Review on maintenance of photovoltaic systems based on deep learning and internet of things

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ABSTRACT

Many solar plants have been installed globally, and they must be continuously protected and supervised to ensure their safety and reliability. Photovoltaic plants are susceptible to many defects and failures, and fault detection technology is used to protect and isolate them. Despite numerous inter-national standards, invisible photovoltaic defects continue to cause major is-sues. As a result, smart technologies like artificial intelligence (AI) and internet of things (IoT) are being developed for remote sensing, problem detection, and diagnosis of photovoltaic systems. Solar plants generate not only green electricity but also a lot of data, such as power output. With AI, a clear picture of electricity yields should be possible. The output of entire solar parks could be monitored and analyzed. The AI could also detect malfunctions within a solar park, according to the research. This would speed up and simplify maintenance work. Deep learning (DL) and IoT applications for photovoltaic plants are discussed. The most advanced techniques, such as DL, are discussed in terms of precision and accuracy. Incorporating DL and IoT approaches for fault detection and diagnosis into simple hardware, such as low-cost chips, maybe cost-effective and technically feasible for photovoltaic facilities located in remote locations.

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1. INTRODUCTION

Renewable energy is becoming increasingly significant in the generation of power these days. Fossil resources are not a viable future choice since they are non-renewable energy sources that contribute to environmental degradation. In 2019, 6,963 TWh of electricity was generated from renewable sources. About 6% of this (4,207 TWh) came from renewable hydropower, with the rest coming from wind and solar power (1 412 TWh and 693 TWh, respectively) [1].

Solar energy is one of the world's fastest-growing energy sources, and with countries competing for supremacy in the thriving industry. In Africa, Morocco has set one of the world's most ambitious energy goals. The objective is for renewable energy to account for 42% of total electricity from its solar farms; the world's largest concentrated solar farm [2].

Despite the many benefits of solar panels and renewable energy, solar panels need no maintenance and may be allowed to produce cost-free renewable energy. They may, occasionally, run into one of a few solar photovoltaic (PV) issues. There are a variety of reasons why photovoltaic (PV) modules may fail: temperature cycling, humidity freeze, and ultraviolet (UV) exposure [3].

Solar panels failures ecosystems must be monitored, measured, and analyzed continuously and automatically to better understand the complex, multi-variate, and unpredictable nature of these issues. The internet of things (IoT), a new developing technology that connects physical objects through electrical sensors and the internet, is getting a lot of attention these days. This IoT technology is growing into a wide range of new and interesting application fields, with energy being one of them. For optimal real-time consumption monitoring and performance awareness, energy management integrates IoT technologies to offer the perfect solution. IoT technology, such as energy sensors, makes it possible to gather real-time data on energy usage at many levels, such as the machine, the production line, or the facility level [4]. Deep learning is another technique that has made significant breakthroughs in a variety of fields since its introduction, including computer vision, natural language processing (NLP), energy, anomaly detection, failure forecasting, and many others. Combining these breakthroughs technologies, IoT and deep learning, can provide a viable approach for preventing solar panel failures. In this paper, we provide a thorough literature review analysis on PV failure detection using IoT and deep learning technologies. The structure of this paper is as follows. Section two goes over the terminology. Section three explains the literature review, and the fourth section discusses our findings, and we conclude with a conclusion.

2. BACKGROUNDS

2.1. Photovoltaic (PV)

Photovoltaic (PV) is the direct transformation of solar irradiation into electricity by solar cells; based on the physical principle of photoelectricity (see Figure 1). The direct current generated during this process is usually converted to alternating current by an inverter and then fed into the utility grid [5]. The majority of solar cells are made of silicon semiconductors, which are similar to those used in the production of computer chips. These semiconductors convert electromagnetic radiation (light) into electric current: incident light particles (photons) are absorbed in the semiconductor, raising the electrons of the semiconductor material to a higher energy level and allowing them to move through the material. Semiconductors are designed in such a way that charge separation (electrons or electron vacancies) occurs (thanks to the adjacent differently doped layers). The generated current is collected at the level of the metal contacts [6]. Solar panels are relatively low maintenance. However, nothing is completely foolproof; problems can arise [7], [8]. Delamination and internal corrosion, electrical issues, micro-cracks, hot spots, potential induced degradation (PID) effect, Snail trails, inverter problems, and other issues are some of the most common problems that affect solar panels [9].

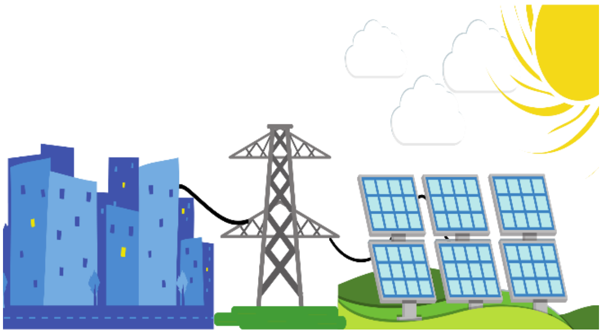

Figure 1. Solar plant ongrid

2.2. Photovoltaic maintenance

The implementation of a maintenance system can help to avoid a slew of issues and boost productivity. Industrial maintenance entails not only facility inspections, but also accurate data collection on the state of infrastructure, equipment, and machinery. Many businesses rely on technology companies that specialize in monitoring industrial processes to accomplish this. These technological tools take daily measurements of key indicators and send out alerts when a measurement deviates from the norm. In addition to that, it is so important to distinguish between the three main types of maintenance: Corrective, preventive, and predictive maintenance [10]. Corrective maintenance, which consists in intervening on an equipment when it fails, as opposed to preventive maintenance, which consists in intervening on an equipment before it fails, in order to prevent any failure. Predictive maintenance is performed based on projections derived from the analysis and evaluation of key parameters of asset degradation. Its basic premise is that any element will show signs of degradation, whether visible or not, that indicates its failure. The key is to understand how to recognize these warning signs. Many existing devices (sensors and thermal cameras) allow the measurement of this degradation, which can take the form of changes in temperature, vibration, pressure, size, position, and noise, among other things. Physical, chemical, behavioral, electrical, and other types of degradations can occur [11]. In this context, numerous prior studies have examined photovoltaic failure categories. While large-scale solar farms tend to receive more research funding, the bulk of current PV technology research has focused on these larger projects due to the increased funding and incentives that larger projects can offer. But some PV system problems are common to both large and small-scale systems. Frequent system failures include the following types of typical PV (system) issues, as described in the literature [12].

2.2.1. Ground faults (zero efficiency faults)

In an electrical system, the most common type of fault is the ground fault. When the insulation is degraded, it becomes porous and is ultimately unable to protect the wires and equipment, and this occurs when it is exposed to excess current, extreme temperatures, and aging, and in some cases when voltage levels are abnormal. Without insulation, the conductor may be in contact with an external object. However, if another ground defect occurs, a leakage current circulates through the ground to return between ground defects [13].

2.2.2. Line to line faults

To reach both voltage and power levels, strings of panels are connected in series and then the strings are connected in parallel to create an array. Unintentional connections between two different points in a PV array are known as line-to-line (L-L) faults [14]. DC connectors damage, animal chewing, and cable age may cause the L-L faults [15].

2.2.3. Inverter failures

Solar panels provide electricity that is used to power household appliances through solar inverters, which need minimal maintenance if set up properly. Inverters include more electrical components than solar panels. In comparison to microinverters, string solar inverters have a lifespan of around ten years. However, even though inverters are designed to endure for decades, a variety of conditions may impair their function during that time period, such as such as heat, faulty installation, humidity, poor maintenance, edge delamination, water penetration, and high string voltage [16]. Components are very sensitive to temperature. Too much heat may decrease electrical production. Clean dust filters and unimpeded inverter airflow are essential [17].

2.2.4. Arc faults

In PV systems, arc faults are a frequent occurrence. A prolonged arc's high-temperature plasma may harm system components severely. Solar PV systems are susceptible to two kinds of arc faults: series and parallel (including grounding arc-fault). Due to the significant difference in potential between a parallel and grounding arc fault, a considerable quantity of fault current is drawn, making it simpler for conventional protection systems to detect. A series arcing fault current that is lower than the usual operating current level will not melt or trigger overcurrent safety mechanisms because of the nature of a photovoltaic solar cell. Due to this, the arc fault in series does not draw an opposite current like the arc fault in parallel and the total fault current is derived from the normal load current [18].

2.2.5. Microcracks

PV modules have a real issue with microcracks in solar cells. They're difficult to prevent and, as of yet, almost impossible to measure in terms of their long-term effect on the module's efficiency. A fresh module's power may be somewhat reduced by the existence of microcracks, as long as the various components of the cell are still electrically linked. A repetitive relative movement of fractured cell components may cause an electrical separation as the module ages and is exposed to heat and mechanical stressors [19].

2.2.6. Hot spots and shading

Shading is the most common issue that affects all solar-electric systems. Because clouds and barriers cannot be physically moved, it is critical to identify and eliminate any sources of hotspots, thereby reducing the negative effects of partial shading. In the case of non-homogeneous radiation striking PV surfaces, the use of photovoltaic panels with internally integrated bypass diodes prevents the possibility of PV burning from occurring [20].

2.3. Internet of things (IoT)

The Internet has expanded dramatically over the last 50 years, from a local research network with only a few nodes to a ubiquitous global network with over a billion users. The ability to obtain distant sensor data and manage the physical world from a distance is made feasible by connecting physical objects to the Internet. The combination of captured data with data acquired from other sources, such as data on the Internet, results in new synergistic services that go beyond what an isolated embedded system can deliver. This vision is the foundation of the IoT [21]. A smart device is just another name for an Internet-connected embedded device [22].The IoT is a network of interconnected computing objects/devices, digital and mechanical, or items with unique IDs and the capacity to transfer data without the need for human interactions. A single device on the Internet can be a human with a cardiac eHealth device, an animal with a biochip transponder, a car with integrated sensors, or like in our case a smart photovoltaic panel that transfers the telemetries via the internet (see Figure 2) [23].

Figure 2. Internet of things

2.4. Machine learning (ML)

Artificial intelligence and machine learning (ML) techniques revolutionize several industrial and academic sectors such as natural language processing, computer vision, cybersecurity, speech recognition, and autonomous driving [24]. ML is a data analysis technique that automates the construction of the analytical model. It is an AI branch that believes that systems can learn from information, detect patterns, and decide with a minimum of human interaction [25]. ML approaches were limited in processing natural data in their raw form and require considerable knowledge in the construction of an extractor that turns raw data into a suitable representation [26]. Deep learning has come to overcome this challenge by providing simpler depictions [23].

2.5. Deep learning (DL)

Deep learning algorithms can be viewed as a more complex and advanced version of machine learning algorithms. As a result of recent advancements, the field has attracted a great deal of interest, and with good cause. Notably, supervised and unsupervised learning both allow for this [27]. DL applications utilize an artificial neural network (ANN) to achieve this. A neural network inspired by the human brain's biological neural network is used to create an ANN that is much more competent than traditional machine learning models at learning [28].

2.5.1. Artificial neural network (ANN)

An artificial neural network is a system that consists of linked units that include a high number of neurons. Each neuron in the network has the ability to receive, process, and output input signals. It is composed of a set of weighted connections, an adder for combining input data weighted by synaptic strength, and an activation function for limiting the intensity of the neuron's output [29]. Multilayer feedforward networks and recurrent networks are two fundamentally distinct types of network topologies.

2.5.2. Feedforward neural network (FNN)

Feedforward networks are currently being employed with remarkable success in a number of applications. It consists of many neurons organized in layers. Each layer of neurons is connected to all the neurons preceding it in the layer (see Figure 3). These connections aren't all created equal; each one may differ in terms of strength or weight [29]. The term "single-layer" refers to a neural network with only one layer [30]. A network multilayer feedforward consists of a source unit input layer, one or more layers, and an output layer.

The hidden layers in the FNN are not directly visible either from the network's input or output layer. These hidden layers allow the neural network to retrieve statistical characteristics in greater order from its input [31].

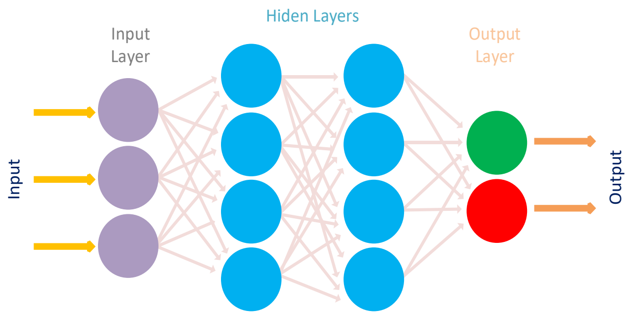

Figure 3. Feedforward neural networks layers

2.5.3. Convolutional neural network (CNN)

The ConvNet/convolutional neural network (CNN) is a DL algorithm that can take an input picture, assign significance (weights and biases) to numerous aspects in an image, and differentiate between them [32], CNN are a regularized versions of multilayer FNN. When compared to other classification methods, the amount of pre-processing required by a ConvNet is significantly less. While basic techniques need hand-engineering of filters, ConvNets can learn these filters/characteristics with enough training. The ConvNet design is similar to the human brain's connection network, and it was inspired by the visual cortex organization [33]. For a convolutional neural network, there are four sorts of layers: the convolutional layer, the pooling layer, the ReLU layer, and the fully-connected layer (see Figure 4) [34].

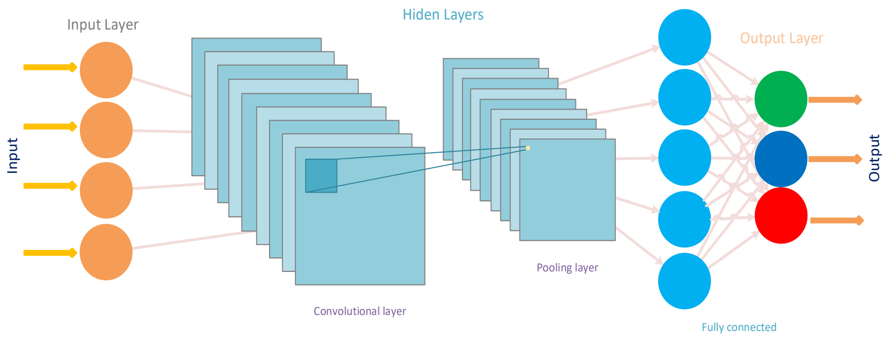

Figure 4. CNN layers architecture

2.5.4. Recurrent neural networks (RNN)

The RNN is a form of artificial neural network that employs sequential data or a series of temporal data. This DL algorithm is often used for regular or temporal issues such as linguistic translation, language processing (NLP), speech recognition, and image subtitling [35]. They can also be used for other applications. Recurring neural networking use training data to learn, like feedforward and CNN. They are characterized by their "memory", which allows them to alter current input and output by using knowledge from previous inputs (see Figure 5) [36]. RNNs typically experience two issues throughout this process: exploding gradients and vanishing gradients [37], To address these problems, the most well-known RNN versions; the long short-term memory (LSTM) and gated recurrent unit (GRU), are used.

2.5.5. Long short-term memory (LSTM)

Long short-term memory (LSTM) includes a series of recurrently connected subnetworks, consisting of memory blocks. These blocks include one or more self-connected memory cells, which they retain for the remembering of past data and 3 components known as gates: an input gate, gate forget, the external gate which is an ongoing equivalent of writing, reading and retrieving (see Figure 6), [38]. The principal difference with simple RNN is that the nonlinear units are superseded by memory blocks in hidden layers [39].

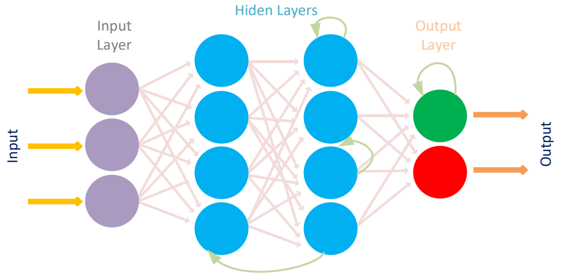

Figure 5. Recurrent neural networks layers

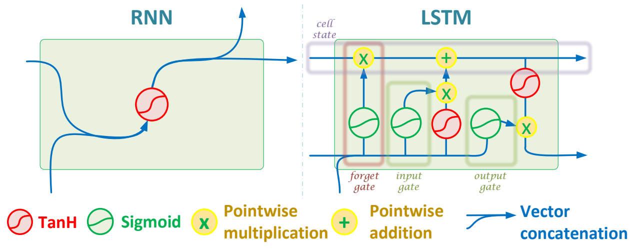

Figure 6. RNN and LSTM blocks

2.5.6. Generative adversarial network (GAN)

Generative adversarial network is one of the most prominent techniques for deep generative modeling currently. Instead of the data distribution. Generative modeling is an unsupervised learning form of ML which automatically includes the discovery of regularities or patterns in input data in a way in which new instances which would likely have been chosen from the original dataset may be generated or produced by the model [40]. GANs are an intelligent process of developing a generative model by framing the problem as an under-controlled learning problem with two sub-models: the model Generator, which trains to produce new examples, and the model discriminator, which attempts to categorize examples as either genuine (real) or fake (generated). The two models are trained concurrently in a zero-sum contest, adversarial until the model of discriminator has been deceived for roughly half of the time [41].

2.5.7. Adversarial autoencoder (AAE)

The AAE is a brilliant idea to mix the autoencoder architecture with a GAN notion for adverse loss. The variative autoencoder (VAE) employs a similar idea except that the latent code is regulated using adverse loss, instead of the KL-divergence used by the VAE [42]. In variative autoencoder, a KL-divergence is used to match the encoded latent code with a normal distribution (or any arbitrary distribution) [43]. AAE substitutes this with an adverse loss if the encoder adds an extra discriminating element. Unlike GAN, where the generator's output is the produced data (mostly picture) and the discriminator's input is both genuine and phony data, AAE's generator creates a latent code and attempts to convince the discriminator that the latent code is sampled from the selected distribution (see Figure 7) [44].

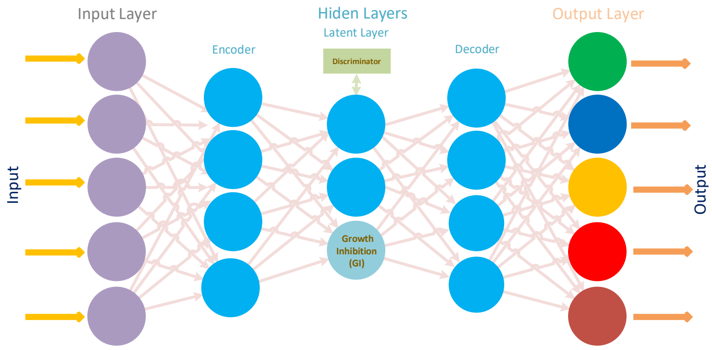

Figure 7. Adversarial autoencoder layers [44]

2.6. DL evaluation metrics

It is essential to have a good evaluation metric in place to help find a classifier throughout the classification training. A proper assessment measure is therefore a crucial element in making a distinction and getting the best classifier [45]. When evaluating deep learning models, certain metrics must be used, such as accuracy, precision, recall, F1 score, MSE, MAE, and the AUC. In order to calculate these metrics, four different measures are used [46]:

- True Positive (TP): is the number of positive class records classified correctly.
- True Negative (TN): is the number of negative class records classified correctly.
- False Positive (FP): is the number of negative class records classified wrongly.
- False Negative (FN): is the number of positive class records classified wrongly.

2.6.1. Accuracy

Is the percentage of correct predictions among all predictions [47], and it is calculated using (1):

$$Accuracy = \frac{TP+TN}{TP+TN+FP+FN} \quad (1)$$

there are many flaws in accuracy, however, including a lack of uniqueness, a lack of discriminability, a lack of informativeness, and a preference for data from the majority class [45].

2.6.2. Precision

Is the percentage of all positive results that were accurately identified [48], and it is calculated using (2).

$$\mathrm{Precision} = \frac{\mathrm{TP}}{\mathrm{TP+\ FP}} \quad (2)$$

2.6.3. Recall

Is the proportion of accurately identified positive results among the total number of existing positive classes [48], and it is calculated using (3).

$$Recall = \frac{TP}{TP+\ FN} \quad (3)$$

2.6.4. F1-score

The F1-Score is a subtle combination of precision and recall. It is interesting, even more than accuracy, because the number of true negatives (TN) is not considered [49]. A high number of true negatives (TN) will have no effect on the F1-score. It is calculated using (4).

$$\mathrm{F1} = \frac{2}{\mathrm{P}^{-1}+\ \mathrm{R}^{-1}} \quad (4)$$

2.6.5. Receiver operator characteristic (ROC)-Area under curve (AUC)

ROC curve is a binary classification task evaluation metric. It is a probabilistic curve that plots the ‘true positive rate’ against the ‘false positive rate’ at various threshold levels, separating the 'signal' from the 'noise.' The area under the curve (AUC) is a measure of a classifier's ability to differentiate between classes which are used to summarize the ROC curve. The greater the AUC, the better the model's accuracy in differentiating between positively and negatively categories [50].

2.6.6. Mean absolute error (MAE) and root mean squared error (RMSE)

MAE and RMSE are two of the most widely used metrics for evaluating the accuracy of continuously varying variables [51]. MAE measures the average erroneous magnitude without taking into account the direction of the errors. All disparities have the same weight in the test sample, so the average of the absolute errors between prognostication and actual observation is used [52]. It can be calculated using (5):

$$MAE = \frac{1}{n}\sum_{j=1}^{n}\left|y_j - \hat{y}_j\right| \quad (5)$$

RMSE is a quadratic evaluation rule that also measures the average magnitude of the error. The difference between what was predicted and what was observed squared is the square root of that difference [52], It can be calculated using (6).

$$\mathrm{RMSE} = \sqrt[2]{\frac{1}{\mathrm{n}}\sum_{\mathrm{j}=1}^{\mathrm{n}}\left(\mathrm{y_j} - \hat{\mathrm{y}}_\mathrm{j}\right)^2} \quad (6)$$

3. METHOD

For our research we applied the following combination of the related keywords, "("deep learning" AND (IoT OR "Internet of Things") AND ("PV" OR photovoltaic OR "solar panel")) " that corresponds to the purpose of this review and obtained approximately 32 documents as a result, published from 2018 until September 2021 (Figure 8). Following that, we excluded some papers for the reason that they were only the first few pages of conference proceedings and not actual articles, and we also excluded some irrelevant papers due to their relevance to our research area; they concentrated on forecasting solar radiation without including the maintenance context and that has no bearing on our subject. These gathered papers (see Table 1) were extracted from the Scopus database, which is the largest abstract and indexing database of peer-reviewed literature, containing publications, conference proceedings, patent records, and websites in the most important subject fields [53].

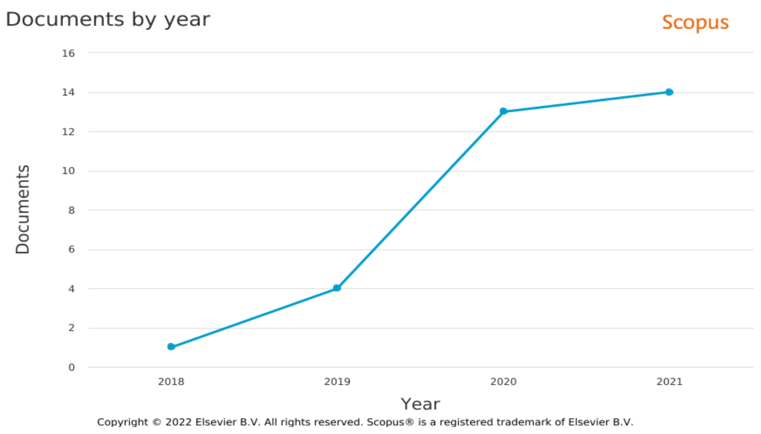

Figure 8. Scopus indexed papers per year

Table 1. Summary of reviewed literature

Year	Article	Title	Deep Learning Model	Type of maintenance	Anomaly /Goal	Context /Dataset	Best performance results
2021	[54]	Digital twins in solar farms: An approach through time series and deep learning	DT: CNN and LSTM	Preventive	General anomalies	Own collected data: 22427 Samples	Precision: 0.53 Recall: 0.92 AUC: 0.97
2021	[55]	Deep Learning Enhanced Solar Energy Forecasting with AI-Driven IoT	CNN and LSTM	Predictive	Power Prediction	Own collected data	RMSE (STP): 1.30
2021	[56]	Deep Learning at the Edge for Operation and Maintenance of Large-Scale Solar Farms	ANN	Preventive	Shading	Own collected data	RMSE<0.05
2020	[57]	Using Siamese networks to detect shading on the edge of solar farms	ANN-Siamese Neural Network	Preventive	Shading	Own collected data: 600 samples	F1 Score: 0.94
2020	[58]	Very Short-Term Solar Irradiance Forecasting at a Sub-Minute Scale Based on WT-Cnns	WT-CNN	Predictive	Power prediction	Own collected data	MAE: 1.63 RMSE: 2
2020	[59]	IOT based solar energy prophecy using RNN architecture	CNN-LSTM	Predictive	Power prediction	Own collected data	MAE: 0.2 MSE: 0.1
2020	[60]	A new architecture based on iot and machine learning paradigms in photovoltaic systems to nowcast output energy	CNN-LSTM	Predictive	Power Prediction	Opera digital systems Dataset [61]	MAE: 274.87 RMSE: 531.08
2020	[62]	Integrating iot devices and deep learning for renewable energy in big data system	LSTM	Predictive	Power prediction	Own collected data	RMSE: 85.49
2020	[63]	Power Prediction via Module Temperature for Solar Modules Under Soiling Conditions	MLP	Predictive	Power prediction	Own collected data: 800 samples	MAE: 0.08 RMSE: 0.10
2020	[64]	Deep Convolutional Neural Network for Automatic Detection of Damaged Photovoltaic Cells	CNN	Corrective	Physical crack	Own collected Data: 3336 samples	Recall: 0.74 Precision: 0.70 F1 Score: 0.69
2019	[65]	DA-DCGAN: An Effective Methodology for DC Series Arc Fault Diagnosis in Photovoltaic Systems	DA-DCGAN	Preventive	Arc faults	Own collected Data: 40 000 samples	Accuracy: 98.5%
2019	[66]	CNN based automatic detection of photovoltaic cell defects in electroluminescence images	CNN	Preventive	Cracks and microcracks	elpv Dataset [67]	Accuracy: 93.02%

4. FINDINGS

These research findings in the preceding part (Table 1) will be examined in this section; first, we will illustrate the comparison criteria used:

- Deep learning model: The deep learning models utilized in the mentioned papers
- Type of maintenance: Corrective, preventive, and predictive maintenance
- Anomaly/goal: Define the type of default detected/the main purpose of the model
- Context/dataset: the data used to train and test the proposed deep learning model
- Best performance results: This criterion displays the highest results for the proposed model or the used metrics such as accuracy, recall, precision, F1 score, MAE, MSE, AUC, or others.

Regarding the used data in each paper, big and small datasets are used to train the DL model; some include thousands of entries, while others contain just a few; these entries may be realistic or synthetic, created by the authors [54]–[59], [62]–[65]. A number of datasets are created by researchers for their own study purposes, while some are taken from well-known and publicly available datasets [60], [66], such as "elpv-dataset". In general, the more data needed to solve a problem, the more complex the problem is. As an example, training models for tasks such as class identification when there are many classes and/or little variation among the classes necessitates using a large number of input data. Too little training data, as is well-known, leads to poor approximations. With an over-constrained model, it will be difficult to learn from the limited training dataset, while with a model that is under-constrained, it will be much easier. An overly optimistic and too high variance estimate of model performance will be the consequence of using insufficient test data.

From a technical perspective, almost all of the research papers used the widely-used CNN or LTSM algorithms [55], [62], [64], [66]. Besides some developed their own variants of the CNN or LTSM models [54], [55], [58]–[60], and the rest of them worked on the traditional ANN and MLP [56], [57], [63], and one paper worked with a GAN variant named it "DA-DCGAN" [65]. The authors applied classification classes ranging from 2 (binary anomaly detection) [56], [57], [64]–[66] through to 3 for the [54] (multiclass classification), other authors used regression methods to predict the output power of the solar plant [55], [58]–[60], [62], [63]. The number of model outputs in these studies matched the number of classes. For each of the possible classes of input data, the model produced a probability value, and the highest probability value was selected as the predicted class.

In accordance with the main objectives of these research papers (the maintenance of photovoltaic solar panels), some are attempting to build a model able to detect any default occurring while the solar plant is running in order to prevent any breakdown. The first thing that stands out is that the majority of the papers are dealing with the power prediction [55], [58]–[60], [62], [63]. The connection between the system output prediction and his maintenance is not immediately apparent at first glance, but in fact, PV maintenance can be effectively aided by forecasting power generation: it is considered as a reference for alert thresholds, and more important is the stability of the electrical network, when our plant is ongrid. The shading phenomenon is also considered as a major factor of degradation in the solar PV industry. It is to blame for the module's temperature rising, resulting in a reduction in power output. The proposed models in the papers [56], [57] are showing good results, with an error value lower than 0.05 (RMSE). For the rest, they are specialized in the physical anomalies such as cracks microcracks. With the help of these models, the maintenance team could plan an intervention to correct the default or a modification in the operating process, for a better productivity in the future.

There are a variety of metrics used by the authors to evaluate the DL models performance, and each one is tailored to the model that was used in that particular research. For each article, we provide the best resulting metric in Table 1. The most often used metric was RMSE in [55], [56], [58]–[60], [62], [63], followed by MAE in [58]–[60], [63], both of these metrics represent an average model prediction error in units of the variable of interest, although calculating the square root of the average squared errors has some interesting consequences for the RMSE, and since the errors are squared before they are averaged, the RMSE provides a relatively high weight to big mistakes, this implies the RMSE should be more helpful when big errors are especially undesirable. The previous research used other metrics such as Precision and Recall [54], [64]; where the precision focuses on how precise/accurate the model is at predicting the positive outcomes, it is a useful metric to evaluate when the cost of false positive is significant, and the Recall essentially determines how many of the actual positives the model obtain via classifying it as Positive (True Positive), it is a useful metric to determine the best model if there is a significant cost tied with false negative. Where [57], [64] used the harmony and a balance of these last two metrics; the F1 Score. [65], [66] evaluated their DL models using the accuracy which is the most widely used classification model evaluation metric for its simplicity of use and understanding, where when it comes to this metric, many true negatives contribute very little, whereas false negatives or false positives usually incur the costs, so the F1 Score may be a better indicator to use if we want to strike a balance between precision and recall and there is an uneven distribution of classes, and in one paper [54] the authors evaluated their model using the AUC metric in addition to other metrics such as precision and recall. Most of the reviewed papers used this type of evaluation (a mix of measures) to evaluate their models. We have seen that sometimes metrics have to be compromised for each other as showed in the paper [64]. Indeed, the model has a good performance regarding the recall metric (0.90), but the precision metric is showing a lower value (0.65).

We notice that comparing papers is difficult, if not impossible since different metrics are used for different tasks, taking different models, datasets, and parameters into consideration. As a result, the reader should proceed with care while considering our opinions in this area. Another disadvantage of these models is the number of defaults that are discovered. These proposed methods are relatively performant when they are dealing with one default and this particularity could not encourage the implementation of this model in the maintenance industry.

5. CONCLUSION

Ensuring good performance over long periods of time is only possible by keeping an eye on and maintaining a PV power plant. To estimate the degradation of PV cells deep learning approaches were used. The goal of this research was to survey the trends in PV system maintenance based on deep learning and IoT during the last three years and look for ways to combine the two for fault detection and diagnostics in PV facilities in remote areas. According to our analysis, almost all of the studies used the well-known CNN or LTSM algorithms, and as a precaution, some researchers developed a model that can detect defaults that occur while the solar plant is operating, and most of them specialized in physical anomalies. Even while these proposed solutions are relatively performant when dealing with a single default, their performance may not be enough to entice the maintenance sector to use them. In this regard, there is a need that further research should focus on dealing with multiple defaults at the same time using the same model. This is the direction of our future works.

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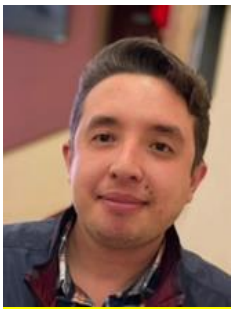

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