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Applications of Machine Learning Algorithms for Photovoltaic Fault Detection: a Review

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Abstract Over the years, the boom of technology has caused the accumulation of a large amount of data, famously known as big data, in every field of life. Traditional methods have failed to analyse such a huge pile of data due to outdated techniques. In recent times, the use of photovoltaic systems has risen worldwide. The arena Photovoltaic (PV) system has witnessed the same unprecedented expansion of data owing to the associated monitoring systems. However, the faults created within the PV system cannot be detected, classified, or predicted by using conventional techniques. This necessitates the use of modern techniques such as Machine Learning. Its powerful algorithms, such as artificial neural networks (ANN), help in the accurate detection and classification of faults in the PV system. This review paper introduces and evaluates the applications of Machine Learning (ML) algorithms in PV fault detection. It provides a brief overview of Machine Learning and its concepts along with various widely used ML algorithms. This review various peer-reviewed studies to investigate various models of ML algorithms in the PV system with the main focus on its fault detection accuracy and efficiency.

Keywords Machine Learning, photovoltaic system, PV fault detection, artificial neural network.

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1. Introduction

With an ever-increasing scope of the latest technology, the use of modern techniques and tools for the analysis of available information has also increased. Most of the technologies have witnessed an amelioration after the incorporation of Machine Learning [1]. It is because the traditional methods have proved to be insufficient to analyse the Big Data that have been accumulating every single day. Machine learning, a data mining technique, is used in case the of extracting relevant data from the enormous pool of data. ML is one of the most fast-growing fields in data science and its uses and applications have become immense [2]. ML mainly focuses on enabling machine programs to learn through experience and execute functions without relying on external supervision in the form of rule-based programming. ML is often confused with artificial intelligence and both terms are used interchangeably. However, it is important to remember that id ML is only a large subset of AI [3]. ML aims to improve the ability of machines to perform troubleshooting without any particular computer program [4]. In order to draw inferences from the available or stored big data, which can be in the form of structured or unstructured data, automated reasoning is necessary. Machine Learning helps in making predictions about the pattern based on stored data.

In recent times, the use of photovoltaic technology has risen to a great extent among homeowners and

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various solar plant entrepreneurs and investors. The reason being it is viewed as a low-risk industry that has great potential to return profits [5]. However, the problems of troubleshooting associated with this system had also increased. There are many factors can impede PV systems operation. These factors can be split into three categories: Physical, Environmental and electrical [6], as shown in Figure 1.

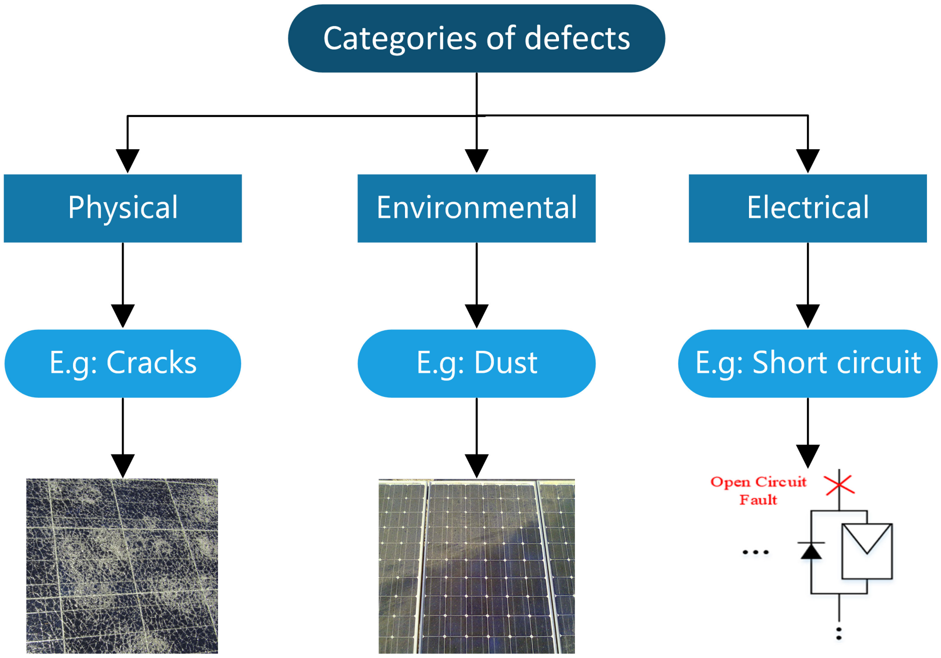

Figure 1. Type of faults in PV panels.

Because of this, most of the photovoltaic systems have been equipped with monitoring systems. These systems have caused the accumulation of a huge amount of data or Big Data [7]. The presence of big data in PV systems has made it necessary to used advanced methods of data mining that can detect faults accurately and increase the efficiency of the system. In such a scenario, the use of Machine Learning for fault detection in PV systems seems quite pertinent and logical [8]. The use of the ML technique has become very accurate these days due to highly developed software and computational devices. Machine Learning employs the use of efficient algorithms that work to train the system on the basis of huge historical data available. As a result, the system becomes able to predict faults in the future and classify them accordingly. Moreover, the accuracy of fault detection is unprecedently accurate when ML algorithms are employed [9].

In this paper, an outline of machine learning along with a comprehensive review of the implementation of Machine Learning for fault detection and classification in a PV system is provided. In Section 2, the concept of Machine Learning is elaborated with the help of its various algorithms (supervised, unsupervised and reinforcement). To this end, a number of the latest and relevant research papers have been put under study. In Section 3, a number of recent research articles have been reviewed to gauge the performance of ML algorithms in improving the photovoltaic system. The main features of various Machine Learning models applicable in the photovoltaic system are presented in terms of year, accuracy, detection, classification and limitations. Section 4 briefly illustrates various challenges in the implementation of ML techniques in PV fault detection, whereas Section 5 summarizes the main conclusions of the present work.

2. A Brief Overview of Machine Learning Algorithm

Machine Learning is generally separated into three learning classifications: unsupervised learning, supervised learning and reinforcement learning [10], as described in Figure 2. A detailed overview of

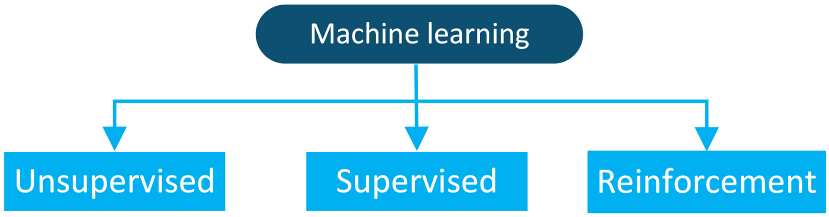

Figure 2. Machine learning classifications.

supervised and unsupervised ML algorithms is provided below:

2.1. Supervised ML algorithms

In supervised learning, the algorithms are trained on the historical dataset which enables them to propose accurate predictions for all available inputs [11]. It includes the following algorithms [12]:

- K-nearest neighbours: It is regarded as one of the simplest ML algorithms for the prediction of inputs in the training dataset. This algorithm works on the concept that prediction is made on the basis of the closest neighbour of the input whose output is to be predicted.
- Linear Regression algorithm: This algorithm makes predictions about the available data on the basis of a linear function.
- Logistics Regression algorithm: This algorithm is employed where classification-related tasks are concerned. It predicts the correspondence of certain available inputs with relevant classes.
- Artificial Neural Networks: This algorithm is based around the utilization of network or interconnection of various computing cells (also known as neurons) in order to enhance system performance. In the case of certain intricacies of functions and features, neural networks provide an alternate way of performing Machine Learning on the available inputs.

2.2. Unsupervised ML algorithms

In unsupervised learning, the form of results is unknown. The algorithms extract results from the available dataset after pinpointing the similarities among the inputs [11]. The most common unsupervised learning algorithms are as follows:

- K-means Clustering algorithm: This algorithm functions by forming k-unique clusters automatically. In this algorithm, clusters are formed by grouping the closely related variables present in the data [13].
- Dimensionality Reduction algorithm: This algorithm functions to reduce the error in prediction by reducing the size of a large number of features or factors into a smaller number of factors. For instance, Principal Component Analysis (PCA) is done to achieve this purpose.

2.3. Reinforcement ML

The reinforcement ML involves no labelled dataset. One of the most famous reinforcement ML algorithms is Markov Decision Process (MDP) [14]. Decision Tree, Boosting, Naïve Bayes and Kriging algorithms are some other ML algorithms. However, these are used less frequently.

Machine Learning operates by first dividing the available dataset into three parts. The first part is the training dataset which is used to train the algorithm. The second part is used for cross-validated in order to choose the suitable model. And the third one is used to test the efficiency of the algorithm in terms of prediction accuracy [12].

3. Use of Machine Learning Algorithms for the PV Fault Detection

In the literature, there are many techniques have been proposed for detecting the faults in PV systems. These techniques can be categorized into two types: Electrical and nonelectrical techniques [15]; electrical methods are mainly based on current and voltage measurements, whereas the nonelectrical techniques are based on Infrared or Electroluminescence imaging as presented in Figure 3 [16].

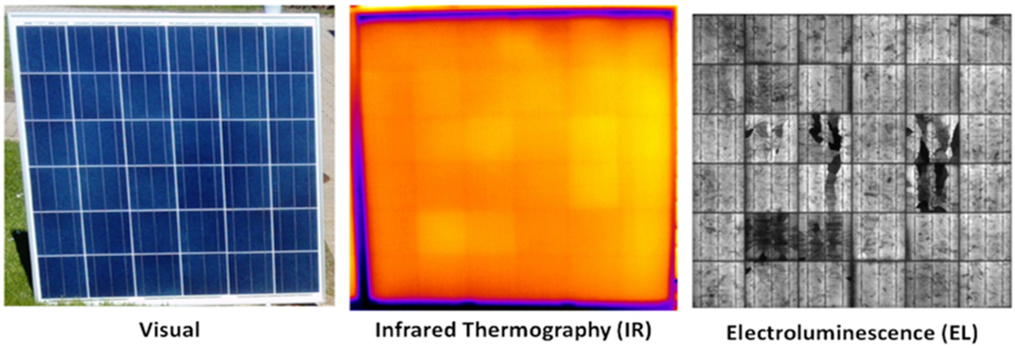

Figure 3. Visual, IR and EL images of the same PV panel.

However, these techniques are weak in terms of accuracy and the number of faults that can be detected. For addressing that, a number of researches have contributed to study the implementation of Machine Learning algorithms and electrical/nonelectrical methods for fault detection in photovoltaic systems. It is widely expected that Machine Learning has the capacity to terminate PV faults and significantly improve the efficiency of the system. It can also maintain an optimal level of accuracy in making predictions and classifications about the PV system faults, leading to a reduced number of required simulations. In this section, a detailed review of peer-reviewed research articles on the use of Machine Learning for PV fault detection systems has been provided. The models used in these studies along with salient features and ML algorithm have also been reviewed.

Examining the literature, most of PV fault detection and classification using machine learning algorithms are based mainly on CNN and ANN, which rely on PV images (Infrared, RGB and EL) and PV characteristics as inputs, respectively, as presented in Figure 4.

In Table 1, various research works concerning machine learning to detect and classify faults in photovoltaic panels have been listed and compared in terms of year, accuracy, detection, classification and limitations. In the study performed by [17], a CP system approach was used for the detection of a fault in photovoltaic arrays. The model used, Simulink Model, helped not only in the fault detection but it also detected the type of fault that caused losses to the performance of the PV system. They used Artificial Neural Network (ANN) algorithm in this model. The use of such a model led to a considerable reduction in the Mean Time to Repair (MTTR) PV arrays as many other recent studies also suggested [18, 19, 20].

[21] proposed an intelligent fault detection architecture that was based on the implementation of a probabilistic neural network (PNN), a non-linear ML algorithm used in both supervised and unsupervised learning to detect and classify and fault into detectable fault types. The datasets were collected for both normal and default PV in winter conditions. It is because during the winter season current/voltage of a faulty PV system resembles a lot with the current/voltage of a normal state PV system. Their trained model showed an impressive performance and accuracy in terms of PV fault prediction. In spite of that,

this study still has many shortcomings, such as the types of faults that can be detected (Capable of detecting only 2 faults). A monitoring system (MS) model was presented by [22] for the fault detection

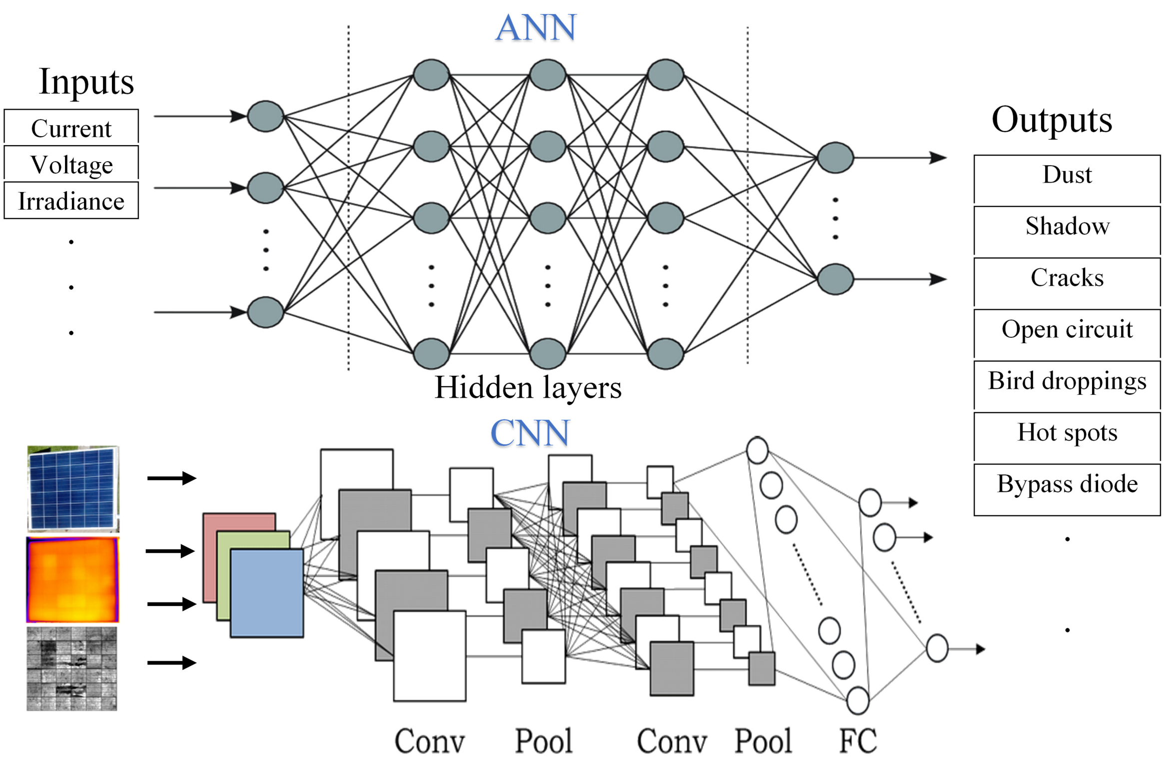

Figure 4. CNN and ANN architecture for PV fault detection and classification.

and classification of the photovoltaic system. They integrated the use of ML algorithms in their online MS as a monitoring system alone insufficient for accurate detection [23]. Using the same model, they designed a recursive linear model. First, the model detected the faults in the PV system. Then, Artificial Neural Network algorithm is employed for the default classification whose accuracy was found to be about 95.44%. The combination of detection and classification in the proposed model gave highly accurate prediction results based on the historical data.

Under certain conditions, the line-line faults in the PV system remain unidentified in low currents of fault conditions which creates problems later when current and voltage are increased. The design of a novel approach for the detection of line-to-line faults in a photovoltaic system is presented by [24]. The model extracted the dataset from faulty and normal PV system states. In the model, they developed an ensemble algorithm, which entails the use of a number of ML algorithms. It was shown that the use of the ensemble algorithm model gives better results than the utilization of individual algorithms for fault detection in the PV system. Its accuracy was much higher than the individual algorithms. In order to get results more convincing, this study still needs to be further extended for training and testing a large amount of dataset.

[25] executed a study to design a new detection system for the detection of PV default. To this end, two algorithms, Artificial Neural Network (ANN) and fuzzy logic interface (Mamdani and Sugeno) were used. Both interfaces were developed using MATLAB/Simulink software. The newly developed fault detection algorithm was shown to have the ability to detect the various type of PV faults with accuracy. They used four types of ANNs to increase the accuracy to a maximum level. Moreover, [9] designed a model for PV

fault detection using ML algorithms in combination with thermography. The model worked on the basis of extracted features from the datasets which were trained by implementing Artificial Neural Networks (ANN) to classify the PV faults for accurate detection. It showed that the use of ML algorithms poses far more positive impacts on PV system efficiency than the conventional fault classification methods. Nevertheless, these last two studies exhibited an accuracy of 92.1% and 91.7%, respectively, which are inadequate accuracy and need further improvement.

[26] presented a fault detection technique for an integrated PV network having distribution generators. Their model entailed the combined application of Discrete Wavelet Transform (DWT) and SVM. In their model, they used DWT to extract features from fault currents. The model, then, fed these features into the support vector machine (SVM) algorithm in order to detect the fault and execute classification. The proposed model depicted impressive results after testing on the WEKA platform.

A shading fault detection and classification method for a PV system on the basis of the current-voltage curve (I-V curve) was developed by [34]. They employed the use of an unsupervised Machine Learning algorithm, the Principal Component Analysis (PCA) algorithm. First, their model involved the extraction of features from the available dataset of healthy and shading PV system conditions. These features were subjected to PCA for the classification of faults. It was found that the accuracy of the data classification using the PCA algorithm was excellent (more than 97%). This study showed a high ability for detecting 4 classes (one healthy and 3 shading faults); however, the authors did not address the detection of the other PV faults with the proposed model, such as open circuit, making the proposed model incomplete.

Another major contribution to bridge the gap in the literature was made by [31] who compared the efficiency of various Machine Learning algorithm techniques for the detection and classification of PV system faults. In their model, they used many ML-based methods including, Decision Tree, Artificial Neural Network (ANN), Support Vector Machines (SVM) and K-Nearest Neighbours to detect faults that occurred in the PV system. The results explicitly showed that ANN had the highest fault detection and classification efficiency, showing an accuracy of 99.66 %. The SVM depicted similar performance. However, this study still has many limitations, both in terms of training time (Very high for ANN) or accuracy (Inadequate accuracy for Decision Tree and k-NN algorithms). In [27], the authors have proposed a new approach for detection the hot spot with high accuracy in the thermal image of PV panels using Region-based Convolutional Neural Network (R-CNN). This approach has the limitation so that it does not allow the classification to identify its nature.

[32] proposed a model for the string level fault detection in the photovoltaic system. The model was based upon the K-Nearest Neighbour (KNN) algorithm, a supervised machine learning algorithm. In order to run the simulations for the proposed model, MATLAB software was used. The developed model extracted the I-V features from the PV module. After the testing of the data generated from the developed model for fault detection and classification, the accuracy was as high as 98.70. In [30] A methodology to detect the physical faults in PV panels and classify them into four classes (Breakages, Shadows, Dust, and No-Fault) based on CNN and RBG image has been investigated. As can be noted, the main limitations of these techniques that can detect only the physical and environmental faults, which does not demonstrate the generalization for other fault types.

Paper	Year	Algorithm used	Accuracy (%)	Detection	Classification	Limitations
[21]	2020	Probabilistic neural network (PNN)	100	✓	✓	- Limited types of faults
[27]	2020	Region-based convolutional neural network (R-CNN)	99.02	✓	✗	- No fault classification - Insufficient training data
[28]	2019	Convolutional neural network (CNN))	93.02	✓	✗	- Inadequate accuracy - No fault classification
[24]	2020	Ensemble algorithm; used a combination of a various ML algorithms	99.00	✓	✓	- Limited types of faults - Insufficient training data
[17]	2019	Artificial neural network (ANN)	99.00	✓	✓	- Limited types of faults
[25]	2017	Artificial neural network (ANN)	92.10	✓	✓	- Inadequate accuracy
[29]	2018	Deep Convolutional Neural Network (DCNN)	76.00	✓	✗	- Low accuracy - No fault classification
[9]	2019	Artificial neural networks (ANN)	91.70	✓	✓	- Inadequate accuracy
[31]	2019	Decision Tree, Artificial Neural Network (ANN), Support Vector Machines (SVM) and K-Nearest Neighbours (k-NN)	99.65	✓	✓	- High training time (ANN) - Inadequate accuracy (Decision Tree and k-NN) - Limited types of faults
[22]	2020	Artificial neural network (ANN)	95.44	✓	✓	- Limited types of faults
[32]	2018	K-Nearest Neighbour (k-NN)	98.70	✓	✓	- Limited types of faults - Insufficient training and testing data
[33]	2021	Convolutional neural network (CNN)	98.60	✓	✗	- No fault classification - Insufficient training and testing data
[34]	2019	Principal Component Analysis (PCA)	97.00	✓	✓	- Limited types of faults
[35]	2022	Convolutional neural network model and support vector machine	99.49	✓	✗	- Insufficient training and testing data

Table 1. Comparison of different ML algorithms models in the investigated papers.

4. Challenges of Machine Learning

Indeed, Machine Learning has been proved to be quite valuable in enhancing the efficiency of machine systems in every field. However, there are still some major challenges that make the implementation of ML algorithms a difficult task. Some of these challenges include but are not limited to:

- In order to maximise the efficiency of fault predictions and classification, the correct algorithm is to be used. However, the ML technique comprises a large number of algorithms and selecting one accurate algorithm from such a big heap of algorithms seems a daunting task. Moreover, this may also lead to the selection of the wrong algorithm, impacting the overall result and accuracy of detection.

- Most researchers do not use new and better algorithms due to the vast number of algorithms present already. This increases their reliance on previous studies and results, halting the improvement in the detection system.

- Most fault detection ML algorithms work in case of one or two faults at one time. However, in many cases, faults are in multiple numbers.

- For Machine Learning algorithms, a sufficient amount of data is necessary to obtain to make accurate predictions and classifications. In the PV fault system, multiple simulations are needed to be done before extracting a considerable amount of training dataset.

- Another challenge is the pre-processing of the available raw data before the implementation of ML algorithms. To this end, a number of steps such as data cleaning, normalisation, reduction is needed to be performed, making it a hectic and time-consuming task.

- In many cases, high variance and bias occur during the procedure. It makes it necessary to execute some crucial diagnosis methods. One such example is the plotting of learning curves. It can also be time-consuming.

5. Conclusion

Energy consumption has increased very fast over the last years, which requires the improvement of all energy sources. Especially solar energy that provides clean, unlimited, and reliable power. In this context, this paper presented a concise overview of Machine Learning algorithms used in PV systems. However, the main reason behind this review paper is to understand the recent diverse applications of ML algorithms for fault detection and classification in solar panels. To this end, an in-depth and extensive investigation into various recent research works on the application of MLs in PV fault detection has been conducted. Thereafter, these works have been compared in terms of year, accuracy, detection/classification and limitations. Hereafter, these have been compared in terms of year, accuracy, detection/classification and results. Moreover, the challenges in implementing Machine Learning algorithms are also briefly discussed to help align improvement strategies in the right direction. For future research works, we believe that it is crucial to be aware of the limitations of existing methods as a first step towards developing new techniques that achieve more than incremental improvements for a complete faults detection and classification model that can detect all possible faults with high accuracy.

Abbreviations

ANN: Artificial Neural Networks
CNN: Convolutional neural network
DCNN: Deep Convolutional Neural Network
DWT: Discrete Wavelet Transform
KNN: K-Nearest Neighbour
MDP : Markov Decision Process
ML: Machine Learning
MS: Monitoring System
MTTR: Mean Time to Repair
PCA: Principal Component Analysis
PNN: Probabilistic Neural Network
PV: Photovoltaic
R-CNN: Region-based convolutional neural network
SVM:Support Vector Machine

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