reliability and usability of photovoltaic clustering techniques.

2.3. Concurrent identification of multiple faults

The capacity to detect and identify multiple faults in a PV system simultaneously is known as the concurrent identification of multiple PV problems [95]. It contrasts with conventional methods of fault detection, which generally detect single fault at a time [96]. Identifying concurrent or overlapping faults in the PV systems is a significant challenge, due to the complexity of PV systems and the vast range of potential disturbances. The feasibility and effectiveness of the previously discussed deep learning applications have trouble in discriminating between different faults. Furthermore, fault classification becomes complex when numerous failures occur in a system simultaneously.

One approach for simultaneous faults detection in PV systems is to use a CNN, which is a subset architecture class that is preferred for image categorization tasks due to high accuracy. A dataset of images of PV systems with pre-existing faults can be used to train a CNN that can further categorize new unseen images of PV systems, detecting and classifying the presence of anomalies [97]. Initially, the CNN was utilized for feature extraction on the image of the PV module while focusing on capturing the intensity of the current and voltage data. These extracted features determined whether the image was suggestive of a short circuit failure or regular operation. Deep learning algorithms and traditional machine learning based classification algorithm form an alternate paradigm for concurrent faults detection and classification in PV systems. Integrating several approaches can result in a more thorough and accurate assessment of the overlapping faults detection system [98].

Several algorithms such as, RNN [99], auto encoders [73], ensembles [100], SVMs [101], DBN [102], generative adversarial networks [103], DTs [104], RF [105], variational autoencoders [106], and several others are used for concurrent visual faults detection and classification. Detailed analysis of each technique is presented in next section. Deep learning models are used to determine the association between the occurrence of concurrent faults and the likelihood of a subsequent reasons of the faults. The dataset used can be utilized to prioritize maintenance tasks and increase the reliability of PV systems.

However, several challenges must be overcome before adoption of deep learning for faults detection in PV systems, such as, necessity of large datasets of labeled images, efficient training techniques, and the development of robust models capable of efficiently handling noisy input. To increase fault detection accuracy, an approach that can allow the integration of data acquired from various sensors is required, which manages data's inherent uncertainty, including noise and outliers [107].

3. Review analysis of deep learning algorithms

The ability to automatically detect and classify faults is of utmost importance in various power system applications, such as manufacturing PV cells and quality control of renewable industry, where the timely identification of faults can significantly impact productivity and product quality. Several deep learning algorithms reviewed, compared, and analyzed in the context detecting and classifying PV visual faults. Table 5 presents brief overview of working principles and limitations of each technique. However, each technique is reviewed separately in detail as well.

3.1. Autoencoders

AE is a form of multi-hidden neural network connected in cascade by stacking multiple autoencoder networks [109]. A network of auto-encoders consists of two distinct components: an encoder and a decoder. The encoder is responsible for network conversion. The input is introduced into the concealed layer using several techniques such as regularization approach, time frequency technique, layer by layer approach, maximum square approach, etc. The decoder provides the original entity with a depiction of the concealed layer [110]. The working of AE for unsupervised learning and feature extraction is based on the comparison between higher-order frequencies of random variables and Taylor expansions [111]. AE represents complex data patterns by encoding them into a lower-dimensional space. This process successfully summarizes important parts, which makes abstraction easier [112]. Autoencoders reduces complexity by making short representations of important data characteristics. Additional research is required to investigate the efficacy of feature driven development methodologies, particularly in the context of smaller datasets [113]. Any deep learning architecture has a primary objective is to analyse and quantify higher-order interactions evident in dataset. AE provides a computational framework for extracting and detecting these interactions. There are several benefits of extracting interactions in the dataset [32]. Frequency division duplexing technology, most deployed by AE, is one of the techniques that provides better results in extracting higher order

Table 4
Summary of review of evaluation performance of different PV faults classification approaches.

Ref	Clustering Algorithm	Homogeneity	DI	S-Score	CHI	DBI
[66]	K-mean	Low	low	Medium	Medium	Medium
[67]	Hierarchical	Low	High	Medium	Low	High
[68]	DBSC	Not applicable	High	High	Low	Low
[69]	AP	Low	High	Low	Low	High
[70]	MS	Low	High	High	Low	Low
[71]	GMM	High	Low	High	High	Low
[72]	SC	Moderate	Low	High	Medium	Medium
[73]	FCM	Low	Low	High	Low	Medium

Table 5
Overview of working principle of DL/ML Visual fault detection algorithms.

DL Algorithms	Working Principle	Benefits/ Contributions	Limitations	Ref
CNN	It learns and extract features from PV cell image in a hierarchical manner	Good accuracy in image-based crack detection	Computationally expensive and need large datasets	[99]
RNN	It needs to maintain a continuously updated state as it processes the data regularly which enables it to acquire knowledge of extended temporal relationships within the dataset.	Learns long term dependencies and performs well for sequential dataset	Interpretation is difficult and computationally very expensive	[90]
LSTM	It handes data sequences of considerable length. It also effectively records and retain complex patterns in data while mitigating the problem of vanishing gradients.	Preferred form long term data. It can learn dependencies among the different variables of dataset	Difficult to interpret. It needs time stamp	[116]
DBN	Multiple neural network layers. The first layer of a DBN is usually restricted Boltzmann machines (RBM). The subsequent DBN layers are usually fully coupled.	Robust to overfitting. It can learn features from images and time series data.	Can be computationally expensive to train. Can be difficult to interpret.	[93]
GAN	It trains two neural networks alongside each other in tandem. First, the generator network creates realistic visuals. Second, the discriminator network distinguishes actual and false images.	Creates realistic images of healthy and faulty PV modules. These images are often used for training other DL algorithms	Difficult to control the quality of image	[94]
AE	A trained neural network that reconstructs input data. It also learns hidden features to detect faults.	It learns compact features which helps in detecting subtle/minute faults.	High computational resources required	[64]
SVM	It utilizes features from EL images of PV cell and time series data to detect PV visual faults.	Classification of faulty and non-faulty images with high accuracy	Sensitive to variation of hyper parameters	[92]
VAE	It is like AE that adds a latent variable to learn a more complicated features to detect image-based faults.	It learns compact features which helps in detecting subtle/minute faults.	Training takes more time and resources	[97]
RF	It uses several decision trees, making it more overfitting-resistant and improving PV fault detection.	Robust to overfitting.	Sensitive to selection of hyper parameters	[96]
DT	Based on user defined rules, it divides data into smaller subsets. Rules are usually generated for finding features that best classify data.	Easily understood and interpreted. It can be used for PV fault detection where clarity is essential.	Sensitive to variation of hyper parameters.	[95]

interactions [114]. As stated previously, most of the benefits can be achieved, if data is collected PV systems directly or indirectly. SAE network topology is renowned for its simplicity and straightforwardness; observes input signals from real time systems unidirectionally [115].

AE uses the layer-by-layer training mechanism, which is advantageous for learning purposes, particularly when complex PV system data characteristics are considered. It is impossible to overstate the importance of sample utilization and dispersion mitigation in deep network models. Second approach followed by AE for fault detection rely heavily on time-frequency analysis techniques applied to the acquired signals [117]. It has been observed that autoencoder exhibit a high degree of robustness across various PV applications. The performance's capacity to produce the desired results and meet the predetermined objectives determines its effectiveness. The effectiveness of time frequency analysis technique was determined by analysing its effects. Input volume and structural complexity are the two main factors that affect an algorithm's performance. Authors in Ref. [118] justifies that the investigating sparsity and denoising is paramount, as they serve as indispensable constraint criteria. The analysis of the input is derived by extracting the frequency spectrum from the time series. Innovatively utilizing the SAE architecture for the implementation of multiple FDDs is the novel approach presented in Ref. [119]. In the investigation of [120], a novel methodology was devised. Author used signal analysis; the technique proposed generates composite features for the purpose of obtaining additional information. To effectively address the issue of non-stationarity, it is essential to incorporate information that distinguishes among alternatives. Multiple fractures are hypothesized to be responsible for the occurrence. In the context of multiple fault classification, due to inherent limitation of AE, the transmission of information is predominantly characterized by reflection [121]. Authors in Ref. [122] incorporated a weight factor to the proposed methodology of [111].

Utilizing regularization techniques for the acquisition of facial representations that are invariant to weight changes. Sparse-stacked denoising autoencoders and Deep Boltzmann machines have received considerable attention for employing regularization [123]. One interesting approach for solving the issue of the limited availability of training data, the researchers in Ref. [124] utilized "discard" method in the concealed layer of the proposed architecture to mitigate the issue of data overfitting. Author in Ref. [125] performed classification using an auto-encoder neural network. The proposed methodology utilizes a prior distribution for the latent variable and investigates the correlation between the utilization of spatial elements and the quantity of mutual information obtained from the dataset. Additionally, cross-machine approach for visual fault detection is proposed in Ref. [126] which has the potential to substantially reduce the amount of data collection required for model development, entails substantial computation cost.

The authors in Refs. [127,128] introduced the concept of the maximum square approach to analyse the likelihood of process errors in multi-modal operation. MSD is a non-parametric distance estimation technique. This study examined the relationship between two distributions and introduced the concept of migration learning. The implemented methodology yielded favourable results, particularly in terms of specificity. The training data attributes exhibited similarities in scenarios by an uneven distribution of testing data. Author in Ref. [129] has used time series data as input for network models for improving the effectiveness of AE various fault detection scenarios. This paper explores the various temporal dimensions within the context of dynamic PV systems. Major limitation of [118–120] is higher dimension of inner layer of AE, which makes detection and classification process slow.

To restrict the dimensions of the hidden layer [130], employed a Stacked Autoencoder (SAE) neural network with a sparse configuration. This research work investigated the characteristics of the concealed layer, a statistical investigation was also conducted.

3.2. Deep belief networks

DBNs consist of restricted Boltzmann machine based sub blocks [131]. RBM is a class of neural networks characterized by a bi-layered architecture comprising a visible and hidden layer. The energy function characterizes the most significant level of interaction among variables of dataset [132]. The term 'restricted' denotes where every edge of the bipartite graph establishes a connection between visible and concealed layer [133]. RBM assumes that for a given the input data, the activation states of the individual hidden layers are conditionally independent and for the given hidden layers, the activation function of visible layer is independent [134]. As described in book chapter [123], the hidden layer facilitates data transmission and enables feedback correction from higher layers to lower layers. According to authors in Ref. [135], it has been theoretically demonstrated that the RBM has the potential to effectively represent any discrete distribution, provided that a substantial number of hidden units are utilized.

Moreover, the utilization of FDD with DBNs offers some additional benefits. These benefits include improved scalability and efficiency in handling large datasets. Additionally, FDD with DBNs allows for better handling of missing or incomplete data, making it a valuable tool in real-world applications [136,137]. It is of utmost importance to know the distribution of the data samples which may not always adhere strictly to the assumed conditions [138]. Utilizing generative learning methodologies, the RBM can make predictions regarding the probability distribution of incoming samples. The stochastic unpredictability of fault occurrence in PV system is one of major factors for consideration while training the DBN architecture [139]. Unsupervised learning enables RBM to model the data effectively and probabilistically, thereby facilitating the augmentation of sample sizes of PV systems with limited data accessibility. The DBN can generate activation values using feature aggregation sequences. This feature renders it highly suitable for the simulation and regulation of multivariable nonlinear systems, specifically in the context of unstructured control of PV systems [140]. The utilization of DBMs that effectively incorporate a multitude of multimodal feature properties has been demonstrated by the authors in Ref. [141]. The primary objective of this research is to employ representation learning methodologies for features derived from the domains of time, frequency, and time-frequency based input. Proposed strategy integrated fusion diagnostics within the decision-making process. The authors in Ref. [142] proposed an advanced convolutional DBN to cater to the needs of frequency division duplexing applications. In the preliminary stage, an auto-encoder is employed to compress data and minimize dimensions. The deep model is then constructed utilizing Gaussian visible units to impart similar characteristics. This technique exhibited superior precision performance compared to traditional deep learning frameworks. The modelling technique presented in Ref. [133] was enhanced by Ref. [143] using extra hidden layers into the activation function of the sparse sacked autoencoder network. The proposed modification enabled DBN to identify and extract salient features from the given dataset more precisely.

Moreover, authors of [144] proposed a novel approach, the dual-tree complex wavelet packet method, to generate an initial feature set. Additionally, to increase features extraction accuracy the author in Ref. [145] presented an enhanced iteration of the RBM incorporating a novel regularization term. The authors in Ref. [146] utilize the Teager-Kaiser energy operator which serves as a method for computing the envelope of the instantaneous inputs from images of PV cell and extracting statistical characteristics from it. The authors in Ref. [147] introduced the Gaussian-Bernoulli restricted Boltzmann machine as a foundational framework of DBN for real time faulty images classification. In Ref. [148], the authors propose an enhanced implementation approach for FDD by incorporating DBN. The principal objective of this investigation was to mitigate the loss of information through the utilization of stacked sparse auto-encoders for the construction of deep defect data models. In contrast [149], proposed an innovative approach that synergistically integrates the capabilities of fuzzy Petri nets (FPN) and dynamic Bayesian networks. This paper presents a novel adaptive arc-generating approach that integrates label weight based on confidence weight to enhance fault identification. To enhance diagnostic precision at every temporal iteration, a proficient DBN model was formulated in Ref. [150]. This model integrates an optimal allocation of network characteristics at every hierarchical level.

3.3. Recurrent neural network

RNNs are network designs with a chain-like structure due to a sequential arrangement of coupled layers. The networks were explicitly designed to process and interpret time-series data [151]. RNNs can learn sequences with temporal fluctuations that multi-layer perceptron's do not [152]. This is due to their intrinsic ability to discern temporal changes and retain knowledge of earlier network states. LSTM and GRU networks are the most common types of RNN used in modern applications [153]. However, it is critical to understand that RNNs are constrained by a sequence duration constraint, as gradient bursting and disappearing phenomena may occur [154]. To address the challenges of long-sequence prediction, researchers developed variants of RNN, specifically the LSTM [144] and GRU [145] models. The benefits of using a RNN-based FDD is to fed the time-series data, the depth of which is determined by the length of the input sequence. This property enables RNN to monitor and forecast dynamic PV systems. The turning completeness of RNN has been empirically verified, confirming its ability to simulate any Turing machine.

RNN uses chain connection mode for easy extraction and visualization of the dynamic nonlinear features in EL images of PV systems. Usually, RNN takes input sequences in a periodic time difference. When the durations of the sequences used for learning and testing differ, the stability of a RNN becomes visible. This characteristic is essential in the field of PV system control since it usually includes sequences of varying lengths and complexity [155]. Monotonicity and correlation values are used to choose characteristics as inputs for the RNN model in the context of time-series data from PV systems. Authors in Ref. [156] proposed a design for an encoder-decoder system that used LSTM. The decoder architecture uses the vector created by the encoder architecture to synthesize the intended sequence and calculate the reconstruction error, which directs decision-making algorithms. The encoder architecture oversees turning the input sequence into a vector of a specific length. To address the problem of fault detection and classification, the authors in Ref. [157] created three distinct RNN structures: vanilla RNN, LSTM, and GRU. According to the findings of [148], LSTM and GRU models beat the vanilla RNN. A significant decrease in failure occurrences and noise reduction is observed in LSTM and GRU. GRU in Ref. [158] is used to optimize the parameter count and handle the gradient explosion or disappearance issue. The authors of [159] achieved sequential frequency duplex using a LSTM neural network. The proposed method can classify raw process data without requiring specialized feature extraction and classifier construction. The system can extract real-time information from raw data flexibly and customizable [160]. extracts feature LSTM networks. The selected attributes are fed into a SoftMax regression classifier for fault diagnostics. Data from a PV system within the observed area displays temporal relevance and geographical dependency. Table 6 presents the summary of the above-mentioned analysis.

3.4. Convolution neural network

CNNs are built with three distinct layers: convolutional layer, pooling layer, and the fully connected layer [161]. CL oversees multiplying the elements of a matrix with the input data from the perceptual field. It employs the concept of deviation to extract features from the input data or upper layer characteristics. The size of the convolution kernel in the CL determines the extraction of local spatial correlation characteristics from the input data. This kernel can improve the original input's specific properties while reducing the noise impact [162]. The PL's primary function is to reduce the spatial dimensions of the convolved feature by using dimensionality reduction techniques [163]. Furthermore, it helps keep the training process effective by identifying relevant characteristics that show rotational and positional invariance [7]. Incorporating a FCL allows for the successful acquisition of nonlinear combinations of high-level properties.

The following are the benefits of using CNN:

- The data obtained from industrial systems is heterogeneous due to its diverse origins.
- CNN can effectively process multi-source information, making them suitable for a wide range of inputs such as time series data, spectrograms [164], and images [165].

Furthermore, complicated PV systems frequently experience sporadic intense magnetic interference and elevated temperatures. The incorporation of translation invariance in features derived CNN improves the robustness of the diagnostic process of magnetic interference and strengthens CNN's generalization capacity. Usually, the abundance of real-time data frequently contains the necessary information for detecting faults in PV systems. The constructed modified CNN networks have the potential to acquire information about the probability distribution of real data [166], allowing them to generate samples effectively, particularly in scenarios with limited sample sizes. The vector matrix proposed by the authors in Refs. [167–169] includes statistical features such as the frequency domain signal's root mean square and the temporal domain signal's standard deviation, skewness. This vector matrix is fed into the CNN for classification purposes. To obtain the wavelet scale map of the signal, the authors used a Morlet wavelet decomposition tool [170,171]. The map was fed into the CNN as part of the classification phase. The rectified linear unit (ReLU) was then used as an activation function in the proposed methodology to incorporate nonlinearity into the network. The study mentioned in Ref. [172] used an adaptive learning rate to create a hierarchical framework comprised of two CNNs. As a result, the magnitude of the mode and the rate of change of the adaptive learning rate can increase the algorithm's convergence speed while decreasing the likelihood of the gradient disappearing. Furthermore, due to the limitations of the traditional linear model in effectively capturing the intricate correlation between sensor data and remaining useful life, the researchers in Refs. [173,174] used time series data from multiple sensors. CNNs can also be applied directly to one-dimensional (1D) time series data. The authors of [175] created a 1D kernel filter to convolve the signal. The proposed methodology aims to extract high-resolution features to identify flaws. The research described in Ref. [176] involved integrating feature extraction and post-processing methods on raw data to effectively apply a one-dimensional 1D CNN for fault identification. To address the issue of small sample sizes [177], devised a methodology that entailed converting conventional knowledge into atypical data by incorporating imprecise fault information and utilizing advanced generative adversarial networks. The proposed methodology aims to supplement unprocessed fault data by converting it into a format that can be easily compared to actual errors observed in the real world. In Ref. [178], the authors used a GAN to generate samples that conform to the original distribution of a specific input. The network was subjected to apply stacked denoising auto-encoding before the start of the feature extraction process. SDAE aided in the extraction of fault features and allowed for accurate determination of the validity of the generated samples. When applied to small samples, SDAE demonstrated a significant level of effectiveness in noise reduction, indicating a notable ability to withstand noise interference. Additionally, in Ref. [179] the author used a GAN to process seismic PV cell images. The feature extraction algorithm implementation allowed local and global features to be extracted from the high-resolution images. This procedure was designed to address the issue of imprecise intermediate probability values and improve the substantiation of the fault overlapping area. The original data and frequency domain information was preserved because the reconstruction network used a denser sample rate to produce a high-sensitivity image.

Table 6
Overview and summary of different RNN based fault detection approaches.

Architecture	Capabilities	Limitation
Vanilla RNN	Easy to implement and train.	Less effective than LSTM and GRU for modelling long term dependencies
LSTM	Easily handles long term dependencies in the dataset	Complex and difficult to train
GRU	Less complex than LSTM and can perfectly model long-term dependencies.	Less accurate than LSTM
Bidirectional RNN	Can extract and model dependencies in both direction, that helps in fault detection	More computationally expensive
RNN Encoder-Decoder	Learns relationships accurately between input and output	Difficult to train as compared to other architectures

3.5. Deep transfer learning

The quantity of data collected directly influences the efficacy of frequency division duplex models based on DL [180]. DL-based models exhibit superior performance when a large amount of data is utilized. However, their accuracy and reliability tend to deteriorate when limited training datasets are available. The discussion on the influence of deep models with multiple hidden layers on the performance of the approach can be found in reference [181]. Deep learning-based models' training and testing datasets have the same feature space and distribution. This means that statistical models need to be set up again using the new training data. Establishing a new dataset of PV systems under different conditions, specifically concurrent faults, is widely acknowledged to reduce computational costs [182]. One potential strategy for addressing these challenges is DTL, a novel DL technique that aims to optimize data attribute parameters by leveraging prior knowledge to overcome obstacles in various interconnected domains. The transfer technique in fault detection has garnered significant attention considering its capacity to attain high accuracy in intricate scenarios and facilitate the establishment of a comprehensive diagnostic model. The primary objective of deep learning-based fault detection is to partition the training and test datasets into two distinct classes: normal and defective data. The target domain leverages the information acquired from the source domain to facilitate fault detection. In the provided context, the utilization of FDD in the pertinent domain is deemed appropriate due to the discrepancy between the erroneous data in the source and target domains [183].

Transfer learning techniques can be categorized into four distinct classes, namely: instance-based domain transfer learning, feature-based domain transfer learning, network-based domain transfer learning, and adversarial-based domain transfer learning. Instance-based domain transfer learning refers to adjusting the weights of samples obtained from the source domain to apply them effectively to tasks within the target domain. The fundamental aim of the feature based DTL technique is to ascertain the common feature space between the source and destination domains [184].

In recent years, there has been a significant surge in interest surrounding the notion of digital twin learning, which has found extensive application across domains such as FDD, image identification, text recognition, and PV fault detection. To enhance the accuracy of classification, the authors in Ref. [185] propose an adaptive FDD technique capable of effectively managing diverse operational scenarios. The researchers in Ref. [186] proposed an automated fault detection and diagnosis solution for PV systems utilizing dynamic time warping (DTW) and machine learning techniques. The conducted experiments have yielded empirical evidence substantiating the proposed diagnostic technique's notable accuracy across a range of simulated scenarios. However, differential threshold logic has demonstrated its utility within domain of FDD; nevertheless, it remains restricted by several limitations. The challenge of conducting a comprehensive investigation of dataset across multiple domains and efficiently applying its information to a novel and interconnected issue is worsened by the abundance of noisy data.

Numerous recent advancements have been achieved, encompassing the refinement of fundamental performance metrics, including the mitigation of computational overhead, failure against uncertainties, and precision. However, enhancing efficiency in scenarios characterized by intricate, unpredictable, extensive, and noisy data is of utmost importance, and the acknowledgment of the necessity for enhanced data-adaptive fault detection and diagnosis has been observed in recent times.

3.6. Hybrid models

The significance of hybrid deep learning models for solar PV fault detection lies in their ability to combine the benefits of different deep learning models, which helps them attain enhanced performance [187]. CNN has been widely recognized as highly suitable for the extraction of local features from images. On the other hand, RNN has demonstrated exceptional ability to capture long-term dependencies. By combining these two types of models, a hybrid model can attain superior performance compared to either model alone. Detecting PV faults form EL images of solar modules at a large scale are challenging task. Several hybrid models are developed in the literature to detect faults at large scale, but none has demonstrated convincing results [188–191]. Author in Ref. [192] used dataset of 3629 faulty PV images, but his proposed attention feature pyramid network detected 2129 correctly. Proposed architecture was hybrid model of feature pyramid network and region proposal network. The proposed model has shown satisfactory results. This research work prominently highlighted the substantial fault detection errors. Modified CNN which is termed as "deep CNN" was proposed in Ref. [193] to detect cracks in crystalline silicon PV wafers. Eddy current thermography was utilized to achieve infrared based thermal images of solar PV faulty wafers and cells. Results of the proposed techniques were compared with other deep learning-based classifier models such as VGG-16, Google Net, and LeNet-5. Author in Ref. [191] proposed hybrid model by combining the short and long terms features of EL images of PV cells. In this research series of natural images generated through CNNs were considered long terms features, whereas short terms features are taken from current knowledge gained from the series of images through denoising auto-encoders. This research work showed better performance in detecting micro cracks. Dust is another major problem common in desert locations, that can lead to degradation, corrosion, eruption, and various other defects. Authors in Ref. [194] proposed modified CNN architecture with denoising based on status of dust on PV module. This research work implemented several combinations of CNNs, VGG-16, ResNet-50, AlexNet. Hybrid model of CNN with ResNet-50 produced better result for evaluating dust in real-time. Table 8 summarizes PV fault detection using deep learning-based hybrid models. Table 9 present SWOT analysis of DL algorithms in context of PV fault detection.

4. Data augmentation of PV images

The idea of data augmentation is extremely important when it comes to deep learning applied to solar cell image analysis for fault diagnosis. Solar cell images are used for identifying anomalies in solar panels, such as issues like cracks, hotspots, and discolorations that might affect the panel's operational performance. In the case of fault detection, data augmentation is a key tactic. It increases the volume and diversity of the dataset by utilizing a variety of strategies, which lessens the negative effects of data scarcity during model training [195]. The complex image modification techniques used in these augmentation techniques—such as rotation, flipping, zooming, and cropping—replicate different solar panel orientations, lighting angles, and perspectives. Additionally, artificial anomalies that point to faults can be added to the photos, enhancing the dataset with a wider range of fault appearances [196]. Beside the watchable visual disturbances, augmentation includes the addition of controlled noise to images to mimic changes in sensor readings and ambient circumstances. Moreover, data fusion replicates real environmental fluctuations by using photographs taken at various angles and locations. Modifying color and channel layouts allows for adaptation to changes in lighting conditions and spectral characteristics. The combination of augmented batches, defined by the augmentation strategies, greatly improves the adaptability of the model during training. When data augmentation methods are used in a well-thought-out way, they create a model that can accurately identify and classify a wide range of PV visual faults. This gets around the problems caused by small training datasets. By giving the model the necessary adaptability to handle a variety of real-time scenarios, augmented data improves the model's overall performance. Underscoring the need for carefully adjusting the intensity of augmentation is essential to ensuring the model's integrity and avoiding unwarranted extrapolation from artificially fabricated situations.

CNN models demonstrate exceptional proficiency in integrating spatial data. However, it is worth noting that these models exhibit a deficiency in equivariance when it comes to rotation and scale transformations. To mitigate this constraint, it becomes important to augment the data through rotation and scaling operations, as stated in Ref. [141]. To enhance the generalization capabilities of the networks [197] have discussed in detail the importance of data augmentation in DL techniques for two main reasons: first, to deal with the problem of limited data availability, which is especially important when training DL models, especially for tasks that involve multi-level classification; and second, to deal with new and very different images that were not seen during the training phase.

Data augmentation provides a solution by enabling the generation of new images that capture important features from preexisting images, thus enlarging the training dataset. By utilizing a variety of transformations in the process of data augmentation, the original training dataset can be substantially enhanced, thereby addressing concerns related to the limited availability of data. Authors in Refs. [198,199] have also proposed CNN architectures for PV fault detection and classification. These studies have also highlighted the significance of employing data augmentation techniques to improve the overall performance of the models. Table 7 shows a trend of data augmentation techniques used in literature: many the studies looked at show a tendency to use data augmentation methods, with flip and rotation being the most common operations.

5. Conclusion and future recommendations

This paper provides a comprehensive overview of the deep learning techniques used in solar PV visual fault detection. Deep learning techniques can detect visual faults, such as cracks, discoloration, and delamination. Most of the classification and detection techniques have accuracy of more than 90 % with positive results. However, the performance of some DL models suffers due to their inadequate structure or inability to distinguish input features effectively. It is also concluded form that the hybrid models are superior to other in terms of performance, with the degree of improvement dependent on the integrated approaches. Several researchers have widely acknowledged the effectiveness of data augmentation techniques in improving model performance. The most frequently employed augmentation technique is flipping and rotation. Another major observation is that over sixty percent of the DL algorithms can conduct two-fault classification tasks i.e., whether a given module is defective or healthy. While some research has attempted multi-class classification, it has been observed that their performance in terms of accuracy is generally less than that of two-class applications. It is also concluded that the complexity of precise solar PV fault identification using image processing techniques is more than other statistical approached. Exploring deep learning models with different input features can help in future research regarding concurrent and complex PV faults detection.

The majority of research regarding the identification and classification of faults in PV systems focuses on two primary areas: The first is improvement of data preprocessing techniques whereas the second is using multi scale data for enhancing accuracy. Traditional DL techniques perform better for uniform and regular datasets, but for enhanced and concurrent fault detection, there is a need of development of alternative DL techniques which can handle irregular distribution in datasets. Size of the training data has the opposite influence on the computational time required to make a fault diagnosis. To overcome this limitation, enhanced methods that rely on data-reduction frameworks is suggested, such as K-means metric, hierarchical K-means clustering, and Euclidean distance. The success of a diagnostic procedure depends on the quality of the available training data, which usually consist of noise and self-correlation. Multiscale data representation is a potent instrument for data analysis that can enhance the efficacy of data preparation procedures. Considering measurement noise and the way the PV system evolves over time, the developed alternative methods will be utilized to

Table 7
Different augmentation operation for PV cell images used in literature.

Ref.	Solar cell image augmentation operations
[200]	Gaussian noise
[201]	Brightness and contrast
[202]	Flip, rotate and then flip
[203]	Simple flip
[204]	Multiple rotations with mirroring
[205]	Shift, flip, and rotation
[199]	GAN based augmentation operation
[206]	Cropping and flip
[202]	Rotation and flip
[207]	Translation and flip
[208]	Blurring and brightness adjustment

Table 8
Summary and review of DL based approaches for PV faults detection and classification.

PV fault detection algorithm	Observations and results	Contribution and practical implications	Ref
RNN based LSTM with Discrete wavelet transformation	• Classification accuracy: 91.21 % • LSTM classifier success rate: 92.42 %	Accurate detection of high impedance fault (HIF) in real time	[99]
Deep neural network	• Classification accuracy 93.69 %. • Effects of hyperparameters and data augmentation are also examined.	Accuracy is improved by adjusting hyper parameters and using data augmentation.	[3]
Manual inspection of labeled faults	Neural net has accuracy of above 90 % with 28 passes.	It detects potential bugs or design inefficiencies	[209]
Two dependent ANNs	Prediction of normalized degradation with higher accuracy	Monitoring degradation of solar cells in photovoltaic modules	[210]
Deep residual neural network (DRNN)	MAE of the DRNN is 78.7 % and 3.67, respectively.	- Improved and enhanced identification method for uneven dust accumulation	[211]
Three layered NN with 50 neurons at each layer	Neural network pruning strategies gives better results	Optimized neural network architectures for fault classification	[212]
P&O based ANN	MSE and regression accuracy are >93 % in many cases	Effective results using artificial neural network	[213]
Graph-based semi-supervised learning (SSL) method	Graph-based SSL classifies new PV operating data	Graph-based semi-supervised learning for real-time operation	[214]
Feed forward NN	Detection and identification of eight different faults with accuracy of 83 %	Improved efficiency in PV array fault detection and classification	[215]
Infrared thermography-based CNN	Anomaly detection accuracy 92.5 % Classification accuracy: 78.85 %	Reduced operation and maintenance costs	[216]
Ensemble of multiple CNN model architectures	95 % cell-level fault prediction accuracy - High recall	Reduced warranty and repair costs of PV module	[217]
ANN with Sugeno fuzzy logic	99.28 % accuracy fir short circuit fault 99.43 % accuracy for Open circuit fault	Increased accuracy in identifying faulty modules and disconnected strings	[218]
ANN	Short circuit fault detection with accuracy of 97 %	Reduces workmen effort in identifying faults	[219]
Fuzzy NARX algorithm	Tree-like hierarchy modeling - Fuzzy nonlinear autoregressive network with exogenous inputs (NARX) and have RMSE of 0.0256	Detecting concurrent faults	[220]
Alex Net CNN	Potential for detecting various PV faults with accuracy of >90 %	Automatic defect inspection of solar panels	[221]
Threshold detection method with ANN	Detection accuracy is 94.0 % - Accurately detects 564 out of 600 samples	Prevention of production and performance reduction in PV systems	[222]
Adaptive Genetic Algorithm (AGA) - Deep Belief Networks (DBN)	Convergence speed and recognition accuracy significantly improved. -	Increased Classification accuracy	[223]

(continued on next page)

Table 8 (*continued*)

PV fault detection algorithm	Observations and results	Contribution and practical implications	Ref
CNN	Accuracy >85 %	Localization of faults within the PV array	[224]
ANN	Method allows classification of PV system states	Efficient detection and identification of faults in PV arrays	[225]
Deep belief networks (DBN) - Fisher Discriminant Analysis (FDA)	Effective performance with TEP benchmark	Effective fault diagnosis using hybrid method	[226]
Deep learning approach using YOLOv3-tiny model	Proposed DL model achieved high performance	Utilization of unmanned aerial vehicles for thermal imaging	[227]
DBN	High accuracy in quickly detecting defects	Automatic detection of faults in PV cells	[228]
Elman Neural Network (ENN)	- Training time is less than 2s.	Reduction of risk of power plant failure	[229]

enhance tracking and diagnostics.

The multiscale data preprocessing incorporates the advantages of multiscale estimation and data preprocessing methods so that real time DL approach for diagnostic of PV systems can more effectively deal with uncertainties, such as inaccurate measurements, noise, and variations in current and voltage. Incorporating uncertainty regarding irradiance, current, voltage, and temperature, the alternative DL methods for data preparation will also supplement the existing techniques. Interval-valued data representation and dimensionality reduction techniques are another alternative approach. These approaches might be able to reduce the uncertainty of real time PV systems. This method will improve the accuracy of the model and eliminate the need for time- and resource-intensive data preparation techniques. Interval-valued data set can also be established using multiple distance formulas such as Euclidean and others, to eliminate irrelevant and duplicate data samples.

Another alternative DL based CNN approach is to focus on the selection of optimal number of hidden layer nodes and the choice of activation function, so that features can be extracted, and data inputs can be rebuilt. This approach will reduce and ease parameter tuning procedure, which can enhance the diagnostic performance. Several researchers suggest that combining multivariate statistical studies, signal processing techniques, and other methods with deep learning models to enhance the performance and accuracy of PV fault detection and decision-making processes, could also be another alternative approach. This research work also recommends employing diminished extensions for kernel principal component analysis (KPCA), in which various measures for dimension reduction are used to select the optimal samples for constructing the KPCA model.

In conclusion, this research work proposes several alternative approaches for enhancing the efficacy of diagnosis using an advanced multiple deep learning technique. It is concluded that hybrid approach that combines high-level knowledge with multiple deep learning architectures and combines various deep learning models are currently the best approach for PV fault detection and diagnosis. This research work also recommends efficient way of dataset establishment with less noise, more practical dataset, highly efficient preprocessing techniques, and hybrid DL models with less computational time. It is also concluded that CNN is comparatively better tool if combined with efficient data preprocessing mechanism. The most challenging future research work is multi labelling of concurrent and overlapping faults. Such as labelling of overlapping shading, hotspot and other faults.

Table 9
SWOT analysis of DL algorithms in context of PV visual fault detection.

DL Algorithm	Strengths	Weaknesses	Opportunities	Threats
CNN	Very accurate in detecting visual faults	Training larger dataset is computationally expensive	CNN is to be applied on mega scale PV parks across the globe for fault detection.	CNN may be threatened by newly established AI-based fault detection methods.
ANN	Versatile and equally effective in detecting any kind of fault	Deployment and training are computationally expensive	Development of new ANNs and modification of existing ANN architecture can improve accuracy	PV systems are becoming more complex, making it harder to construct models using ANN that can precisely detect PV faults.
RNN	Efficiently extracts long term dependencies	Deployment and training are computationally expensive	Time series data is becoming more accessible, allowing RNN training on larger and more diversified datasets.	RNN may be threatened by newly established AI-based fault detection methods.
AE	Extremely efficient in extracting latent features of PV systems	Deployment and training are computationally expensive	Training and testing autoencoders on larger data set is required	Day by day dataset is becoming larger and complex, AE is becoming expensive option for fault detection
DBN	Good in learning the complex relationships between input and output data	Deployment and training are computationally expensive	Development of new DBNs and modification of existing DBNs architecture can improve accuracy	DBN models may become harder to design as PV systems get increasingly sophisticated.
TL	It improves the accuracy by learning interdependences among different variables of data set	Accuracy of TL depends upon the relationship between input and expected output	Improved transfer learning methods are always being developed.	TL may be threatened by newly established AI-based fault detection methods.
Hybrid algorithm	It combines strength of different DL algorithms	Less accurate than NNs	The continuous advancement of novel hybrid deep learning methodologies is consistently enhancing their overall performance.	The complexity of PV systems may make it harder to construct hybrid deep learning models that can effectively detect faults

CRediT authorship contribution statement

Marium Jalal: Conceptualization, Formal analysis, Investigation, Methodology. **Ihsan Ullah Khalil:** Writing – original draft, Methodology, Investigation, Funding acquisition, Data curation, Conceptualization. **Azhar ul Haq:** Writing – review & editing, Validation, Supervision, Methodology, Funding acquisition, Conceptualization.

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

No data was used for the research described in the article.

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