Employing deep learning framework for improving solar panel defects using drone imagery

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***Abstract* - This research describes a unique method for identifying and categorizing solar panel problems using RGB and thermal pictures captured by drones. The first step of the suggested technique is to identify solar panels in the photographs by using a CNN based on YOLOv5 architecture model that was trained and tested on an annotated dataset of solar panels. A number of computer vision techniques were used to separate the panels from their backgrounds in order to get around the accuracy issues with the detector. The panels were then classified as normal or anomalous using a state-of-the-art EfficientNet classifier, which was trained on a synthetic dataset. The anomalies were then divided into four categories: cell, multi-cell, diode, and multi-diode. The results obtained from this research demonstrate the viability and potential of employing drones to identify and categorize solar panel problems and emphasize the significance of creating precise models to enhance solar park management.**

Keywords - Solar panels; Thermal imaging; Computer vision; Deep learning; Anomaly detection; Fault detection; Image segmentation; Drone-based inspection

I. Introduction

As a viable replacement for fossil fuels, solar energy has attracted a lot of interest in recent years. It is a renewable and sustainable energy source. Nevertheless, several defects, such as cells, diodes, or multiple cells and multiple diodes, might have an impact on the effectiveness and performance of solar panels. The generation of energy can be significantly reduced by these flaws, thus it's critical to identify and categorize them as soon as feasible.

The traditional technique of evaluating solar panels involves personnel visiting the solar park and visually inspecting each panel. This method is time-consuming and leads to errors many times. Because of improvements in deep learning and computer vision technology, automation of this process is now feasible, which will make it quicker, more effective, and less expensive.

The use of drones and computer vision techniques to identify and categorize solar panel defects has been suggested in several papers. To detect damaged photovoltaic cells with a high detection rate, [1] suggests a deep learning-based strategy utilizing VGG-16. A completely automated drone and cloud-based infrared monitoring system for sizable photovoltaic plants is presented in [2]. The technology has a high rate of accuracy in identifying solar panel flaws including hotspots and fractures. In [3], the author discusses a real-time fault detection system for solar cells that uses cameras placed on drones and reports that the system can detect hotspots and cracks.

To find abnormal areas in thermal pictures taken by drones, [4] combines image segmentation and clustering methods. Moreover, they employ an unsupervised machine learning method to categorize the discovered abnormalities automatically. Real-world photovoltaic plant's data is used in [5] to compare and assess the performance of various fault detection methods for photovoltaic systems. This study demonstrates that modern techniques, particularly those utilizing deep learning and drone technology, are faster and more accurate than older ones.

Reference [6] suggests a monitoring system for solar plants. The technology has been tested on a real-world solar plant with a high accuracy rate and employs machine learning techniques to detect and categorize errors in real-time. Lastly, [7] suggests a way for advanced inspection of solar systems utilizing these techniques. The technique can accurately identify flaws in solar panels such as hotspots, fractures, and damaged cells. In this paper, we propose a novel approach for detecting and classifying faults in solar panels using drone acquired RGB and thermal images. Our approach utilizes YOLOv5 and EfficientNet to detect and classify solar panel faults and aims to overcome the limitations of existing methods using computer vision techniques.

II. METHODOLOGY

The methodology section of this paper describes the steps taken to detect and classify faults in solar panels using drone acquired RGB and thermal images. The proposed method consists of four main stages: panel detection using CNN based on YOLOv5 architecture, image preprocessing using computer vision techniques, panel classification using an EfficientNet classifier, and thermal statistics analysis using machine learning. In the following sub-sections, each stage will be explained in more detail, including the specific techniques

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used, the datasets and the evaluation metrics used to evaluate the performance of the proposed method.

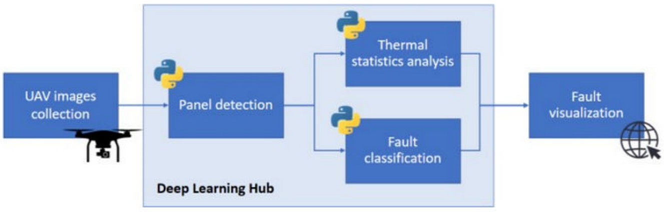

Fig 1: Workflow pipeline

A. Panels detection

The detector used for the initial panel detection was a deep convolutional neural network based on Yolo architecture to determine the bounding box of each panel. At first, we had to collect images containing panels from solar parks. We used a drone equipped with Autel camera to get colored images and the corresponding thermal. The flight was made by setting the necessary specifications. Over 200 drone images were collected containing over 300 single panels.

For object detection tasks we need to annotate the images before we fit them for training. So, we manually created rectangles around every single panel in our images and we extracted the corresponding txt file by using CVCAT website. The TXT file contains all the necessary information for our object detector to get trained. It contains the exact location of the detected panel rectangles.

The training was done over our own annotated dataset for images with size 640 for 80 epochs with batch size 8. We also added random rotations to images before we feed them for training so that our detector can handle images with small rotations in case the user does not follow the flight instructions accurately.

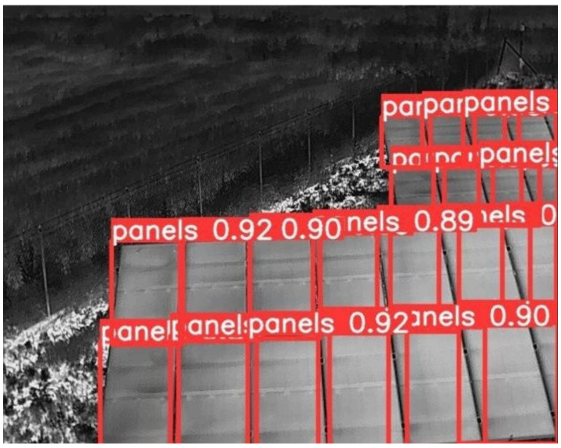

Fig. 2: Detector's results

Figure 2 presents the result of our detector in a new image with the bounding boxes over every panel detected and the probability about how certain our model is that in this place there is a panel. As anyone can notice, our detector managed to detect all the panels in the test image, even the ones from the background with high accuracy and the probability is about 90%.

B. Image preprocessing

The main goal is to classify the panels into faulty or not faulty classes. So, after detecting the location of every single panel in the input image and creating a separate image for each one, we have to feed them to the classifier. However, if we feed the panel images in this way, we will not be able to achieve high accuracy because every image contains unnecessary information of the background and not only the interior of the panel.

To isolate the interior of the panel in panel images we implemented another convolutional neural network model based on Unet architecture. The main idea behind this architecture is called decoder-encoder where the decoder decomposes the image into basic features and the encoder uses them to construct the mask image.

To train this model, we first had to prepare the training dataset. The dataset consists of images similar to those given as a result by our detector and the corresponding mask image. The mask image is an image with same dimensions as the panel image which is completely black besides the area that represents the panel. Our model has in total 1.941.139 trainable parameters and is trained for 75 epochs over 1062 images for training, 304 images for validation and 151 images for testing with size (128, 128). With this method over eighty five percent of pixels are classified correctly. Figure 3 shows the implementation of the segmentation model.

Fig. 3: Panel segmentation

After taking the forecast from our model, we have to cut the mask image exactly where the color is white. At first, we apply the canny method from OpenCV library to detect the edges of the mask image and then the findContours method to check if we correctly detected a shape with 4 edges in order to cut the image and save it as a new image. With this method we manage to keep the interior of the panels in 87% of our test images.

To raise the accuracy of keeping the interior of the panels and hold only the area of our interest, we implemented a computer vision method when the decoder-encoder model fails. As we can see in the figure 4, the process is the same, but we added some more steps. After applying the canny method to our mask image, we use the HoughLinesP method from OpenCV library to detect straight lines in the canny image. The next step is to extend these lines in order to get close shapes because the previous method might have some spaces in the detected lines. The last step again is the findContours method combined with warpPerpective in order to adjust the four edges of the close shape we detected in extended line image into our final image with standard dimensions.

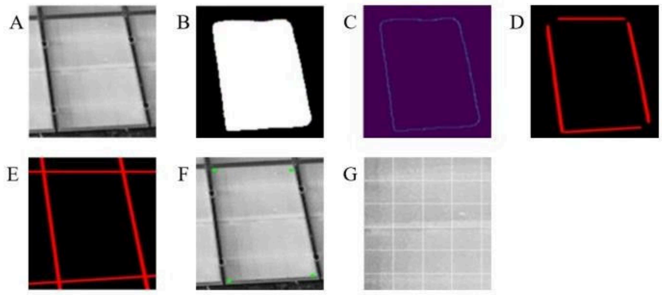

Fig. 4: A:Original image, B:Mask Image, C:Canny Image, D:Line Image, E:Extended Lines, F:Contours Image, G:Final Image

C. *Panel classification*

To classify every panel of the user's solar park into fault or no-fault categories, our first approach included training on several online datasets of solar panel faults, but the results couldn't be applied to real data. So, we decided to create a synthetic dataset by using panel images with no faults and we add random anomalies. In total as we can see in figure 5, four different fault classes were created, Cell, Diode, multi-cell and multi-diode.

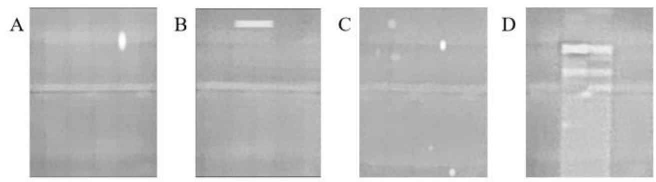

Fig. 5: A:Cell, B:Diode, C:Multi-Cell, D:Multi-Diode

The final dataset contains 5000 images for training, 1000 for each synthetic class and 1000 for panels without anomaly (no-anomaly class), 1500 images for validation and 500 images to test the results. The shape of the images is 300x300x3 which represents a squared colored image with length of 300 for each side.

After testing many different architectures (figure 6) and exploring a lot of parameter values, we ended up with EfficientNet classifier which is proposed by Google. The training is done for 25 epochs and small augmentation methods applied when feeding the data images to make the model more generic and has higher accuracy on distorted images.

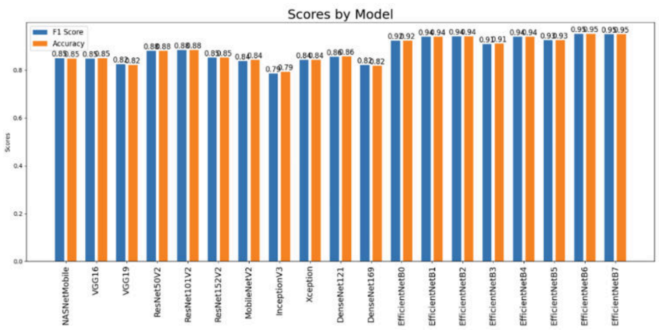

Fig. 6: Comparison of Classifiers

The classifier manages to predict the class of the panels with 95% accuracy. So, we are now able to make predictions for every single panel of the user's solar park with high accuracy and provide information about the anomaly for each one. In figure 7 we can see a thermal image of a panel as well as the areas the model uses to make the prediction. Areas with color near red are more important for the final decision than areas with color near blue.

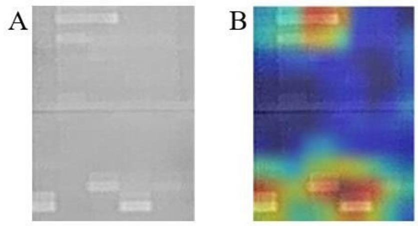

Fig. 7: A:Thermal Image, B:Heatmap

D. *Thermal analysis*

In addition to the classifier, the deep learning hub also analyzes the thermal data for every panel image by calculating the statistics. The statistics we are taking into consideration for this task are maximum, minimum, mean, median value in panels thermal list, kurtosis, standard deviation and skewness distributions of the list. This is used to identify offline panels that can't be detected from the classifier and to confirm the classifier's predictions. In figure 8 we can see the difference between the histogram of a panel without faults in the left and a panel with multi diode anomaly on the right. It is worth noting the great variety of the standard deviation values in these two cases. By finding the down outliers of the mean value in all panels detected in the solar park, we can detect offline panels.

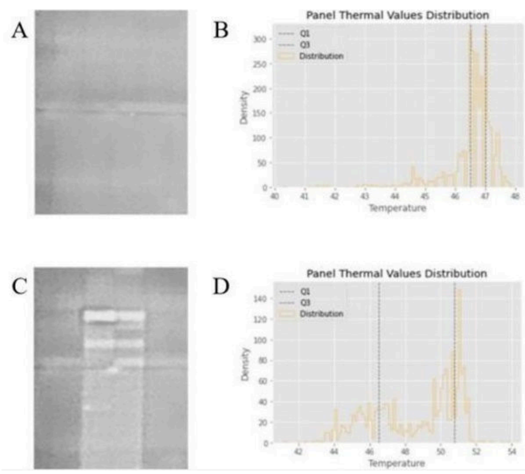

Fig. 8: A:Panel without faults, B:No fault panel Histogram Std = 0.82, C:Multi-Diode anomaly panel, D:Multi-Diode panel Histogram Std = 2.42

This data can be also used to classify the panel as faulty or no faulty. We may not be able to make predictions about the type of anomaly for every panel like the classification model but for instance, if the minimum value of a panel is too low that may be a sign of a fault. For this purpose, a machine learning model was implemented.

Our dataset for this task consists of 1146 rows that represent the statistics of the panels labeled as faulty or no faulty. Unfortunately, only 24 of them represent faulty panels. So, at first, we created more faulty data by using the smote method and we split dataset into training and testing, 30% of data for testing.

Many machine learning models were trained, and we compared them. We also implemented feature selection and PCA methods but none of those had a great impact on accuracy. Then we tried scaling methods and visualized all the results. The best model we came up with is random forest which achieves 95.7% accuracy with "criterion" parameter with value of gini, "max_depth" of 10 and "n_estimators" of 80 without feature selection or data scaling.

III. Results

This paper proposes a methodology for identifying and categorizing solar panel problems using RGB and thermal pictures taken by drones. The approach is divided into four basic steps: panel identification using a CNN based on YOLOv5 architecture, image preprocessing using computer vision methods, panel classification using an EfficientNet classifier, and thermal statistics analysis using machine learning.

A deep convolutional neural network based on YOLOv5 architecture, is used in the first step to identify the bounding box of each panel in the photos. Rectangles were manually drawn around each panel in the images, and training was carried out using random rotations across the annotated dataset to handle slight image rotations. The accuracy of the detector was evaluated using a test image, where it successfully detected all the panels in the image with a probability of 90%.

The inside of the panels in panel pictures are isolated using a convolutional neural network model based on Unet architecture in the second step. The model's decoder-encoder architecture breaks the picture down into its constituent parts, which the encoder then utilizes to create the mask image. The findContours technique is used to see if a form with four edges is appropriately recognized to cut the picture and save it as a new image after the mask image has been processed to detect its edges using the canny method. When this method's accuracy is tested, 87% of the test images successfully maintain the inside of the panels.

The third stage is classifying each solar panel in the user's solar park into groups with or without faults. Using panel pictures without any defects and a synthetic dataset, four separate fault classes are created: Cell, Diode, and Multi-Cell. After examining several architectures and parameter values, the EfficientNet classifier is utilized. In order to broaden the model's applicability and improve its performance on distorted photos, the classifier is trained for 25 epochs with minor augmentation techniques employed while feeding the data images.

In order to find any defects not found in the other steps, the last stage uses machine learning to examine the thermal data of the panels. Overall, the suggested approach has the ability to accurately identify and categorize solar panel problems utilizing RGB and thermal pictures taken by a drone.

IV. Conclusions

In this research, we presented an approach for identifying and categorizing solar panel problems utilizing drones that can take RGB and thermal photos. The suggested method is divided into four primary stages: thermal statistics analysis using machine learning, panel identification using CNN based on YOLOv5 architecture, panel classification using an EfficientNet classifier, and picture preparation using computer vision techniques.

A deep convolutional neural network based on YOLOv5 is used in the panel detection step to identify each panel in the input picture. The image preprocessing stage isolates the interior of the panel in panel images using a convolutional neural network model based on the UNet architecture. An EfficientNet classifier that has been trained on a synthetic dataset of solar panel failures is used to categorize panels, and it performs the task with excellent accuracy.

The suggested approach was evaluated on a dataset of over 200 drone photos with over 300 single panels. The findings reveal that the panel detector can detect all panels in the test photos with a 90% certainty. In 87% of the test photos, the image preprocessing stage effectively separates the interior of the panels, and when the UNet model fails, a computer vision approach is utilized to increase the mask image's accuracy. With an F1-score of 0.93 for the no-fault class and an average F1-score of 0.83 for the fault classes, the panel classification stage achieves great accuracy in categorizing panels into fault or no-fault categories.

The proposed methodology has the potential to increase the efficiency and accuracy of solar panel inspection, which is critical for solar park maintenance and energy output optimization. The suggested approach might be integrated into an autonomous drone inspection system in the future, allowing for continuous monitoring and real-time identification of problems in solar panels. Furthermore, the suggested approach might be expanded to other types of solar devices and tailored to other examination settings.

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