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Review

A Survey of CNN-Based Approaches for Crack Detection in Solar PV Modules: Current Trends and Future Directions

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Abstract: Detection of cracks in solar photovoltaic (PV) modules is crucial for optimal performance and long-term reliability. The development of convolutional neural networks (CNNs) has significantly improved crack detection, offering improved accuracy and efficiency over traditional methods. This paper presents a comprehensive review and comparative analysis of CNN-based approaches for crack detection in solar PV modules. The review discusses various CNN architectures, including custom-designed networks and pre-trained models, as well as data-augmentation techniques and ensemble learning methods. Additionally, challenges related to limited dataset sizes, generalizability across different solar panels, interpretability of CNN models, and real-time detection are discussed. The review also identifies opportunities for future research, such as the need for larger and more diverse datasets, model interpretability, and optimized computational speed. Overall, this paper serves as a valuable resource for researchers and practitioners interested in using CNNs for crack detection in solar PV modules.

Keywords: photovoltaic; crack detection; artificial intelligence; convolutional neural networks

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1. Introduction

The urgent need for the development of renewable energy sources is becoming increasingly evident in today's world, in which environmental challenges are ongoing and traditional fossil fuel reserves are rapidly declining [1,2]. Among these energy sources, PV technologies have emerged as the most promising due to their remarkable advantages [3]. PV systems offer energy efficiency, reliability, and environmental sustainability, making them an ideal choice for sustainable power generation [4]. By utilizing the abundant energy available from sunlight, PV technologies pave the way for a cleaner and greener future. With their ability to convert sunlight into electricity, PV systems provide an efficient and environmentally friendly way to meet modern society's growing energy demands [5].

However, the range of defects that can occur in PV modules is diverse and can include a variety of physical, chemical, and structural anomalies. Among the most prevalent are microcracks, which are often too small to detect with the naked eye but which can spread and worsen over time. Additionally, material delamination, corrosion, and oxidation can potentially contribute to further deterioration. Other defects, such as hotspots, shadows, and soiling, can arise from environmental factors and adversely impact PV energy output.

However, ensuring the optimal performance and longevity of PV modules is crucial for maximizing their energy-production potential. In recent years, CNN has emerged as a powerful tool in crack detection, enhancing the accuracy and efficiency of PV module inspection [6]. These deep learning algorithms have demonstrated their effectiveness in detecting and classifying cracks in solar PV modules, enabling timely and effective maintenance and repair. An overview of the CNN flowchart for detecting cracks in PV is shown in Figure 1.

Convolutional neural networks (CNNs) are a class of deep learning algorithms specifically designed for processing grid-like data, such as images or audio. They have revolutionized image-analysis tasks and are highly effective for tasks like object recognition and detection. These networks consist of several key components. The core building blocks are the convolutional layers, which apply a set of learnable filters (kernels) to the input data. Each filter convolves across the input image to detect specific features. For instance, early layers might detect edges, while deeper layers may learn more complex patterns.

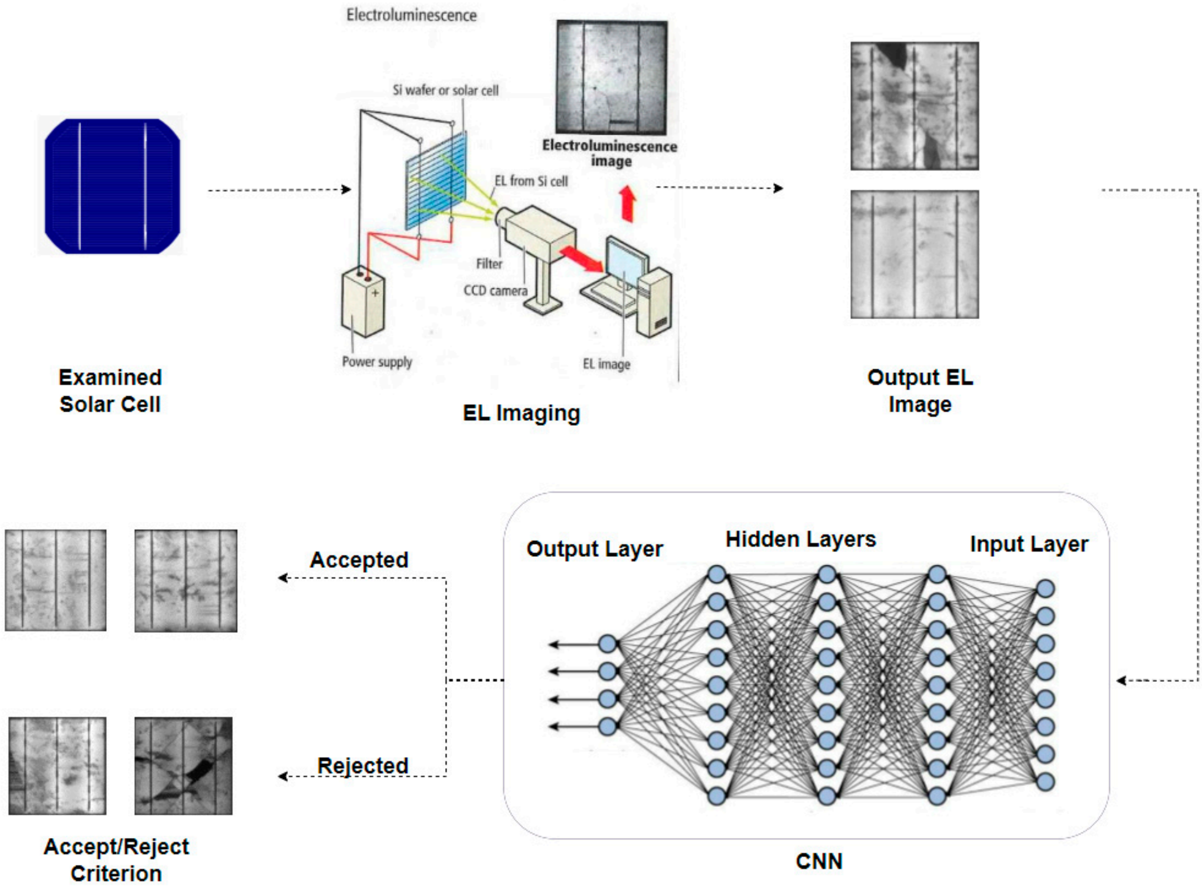


Figure 1. Summary of CNN-based identification of PV cracks.

Pooling layers come next, downsampling the spatial dimensions of the data. This reduction in computational complexity is achieved while retaining important information. Common pooling operations include max pooling and average pooling. Non-linear activation functions, such as ReLU (Rectified Linear Unit), are applied to the output of convolutional layers. They introduce non-linearity into the network, allowing it to learn complex relationships. In the latter part of the network, fully connected layers are typically employed. These layers connect every neuron in one layer to every neuron in the next layer, allowing for high-level reasoning.

Several notable architectures and techniques have been developed within the CNN framework. LeNet, created by Yann LeCun, was one of the earliest successful CNN architectures and was primarily used for recognition of handwritten digits [7]. AlexNet, introduced by Alex Krizhevsky et al., gained significant attention by winning the ImageNet Large Scale Visual Recognition Challenge [8]. It employed deep layers and GPU acceleration and set a new standard in CNN performance. VGG, proposed by the Visual Geometry Group, stands out for its simple and uniform structure. It is characterized by its use of small 3×3 filters within a deep architecture [9].

GoogLeNet (Inception) introduced the concept of inception modules, which allowed the network to learn multi-scale features [10]. It used 1×1 convolutions to reduce computational complexity. Residual Networks, or ResNet, introduced by Kaiming He et al., addressed the vanishing-gradient problem in deep networks [11] by introducing shortcut connections that bypass one or more layers, enabling the training of very deep networks. SqueezeNet was designed for efficiency, achieving accuracy comparable to that of larger networks with significantly fewer parameters [12]. This efficiency made it an attractive choice for resource-constrained environments where computational resources are limited.

CNNs have demonstrated their efficacy in identifying physics-related features relate to detecting cracks in solar cells. Various methods can be leveraged to extract and interpret relevant physical and chemical characteristics. For example, CNNs can recognize specific textures linked to distinct crack types. Microcracks, for instance, may exhibit unique textural patterns compared to macrocracks. Through extensive training on a diverse dataset, CNN can differentiate between these textures.

Moreover, CNNs are effective in recognizing repeated patterns or structures within images and thus have promise for identifying patterns characteristic of specific crack types. This application includes identifying stress patterns around microcracks or recognizing specific shapes associated with defect categories. Materials' physical properties may affect the appearance of a crack. For example, material brittleness or hardness can impact crack shape and propagation. CNNs associate specific features with material properties.

Solar cells exhibit unique reflectance and absorption spectra that can be influenced by cracks or defects. CNNs are capable of recognizing alterations in these spectra that potentially indicate cracks. Similarly, thermal imaging of solar cells reveals temperature variations correlated with defects. CNNs, when trained on thermal images, can potentially identify temperature gradients or changes corresponding to cracks.

In addition to their success in crack detection in solar cells, CNN-based architectures have demonstrated significant efficacy in diverse domains, particularly in materials science. These instances of success not only highlight the adaptability of CNN models, but also serve as convincing evidence of their robustness in defect detection across various materials. For instance, Lew et al. presented a deep learning model that predicts fracture mechanisms in graphene, a material known for its exceptional strength and potential for applications in various industries [13]. This breakthrough in understanding fracture mechanisms at the nanoscale exemplifies the power of CNN in materials science.

Moreover, Chang et al. utilized a CNN to predict crack patterns and stress-crack width curves in 3D-printed concrete structures, a material of increasing importance in construction and engineering applications [14]. CNNs' successful application to predicting crack behavior in such complex materials underscores their versatility. Elapolu et al. introduced an innovative approach utilizing machine learning algorithms, including CNNs, to study crack propagation in polycrystalline graphene [15]. This pioneering work delves into crack behavior at the microstructural level, showcasing CNNs' potential for use in materials science research.

Additionally, Perera et al. explored the use of graph neural networks (GNNs) for simulating crack coalescence and propagation in brittle materials [16]. While it does not examine a CNN, this study exemplifies the broader application of neural network architectures, including CNNs, in simulating crack behavior in materials. These studies collectively constitute a compelling body of evidence demonstrating the efficacy of deep learning techniques, including CNNs, in predicting and understanding crack patterns across various materials.

The selection of literature for this review paper followed a rigorous and systematic process to ensure the inclusion of high-quality, relevant studies. A comprehensive search was conducted in reputable academic databases, including but not limited to IEEE Xplore and Google Scholar. Keywords such as "PV module defect detection," "solar cell crack detection," and "CNN-based defect detection" were used to retrieve relevant articles.

The initial selection of literature was based on predefined inclusion criteria. Only studies published in peer-reviewed journals or presented at reputable conferences were considered. The publication date range was limited to the past four years (2013–2023) to ensure the inclusion of the latest advancements in CNN-based defect-detection methods for PV modules.

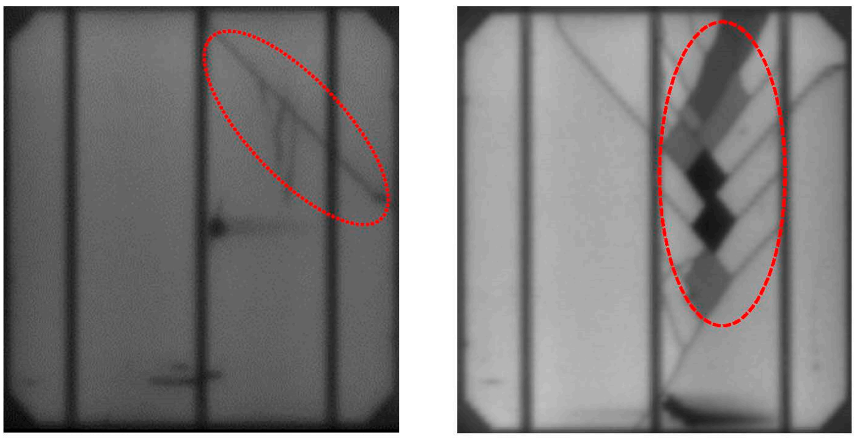
Titles and abstracts of the retrieved articles were screened to determine their relevance to CNN-based defect detection in PV modules. Studies not related to this domain were excluded. The remaining articles were subjected to a thorough full-text evaluation. Each article was carefully examined for its methodology, experimental setup, results, and relevance to the review's objective.

Articles were excluded if they did not apply CNN-based defect-detection techniques to PV modules. Additionally, studies lacking adequate experimental validation or those with insufficient detail on the CNN architecture were excluded. Special attention was given to including recent studies that demonstrated significant advancements in the field. Moreover, studies that provided comprehensive experimental data, comparative analyses, and practical implications were prioritized.

In this review paper, we aim to provide an extensive overview and comparative analysis of different CNN architectures and methodologies specifically utilized for crack detection in solar PV modules. By exploring advancements in this domain, we seek to shed light on the significant contributions made by CNNs to enhance PV module inspection detection capabilities and performance. Through a comprehensive examination of various CNN approaches, including their strengths, limitations, and real-world applications, we aim to provide valuable insights into state-of-the-art techniques and establish a basis for further advancements in the detection of cracks in PV modules.

2. Solar PV Module Cracks Impact on PV Output Power

Cracks in solar cells are one of the most prevalent defects in PV modules [17]. These cracks can occur in the form of a microcrack, as shown in Figure 2a, or in the form of a major breakdown, as depicted in Figure 2b. Multiple factors can contribute to the cracking of solar cells, such as extreme temperature fluctuations, mechanical stress, contraction, and thermal expansion, among others [18–20]. While these factors can cause cracking in solar cells, the severity of the damage depends on the number and size of the cracks that form, as well as the material properties of the solar cell itself. Cracking can reduce the efficiency of the solar cell and lead to a decrease in the amount of power that it can generate. Therefore, it is important to identify and address the causes of cracking to maximize the performance of the solar cells.



(a) (b)

Figure 2. An EL image of a cracked solar cell (**a**) Mini-crack; (**b**) Major-crack.

The presence of cracks in solar cells can contribute to the development of photovoltaic (PV) hotspots due to several factors. Firstly, PV cracks can contribute to moisture intrusion into the module, resulting in the formation of localized areas of high temperature known as hotspots. Secondly, PV cracks can create an electrical short circuit, leading to an increase in electrical current flow and subsequent hotspot formation. Lastly, PV cracks can lead to a decrease in power output, which in turn can cause an increase in temperature and thence to hotspot formation [21].

In a recent study [22], cracks in solar cells were investigated by using different crack sizes grouped into four different modes, the first mode being crack-free, the second mode including microcracks, the third mode including shading areas, and the fourth mode representing breakdown. That study found that a larger crack results in increased power loss, ultimately accounting for about 60% of the total power loss, as shown in Figure 3. Moreover, another study suggests that larger cracks lead to higher temperatures in the solar cell. Higher temperatures have a detrimental effect on the PV module's performance and can ultimately contribute to power degradation [23].

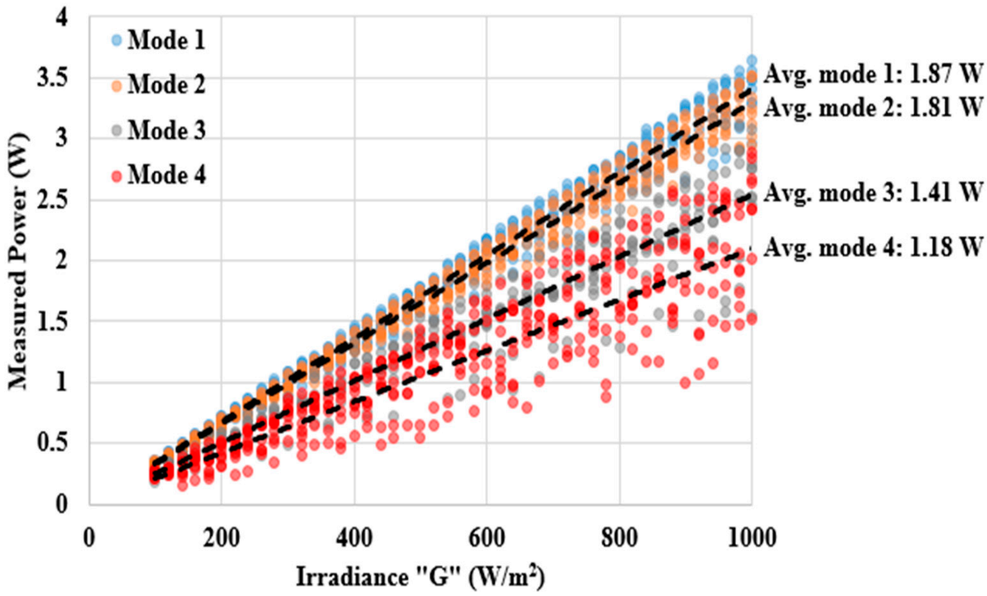


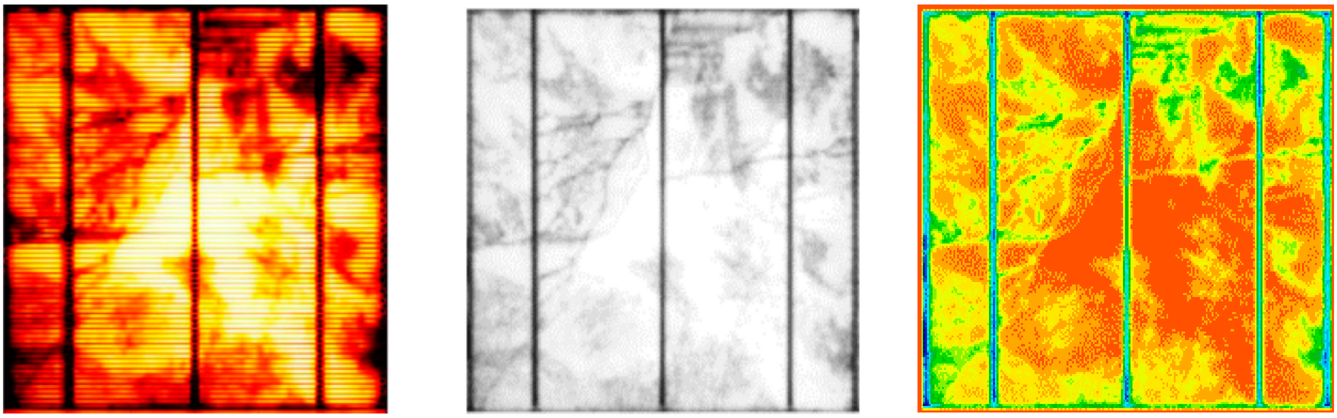
Figure 3. Measured power vs irradiance of the examined solar cells [22].

As the effects of cracks on the PV modules are known, it is possible to take several measures to minimize these effects. First and foremost, it is advisable to use PV modules that are more resistant or flexible [24]. A second approach is to make sure that the PV modules are properly sealed to ensure that extreme temperature fluctuations are prevented. Another approach is to inspect the PV modules regularly to prevent cracks from occurring and to handle the PV properly during all maneuvers and transportation [25]. Finally, it is important to design installations that account for unusual environmental conditions, such as strong winds, to ensure the durability and optimal performance of the PV modules [26].

3. Solar PV Module Cracks Detection Techniques

Detecting cracks is one of the most challenging tasks in PV, as it requires sophisticated technical equipment. Moreover, detection of cracks tends to be difficult, as cracks are often small or hidden. A variety of methods are available for detecting cracks in solar cells, including using ultrasonic resonance vibrations (RUVs) to examine the solar cell. It is easy to find cracks using this method, but it is not possible to pinpoint their exact locations [27]. Furthermore, RUVs are not always reliable and can be limited in their ability to pinpoint the precise location of a crack.

Consequently, photoluminescence (PL) was developed to identify the location of the crack [28]. PL is based primarily on the principle that when luminescence excites certain particles, they pass through different states called "excited" and "equilibrated" before returning to their normal state. During this process, there is interaction between light and these particles. The light emitted as a result of exciting extra particles through light exposure is referred to as PL, as shown in Figure 4a [29]. PL is, therefore, an ideal technique for detecting cracks, as the light emitted can be used to detect the crack and pinpoint its location. However, there are several limitations to this method, such as the need to use expensive cameras and the risk of irradiation light damaging the solar cells during the inspection [30]. Additionally, PL is not suitable for inspecting certain types of materials, such as those with a high degree of reflectivity [31].



(a) (b) (c)

Figure 4. Solar cells inspected by three different industrial inspection methods: (**a**) PL, (**b**) EL, (**c**) thermal.

Alternatively, another effective method to detect cracks involves using electroluminescence (EL). This approach is performed by inducing current to the PV module, which causes the electrons in the solar cell to become excited in the conduction band and resulting in an EL image, as shown in Figure 4b [32]. Among the most important features of EL imaging is its utility in inspecting both small and large cells, specifically both solar cells and PV modules [33]. This method is more effective that others at detecting cracks because it detects even the smallest cracks that may not be visible to the unaided eye. It is also more reliable because it produces a clear image of the module surface, which allows for a more accurate evaluation of any potential damage. To avoid interference between EL waves and light waves, EL imaging should be performed at night or in a completely dark room [34]. This need arises because EL imaging works by detecting the light emitted by the module surface when an EL wave is applied. This light emission is visible only in a dark environment and makes it much easier to detect small cracks. Moreover, the clear image produced by EL imaging can provide detailed information about the module surface, allowing for a more precise evaluation of any cracks or damage [35].

Inspection of PV modules is not typically limited to single solar cells or small-scale PV modules; however, there are scenarios that require an examination at a larger scale of insolation and may involve thousands of PV modules. As a result, drones were employed for thermal imaging [36]. A drone was fitted with a thermal camera and flown over the PV installation [37,38]. The data were then stored and used to inspect the PVs later by identifying hotspots and malfunctions, as shown in Figure 4c. By using these drones with thermal--imaging technology, engineers were able to quickly and accurately identify areas of the PV installation that could be malfunctioning or overheating. This procedure allowed for quick and precise repair of any issues, ensuring that solar power was consistently working at peak efficiency. It is worth noting that one of the main disadvantages of this method is that it is very labor-intensive and entails a good deal of human labor [39].

Cracks in solar cells can be inspected in a variety of ways, including both conventional and modern methods. Each approach has its own strengths and limitations, and each is chosen according to the demands of the situation. Figure 5 summarizes four methods for detecting defects in solar cells. In conclusion, it is crucial to be aware of the different techniques available and select the appropriate technique according to the specific application.

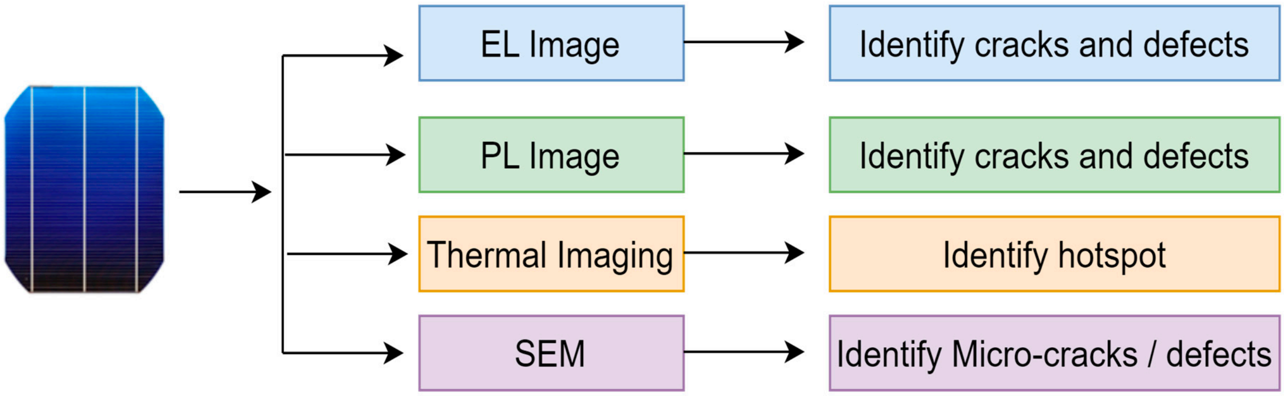


Figure 5. Different methods of detecting solar cell defects.

4. Fundamentals of Convolutional Neural Networks (CNN)

Convolutional neural networks (CNNs) have emerged as a dominant and highly effective deep learning technique, consistently surpassing other machine learning approaches across diverse real-world applications [40–42]. Prominent CNN architectures like GoogleNet3, ResNet4, and DenseNet5 have achieved remarkable performance, benefiting from the expertise of domain specialists who possess extensive knowledge in data analysis and CNN development. However, not every user interested in a specific domain possesses such specialized knowledge [43–45]. For instance, individuals proficient in handling data may lack the expertise to construct CNN algorithms, or conversely, those familiar with CNNs may lack domain-specific insights. Consequently, there is a growing demand for automation of CNN architecture design, enabling users without domain expertise to transparently fine-tune CNN models [46–48]. The availability of CNN architecture-design algorithms can foster widespread adoption of CNNs, contributing to the advancement of artificial intelligence (AI) in various domains.

Different categories of CNN architecture-design algorithms can be distinguished based on the domain knowledge required for implementation. The first category involves a combination of automatic and manual tuning, wherein expertise in designing CNN architectures is essential but facilitated by automatic tuning. Genetic CNN methods and hierarchical representation methods fall into this category. On the other hand, there is automatic CNN architecture design, which eliminates the need for manual parameter adjustment by users. "Automatic + manual" tuning designs often outperform fully automated designs, benefiting from the additional insights provided by human expertise in CNNs [49]. However, the automatic designs have a distinct advantage in that they require no manual tuning, making them more appealing to users without domain knowledge of CNNs.

One notable innovation in deep CNN infrastructure is Hypotheses-CNN Pooling (HCP) [50]. This approach incorporates multiple-object segment hypotheses as inputs, with each connected to a shared CNN. The CNN outputs for each hypothesis are then aggregated using max pooling to generate the final multi-label predictions. HCP infrastructure offers unique features, such as not requiring ground-truth bounding box information for training and robustness to noise and redundant hypotheses. In another study [51], it was discovered that significant image degradation leads to decreased performance in classification, especially when training images fail to reflect the degradation levels seen in test images. Visual analysis of the CNN layers revealed the loss of critical low-level features in the early layers, which directly impacted accuracy.

Concerning medical imaging applications, a recent experiment compared three techniques [52]: support vector machines with rotation and orientation-free features, transfer learning on CNN networks, and capsule network training. CNN methods outperformed traditional methods due to their ability to learn and select features automatically. Transfer-learning models demonstrated the highest accuracy in the experiment.

Convolutional neural networks (CNNs) have completely transformed various fields by their remarkable applications. In computer vision, these networks have proven to be incredibly powerful, helping us detect objects, classify images, and even recognize faces accurately [53]. Their contribution to autonomous driving is especially noteworthy, as they enable precise object detection on roads [54]. In healthcare, CNNs have played a crucial role in interpreting medical images like MRIs and X-rays, aiding doctors in diagnosing diseases effectively [55]. Beyond vision tasks, CNNs have also been utilized in natural language processing, wherein they excel in understanding sentiment, translating languages, and generating brief summaries. Additionally, industries ranging from finance, wherein they help to detect fraudulent activities, to environmental monitoring, wherein they analyze satellite imagery, have benefitted from CNNs' flexibility and impact [56]. The wide range of applications of CNNs continues to drive innovation and reshape a variety of industries worldwide.

A CNN's architecture is composed of several layers that serve as cornerstones, all of which contribute to building an architecture capable of performing a specific task with a high level of validation accuracy. Each of these layers is important for building the CNN, which cannot be constructed without them. Table 1 summarizes each of the main layers.

Table 1. Main layers of a CNN's architecture.

Layer Name	Function	References
Input layer	Indicates the dimensions of the input image or volume, such as its height and width and the number of color channels.	[57]
Convolutional layer	Consists of filters learned during the processing process and is smaller than the actual image.	[58]
Normalization layer	maintains regularity and avoids excess fitting, while simultaneously speeding up computation by the CNN	[59]
Rectified Linear Unit (ReLU)	Eliminates all negative digits and substitutes their values with zero.	[60]
Pooling layer	Retrieves values from segments of images bounded by kernels.	[61]
Fully connected layer	Linearly transforms input vectors are linearly using weight matrices in order to solve problems.	[62]
SoftMax function Layer	Predicts a distribution of probabilities in a multiple-classification situation	[63]
Classification layer	Utilizes a set of rules to classify inputs into categories.	[64]

When assessing the performance of CNN-based models in defect detection for PV modules, several standard evaluation metrics are employed. These metrics help to quantify the models' accuracy, effectiveness, and reliability. Accuracy is one of the most straightforward metrics, representing the ratio of correctly predicted instances to total instances. It provides an overall measure of how well the model classifies defects. Precision, also known as positive predictive value, calculates the proportion of true positives (correctly predicted defects) to the sum of true positives and false positives (instances wrongly classified as defects).

Recall, also known as the true positive rate or sensitivity, is the ratio of true positives to the sum of true positives and false negatives (instances of defects wrongly classified as non-defects). It quantifies the model's ability to identify actual defects. The F1 score is the harmonic mean of precision and recall. It provides a balanced measure of a model's precision and recall, making it an effective metric when dealing with imbalanced datasets. Specificity is the ratio of true negatives (correctly predicted non-defects) to the sum of true negatives and false positives. It indicates the model's ability to correctly classify non-defective instances. Mean absolute error (MAE) measures the average absolute difference between predicted and actual values. It is used in regression tasks and provides insight into the accuracy of model predictions.

Mean squared error (MSE) calculates the average squared difference between predicted and actual values. It treats larger errors more severely than MAE, which can be useful in tasks wherein larger errors are of serious concern. The root mean square error (RMSE) is the square root of the MSE. It provides an interpretable measure of the average prediction error and is in the same units as the predicted values. ROC curves are used for binary classification tasks. They plot the true-positive rate against the false-positive rate at various thresholds. AUC quantifies the model's overall ability to discriminate between favorable and negative classes.

A confusion matrix provides a detailed breakdown of the model's performance by showing the numbers of true positives, true negatives, false positives, and false negatives. These metrics collectively offer a comprehensive evaluation of CNN-based models, considering aspects such as accuracy, precision, recall, and the ability to handle false positives and false negatives. The choice of metrics depends on the specific goals and nature of the defect-detection task. When assessing the performance of CNN-based models in defect detection for PV modules, various standard evaluation metrics play a crucial role. These metrics quantify the accuracy, effectiveness, and overall reliability of the models, providing valuable insights into their capabilities.

5. CNN-Based Crack Detection Methods

In the last decade, the production and installation of PV modules have grown significantly, which has in turn led to an increase in the demand for automated defect detection. Consequently, various CNN architectures have been implemented in the PV industry. Generally, architectures can be divided into two categories: custom architectures that are developed from scratch and trained to perform the task, and transfer learning architectures that, instead of being trained from scratch, utilize pre-trained architectures to perform the task. Custom architectures require more processing power to train, while transfer learning architectures need fewer resources and less time to develop. Transfer learning architectures are more commonly used in the PV industry due to their efficiency and speed. They also require less training data. However, custom architectures are better suited to more complex tasks as they can be customized to the specific problem. This section will discuss the state of the art and all the recent studies that describe employing CNN as an automated defect-detection method, either as a custom architecture or as a method of transfer learning.

Based on the light CNN network, Hussein et al. developed a sophisticated CNN architecture called PV-CrackNet that detects microcracks, as shown in Figure 6 [65]. The study highlights the difficulty of obtaining representative data due to the ambiguous nature of solar cells and proposes a strategy for mitigating the problem known as filter-induced filter augmentation flow (FAI), as shown in Figure 7. FAI applies different filters to images of PV modules to simulate various lighting and environmental conditions. According to the study, PV-CrackNet has an accuracy of 97.42% and the highest recall and precision of all state-of-the-art architectures. Additionally, the FAI strategy proposed in the study presents an effective solution for mitigating the challenge of obtaining representative data, as it can simulate various lighting and environmental conditions with the use of different filters. This strategy helped to improve the accuracy of PV-CrackNet to 97.42%, with the highest recall and precision among state-of-the-art architectures.

In another study [66], light CNN architecture was proposed as a novel CNN architecture approach with 93.02% accuracy. As this method was trained with fewer images, it does not require GPU computers. To avoid data scarcity, the proposed method used rotation and contrast flipping by rotating the images 90, 180 and 270 degrees. Through these data-augmentation strategies, the accuracy of the data was improved by 6%, and the proposed method was able to perform single-image prediction in 8 milliseconds. In that study, it was suggested that the accuracy could be improved by increasing the size of the dataset, which could then be divided into different categories of defects. By augmenting the data through rotation and contrast flipping, the model was able to learn from both the original images and the rotated/flipped versions, thus increasing the diversity of the data, which led to more accurate predictions. Furthermore, increasing the size of the dataset also enabled the model to learn from different categories of defects, thus further improving its accuracy.

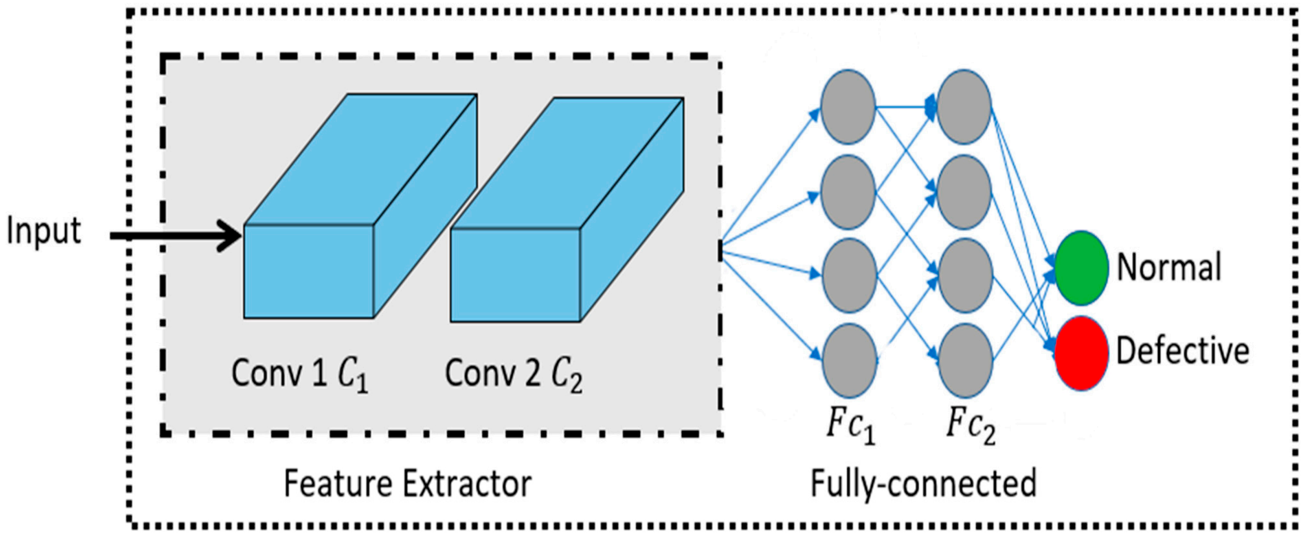


Figure 6. Proposed CNN PV-CrackNet architecture [65].

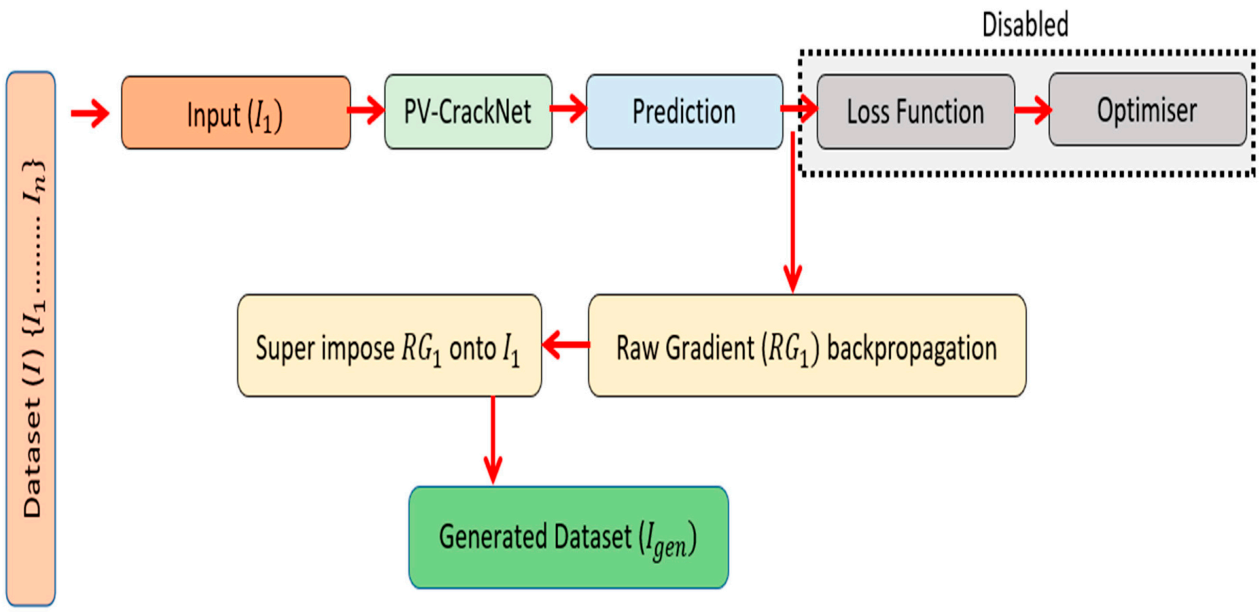


Figure 7. Filter-induced augmentation flow (FIA) [67].

A recent study utilized the pre-trained CNN architecture AlexNet. By default, AlexNet can classify more than 1000 outputs, as shown in Figure 8 [67]. However, in that study, AlexNet was modified to classify the outputs into two categories: defective and non-defective solar PV modules based on a training dataset of 392. The model achieved 85.16% accuracy. However, there was insufficient training data, which limited the model's accuracy. The model's accuracy was improved by using machines capable of high-performance computing and by better training. This result demonstrates that with an increased amount of training data, AlexNet was able to achieve higher accuracy. When machines capable of high-performance computing are used, more training data can be processed in a shorter amount of time, which can lead to better model accuracy. Better training techniques, such as data augmentation, can also improve the model's accuracy.

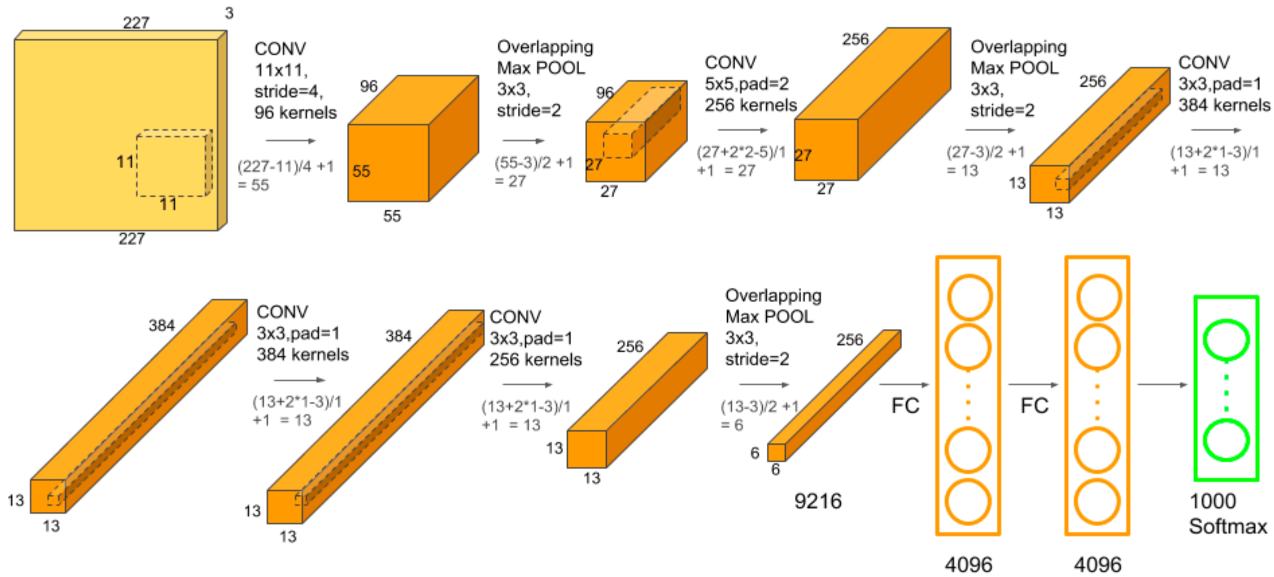


Figure 8. Pre-trained AlexNet CNN architecture [66].

A comparison study was conducted by Rahman et al. on six of the most sophisticated transfer learning architectures—VGG-16, VGG-19, Inception-V3, ResNet50-V2, ResNet-V2, and XCeption—for identifying microcracks [68]. The method was to identify each microcrack individually, then aggregate the results using ensemble methods. In the study, 2624 EL images were used with augmentation by horizontal flip rotations of 90 and 270 degrees. As each pre-trained individual was assessed, it was compared to the proposed method, which is based on a method of ensemble learning in which the pre-trained networks are combined and aggregated into a single network to achieve a final result, as shown in Figure 9. Although there are different ensemble methods, such as voting or stacking, soft voting was utilized in this study because it is based on taking an average of the expected probability before applying the threshold, which minimizes the risk of error. Moreover, soft voting works well with complex models, as averaging the probability helps to reduce the variance of the voting system. Table 2 indicates that the ensemble method achieved the highest accuracy for both monocrystalline and polycrystalline solar panels, 96.97% and 97.06% respectively, although all other pre-trained architectures also achieved a very high level of accuracy, between 90.91% and 96.97% in monocrystalline and 85.29% and 94.12% in polycrystalline. Additionally, the study noted that models' accuracy can be enhanced by increasing the amount of training data, as well as by increasing the training time.

According to another study [69], a hybrid method involving a CNN pre-trained network of VGG-16 and support vector machines (SVM) has been proposed as an effective method of detecting cracks in PV panels. This model works by extracting features from EL images and making predictions about whether they will be accepted or not, as shown in Figure 10. That study claims that limitations of the dataset played a significant role in the selection of this model, based on results obtained from training the model on two different sets of data: 2624 EL images with a resolution of 300 × 300 pixels and 2624 EL images with a resolution of 250 × 250 pixels. SVM a supervised deep learning algorithm. Essentially, the main objective is to determine the most appropriate dividing line by maximizing the gaps between sets of data points.

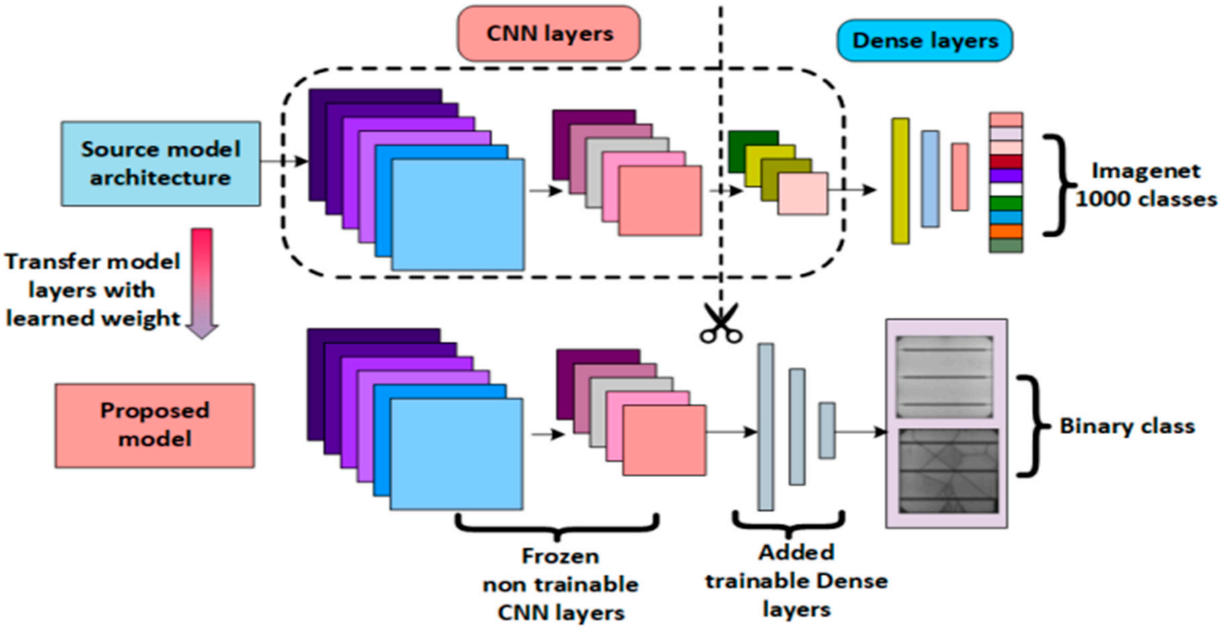


Figure 9. Proposed ensemble learning architecture [68].

Table 2. Accuracy of pre-trained networks and ensemble learning for monocrystalline and polycrystalline solar panels [68].

Architecture	Accuracy of Pre-Trained Networks and Ensemble Learning for Monocrystalline Solar Panels	Accuracy of Pre-Trained Networks and Ensemble Learning for Polycrystalline Solar Panels
VGG-16	90.9%	91.2%
VGG-19	96.9%	88.2%
Inception-v2	96.9%	88.2%
ResNet50-v2	90.9%	88.2%
ResNet-v2	96.9%	94.1%
Xception	93.9%	85.3%
Ensemble	96.9%	97.1%

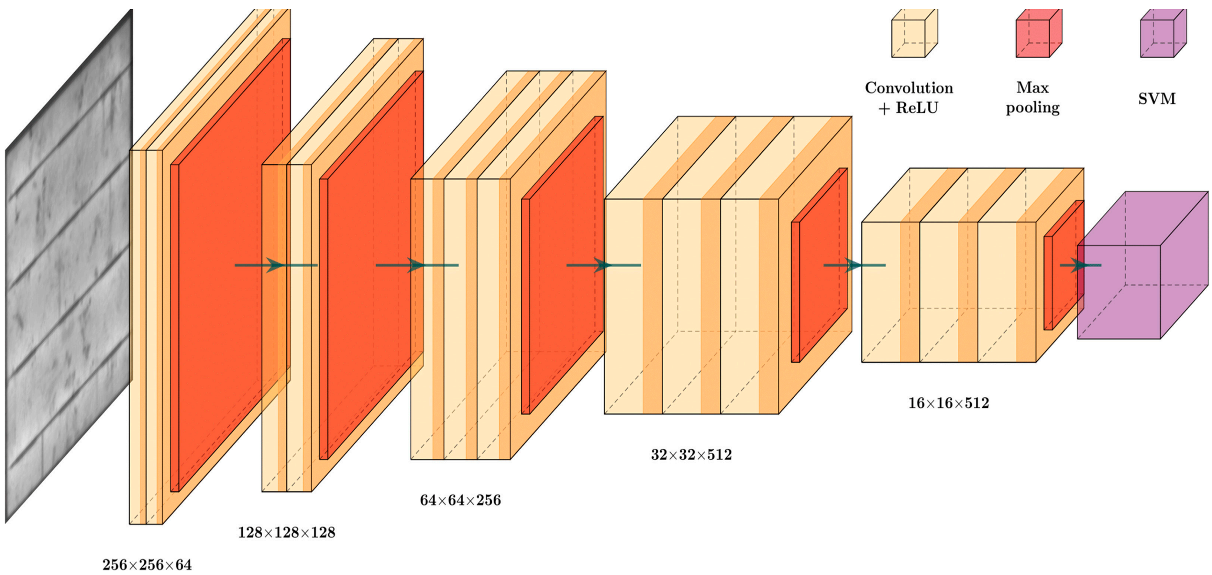


Figure 10. Combined architecture including VGG-16 and support vector machines [69].

This technique focuses on enhancing the distance between separated sets of data, as shown in Figure 11. It is important to note that the proposed model has a high degree of accuracy (99.49%), but the main limitation is that it does not identify cracks in the corners of the solar cells. This limitation can be overcome by enhancing the dataset. Therefore, it is necessary to accurately identify the optimal hyperplane that best separates the data points while providing a high degree of accuracy for the proposed model.

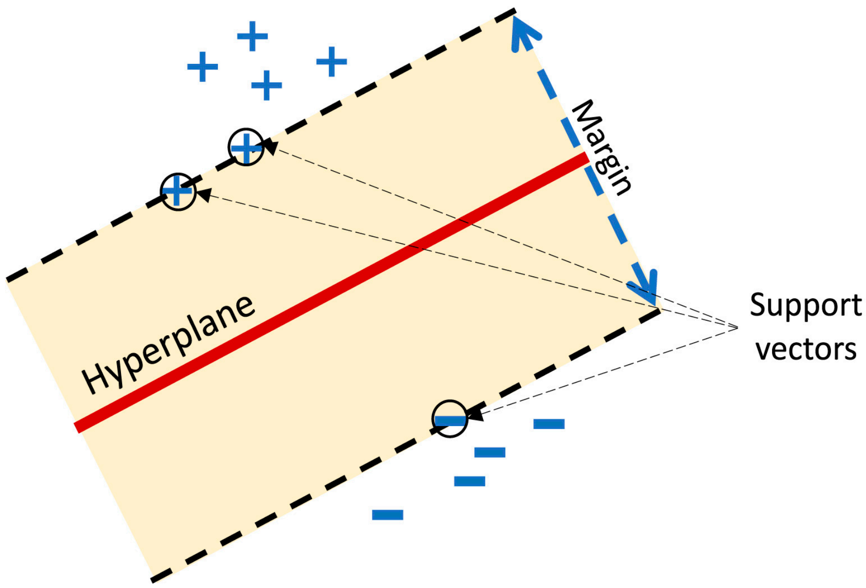


Figure 11. Optimal hyperplane for SVM [69].

As shown in Figure 12, another study has proposed a novel CNN architecture based on a multi-scale CNN with three branches [70]. This multi-scale architecture was modified based on the pre-trained AlexNet architecture, which normally is composed of five convolutional layers. In this instance, two additional convolutional layers with dimensions 3×3 have been added, along with a new layer of fully connected layers. Based on a dataset of 20,000 images, the proposed CNN architecture was trained to detect 11 different defects, including cracking, hotspots, shadows, and soiling, as well as divisibility into anomaly and non-anomaly. These defects were categorized to enable the network to accurately identify anomalies and accurately classify them as either defective or non-defective. According to the authors of the study, the multi-scale CNN was able to accurately classify defective components with an accuracy of 97.32%, while the original AlexNet was able to do so with an accuracy of 93.20%, demonstrating that the multi-scale CNN can correctly classify defective components. The study's findings indicated that the suggested approach could be improved through the implementation of a high-quality optimization algorithm.

Using faster R-CNN as a basis for crack detection in solar cells, another study proposed an improved sophisticated model [71]. As faster R-CNN does not normally have high accuracy, the model in that study was modified to improve its accuracy by adding a feature pyramid network (FPN). The FPN enhanced the feature-extraction process, and with the addition of guided anchoring RPNs, improved the model's ability to predict crack locations. With the combination of the FPN and guided anchoring RPNs, the model is able to extract more detailed features, such as edges, corners and textures, from the images. Thus, it can more accurately identify cracks. Additionally, the FPN helps to increase the model's overall accuracy by providing better feature representation, while the guided anchoring RPNs help to improve the model's ability to localize cracks. A dataset of 5000 images with varying brightness was used to train the model. As a result, the modified model had higher accuracy, 94.62%, than 11% of the faster R-CNN, and the rate of crack detection improved from 0.91 s to 0.19 s per image. Furthermore, the improved feature representation and effective localization of the cracks allowed the new model to outperform traditional methods and significantly reduced inference time. In addition, increasing the size of the training dataset will lead to a significant improvement in the model's accuracy.

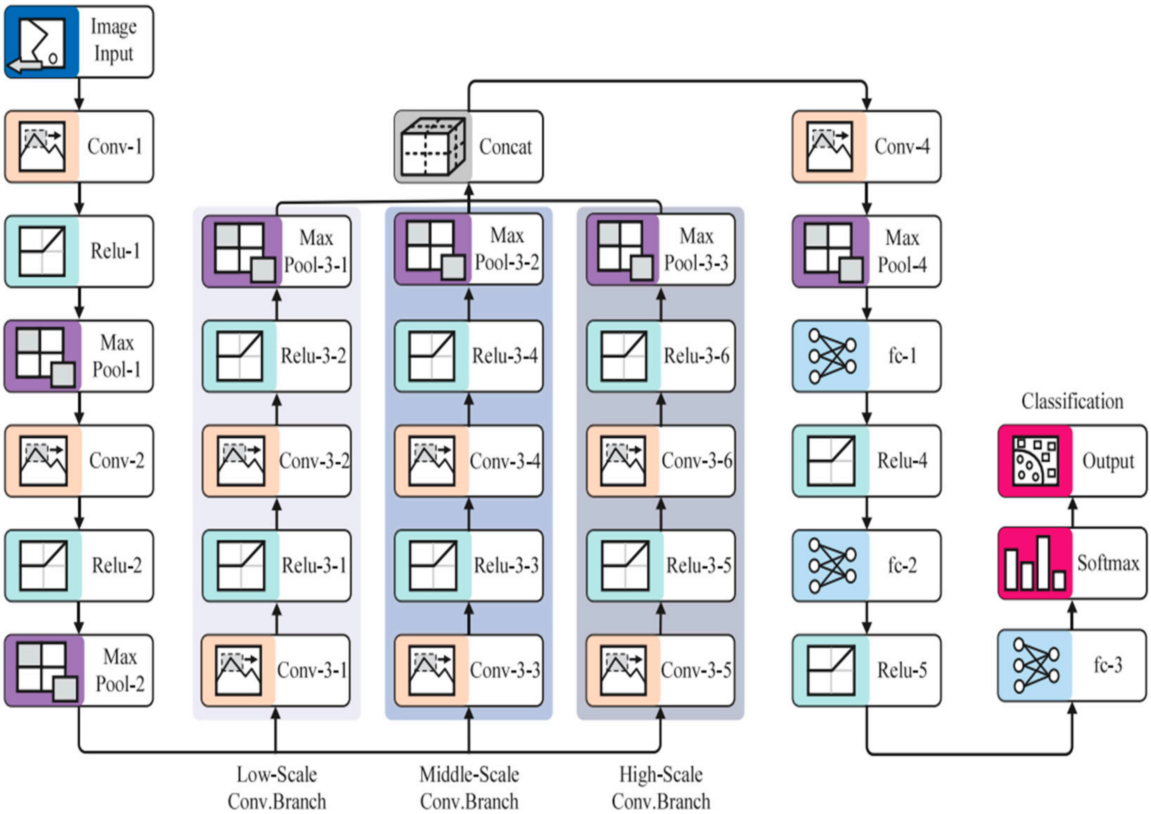


Figure 12. Multi-scale CNN architecture [70].

Table 3 provides an extensive evaluation of various convolutional neural network (CNN) algorithms employed in the detection of cracks in solar cell images. The table encompasses key metrics such as detection accuracy, which refers to the ability of the CNN algorithm to correctly identify and classify cracks within the images. Higher accuracy indicates more reliable detection. Detection speed, on the other hand, pertains to the efficiency of the algorithm in processing the images and providing results in a timely manner. Faster detection speed enables real-time or near-real-time analysis. Network complexity is a measure of the intricacy and depth of the CNN architecture. Complex networks often incorporate more layers and modules, potentially leading to better performance but requiring higher computational resources. Computational speed represents the speed at which the CNN algorithm can perform computations and make predictions. Faster computational speed allows for quicker analysis and decision-making. It is worth noting that these different CNNs can be found in different applications and are widely used in different programming languages such as MATLAB or Python. By considering these factors, Table 3 reveals that certain CNN models, such as GoogLeNet, ResNet-50, and Inception-v3, achieve high detection accuracy. However, it is important to note that these architectures also tend to have higher network complexity and computational requirements. Conversely, models like SqueezeNet and AlexNet strike a balance between accuracy and computational speed, making them suitable options for applications wherein real-time or resource-efficient processing is crucial. The table serves as a valuable resource for researchers and practitioners seeking to understand the trade-offs between accuracy, speed, network complexity, and computational requirements when selecting a CNN algorithm for crack detection in solar cells.

Table 3. Comparison of CNN algorithms for detection of cracks in solar cell images.

CNN Algorithm	Description	Suitable for Detecting	Detection Accuracy	Detection Speed	Network Complexity
GoogLeNet	A deep CNN architecture with inception modules	Various types of cracks including microcracks, corner cracks, and edge cracks due to its ability to capture multi-scale features.	High	Moderate	Moderate
SqueezeNet	A lightweight CNN architecture with fire modules	Surface-level cracks and defects. It efficiently processes images, making it suitable for real-time detection in large-scale PV installations.	Moderate	High	Low
ResNet-50	A deep CNN architecture with residual connections	Complex cracks and defects. Its deep structure allows it to capture intricate details and patterns in the images.	High	Moderate	High
DarkNet-53	A deep CNN architecture used in YOLO (You Only Look Once) object detection	Both micro- and macro-level cracks. It provides efficient object detection, which is crucial for identifying various types of cracks.	High	Moderate	High
VGG-19	A deep CNN architecture with 19 layers	Macro-level cracks and defects. Its depth allows it to capture significant features indicative of larger cracks.	High	Moderate	High
AlexNet	A deep CNN architecture with 8 layers	Surface-level cracks and defects. It can efficiently process images and is suitable for real-time detection in large-scale PV installations.	Moderate	High	Moderate
Inception-v3	A deep CNN architecture with inception modules	Various types of cracks including microcracks, corner cracks, and edge cracks due to its ability to capture multi-scale features.	High	Moderate	Moderate

6. Discussion and Comparative Analysis

The paper comprises an extensive review of the crack-detection methods used for PV modules and solar cells via automated CNN methods. It has become evident from this review that the transition from conventional methods to CNN's deep learning algorithm has done much to increase the rates of crack detection in PV modules and solar cells. CNN has been a game-changer in this field, as it has enabled a major improvement in the accuracy of crack detection in PV modules and solar cells. By providing a more accurate way to detect cracks, CNN has enabled a much smoother and faster process for detecting cracks in PV modules and solar cells. This outcome has greatly increased the process's reliability and efficiency. However, CNN does suffer from limitations and shortcomings, such as the scarcity of large and diverse datasets. Most existing approaches rely on datasets of fewer than 10,000 images, as shown in Table 4. These limited datasets may not accurately reflect the range of conditions that actually occur. Thus, when the model is trained on a small datasets, it may encounter difficulty in accurately identifying patterns and cracks. As a step towards addressing this limitation, future work could focus on collecting more diverse datasets by collaborating with industry stakeholders or research institutions to collect high-resolution images that can be used to demonstrate deterioration over time. As a result of training on such datasets, models become capable of detecting cracks accurately across a wide variety of solar-panel installations, making them more practical and reliable.

Table 4. Comparison between different CNN architectures and models.

Reference	Year	Architecture	Description	Dataset Size	Accuracy
[72]	2023	Custom	DSMP: three layers of convolutional connected with double layers of max pooling	300	96.97%
[73]	2023	Custom	A total of four blocks of convolutional layers, with each block having two 2D convolutional layers	20,000	85.35%
[74]	2023	Custom	A hybrid model based on CNNs and SVMs	8548	94%
[75]	2023	ELCN-YOLOv7	Long-Range Convolutional Network (ELCN) module, designed to enhance defect-detection capabilities in EL images of PV cells, combined with YOLOv7	4500	94.34
[76]	2023	Custom VGG-16	Three convolutional layers connected with three layers of max pooling. Fine-tuned VGG-16	-	99.80% 99.91%
[69]	2022	SVM-VGG-16	Hybrid model of pre-trained VGG-16 and Support vector machine	2624	99.49%
[71]	2022	R-CNN	Faster R-CNN modified to improve its accuracy by adding a feature pyramid network (FPN)	5000	94.62%
[65]	2022	Custom	CNN Architecture composed of two convolutional layers by connecting filter-induced augmentation(FIA)	340	97.42%
[68]	2021	Six Pre-trained architectures and combining them for ensemble learning	Six pre-trained networks: VGG-16, VGG-19, Inception- v2, ResNet50-v2, Resnet-v2 and Xception, assessed individually and aggregated by ensemble learning.	2624	VGG-16-91.2% ResNet-V2- 94.1% Ensemble 97.1%
[77]	2021	U-NET	A semantic-segmentation model based on the u-net architecture for EL image analysis of PV modules	30	-
[78]	2021	Custom	Multi-scale CNN networks, each built based on different techniques	20,000	94.4%
[79]	2021	Custom	CNN composed of multiple convolutional layers, pooling layers, rectified linear unit (ReLU) layers, loss layers and fully connected layers	684	99%
[80]	2020	Custom	Four layers of convolutional layers with 3×3 filters connected to four layers with max pooling	893	99.23%
[81]	2020	Mask-RCNN with ResNet	CNN architecture developed by Connecting RCNN to fine-tuned pre-trained ResNet	5983	97.3%
[82]	2020	Custom CNN with Random Forest	CNN architecture developed from four convolutional layers connected to four layers of max pooling by changing the fully connected layers to Random Forest	11,939	98.14%

One of the limitations CNN faces when it comes to solar energy is the generalizability of application of the different models that are available for the industry. For example, different solar panels have different designs, textures, and manufacturing processes. Furthermore, environmental conditions such as light and soiling differ from installation to installation. Therefore, a CNN model developed for detecting cracks in one type of solar panel will be difficult to use for various other solar panels. This difficulty arises because the CNN model is trained on a specific dataset that has a limited scope and does not account for variety in design, texture, and environment. Therefore, the CNN model is not able to recognize patterns and features that are unique to specific solar panels. This problem can be mitigated through several different approaches, including diversifying the dataset by including samples from various solar panels, or by fine-tuning pre-trained networks such as ImageNet to work on smaller datasets that can detect solar cracks. As a result, it will be feasible to capture a variety of generic features by leveraging the model. Moreover, diversifying the dataset will enable the CNN model to capture unique and specific features of various solar panels, thus making it more accurate and reliable.

Another factor to consider is the user's ability to interpret and explain CNN decision-making. CNN models often seem like black boxes, and it is difficult to interpret the factors contributing to decision-making within the model. It is crucial to building trust in CNN models that the models provide a level of interpretability and explainability such that users can understand why the model made a particular prediction, for example, why it classified a specific cell as cracked. This change will ensure that CNN models can be trusted as reliable and accountable. Therefore, explainability and interpretability must be part of the model-building process. This goal can be achieved by providing visualizations of the model's decision-making process, as well as by providing assessment methods that can be used to determine which features were most important in the model's predictions. There are a number of methods that can be applied to improve the interpretability of the model, such as attention mechanisms, which show what parts of the input image are crucial for the model's to decision-making. Alternatively, saliency maps highlight the pixels in the input image that played a significant role in making a decision.

As part of CNN implementation in solar farms, it is also necessary to consider real-time detection because it is crucial to minimizing damage to or power loss from the PV modules; the greater the size of the PV modules, of the more data the CNN has to process. Real-time detection is important because the faster any potential faults are identified, the quicker the response time that will allow the user to mitigate damage and avoid power losses. Furthermore, the larger the PV modules are, the more data must be processed by CNN to detect any potential problems, making it even more important that the detection be quick and accurate. In order to improve this feature, design of a lightweight CNN or optimization of the inference speed can be achieved by quantization, which reduces the weight, or pruning in order to remove unnecessary parameters from the algorithm. As a result, these techniques can help to ensure that the CNN is able to detect potential problems quickly and accurately, even with large PV modules.

Furthermore, it is imperative to acknowledge the dynamic nature of the solar industry, which necessitates adaptability in crack-detection methodologies. Different solar panels exhibit diverse designs, textures, and production processes, while environmental conditions fluctuate from one installation to another. This variability poses a challenge to applying a single CNN model across the board. To surmount this difficulty, a concerted effort to diversify datasets, incorporating samples from various solar panels, is essential. Additionally, fine-tuning pre-trained networks like ImageNet for smaller datasets holds promise for allowing models to recognize unique features across different panel types.

7. Conclusions

In conclusion, the application of convolutional neural networks (CNNs) has significantly improved the accuracy and efficiency of crack detection in PV modules and solar cells. The reviewed studies demonstrated the effectiveness of CNN-based approaches for detecting cracks and other defects in solar cells, with high accuracy rates ranging from 85.16% to 99.91%.

One of the key factors in achieving high accuracy rates is the availability of diverse and representative datasets. The studies highlighted the importance of data-augmentation techniques such as rotation, contrast flipping, and filter-induced augmentation flow to enhance the training process and improve the accuracy of the CNN models. Additionally, the use of pre-trained CNN architectures, such as VGG-16, AlexNet, and GoogLeNet, in transfer learning approaches proved to be efficient and effective in crack detection.

However, CNN-based crack-detection methods still face challenges and limitations. The scarcity of large and diverse datasets specific to different types of solar panels and environmental conditions remains a significant limitation. Future work should focus on collecting more diverse datasets to improve the capabilities of CNN models for generalization. Interpretability and explainability of CNN models are also crucial to building trust and reliability. Methods such as attention mechanisms and saliency maps can help provide insights into the decision-making process of CNN models, making them more transparent and accountable. Real-time detection is another important aspect to consider, especially for large-scale PV installations. Optimizing the computational speed and efficiency of CNN models through techniques like quantization and pruning can enable quicker and more accurate detection, reducing potential damage and power losses.

Overall, CNN-based crack-detection methods have great potential to improve the reliability and efficiency of PV modules and solar cells. As the existing limitations are addressed and as research in this field continues, CNN models will be able to further enhance crack detection and maintenance in the solar industry, contributing to the optimal performance and longevity of solar energy systems.

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