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Solar Panels Crack Detection using Overhead Images

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Abstract: ***Many countries like India have been working on plans to shift from conventional energy sources to renewable, and solar energy is one of them. The technology of Solar Panels faces defects on a large scale. These defects can be within the cells or on the panel as a whole. Management authorities require automated systems to detect the physical faults on the solar panels. These faults can either be detected by physically looking at the panels or through the energy supply, which requires Machine Learning models. This paper proposes a model with 95.34% accuracy that can be deployed on drones and automatically check for physical damage on the panels. We collected the dataset manually from the internet, cleaned and split it into training and validation parts. Data augmentation was performed to get a better view of the functioning of the model.***
Keywords: Solar Panels, Solar Energy, Renewable Energy, Deep Learning, Machine Learning.

I. INTRODUCTION

There has been a sudden increase in the use of Solar Panels due to the rise in energy prices and a large amount of greenhouse gas released during the production of Energy. With all these issues raised in using non-renewable resources, the awareness of using renewable resources has been increased [1].

Along with other countries, India has tremendous energy potential with the increase in energy needs. The Jawaharlal Nehru National Solar Mission (JNNSM) initiative aims to generate 20GW of power by 2022 [2]. India's perspective in Solar Energy covers both Rural and Urban requirements like Solar Powered Battery well, Solar Powered Vehicles, Solar-powered food preservation facilities, and many more [2].

Looking at the rapidly increasing use of Solar Energy, there is a need to detect faults in solar panels. Many studies cover both Physical as well as statistical methods of fault detection. One of the methods is Therma Image Characterization of solar panel hotspots [3][4]. As in solar panels, the failures occur as hot spots. The poor thermal conductivity of a cell is when the material has reached 100 degrees Celsius of temperature, micro defect in cells with 71.3 degrees Celsius of temperature, and deformation of resins at 136.1 degrees Celsius of temperature [3]. The faults can also be analysed using electricity production monitoring, where produced energy anomalies can conclude to different defects [1]. The Variation in the IV characteristics curve can also help detect PV module degradation [5].

The physical analysis of fault detection includes the visualization of faults in solar cells. Deep learning models like Dense CNNs are used in image classification in the same [5]. In addition to image processing techniques, many pattern recognition methods can be applied to visible defects of the PV modules [5]. Deep Convolutional Neural Networks can also be used to find the surface defects in solar panels.

Our study proposes a Convolutional Neural Network-based model to detect the surface defects of solar panel images. Section 2 covers the related work done by other researchers in solar panels and their defects and faults detection. Section 3 and 4 cover the proposed detection and the experimental results, respectively, followed by the Conclusion and future work in section 5.

II. RELATED WORKS

There have been many studies on Solar Panels and their fault detection due to the gradual increase in the usage of Solar Energy as a replacement of Conventional methods of Energy.

The study [2] covers India's vision and perspective on the use of Solar Energy and concludes the country's capability of solar energy production. It covers the schemes being used by the government and the steps that are important for the better output of solar energy. They also sum up the advancements and encouragements of solar energy generation and usage.

The authors of [1] discussed the methods for detecting malfunctions in solar panels using electricity production monitoring. They proposed a two-stage approach to see the patterns. In the first stage, they selected a representative sample of the production processes in a controlled state. In this stage, they detected the global outliners and local anomalies.

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Following in stage two, they monitored the PV energy production of a new day d. These energy productions were monitored for several years. They have used six sets of PV panels for three years. The proposed model was able to detect minimal changes in energy output.

Thermal image processing can also be used to analyze the defects of solar panels. The study [4] explains the basic working of solar panels and explains the laws of thermology. They present a detailed report on the identification of defects through visual and infrared thermology. They analyzed the temperature variation in different natural conditions, like with panels within the shades of a tree and without. They give a great visualization using 3D temperature plots with MATLAB image processing. Electroluminescence images can also be used, which provide better analysis, as mentioned in [6]. They used the EL dataset obtained from different solar farms installed in the United Kingdom. Their dataset had a variety of different types of solar panels. They characterized four various faults: Crack A, Crack B, Crack C, and Finger failure. They used Support Vector Machines and random forest algorithms and compared them.

A similar type of ELPV dataset was used by [5] in which they proposed a light CNN architecture in EL image classification. The framework works on automatic PV defect detection in the field. They used VGG structure-based layers to train the model and work on fault detection. They used their experimental setup for testing the framework. The authors of [7] also proposed a CNN model on the dataset having photovoltaic module cells in electromedicine images. Their model predicted the defect probability using a CNN model. They tested different models to test their model.

III.PROPOSED METHODOLOGY

To classify whether the solar panel from the surface, a Convolutional Layers based model is thus proposed. The images are classified into two classes, Normal and Broken. This section explains the dataset collected, the building blocks of the proposed model, and the final model, and the algorithm used.

A. Dataset

Initially, 1314 images were taken from the internet. This set consisted of 632 pictures of broken solar panels and 682 photos of working for solar panels. These images were added to two different folders named broken and regular. It was observed that these images had many photos that had many things other than solar panels., these images were manually cleaned, resulting in 338 standard images and 165 broken solar panel images. All the photos were in jpg format. Figure 1 shows images of broken and figure 2 as typical panels.

Fig. 1 Sample overhead images of Solar Panels without cracks

Fig. 2 Sample overhead images of Solar Panels with cracks

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B. Building Blocks of the Model

The layers applied in this model are used from the Keras library of TensorFlow.

1) *Convolutional Layer*: The convolution process could be considered an image convolution, and the convolutional layer is the convolution output of the previous layer. Figure 3 shows the process of Convolution acted upon a nxn input layer with mxm filter [8] [9].

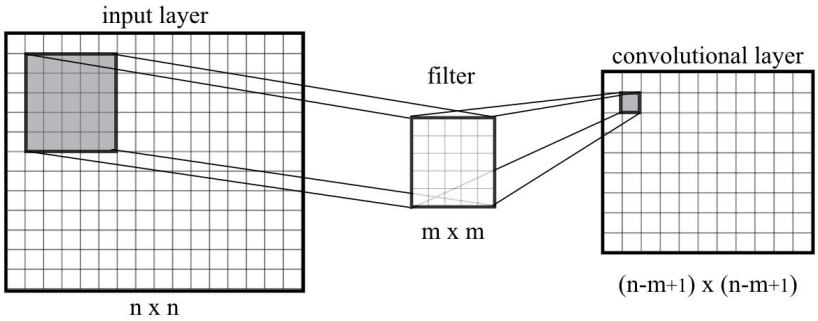

Fig. 3 Convolutional Process

2) *Sampling Layer:* This process is also known as MaxPooling. Pooling can be understood more clearly by the process in figure 4. This layer is applied after a convolutional layer [8] [9].

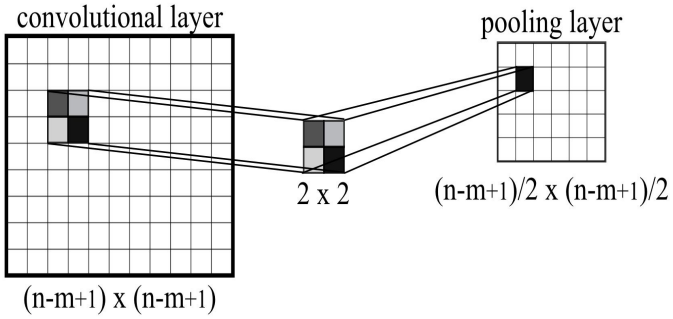

Fig. 4 Sampling Process

3) *Fully Connected Layer:* This layer consists of many perceptrons which individually act as a logistic regression unit. It has input, an activation unit, and output generated after the activation function application on the information. Figure 5 shows the working of a perceptron. *[8]*

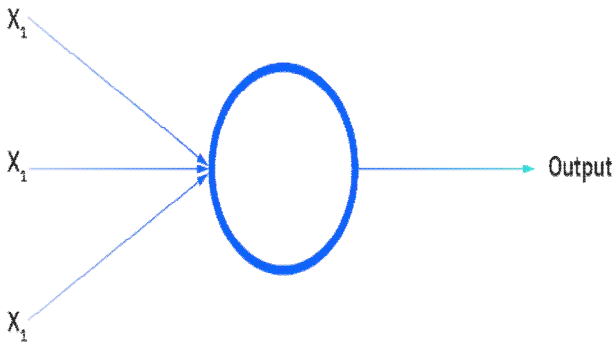

Fig. 5 Perceptron of a Fully Connected layer

4) *Activation Unit:* All Layers of the Network as ReLU as activation units except the last fully connected layer [8]. Equation 1 explains the ReLU function.

$$ReLU: f(x) = \max(0, x) \quad (1)$$

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C. Data Augmentation

Data augmentation is applied to smaller datasets to generate larger datasets using many parameters like rescaling, rotation, shifting, and flipping [10]. Data augmentation is applied to the cleaned dataset in this paper.

D. Model Visualization and Algorithm

All the Layers mentioned above form the proposed model, as shown in the figure below. The images from the dataset are reshaped to 82 x 82 x 3 to be fitted in this model. Figure 6 shows the structure of the proposed sequential model.

Figure 7 explains the step by step algorithm for the pre-processing and training on the clean dataset.

Layer (type)	Output Shape	Param #
conv2d (Conv2D)	(None, 80, 80, 24)	672
dropout (Dropout)	(None, 80, 80, 24)	0
max_pooling2d (MaxPooling2D)	(None, 40, 40, 24)	0
conv2d_1 (Conv2D)	(None, 36, 36, 64)	38464
flatten (Flatten)	(None, 82944)	0
dense (Dense)	(None, 1024)	84935680
dense_1 (Dense)	(None, 64)	65600
dense_2 (Dense)	(None, 1)	65

Fig.6 Structure of the proposed model

ALGORITHM 1: Pre-processing and Training on Dataset

INPUT: Images along with their pixel values.
OUTPUT: Trained Model

STEP 1: Loading images from the train folder.
STEP 2: Load labels from the folder.
STEP 3: Perform Data augmentation and split the data into training and validation batches.
STEP 4: Train the formulated model on training batches.
STEP 6: Save the model for the future.

Fig.7 Algorithm 1, Pre-processing and Training on the Dataset.

IV. EXPERIMENTAL RESULTS

The generated model was trained on Kaggle Notebook Kernel having 13 GB of RAM and 16 GB of GPU memory.The data augmentation done was as follows - rescale=1./255, shear_range=0.2, zoom_range=0.2, horizontal_flip=True, validation_split=0.3.

The model was thus compiled using Adam as an optimizer. Metrics used to check the performance were Accuracy (Equation3) and Binary cross-entropy /Log loss (Equation 4).

$$Accuracy = \frac{(TP+TN)}{(TP+TN+FP+FN)} \quad (3)$$

$$\log loss = -\frac{1}{N}\sum_{i=1}^{N} -(\log(p_i)) \quad (4)$$

Here, TP is True Positive, FP is False Positive, TN is True Negative, and FP is False Negative from equation three, N is the number of data entries, and pi is corrected probability.

The model was trained for 100 epochs. Figures 7 and 8 show the model accuracy and model loss with the increase in epochs, respectively. The model, when tested on the validation set, gave an accuracy of 95.34%.

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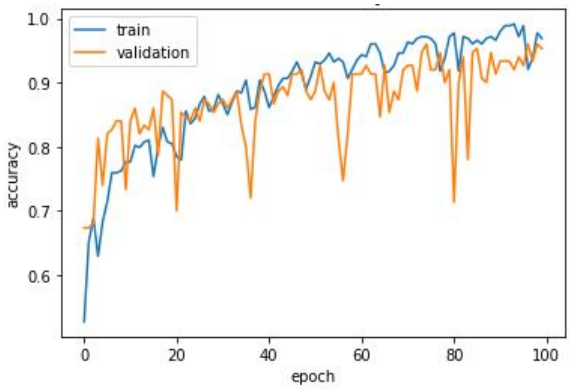

Fig. 8 Model Accuracy vs Epochs

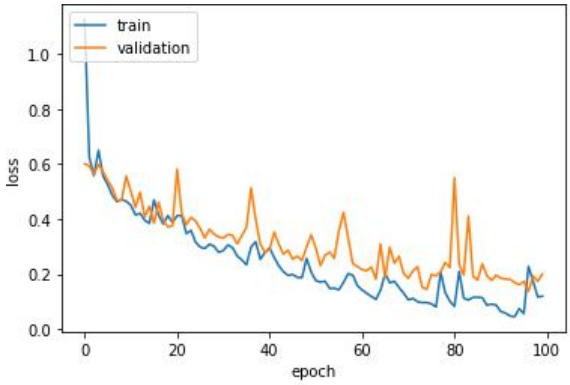

Fig. 9 Model Loss vs Epochs

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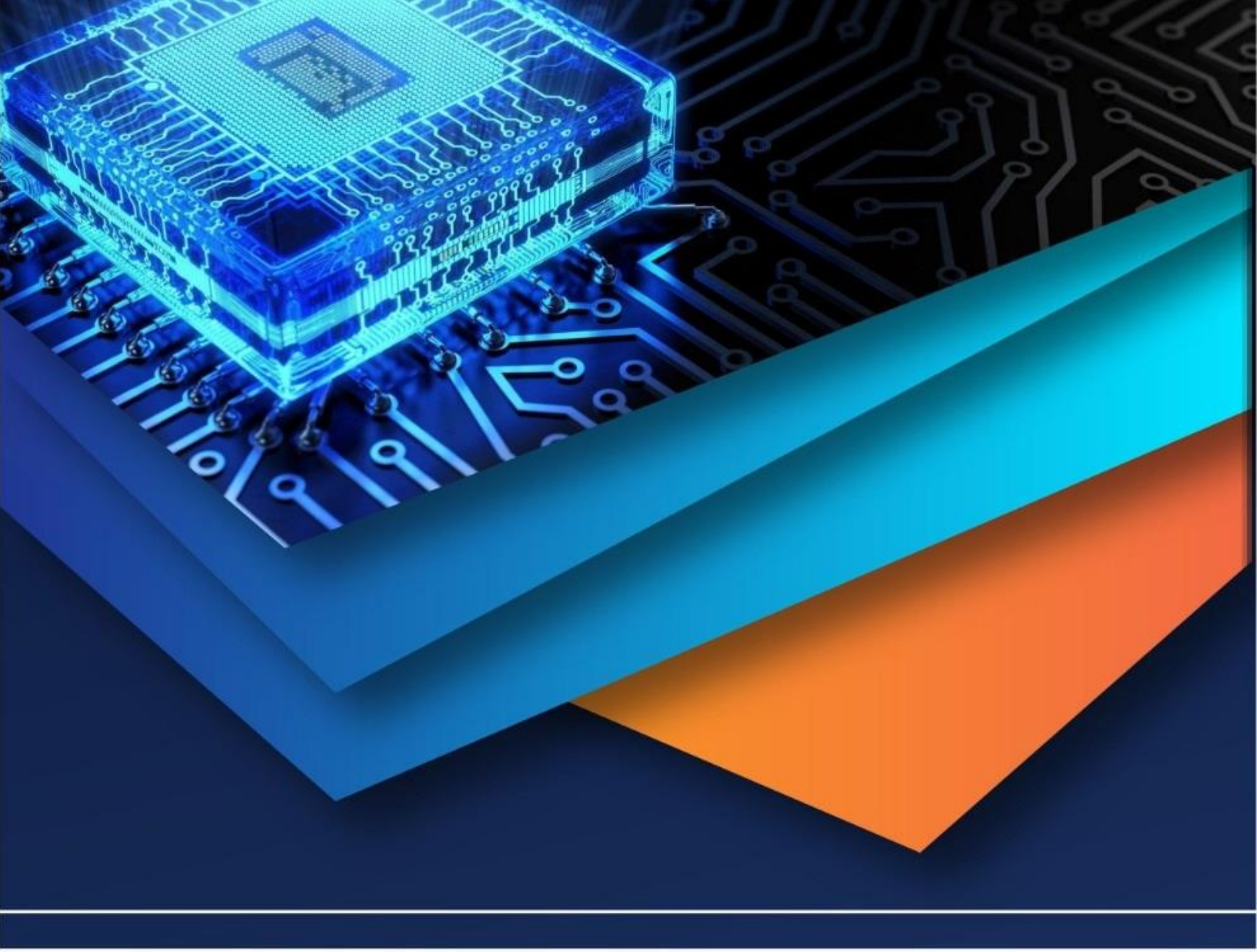

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