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Solar Panel Crack Detection Using Faster Re-Current Neural Network (F-RCNN)

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Abstract: *In this paper we approach a new method of Deep learning Algorithm Convolutional Neural Network for the prediction of cracks in the solar panel. Solar energy is gaining strong momentum as the future clean and renewable source among other sources of energy. Solar power generation has attracted much attention but there are not enough specialists for condition monitoring of the solar panel. Safety and human cost is most valuable thing. Risking of human lives is not acceptable. So, it is a need to find a outcome for reducing the mortality of lives due to carcinogen present in solar panel. The Feature Extraction gives us a broad view about the image which is captured and help us to process the image for preprocessing. The given system has overcomes the errors and has higher efficiency than the current image processing Methods .By the usage of multiple hidden layers such as conv2D, maxpoolD, Flatten and Dense the crack is detected and it can be viewed by the user in the shell of python. By the help of classified image the cracked solar panel is removed before it gets bursts. Cracked Solar Panels may emits high Carcinogen agents so it is necessary to remove it. The covolutional neural network once predict the affected solar panel the data will send to the microcontroller via USBTOTTL. The microcontroller recive the value gps value send to the cayenne web page*

Keywords: Deep learning

I. INTRODUCTION

PV system operates at the best efficiencies if {they area unit |they're} directly facing the sun with minimal /no obstruction and are maintained at a lower temperature (250c). Dirt once settle on a glass of the PV panel, usually hinders lightweight from reaching the sell, thereby lowering overall potency. Because PV panels convert solely the color spectrum into electricity remainder of contribution to system heat. If the layer of dirt will increase the panel needs maintenance and frequent cleansing. Dirt accumulation depends on completely different parameters. Those area unit the inclination of the PV panel, quit installation (standalone or on the trackers), wind direction, humidity, etc. The sun is that the primary supply of energy. This can be directly or indirectly, fuel for many renewable systems. Among all renewable systems, the electrical phenomenon system is that on that includes a nice likelihood to interchange typical energy resources. The solar battery is especially made up of semi conductive materials. Si used because the live part of star panels. The sole thanks to increase the potency of solar battery is to extend the intensity of sunshine falling on that. Star stackers area unit the foremost applicable technology to extent the potency of star panels by keeping the panel aligned with the suns position. These days to harness alternative energy within the best manner star trackers get popularized round the world. So as to maximize potency, frequent cleansing if powerfully suggested. Above all, each weather and style factors influence the dirt accumulation method and connected effect. Necessity thanks to the growing prices of electricity and concern the environmental impact of fossil fuels, eco-friendly energy sources area unit necessary to implement.. Accumulation of dirt on even one panel reduces their potency in energy generation. That's why we want to stay the panel's surface as clean as doable. Thus we have got to develop AN automatic cleansing machine which might clean and simply travel the glass surface of panels that helps in improvement of potency. The most common faults in star panel's area unit involved with crackers that area unit found on the surface of star cells which might prompt to loss of yield. During this case, throughout the assembly and generation processes, it's necessary

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to ensure the getting of an honest upshot. Generally cracks can happen on cell panels at any circumstance. They all specifically influence potency and will decrease the performance. It's necessary to tell a part cracks on electric cell panels and therefore dismiss imperfect merchandise. Various techniques are made to review the electric cell panels, and these have distinctive strengths and short comings. Some assessment frameworks are developed by multispectral FRCNN to classify various defects in solar panels from RGB images. For the formation of the training and validation datasets, a slide-splitting technique was used to partition RGB images of size 1828 × 1828 pixels into smaller patches or regions of interest of size of 469 × 469 pixels. This splitting process produced a set of 15330 and 5915 ROIs depicting negative (with non-defect) and positive samples (panels with various defects), respectively. On the classification dataset PV panel images, the proposed CNN approach achieved an accuracy of 94.9%. Rahman et al. used FRCNN with multi-attention U-net architecture to segment and detect cracked panels from EL images. Deep learning using the convolutional neural networks, provides a seamless approach for accomplishing the feature extraction and classification stages. The solution to this, availability of the labeled data, might be through the transfer learning. The approach enables the extension and fine tunning of readymade deep learning algorithms, optimized and proved high performance levels on other research problems, for other domains. Pierdicca et al. used the transfer learning with the VGG-16 FRCNN network to distinguish between damaged (broken crystal) and solar panel from remote sensing images. However, low resolutions of the images used could be the main drawback of the method. This paper also applies transfer learning with Alex net, a pre trained deep neural network, to inspect and detect defects in solar panels from RGB images. The dataset, collected from online resources, contains images of defect-free panels and panels with various defects including crystal breakage, dirty, spotted past, scratches, and micro cracks, and burned panels) panels.

OBJECTIVE

- To increase the potency of the electrical device by pursuit the utmost strength of sun.
- To keep the electrical device clean by cleanup the dirt when fastened interval of your time to keep up the potency of electrical device.
- To avoid decreasing in potency due cracks on electrical device by victimization crack detection technique.
- The Features of the solar panel image is detected

II. LITERATURE SURVEY

Estimating the impact of defects in photovoltaic cells and panels

Year: 2021

This paper investigates defects in photovoltaic cells and panels which cause notable losses in output performances. Here, the focus lies on the impact of hairline cracks which result in a remarkable drop of the available output current and, thus, the available output power. Firstly, samples were characterised with the help of synchronized thermography (ST) in order to localise and analyse the defects. Secondly, samples were measured with the help of electrical verification to obtain the characteristic I-V (Current-Voltage) curve. Finally, the geometric area of PV cells was calculated which corresponds to the effective area for energy production due to the presence of a defect. Results show the correlation between the available power of PV cells with temperature variations in IR-emissions. Proposed methods are capable of detecting defects in PV cells and quantise the impact on output performances.

Fault detection and identification of solar panels using Bluetooth

Year: 2019

In this project, they proposes an automated inspection system based on a Bluetooth for solar panel application in order to detect any minute cracks which may be appeared on the surface of solar panel. The power value has been calculated based on the current value updated from the current sensor to user by using Bluetooth. The sensor updates status of the solar panels through the android mobile using Bluetooth. This operation is based on the embedded systems. Each solar cell in the panels is connected to individual current sensors. The sensor output is connected to the microcontroller through ADC. When there is a crack in the cell then its output will become low. The microcontroller estimates the current sensor output to the threshold value. If the value is less than threshold then the microcontroller indicates that to

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the Android mobile through the Bluetooth. The user can monitor current and power level. The Bluetooth is more safe and sustainable for power level and it has to collect the output in wireless mode for more efficiency and security.

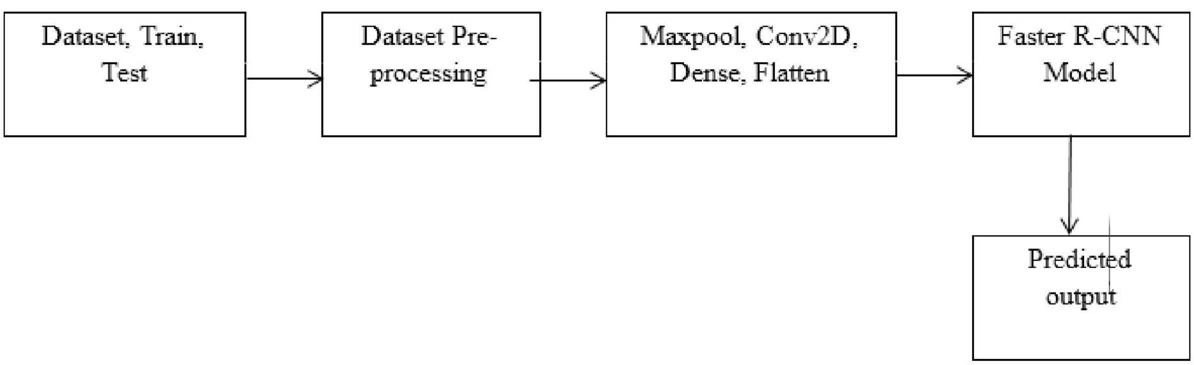
III. EXSITING SYSTEM

Solar energy is that the thickest supply of energy for all the sorts of life on the earth. It's conjointly the fundamental supply for all the source of energy except atomic energy. However the star technology has not matured to the extent of the standard sources of energy. It faces millions if challenges like high value, erratic and unpredictable in nature, would like for storage and low potency. This project aims at increasing the potency of solar energy plants by finding the matter of accumulation of dirt on the surface of solar battery that result in reduction in plant output and overall plant potency.

IV. PROPOSED SYSTEM

For good efficiency, fast, reliable and smooth operation of any process we need a failure free operation. It gives a high production and also ensures high return on investments. A failure free operation is of fundamental importance for modern commercial solar power plants to achieve higher power generation efficiency and longer panel life. So a simple and reliable panel evaluation method is required to ensure that. By using thermal infrared imaging, glitches or defects in the solar panels can be easily detected without having to incorporate expensive electrical detection circuitry. For building computer vision applications using deep learning including the image classification of PV panels and surface defect detection, it is recommend to apply the transfer learning first. The transfer learning is a deep leaning approach allows you to modify existing FRCNN algorithms to solve new image classification problem. This approach is convenient and preferable when the size of the dataset is relatively small and computational resources are limited. The deep learning and convolutional neural network research community have developed many FRCNN networks trained on hundred thousands of images and using many GPUs.

PROPOSED SYSTEM BLOCK DIAGRAM



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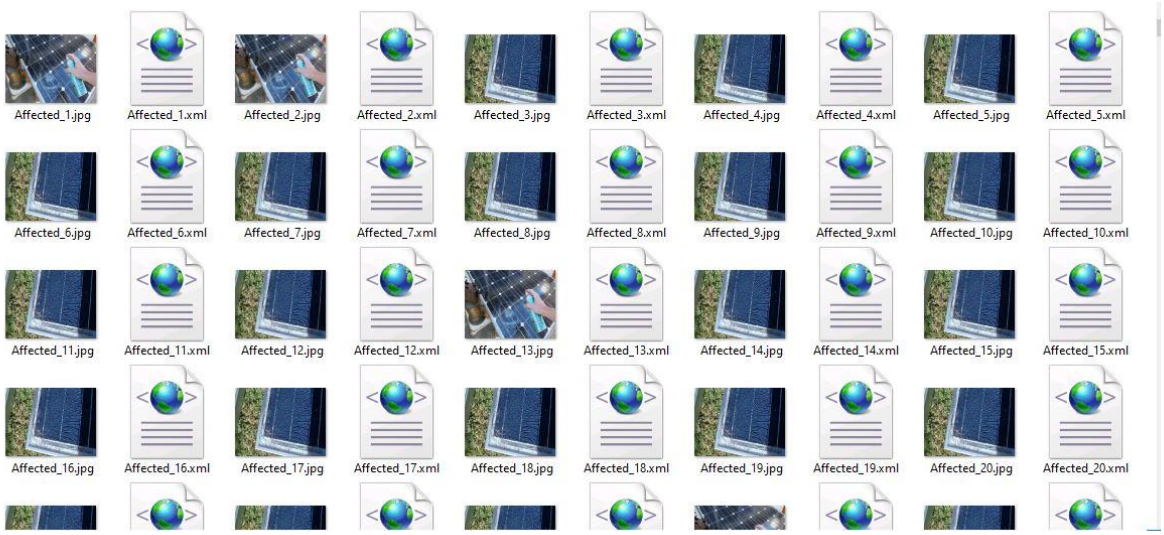
V. BLOCK DIAGRAM EXPLAIN

DATASET

A huge data set consisting of solar panel with very high resolution has been taken with various imaging conditions from Kaggle.



Training Image

PREPROCESSING

The data set was taken from an online platform named Kaggle. The size of the data set was trimmed to 350 images. Before feeding the input directly into the model, the data which is the set of fundus images must undergo some preprocessing steps which includes i. resizing of images size from 3888 *2951.to 786 * 786 dimension. ii. perform flip-flop operations which are rotating the fundus image by 90 degrees. Flipping of images is done in order to exercise the model in an efficient way. The input data set is classified into three different categories. They are a. Training dataset, the dataset that is used to train or exercise the model. This data is labeled data set. b. Testing data set, which is used to test the model. c. Validation data set, the dataset that is used to validate the model. Validation data set is used to ensure that the model is not over-fitting whereas training data helps to minimize the loss function. Updating of weights happens accordingly when the training data set is exercised in the model but validation data set does not involve any updating process. Training dataset and validation dataset are labeled but not the testing dataset.

Training and Testing Data

After preprocessing is done, the dataset is divided into two parts as Training and Testing. The training data is used to train the model whereas, the testing data is used to validate the model.

MODEL ARCHITECTURE –FR- CNN Layers

The architecture consists of six layers: 1 Input layer, 2 pairs of Convolutional layers & Max Pooling Layers, 1 Output Layer.

1. Input Layer This layer consists of 786 x 786 neurons which is equal to the count of pixels of each individual image being passed. Here, the pixels values of the training images are sent to the input layer.

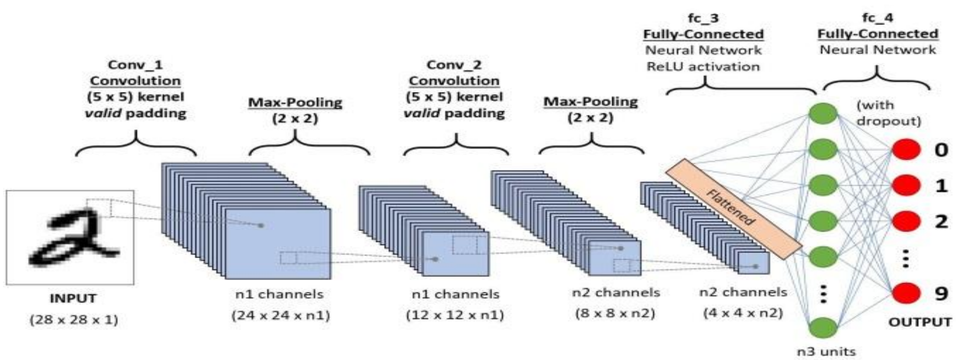
2. Convolutional Layer 1 This layer consists of 32 neurons. There is a connection between each of the neurons present in this layer to all of the neurons in the previous layer. Convolution is performed on the input pixels, which is a process of performing dot product on the pixel values with arbitrary numbers called as filters. So, the layer's output is further passed to the max pooling layer.

3. Max Pooling Layer 1 With the filters provided max pooling operation is performed on the received input which is identification of highest value in each patch of feature map.

4. Convolution Layer 2 The max pooling layer's output is concatenated to a convolution layer (convolution layer 2) with 16 filters, kernel size as 4*4 and activation function as ReLu. This layer is further passed to a max pooling layer.

5. Max Pooling Layer 2 The max pooling layer performs the max pooling operation on the received input. Then the output of the max pooling layer is flattened. Flattening is a process of converting any matrix into one dimensional array. Flatten function is applied on the convolution layer to create a single long feature vector.

6. Output Layer The total amount of neurons existing in this layer is equal to the number of levels the disease is classified into. The neuron consisting of the maximum value ranging between 0-1 will be the output i.e., the level in which the disease is. This output will be compared with the actual values and the error is determined. Based on the error the model tunes its underline parameters such that the error is as minimum as possible. This operation is performed on each and every training image.



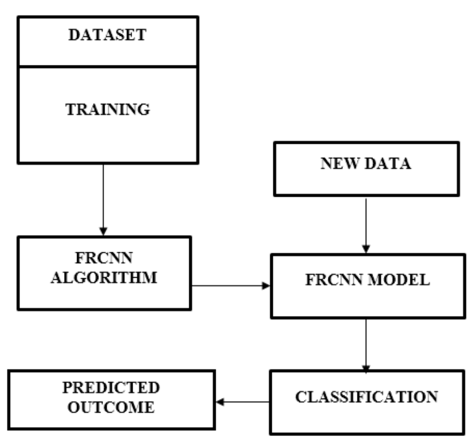
PREDICTION

The built model is now evaluated using the testing data and the accuracy is computed which acts as the performance metric of the model.

TESTING MODEL

I tested my CNN model on 1622 images. I had an validation accuracy of 97.22 %. My model has a precision of 87.31 % and recall of 74.46 %. The model has a specificity of 97.68 %.

CLASS DIAGRAM:



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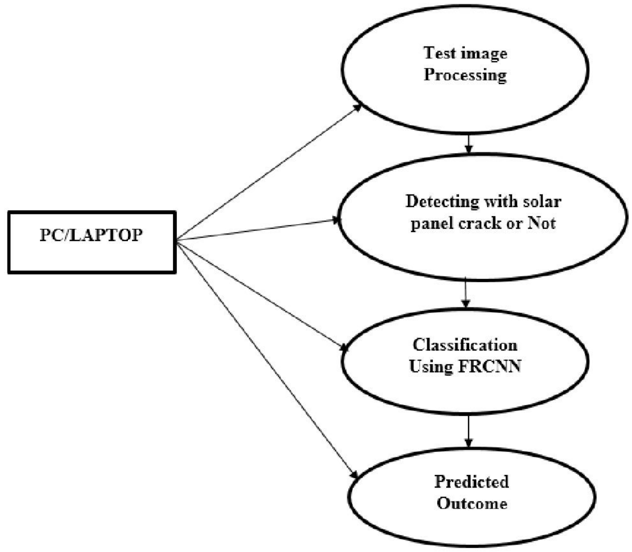
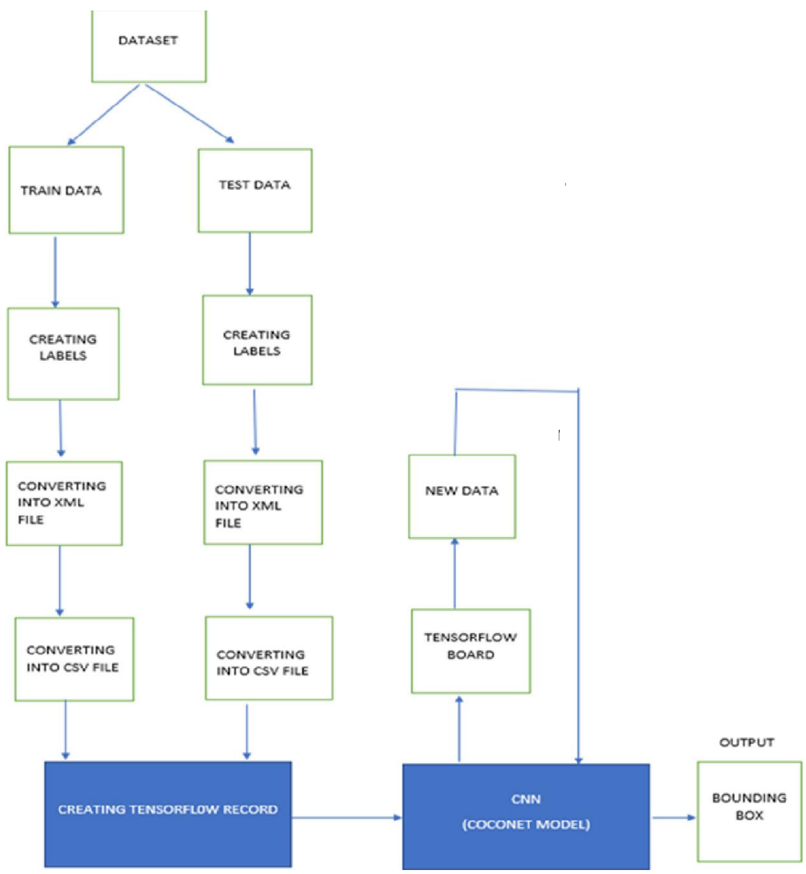
USECASE DIAGRAM



FLOW CHART



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VI. SOFTWARE REQUIREMETS

HARDWARE SPECIFICATION

System	:	PC OR LAPTOP
Processor	:	INTEL / AMD
RAM	:	4 GB Recommended
ROM	:	2 GB

SOFTWARE SPECIFICATION

OPERATING SYSTEM	:	WINDOWS 7/10/11
LANGUAGE USED	:	PYTHON
Backend	:	PYTHON SCRIPT WINDOW
Frontend	:	PYTHON SHELL

FASTER RECURRENT Neural networks are designed to process data through multiple layers of arrays. This type of neural networks is used in applications like image recognition or face recognition. The primary difference between FRCNN and any other ordinary neural network is that FRCNN takes input as a two-dimensional array and operates directly on the images rather than focusing on feature extraction which other neural networks focus on. The dominant approach of FRCNN includes solutions for problems of recognition. Top companies like Google and Facebook have invested in research and development towards recognition projects to get activities done with greater speed.

Let us understand these ideas in detail.

FRCNN utilizes spatial correlations that exist within the input data. Each concurrent layer of a neural network connects some input neurons. This specific region is called local receptive field. Local receptive field focusses on the hidden neurons. The hidden neurons process the input data inside the mentioned field not realizing the changes outside the specific boundary.

If we observe the above representation, each connection learns a weight of the hidden neuron with an associated connection with movement from one layer to another. Here, individual neurons perform a shift from time to time. This process is called "convolution". The mapping of connections from the input layer to the hidden feature map is defined as "shared weights" and bias included is called "shared bias". FRCNN or convolutional neural networks use pooling layers, which are the layers, positioned immediately after FRCNN declaration. It takes the input from the user as a feature map that comes out of convolutional networks and prepares a condensed feature map. Pooling layers helps in creating layers with neurons of previous layers.

A convolutional neural network uses three basic ideas:

- Local respective fields
- Convolution
- Pooling

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VII. METHODOLOGY

A Convolutional neural network basics The main building blocks of a deep convolutional neural network (FRCNN) are the convolutional layer, commonly called CONV2D, the pooling layer, the rectified linear unit (ReLU) layer, and a series of fully connected layers. In other words, as shown in Fig.1, a deep FRCNN basically consists of two subnetwork, a series of 2D convolutional layers and a classical but deep neural network. • Convolutional-2D (CONV2D) layers are the main building blocks of CNN. In this operation, a set of 2D filtering kernel (with size $n \times n$) are applied to an image ($N \times N$) to extract certain features or edges. Key parameters of the CONV2D layer operation are: the stride, the kernel size and number of kernels. The kernels can be design to extract a vertical, horizontal, diagonal edges and any other pattern from the input images. Through the convolutional layers, indeed, the feature engineering and feature extraction, form input images, is performed . If the input image is an RGB image, the size of the input of image is then ($N \times N \times 3$), however, the output from this convolution over a volume is 2D rather than a volume again. To accomplish this each edge detector or kernel will be replicated over the volume with size $n \times n \times 3$. The convolutional layer is usually followed by a Rectified Linear Unit (ReLU) that sets all negative value, produced by the convolution operation, to zeros. • Pooling layers; a very popular type of this operation is the max pooling; A max pooling layer, follows a the convolutional layer, does two functions find the maximum of the region and perform down scaling operation. The pool size determines the amount of down-scaling operation. Average pooling is also possible, however, the max pooling is more common. • Fully connected layers are similar traditional neural network hidden layers for which the number of outputs is the only parameter to consider during the training classical FRCNN algorithms available for application of transfer learning.

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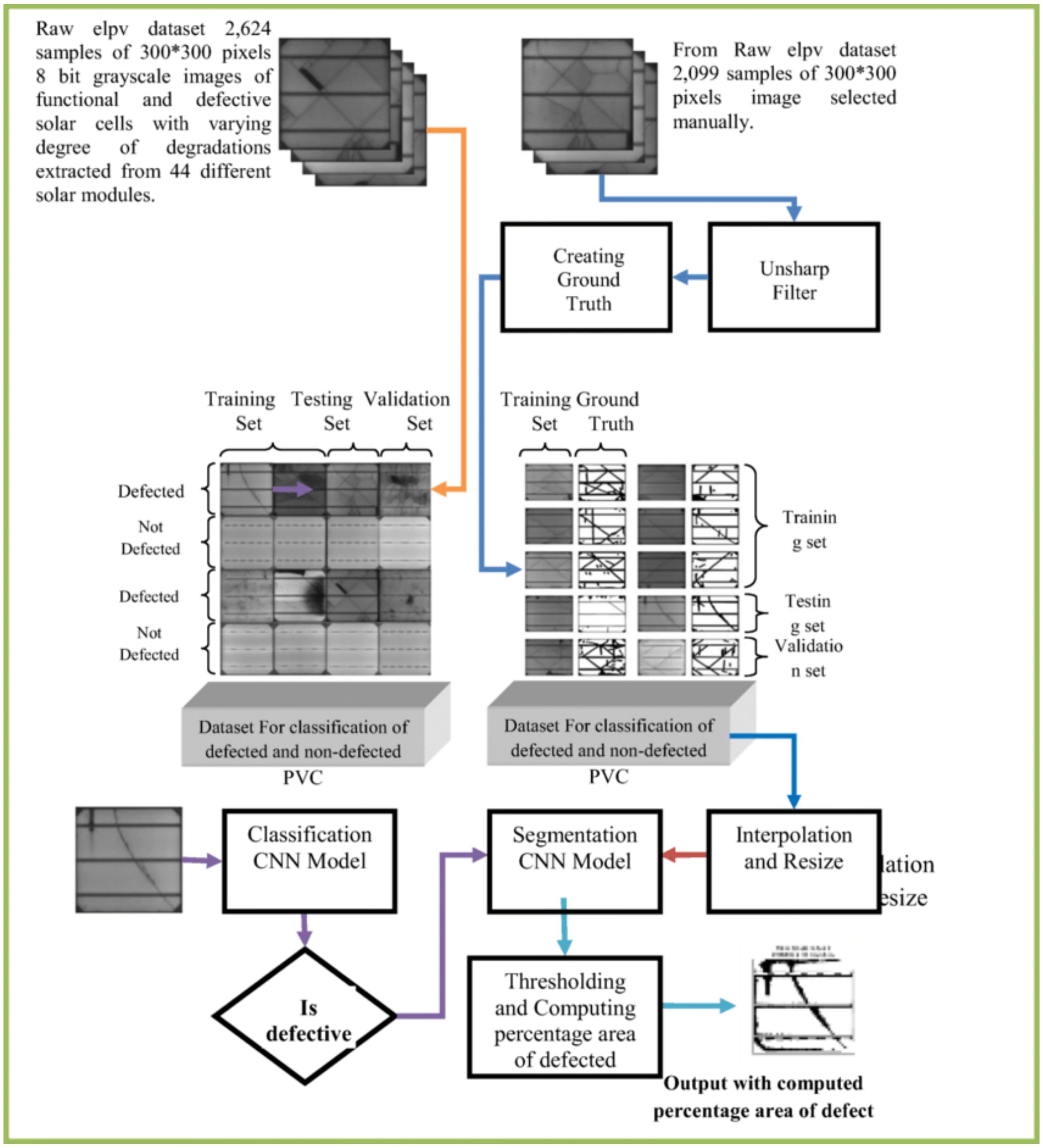

Pre trained models for computer vision

For the use of transfer learning, it is important to have the pre-trained model. The community of deep learning has developed many neural network architectures, which can be found in Python and Keras libraries and the deep learning toolbox of the MATLAB software. For image classification and and object detection the most popular and state of the are are the following: • AlexNet • VGG-16 • VGG-19 • Inception V3 • XCeption • ResNet-50 The differences among these networks are mainly the network architecture (the number and distribution and parameters of the convolution, pooling, and dropout, and fullyconnected layers). And so, the overall number of trainable parameters, the computational complexity of the training process and attained performance.

SOLAR PANEL DEFECT INSPECTION AND DETECTION USING FRCNN

For building computer vision applications using deep learning including the image classification of PV panels and surface defect detection, it is recommend to apply the transfer learning first. The transfer learning is a deep leaning approach allows you to modify existing FRCCN algorithms to solve new image classification problem. This approach is convenient and preferable when the size of the dataset is relatively small and computational resources are limited. The deep learning and convolutional neural network research community have developed many FRCNN networks trained on hundred thousands of images and using many GPUs. Some classical FRCNN algorithms available for application of transfer learning are Alexnet, LeNet, and VGG-16. Other FRCNN algorithms with deeper networks are ResNet and Inception algorithms. Using transfer learning, one can adjust an existing and pre-trained FRCNN, optimized for classifying a set of objects to classify a new set of images. The new images could be totally different for original images. For example, AlexNet is deep neural network, with 25 layers, trained and optimized on a dataset called ImageNet that contains more than a million images with 1000 categories or classes . The components needed for performing the image classification with the transfer learning are: a pretrained FRCNN network,training data, and training options. In this study, transfer learning with AlexNet was applied to classify the surface of PV panel images either normal or defective. The AlexNet is a feedforward deep convolutional neural network with 25 layers. The input image layer, shown in Fig.1, requires an RGB input image of 227×227×3 size. The network architecture enables direct modifications of the network including adding new layers or replacing existing layers. In this paper, to perform classification and defect detection of the surface of the PV panel, a fine-tuning of AlexNet was done. That, classification layers i.e. the last three layers were overwritten as follows: fully connected layer with 2 output neurons, softmax layer, and the classification layer with two classes

Performance optimization using transfer learning

The transfer learning leverages the application of pretrained models, listed earlier, to new domains and image classification tasks. One strategy of of the transfer learning is based on he Fig. 3. Samples of solar panels with defective and normal surfaces. freezing almost all the network layers; CONV2D, pooling, the dropout and fully connected layers. However, such step does not guarantee the desired classification performance. To further improve the classification performance form the transfer learning is by fine-tuning some training options: the momentum parameter of stochastic gradient descent(SGD) optimizer, the initial learning rate, the data augmentation or image preprocessing, the mini-batch size, the number of training and validation epochs. The image dataset was partitioned into 90% for training and 10% for validation. The classification performance was evaluated using the classification accuracy. To achieve the highest classification accuracy of the proposed defect inspection approach, we have examined different values of training options. The momentum of the solver is significant parameter to control the performances of the stochastic gradient descent(SGD) optimizers. The momentum, with typical value between 0 and 1, impacts both the solver's convergence speed and it's ability to avoid the local minima. The results of varying the momentum parameters are ,The initial learning rate (LR) is another parameter to optimize and improve the classification performance. As shown by results in Fig.5, the best the classification results obtained with the learning rate of 10−4. However, if the LR decreased beyond 10−4, the obtained classification is degraded.

VIII. RESULT AND DISCUSSION

For the creation of our proposed model, we have used the tensorflow deep learning. The framework provides for the creation of deep networks by choosing appropriate layers and specifying the preceding and succeeding layers in the design. The inputs to the framework can be in the HDF5 format, which is particularly suitable for the representation of 2D data, such as a kaggle dataset. The steps in preparing the data are explained in the previous section, and are the same for each kaggle dataset images. Hence, we have one HDF5 file representing all the humans, and each HDF5 file has the data along with the label. This label is used in both the training and testing phase.

Batch sizes are also variable, and can be set by the user. For large batch sizes, the learning process is significantly slow (requires a few days) and often terminates due to insufficient memory availability. We have used a batch size of 20 for most experiments. The training of the network is run for 120 iterations. After every 100 iterations the network is tested for accuracy. Initial learning rate is set to 0.001 and for every 100 iteration the learning rate drops by a factor gamma=0.1

IX. CONCLUSION

By doing image processing of defected solar panel and analysis we have found actual location of faults and number of faults in the solar panels. i.e. the faults due to local hot spot or blind spot or break or crack due to fault. Previous methods used were not able to discriminate between dark regions and defected regions. So many a times fault remains unnoticed in the system which cause serious hazards to the PV systems. This method clearly distinguishes between normal region and defected region. So it is very efficient and time saving approach for testing the solar panels.I have used python As software and image processing as a CNN technique to compare two images. I have used for feature extraction of the image and image reconstruction to classify the images as defected or not defected. So it saves time and reliable compare to other conventional method of testing of solar panel. It will definitely help in future to examine the solar panel in less time with lots of cost saving and with reliability

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