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Deep Learning Approach for Crack Detection in Solar Panels using Convolutional Neural Networks

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Abstract

The utilization of solar panels, which are effective power sources for producing electrical energy, allows for the widespread application of solar energy, a clean and renewable substitute for conventional fuels. However, there is a chance that manufacturing, delivery, and installation errors will lower the effectiveness of power generation. Moreover, detecting surface cracks on solar panels is crucial to ensure the durability and effectiveness of photovoltaic systems. By instructing the network to find flaws in photos of solar panels, convolutional neural networks provide a practical way to address this problem. During training, the CNN gains the ability to distinguish between patterns that are normal and those that indicate a fault. After being trained, the network can accurately and effectively detect fractures in recent data.

1. Introduction

Modern times require the usage of new energy sources since non-renewable resources will become harder to locate and less accessible. On the other side, if used properly, renewable energy sources can be more readily available and there won't be any concern about losing them. The Sun's energy is the most readily available and unaffordable resource that has been present for millions of years. As a result, the use of solar energy has garnered a lot of attention recently.

Solar cells and most semiconductor components are silicon-based. Silicon photovoltaic (PV) modules using crystalline silicon (c-Si) are a well-established technology that led the global PV market in 2018 with over 110 GW. Yet, there are significant difficulties associated with the growing trend towards this renewable energy source. The performance of photovoltaic cells under actual weather circumstances, as well as current and projected solar electricity output, must be thoroughly understood to maintain a consistent power source and to guarantee a successful and stable solar installation procedure. (Timothy et al.)

One such issue is that placing solar cells in severe settings, such as high temperatures, windy days, and other potential scenarios, may result in cell damage and the development of fractures on the interior layer of the cell. Lower conversion efficiency and a shorter service life may result from this. Solar cells are necessary for producing energy effectively, but in order to function effectively, they must contain chemicals that may be hazardous to human health. (Ko¨ntges et al.) Any interior cracks could potentially allow carcinogens, substances that can cause cancer, leaked into the environment even if they are enclosed inside the glass covering. Crystalline silicon, a type of semiconductor, is used to make solar panels. Due to its excellent electrical conductivity, silicon is used in many electrical device components. High-purity silicon is obtained through the Czochralski method and is utilised in solar panels. Solar panels use organic materials such as copper indium gallium selenide (CIGS), cadmium telluride (CdTe) and others to capture sunlight and transform it into electrical power. (Prince et al.)

It's worth noting that simply because certain chemicals are present, solar panels aren't always dangerous to use. They are actually a great source of renewable energy, and the advantages of using them outweigh any possible concerns by a wide margin. To ensure that they are handled and maintained safely, nevertheless, it is essential to take the necessary precautions.

The risk of exposure to the hazardous substances must be reduced by having a cracked or broken solar panel fixed or replaced as soon as feasible. Regular inspections and service might help find potential issues before they become significant ones.

Ultimately, it is crucial to utilize and maintain solar panels responsibly to protect both the environment and people. It is crucial to be aware of potential hazards and take the necessary measures to mitigate them if we wish to continue benefiting from renewable energy while safeguarding our safety and well-being. (Madichetty et al.)

To solve this issue, Convolutional Neural Networks were investigated to detect damage in solar panels. After being trained on a variety of images of damaged and undamaged so- lar cells, the CNN successfully and accurately classifies cracks. This paper demonstrates the possibility of employing Deep Learning techniques for raising the reliability and effectiveness of photovoltaic systems and offers a possible solution to the problem of fracture identification in PV modules. The results of the procedure will be communicated to the relevant authorities for subsequent upkeep. This increases the effectiveness of the monitoring system and lessens the possibility of damage spreading to nearby panels. (Lakshmi, Sundari, and Manjula)

2. Related Work

This paper (Zhu et al.) uses the photoluminescence method to identify solar cell cracks. The photoluminescence method is a non- destructive optical characterization tool used to evaluate the electrical properties of a material. A substance must absorb photons for excited electrons to be shifted from the valence band into the conduction band. When these excited electrons combine back with holes, they emit light with a distinctive energy, revealing information about the electrical structure of the material. (Eason, Noble, Sneddon, et al.) Photoluminescence is commonly utilized for material characterization and quality control in both research and industry. It may be used to analyse a wide range of materials, including biological molecules, nanomaterials, and semicon- ductors. Researchers used the photoluminescence technique to conduct the experiment to see if cracks were distributed consistently. When cracks were distributed uniformly, the output power barely changed—the biggest recorded reduction was less than 5 % and V_{oc}(output voltage) didn't change at all. (Silitonga et al.)

The technique of electron microscopy is used in these studies (Dhimish, d'Alessandro, Daliento, et al.) to detect solar cell flaws. High-resolution images of a material are produced using the powerful imaging technique known as electron microscopy using an electron beam. With resolutions spanning a wide range of scales, electron micro- scopes are capable of providing detailed structural information on various materials, including metallic substances, polymer composites, and biological samples. (Satpathy et al.)

Scanning and transmission electron microscopy (SEM/TEM) are the two primary EM subtypes. A concentrated electron beam scans the surface of the sample in the SEM to provide information about the sample's content and architecture, while TEM takes images of tiny samples with great resolution by passing electrons through the substance. Although using a big dataset, our analysis did not make any new distinctions between non-uniform and uniform fracture. The loss of output power caused by fractures, which has so far ranged from 0.9 to 42.8 %, needs to be studied further to establish how variable crack distributions affect them.

Prior studies (Dhimish, D'alessandro, and Daliento) used a range of performance parameters, such as open-circuit voltage, short-circuit current density, and output power, to analyse the negative effects of uniform and non-uniform fractures on solar panel cells. The solar cells were photographed and examined using electron microscope imaging and electroluminescence photography. Nevertheless, these methods require a substantial amount of human labour and a lot of man-hours to locate the damage.

In this article (Su et al.), electroluminescence imaging is used exclusively to identify faults in solar cells. The process of electroluminescence, in which a substance emits light in response to electricity flowing through it, is a common feature of contemporary technologies such as OLEDs, LEDs, and specific types of displays. Electroluminescence (EL) imaging is being used by researchers to find any flaws or abnormalities in solar cells that might impair the functionality and effectiveness of the solar panel. EL imaging involves capturing images of the solar panel as it emits light when an electrical current is applied. This method can detect issues such as cracks, delamination, and defects in cell connections, providing a non-destructive way to assess the quality of the solar panel.

2.1. Disadvantages

Artificial intelligence-based automation is not implemented in the current systems. In previously published works, the cracks are manually found with human assistance, which is subject to human mistake. The current approach monitors each solar cell separately and does not take numerous solar cells into account when detecting them.

3. Proposed Methodology

A well-liked source of clean, renewable energy is solar energy. It's critical to maintain the performance of solar panels in order to maximize their efficiency and performance. Cracks in solar panels can result in a considerable loss of energy and have a detrimental effect on the entire system. This problem may be solved by using a deep learning model trained on the CNN method to detect solar panel fractures.

Cameras are used in the first stage to capture photos of broken and uncracked solar cells. The quality and noise of these photos will be enhanced and reduced during pre-processing utilizing methods like contrast enhancement and noise reduction.

When training a deep learning model to find fractures in solar panels, it is essential to produce a labelled dataset with an equal number of damaged and undamaged solar cells. A substantial amount of training data is necessary to ensure that the model can accurately recognize patterns and detect fractures under different lighting conditions for various types of solar cells.

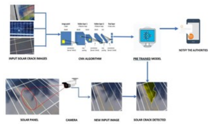

FIGURE 1. **Architecture Diagram**

The model is verified after training to make sure it is ac- curate in identifying cracks and to avoid overfitting. Measures like precision, recall, and F1-score are used to evaluate the model's correctness, and tests on new data are used to validate it. Based on the outcomes of the validation, fine-tuning may also be performed.

In order to identify cracks and damage to solar cells, the trained model is then implemented into a practical system and used. By automating crack detection, this technology decreases the requirement for manual examination and increases detection precision. Also, it reduces energy loss and raises the effectiveness and efficiency of solar panels.

Finally, if any cracks are found, the planned system will alert the plant's maintenance division.

In conclusion, the method provided utilizing a deep learning model trained on a CNN model provides a feasible plan of action to locate fractures in solar panels as shown in Fig. 1. It supports a more effective use of solar energy, which is good for the environment and the economy. It also saves time and resources and increases detection accuracy.

3.1. Algorithm

Convolutional Neural Network

There are six different layers in CNN shown in Fig.2

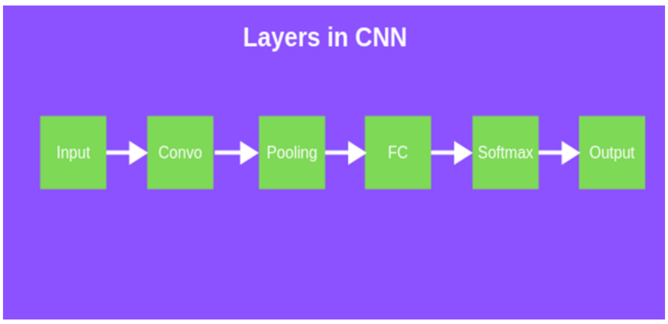

FIGURE 2. **CNN Layers**

3.1.1. Input Layer:

An input layer for convolutional neural networks is designed to accept data as a three-dimensional matrix. In order to build the input when there are ”m” training instances, the matrix must be converted into a single column with the dimensions (784, m).

3.1.2. Convo Layer:

The convolutional layer in a neural net- work is responsible for feature extraction from input data, typically images. This is achieved by applying a dot operation between a convolutional filter and a specific area of the input data, known as the receptive field, which is typically the same size as the filter. The resulting output is a single integer value that represents the sum of the element-wise multiplication between the filter and the receptive field, and it is included in the output volume.

A stride is used to carry out this filter process again on the same picture but with a changing receptive field. Up till every component of the image has been examined, the procedure is repeated. The output of this procedure is then given to the following layer as an input. Moreover, a rectified linear activation function that reduces negative numbers to zero is included in this layer.

3.1.3. Pooling Layer:

In deep learning models, the Pooling Layer is a frequently employed element that helps to reduce the structural properties of processed images from earlier Convolutional Layers. To minimize the processing load associated with fully connected layers, this layer is generally introduced among the convolutional layers. The method known as ”Max Pooling” entails picking the highest value from a specific area of the given picture and can significantly decrease the spatial dimensions of the input image when combined with a specific stride. The filter size (F) and stride (S) are the two crucial hyperparameters for this layer. Fig. 3 demonstrates the impact of using max pooling on the input image’s spatial volume.

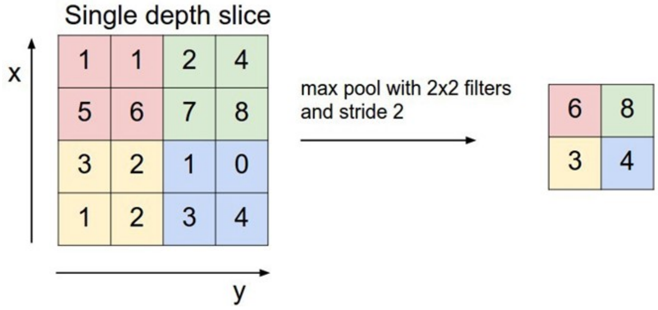

FIGURE 3. Pooling Layer

3.1.4. Fully Connected Layer:

A fully connected layer, which is made up of neurons, biases, and weights that cooperate to simplify incoming data so the network can identify and process it more quickly, is a crucial part of a neural network for image classification. Its primary responsibility is to establish connections across layers of neurons.

3.1.5. Softmax / Logistic Layer:

At the end of a Convolutional Neural Network (CNN), a final layer is typically composed of a softmax or logistic layer that comes after a fully connected layer. The logistic layer is employed for binary classification, whereas the softmax layer is utilized for multi-class classification. The principal purpose of this layer is to convert the output produced by the layer above into a probability distribution that spans across all the classes. By doing this, the network can give each class a possibility, enabling confident classification decisions.

3.1.6. Output Layer:

The final layer of a neural network, as shown in Fig.4, has the duty of generating the ultimate prognosis or prediction for a provided input. In multi-class classification scenarios, the output layer often employs one-hot encoded labels to portray the potential classes. By analysing the outcomes of the previous layer, the network generates a conclusive prediction by identifying the class with the highest likelihood.

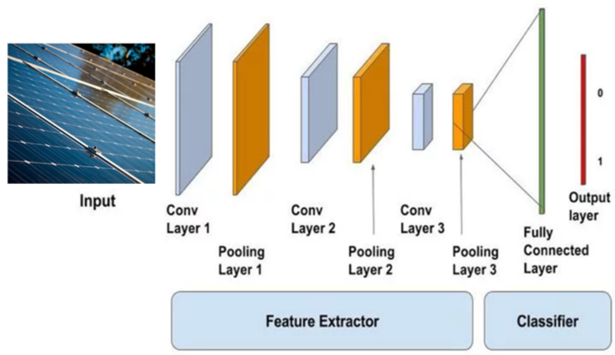

FIGURE 4. Output Layer

3.2. Convolutional Neural Network

To extract features from an input image, a feature detector in the form of a 2D array of weights is utilized. The 3D matrix nomenclature for the feature detector corresponds to its receptive field dimensions. A portion of the input image is subjected to the filter, and the output of the dot product between that region and the input pixel is saved in an array.

By applying the filter to every attainable position of the given image, a feature map is produced, which can also be referred to as an activation map or convolved feature. The ReLu function is utilized to introduce non-linearity into the model, replacing negative values with zero. Several convolutional layers are used in the building of a convolutional neural network (CNN), which uses a hierarchical structure to allow succeeding layers to capture pixels from the receptive fields of earlier levels.

CNN can distinguish complicated patterns by integrating the basic elements. Simpler characteristics, like boundaries or lines, are taught over the network's many levels. By merging data in a receptive field, CNNs employ pooling layers to reduce the complexity and quantity of input parameters. Whereas average pooling determines the average value, max- imum pooling selects the largest value. Pooling may cause a little amount of information erosion, but it also improves network performance and prevents overfitting, shown in Fig.5.

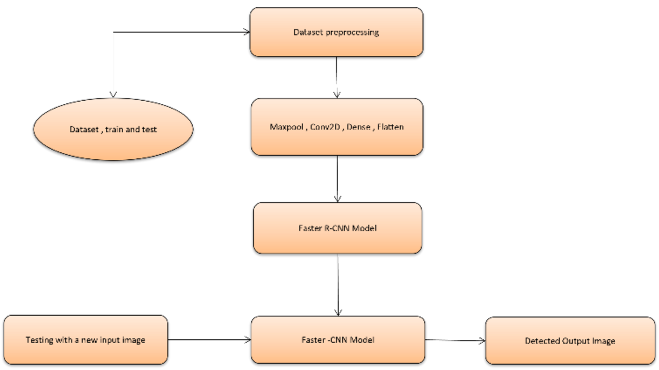

FIGURE 5. CNN Architecture

The layer which links each node in the output layer to a node in the preceding layer is the Fully connected layer. For the purpose of classification, these layers extract filters and features from the preceding layer. Although ReLU activation function may be used in other layers, fully connected layers generally employ a softmax activation function to generate a probability within the range of 0 to 1, which aids in accurate input classification.

3.3. Module Description

FIGURE 6. Sample Images

3.3.1. Image Collection:

A collection of images of solar panels obtained from various sources such as online picture repositories and photographs. Images of solar panels are captured are different from each other to ensure diversity in the dataset. This technique aids in training the model to recognize the attributes of cracks on solar panels across different lighting conditions such as Fig.6.

3.3.2. Image Pre-processing:

In order to make sure that they are in the appropriate structure and measurements for the CNN algorithm, the raw images undergo pre-processing to extract significant features. As part of the image processing step, expanding the dataset size and improve the model's performance, it is typical to carry out many tasks include scaling the photos with a consistent resolution, standardizing the pixel values in a consistent range, and using image augmentation techniques. To extract meaningful information from the images, edge detection or convolutional filters can also be employed. Once the images have been processed, they are input into the CNN algorithm for training, during which the network is learned to identify the features linked to cracks in solar panels.

3.3.3. Importing Modules:

Pre-written code that offers supplementary functionality or tools can be imported into a Python script via modules. For this project, we have utilized several modules including numpy, tensorflow, pillow, cv2, twillio, pytesseract, and sys.

NumPy is a Python library that enables the handling of large, multi-dimensional arrays and matrices, as well as provides a wide range of advanced mathematical operations that can be applied to these arrays.

Tensorflow is a widely used open-source software library that enables dataflow and differentiable programming in various domains, such as deep learning and machine learning. Keras, a high-level neural network API, is built on top of Tensorflow and is utilized for developing and training deep learning models.

The Python imaging library Pillow provides the ability to access, edit, and save a variety of image file types. Due to its powerful image processing capabilities, it is frequently used in applications that utilize computer vision.

Object tracking, feature identification, and image modification are just a few of the apparatus and methods available for working with images and videos within the popular Python computer vision library cv2 module.

The Twilio module in Python provides a simple interface for sending and receiving SMS, MMS, and voice messages. Applications can utilize this package to incorporate messaging and communication capabilities.

Pytesseract is a Python wrapper for Google's Tesseract optical character recognition (OCR) engine, which is compatible with various applications and simplifies the process of extracting text from photos.

The sys module is a built-in module in Python that provides access to the users for several variables that are utilized by the Python interpreter or maintained by it. It is commonly used for command-line parameters and system-specific methods.

3.3.4. Training Dataset:

The training dataset is used by the neural network to determine the characteristics that are most effective in identifying fractures in solar panels. The method employed to accomplish this is known as backpropagation, a typical way to modify a neural network's parameters in order to lower the error. Backpropagation allows mistakes in the model's predictions to be sent backward across the whole network, changing the weights and biases of the neurons, and eventually enhancing the model's accuracy. Several training cycles are applied to the model until it performs satisfactorily on the training dataset.

3.3.5. Testing Dataset:

To enhance the model's accuracy in real-world situations where it will be deployed, it is tested using a testing dataset that mirrors these scenarios. This dataset should contain images captured from a different range of angles, under different lighting conditions, and with various types of cracks. The success of the project is determined only by the accuracy of the model. A high level of accuracy signifies that the model has developed the ability to precisely detect cracks in solar panels and has acquired a generalized perception of what constitutes a crack. The testing dataset helps to determine where the model needs to be improved and acts as a performance indicator.

3.3.6. Camera Interfacing:

A camera which can be attached to the control system, which is linked to the device that is executing the deep learning algorithm, is used to take pictures of the solar panels. The deep learning algorithm may gather and analyse the photos after the camera is connected to the computer. It is crucial to confirm that the camera is precisely calibrated and configured to collect high-quality photos to reliably detect fractures in photovoltaic panels.

4. Result

To maintain the quality and effectiveness of solar panels, this study offers a novel method for finding cracks in them. The suggested approach entails the classification of cracked and uncracked solar cells as well as the identification of their presence. Automated crack detection algorithms are also developed, and these algorithms can accurately and quickly analyse images of solar panels to find the presence of cracks. A collection of pictures of cracked and uncracked solar panels was gathered in order to train the crack detecting algorithms. The information gathered was then utilised to create a monitoring system that can continuously check the effectiveness of solar panels and identify any changes brought on by cracks or other flaws.

The created model analyses the pictures that were acquired with the camera interface and classifying them as cracked or uncracked. The device then alerts the relevant authorities of any discovered cracks, enabling prompt action to maintain the solar panels' functionality and efficiency. A collection of solar panel picture samples was used to test the suggested methodology. The proposed monitoring system can track the efficiency of solar panels over time and identify any changes brought on by cracks or other problems.

5. Conclusion

To guarantee the longevity and efficiency of photovoltaic systems, identifying surface cracks on solar panels is crucial. Convolutional Neural Networks (CNNs) are a potential solution for this issue, providing high accuracy and automated detection of cracks in photographs of solar panels.

During training, the CNN is taught to distinguish between typical patterns and those that indicate the existence of a crack. A substantial number of images is fed to the CNN to differentiate between unbroken and cracked solar panels. After training, the network can be employed to find cracks in new photographs, resulting in prompt maintenance and repairs.

Various research studies have demonstrated the efficacy of CNNs in identifying defects on the surfaces of solar panels. These experiments have revealed the CNN's ability to detect even small or unnoticeable cracks. CNNs can be a valuable tool for identifying flaws in solar panels because of their high accuracy.

The use of CNNs for detecting cracks on solar panels marks a significant advancement in maintaining and preserving photovoltaic systems. This technique can computerize the identification of cracks, reduces time, money, and increases the lifespan of solar panels. With the development of CNNs and related technologies, significant progress can be expected in recognizing and repairing defects in solar panels, leading to a more legitimate future.

6. Future Scope

To differentiate between cracked and uncracked solar cells, a GPS system may be included in this project. To observe solar cells in a large-scale solar power plant, many cameras will be installed. Depending on the camera used, we may determine which section of cells has been damaged, and with the aid of GPS technology, we can pinpoint the specific cell that necessitates repair. By implementing this system, human involvement with the solar cells may be decreased. The project's usefulness in conserving the efficiency of solar cell energy is enhanced as a result.

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