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Solar panel hotspot localization and fault classification using deep learning approach

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Abstract

There has been an exponential increase in Photovoltaic energy over the last decade. The size and the complexity of photovoltaic solar power plants are increasing, and it requires advanced and robust condition monitoring systems for ensuring their reliability. To this aim, a novel method is addressed for fault detection in photovoltaic panels through processing of thermal images of solar panels captured by a thermographic camera. In this paper, two advanced convolutional neural network models are used wherein the task of the first model is to classify the type of fault affecting the panel and the task of the second model is to identify the region of interest of the faulty panel. Proposed approach uses F1 score as a metric to compare several classification models of which the ResNet-50 transfer learning model achieves the highest score of 85.37 %. Mean Average Precision is used as an evaluation metric for object detection models wherein the highest scoring model is Faster R-CNN with a score of 67 %. This paper puts forth an approach to facilitate early identification and fault localization in Solar Panels by minimizing the amount of manual labour involved in the process.

Keywords: Photovoltaic; Thermal images; Faster R-CNN;ResNet-50

1. Introduction

Renewable energy generation has been increasing every year exponentially. The capacity of Photovoltaic (PV) solar power plants has seen a mean annual increase of around 28 % [12]. The increase in capacity is mainly due to increase in efficiency of photovoltaic panels and size of these solar power plants. As the size of solar power plant has grown in recent years, there is need of complex systems to look after the maintenance and operations of these plants. PV modules get degraded over time due to various internal as well as external factors, leading to low power output as low as 50 % for certain severe defects [19]. Hence, these faults must be detected as soon as possible to

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prevent further degradation. Faults in PV modules are factors which reduce the power output, and they can be mainly classified into permanent– electrical disconnection, wiring losses and ageing- and temporary- dust, shadow, bird droppings [15]. It is therefore important to not only identify fault but to also detect the type of fault so that appropriate measures could be taken.

Currently, many solar power plants use manual inspection techniques for monitoring purpose. This method is not viable for power plants stretched over a large area and consisting of millions of PV modules. The operational and maintenance cost of such power plants are very high thus we need an automated system which can help in reducing this cost and making overall system efficient. Existing techniques for fault analysis can be broadly classified as techniques based on electrical characteristics, Infrared Imaging, Visual Inspection, Ultrasonic Inspection, Electroluminescence Imaging, and Lock In thermography [15]. In our study we make use of Infrared/Thermal imaging to detect the faults in solar power plant because of its pertinence in large solar plants and easy accessibility.

The infrared images in the proposed work have been captured using FLIR thermal infrared camera. There are various factors which lead to inaccurate thermal image of solar panel. For example, effect of glass reflection, viewing temperature difference, image captured at longer distances, solar irradiance, low potential thermal contrast, etc. FLIR systems, the best thermal image camera producer has provided guidelines to mitigate or reduce the effect of these factors and provide very accurate thermal images of solar panel. These guidelines must be followed while capturing the images using a thermal camera to get accurate results.

Through this paper, the issue of growing need of automating the process of monitoring photovoltaic plants is addressed. The system identifies whether a fault is present or not and detects the type of fault present. Following types of faults are detected in PV module:

1. Single Cell Hotspot: caused due to overhead objects, broken glass, broken/bent frame, cell material defect, cell cracks.
2. Multicell Hotspot: caused due to overhead objects, broken glass, broken/bent frame, cell material defect, cell cracks. causes are same as single cell hotspot but appears in multiple regions in solar panel.
3. Dust and Shadow Hotspot: caused by shadow and dust.
4. Diode Fault: caused by increase in reverse bias current of bypass diode because of higher temperature caused by incomplete dissipation of heat from PV solar modules.
5. Potential Induced Degradation (PID): It is caused because of moisture, humidity, and temperature increases, a high voltage exists between the encapsulated solar cells and the front glass surface, which is grounded through the frame or substructure, causing undesirable charge migration.

Moreover, proposed system also identifies the location of hotspot on the solar panel. The system is implemented using state of art deep learning approach by using ResNet-50 convolutional neural network to identify the fault type and faster R-CNN object detection model to find the region of hotspot.

2. Previous work

This section discusses the previous attempts to identify and classify faults in Solar Panels and the limitations of those approaches. Aghaei et al. [1] developed a thermography-based algorithm for detecting defects and faults in PV systems. Infrared images with a hot temperature region were detected by their algorithm. To minimize noise, the original image was first converted to grayscale, then Gaussian filtering was applied. The images were then subjected to a binary model to differentiate between hot and cold regions in the PV modules. Finally, the Laplacian model was used to present the characteristics of faulty parts and assess the panel's boundary region.

Jaffery et al. [14] proposed an algorithm for fault diagnosing with the help of infrared technology. Fuzzy logic is used for intelligent and automatic detection by the diagnosing system. Significant difference in color pattern of faulty panel and healthy panel is considered as the base for classification of different faults. Fuzzy rule base is defined based on the knowledge for classification. Still this paper gives only the type of fault and not the location of the fault and the region of the fault.

A M-class Support vector machine algorithm is proposed in this study by Wang et al. [20] for fault diagnosis. Line to line fault and abnormal degradation fault are classified based on the parameters like fill factor (FF) and fault type factor (K). Also the nonlinear problem is addressed by using SVM with One against One(OAO) algorithm. But as there are multiple types of faults, and this study classifies the faults in only 2 types which can be improved.

This study by Dunderdale et al. [5] tries to detect and classify the thermal infrared images of PV modules using scale invariant feature transform (SIFT) feature descriptor, spatial pyramid matching, and deep learning. For defect detection SIFT descriptor is used with random forest model and SVM kernels namely the polynomial and radial basis function. Random forest is found to have better accuracy in this 2-class classification problem. Defect classification is done based on 5 classes using approaches like bag of visual words model, spatial pyramid matching and deep learning. Deep learning models used VGG-16 and MobileNet performed better compared to the feature-based approaches. Best defect detection accuracy is 91.2% and classification accuracy is 89.5% from the implemented models. Still this study has not used enough data and location of fault is not identified which would have made the maintenance tasks a bit easier.

Phoolwani et al. [16] has proposed the combination of identifying the faulty panel by studying the V-I characteristics of panels under different conditions and contours obtained from thermal images which are obtained for identifying the faulty panel. But not enough quantitative results are present. It also doesn't talk about the type and location of faults.

Study done by Greco et al. [7] has addressed the flaws in current PV panel detection algorithms like lack of quantitative results, higher processing time, PV plant specific algorithms, etc. To address these issues a method based on a modern deep object detection framework is proposed named as YOLO. Version 2 and 3 of YOLO are used in this study and their performance is evaluated based on the Precision (P), Recall (R) and F-Score (F). But this study doesn't identify the type of fault.

For fault detection in PV solar panels, Herraiz et al. [12] suggested combining thermography, GPS positioning, and convolutional neural networks (CNN). An R-CNN based system is created and trained using real images of solar panels. New data from the IR-UAV system is processed using the R-CNN, and the results are provided in a report that contains both telemetric and thermal data. A common limitation all of these approaches possess is that they fail to specify the type of fault of the panel and only classify whether or not the panel is faulty.

Henry et al. [11] proposed a method for automatic identification of faulty PV Modules Using Drone with Thermal Cameras. In this approach the drone was mounted with thermal cameras and its flight path was automatically determined through a flight planning algorithm. The drone flew over its path autonomously and captured images of Solar Panels on its way. These images were saved directly to an SD card along with the GPS information which were then processed using the Image Processing algorithm developed by them. In this, based on the maximum, minimum and average temperature values of the thermal image, the higher and lower temperature threshold values were calculated which were then used to determine whether the panel is faulty.

Abdelilah et al. [6] has proposed a K-means clustering algorithm for automatic fault detection in solar panels. As quality of clustering depends on the number of clusters optimal number is calculated using elbow and average silhouette method. But this study doesn't identify the type of fault.

3. Methodology

The workflow diagram of proposed method is shown in figure 1. First step involves the training of two models- Fault Classifier and Hotspot Identifier. Second part involves capturing the thermographic image, pre-processing it, and then passing the image to the trained models. In the final part the report is generated based on the output of the models.

The entire system can be divided into three processes i.e., Training, Data Acquisition and Processing and Results. Training process involves training of two models - Fault Classifier and Hotspot Identifier - which are discussed in detail in this section. The entire process consists of two parts:

1. Identifying the type of fault present in the photovoltaic cell using deep transfer learning convolutional neural network model (ResNet-50).
2. Finding the region of the hotspot present on the solar cell using transfer learning on object detection model (Faster R-CNN).

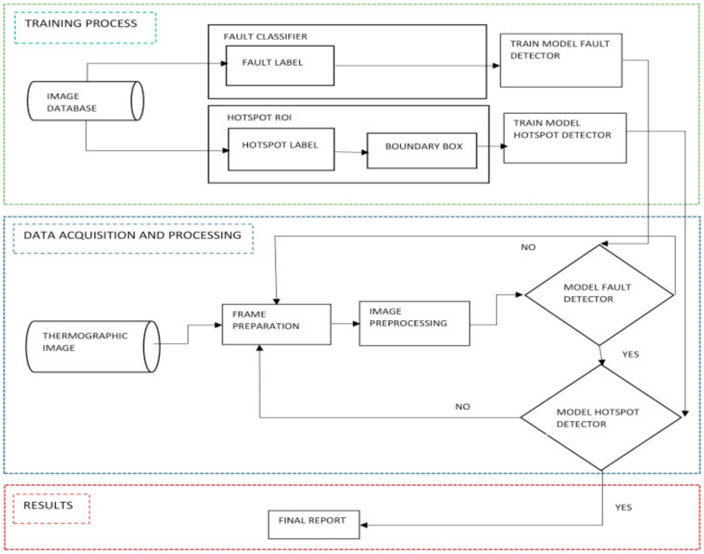

Figure. 1: Workflow Diagram of proposed approach.

3.1. Components and Equipment

The entire application was built on python and its libraries. Tkinter is used to develop the GUI of the application. Various deep learning models required for the study are developed using TensorFlow. OpenCV is used mainly for image pre-processing part of the study. The hardware requirements for training the deep learning models were met by using Google Colab.

3.2. Data Description

The dataset consists of thermal images of solar panels captured using FLIR C2 and E4 thermal cameras from different solar sites in India. Dimension and format of each image are 320*240 pixels and jpeg respectively.

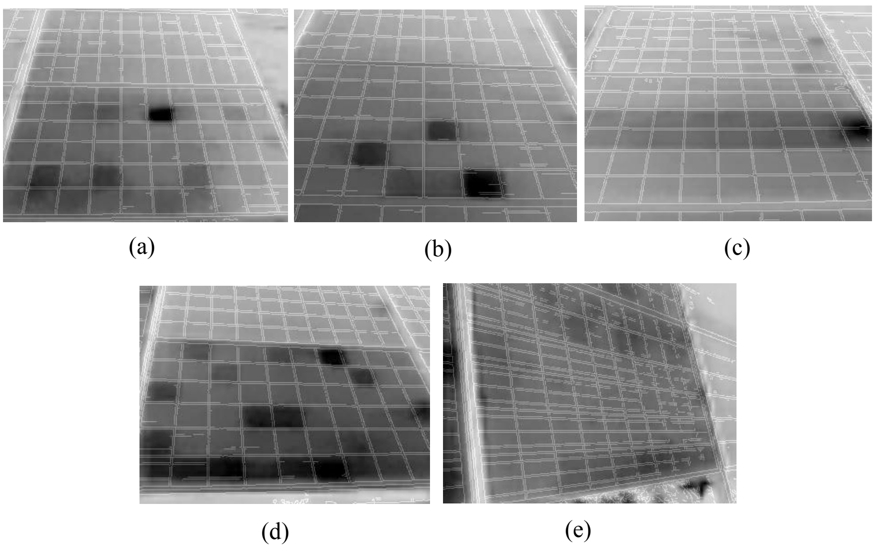

Figure 2: Sample thermal images: (a)Single cell hotspot (b)Multicell hotspot (c)Diode fault (d)PID effect (e) Dust shadow hotspot

The sample thermal images belonging to above mentioned faults are shown in figure 2. The dataset consists of total 837 images and 5 classes. The five faults/classes are as follows:
1. Single Cell Hotspot
2. Multi Cell Hotspot
3. Diode Fault
4. PID defect
5. Dust and Shadow Hotspot

The image is captured using FLIR thermal camera. Out of the total dataset 80% of images are used for training while the remaining for validation and testing.

3.3. Data Pre-processing

Following two methods were performed on the dataset prior to the training process:
1. Histogram Equalization: To mitigate biases like varied color contrast, dynamic range, etc. that might be present in the images. The model may learn to discriminate the dataset on these biases which will give us inaccurate results.
2. Data Augmentation: To increase the size of dataset and improve the generality of the models, data augmentation is applied on the dataset.
3. Normalization: The images were scaled to [-1,1] from [0,255].

3.4. Fault Classifier

The fault classifier is built by performing transfer learning on ResNet-50 [9] model with initial weights trained on ImageNet dataset. With the advancement of Deep Convolutional Neural Networks, the efficiency and accuracy in computer vision task has increased steadily. Deep learning has now become the state-of-art approach for computer vision tasks. For this model, the architecture of the ResNet-50 model is used as it is while adding one dense layer with SoftMax activation as classifier. In this model the pre-trained model plus the dense layer is used to extract the important features from the image and the SoftMax layer is used to classify the image based on the extracted features. Learning rate of 0.01, RMSProp optimizer, Categorical Cross Entropy as loss function, and batch size of 32 is used for training.

3.5. Hotspot Identifier

To identify the region of the hotspot in the solar panel, transfer learning on pre-trained Faster R-CNN [17] model is performed. The Faster-RCNN model is pretrained on MS COCO dataset. Faster R-CNN gives very accurate results as compared to single stage object detector like YOLO. ResNet-101 model is used as the base convolutional neural network. The following steps are typically involved in Faster R-CNN object detection model:
1. The Convolutional Neural Network (ResNet-101) takes image as the input and returns the features extracted from it.
2. The object proposals and its objectness score is fetched by applying region proposal network on the features.
3. Now, to make all the proposal to the same size, an ROI pooling layer is applied.
4. Finally, fault detection results are obtained along with the bounding boxes of the object when these resized proposals are passed onto the dense/fully connected layers which has a SoftMax layer and a linear regression layer at the top.

The backbone CNN architecture used for this model is ResNet-101 [9]. For training, a batch size of two is used. The backbone strides used are 4, 8, 16, 32, and 64. The standard deviation of bounding box is set to 0.1, 0.1, 0.2, and 0.2. Maximum dimension of image set to 1024 and 2 images used per GPU. Learning rate is set to 0.001 and learning momentum to 0.9. The Weight decay is set to 0.0001.

4. Results and Discussion

Proposed approach works in two phases wherein the first phase deals with locating the potential hotspots that need to be examined while the second phase deals with classification of type of fault affecting the Solar Panel.

4.1 Hotspot detection:

Figure 3 shows output images from object detection model where the possible hotspots are represented by drawing bounding boxes around them. These give the location of hotspots in terms of x and y coordinates which simplifies the task of locating these hotspots on the actual panel.

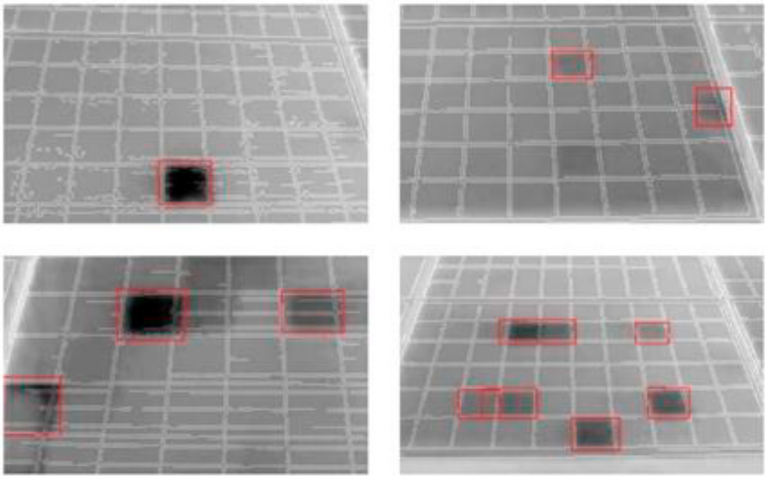

Figure 3: Results of the Object Detection model

Table 1 summarizes approaches used for identifying the region of interest i.e., the hotspots. These include both Deep Learning as well as a Machine Learning approach. The metric used to evaluate the performance of these object detection models is Mean Average Precision (mAP).

Table 1. Object Detection Results

Technique	mAP
Faster R-CNN	0.67
YoloV3	0.34
KMeans	0.48

4.2 Fault classification:

Figure 4 showcases the results of all the methods adopted in our study to classify the type of fault. The blue bar represents Machine Learning approaches whereas the red bar represents Deep Learning approaches. As the data is not uniformly distributed among the 5 classes, F1 score is selected as the metric to evaluate the performance of these models. Closer inspection of Machine Learning approaches show that the best performing model is Random Forest [2] with an F1-Score of 61 %. XGBoost [3] gives similar results with an F1 Score of 60 %. Performance of KNN [8] with the number of neighbors set as 12 is the lowest with an F1-Score of just 48 % while Support Vector Machine [10] produces results close to that of Random Forest and XGBoost with a score of 58%. To utilize the best features of the two highest performing models, stacking was used with Random Forest and XGBoost being the stacked models however the results still weren't satisfactory with an F1 score of just 56 %. Overall, even the best-performing Machine Learning model generated disappointing results, making it unsuitable for use as our final strategy. A better look at the Deep Learning approaches adopted to classify the type of fault highlights that the best performing Deep Learning model was ResNet-50 [9] with an F1-Score of 85 %. Xception [4] also gave satisfactory results with an F1 score of 82 %. Apart from these two models, results of the other Deep Learning models were underwhelming, with DenseNet-169 [13] having the best performance among the rest with an F1 score of 72 %. The VGG [18] models received a 66 % F1 score, while DenseNet-121 [13] received a 68 % score.

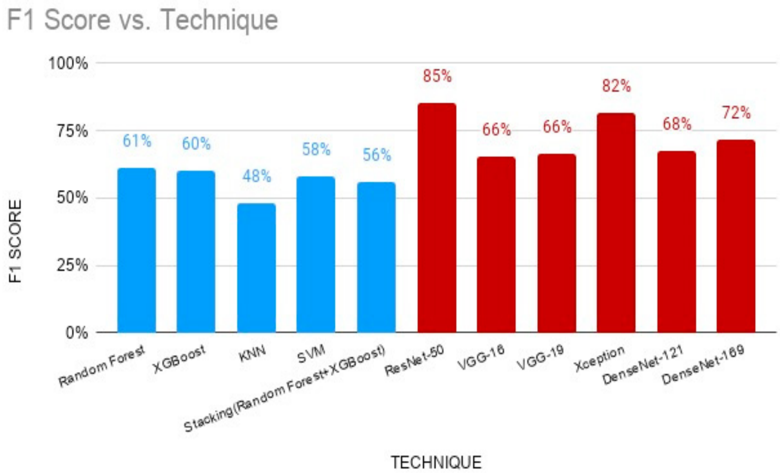

Figure. 4: Comparison between various approaches based on Machine Learning and Deep Learning adopted to classify the type of fault that is degrading the Solar Panel.

The outcomes in figure 4 clearly demonstrates that, for our purpose, Deep Learning methods were much more reliable than their Machine Learning counterparts. Even the lowest performing Deep Learning model gave better results than the best Machine Learning method by 5 %. Of all the approaches, the most satisfactory results were yielded by the ResNet-50 model. Owing to its high F1 score of 85 %, ResNet-50 was chosen as the model to classify the type of fault in the final approach. The highest performing model is the Faster R-CNN with mAP score of 67%. Although it is the highest performing model among the rest it still faces issues with False Positives which drags the mAP score down. YoloV3 was also trained for object detection however the model significantly underperformed with mAP score of only 34%. An unsupervised Machine Learning approach through KMeans clustering was also adopted. Its results were better than YoloV3 however still not good enough with mAP of 48% and as a result the highest performing model i.e., the Faster R-CNN was selected as the object detection model to locate hotspots in our novel approach.

Table 2 showcases all the previous approaches adopted which were encountered during the literature survey with their degree of success. Based on the literature survey it was identified that a major shortcoming of these approaches is that they simply classify the panel as faulty or non-faulty. To further identify the type of fault there needs to be human intervention.

Table 2 Comparison with other methods

Method	Accuracy	Number of images	Number of classes
Statistical analysis based on intensity-related statistics	97.06 %	3	2
MSER algorithm	97 %	400	2
SVM	97.78 %	135	2
R-CNN	99.02 %	900	2
Proposed Method	85 % (F1 Score)	954	5

As shown in the Table 2, proposed method helps classify the fault into 1 of 5 categories which significantly simplifies the process of taking preventive measures to mitigate the damage as the reason for fault is already identified. Proposed novel approach even goes one step further as it uses Object Detection models to locate the potential hotspots on the panel. Based on the available data, this study yields satisfactory results, with the potential for further improvement with additional data for each of the five classes.

5. Conclusion

Major goal of this research is to mitigate the need for Human interaction as much as possible. Through the proposed approach, this issue is tackled by going beyond the process of simple classification in two classes and try to identify the type of fault that is deteriorating the panel to allow maintenance engineers to take early and appropriate measures. A deep learning approach is used to find hotspots as well as to detect the type of the fault in the solar panel. In the proposed system, an F1 score of 85.37 % is achieved using the Resnet-50 model for classification and MAP of 0.67 for detection of hotspots using faster RCNN. Considering the benefits of early detection of faults in solar panels, the proposed model is a big step in that direction aiming to make photovoltaic plants more efficient to operate. The future scope intends to expand on this aim and achieve total autonomy by making use of automated drones.

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