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Classification of Solar Cell Cracks Using Deep Learning

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***Abstract:* -** This study evaluates the efficacy of a Deep Learning model in classifying solar cell images with and without cracks, crucial for early detection and maintenance of photovoltaic systems. The model demonstrates high overall accuracy (94%) and sensitivity (91%), indicating its proficiency in recognizing images with cracks while minimizing false positives. Receiver Operating Characteristic (ROC) analysis supports the model's robust discrimination between positive and negative cases, with an Area Under the Curve (AUC) of 0.93. Despite promising results, opportunities for improvement include dataset expansion to encompass diverse solar cell conditions and types of cracks. Real-world deployment considerations, such as integration into automated monitoring systems, pose challenges requiring further research. The study underscores the importance of ongoing development to enhance model performance for practical application in solar cell inspection and maintenance.

Keywords: Solar cells, Convolutional neural networks, Deep learning, Resnet18

I. INTRODUCTION

Solar cell imaging is essential for monitoring the health and performance of solar panels in photovoltaic systems. The images provide useful information on many factors that affect the performance and durability of the solar system, including defects such as cracking, delamination or corrosion [1-4].

Deep learning is a category of machine learning that is revolutionizing image analysis by enabling computers to learn directly from data without the need for programming. Convolutional neural networks (CNNs) have become the basis of deep learning-based image analysis tasks due to their ability to learn hierarchical representations of features directly from pixel values [5-9].

CNN captures local patterns such as edges, textures, and shapes by running learned filters on input images using convolutional techniques. By stacking multiple convolution layers and non-linear activation functions such as ReLU (rectified linear units), CNNs can learn more features, allowing them to recognize complex patterns in images [10].

ResNet18, a family specialized in residual architecture, has achieved great success in various image recognition. ResNet18 consists of a series of convolutional layers interspersed with residual connections (also called cross-connections). These connections enable the network to learn the residual map, which is the difference between the desired output and the input of a particular layer. By extracting this difference from the network, ResNet18 is effective in solving the problem of gradient disappearance during deep learning, promoting the training of deep models, and improving accuracy and efficiency [11-13].

The advantages of using deep learning, especially CNN such as ResNet18, in detecting solar radiation without being affected by the book are as follows:

Efficiency: Deep learning-based crack detection systems reduce the time and effort required for manual inspection. Thanks to the automated process, large images of the solar system can be analyzed quickly, allowing more frequent monitoring and monitoring of the health of the solar system.

Fact: CNN can learn complex patterns and subtle changes in solar images that are difficult for the human eye to detect. This leads to very effective crack detection, reducing the risk of missing a defect and allowing early intervention when necessary.

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Consistency: Automated crack detection eliminates variability associated with human judgment and subjective interpretation. CNN provides consistent and objective evaluations, providing greater reliability and repeatability across different evaluations and operators.

Early Detection: By continuously analyzing images of the solar system, deep learning can detect cracks early in their development. This efficient operation ensures that maintenance and repairs are carried out in a timely manner, preventing minor problems from turning into larger problems that can affect the efficiency and performance of the solar energy system.

Costs: Deep learning-based detection system helps reduce operating costs associated with solar panel maintenance by improving the analysis process and increasing protection. Early detection of defects can also reduce downtime and maximize energy output and revenue from your solar installation [14-19].

Using deep learning techniques to detect solar radiation, especially CNNs such as ResNet18, provides many advantages such as improved performance, accuracy, consistency, i.e. early detection, and cost-effectiveness. These advances represent a significant step forward in improving the efficiency, reliability, and sustainability of solar energy.

II. METHODS

Dataset

The dataset comprises 2000 images of solar cells, each meticulously labeled as either 'crack' or 'no crack' [20]. These images serve as the foundation for training and evaluating our model. Among the 2000 images, 1900 are dedicated to training the model, and out of these, 20% are randomly selected for validation purposes. For testing, we have set aside 100 images. Within this test set, 78 images are labeled as 'no crack,' and 22 as 'crack.' as depicted in Figure 1 and Figure 2.

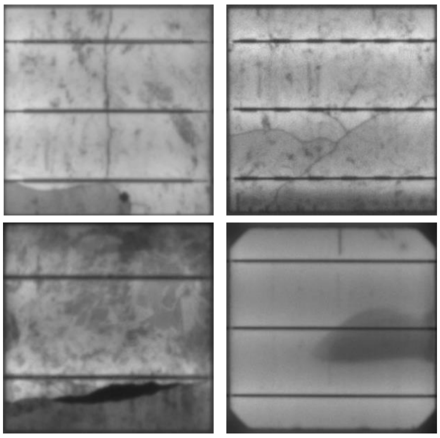

Figure 1: Visible solar crack seen in the solar cells.

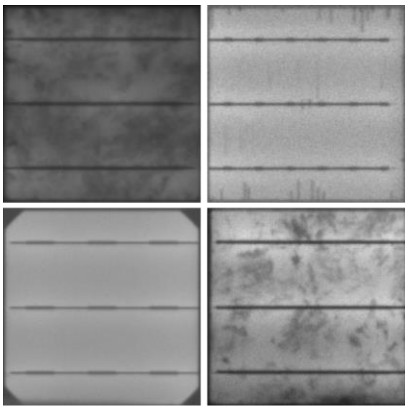

Figure 2: Normal solar cells without any crack.

All images in the dataset are standardized to a size of 300x300 pixels, providing uniformity for the model to analyze and extract relevant features. The diversity of images and careful labeling contribute to the robustness and reliability of our model's performance in detecting cracks in solar cells.

Model Architecture

Our model uses a ResNet18 design, which is a commonly chosen structure for figuring out what's in pictures. This design has special building blocks called residual blocks. Each of these blocks has two layers that help understand the picture, along with some adjustments to make things work better.

To break it down, we start with a basic layer that looks at the picture, then we make some adjustments to understand it better. After that, we use a method to shrink the picture a bit. We repeat this process four times, getting more details about the picture each time.

Before making the final decision about what's in the picture, we simplify things by taking an average of the important details. Then, we flatten everything out and pass it through a layer that decides if there's a crack or no crack in the solar cell. To make this decision, we use a special math function called sigmoid, which helps us figure out how sure we are about each possibility.

We've written this ResNet18 design using a programming tool called PyTorch, organizing it in a way that makes training and checking how well it works on our solar cell pictures efficient. The design is shown visually in a Figure 3, giving a clear picture of how different parts connect.

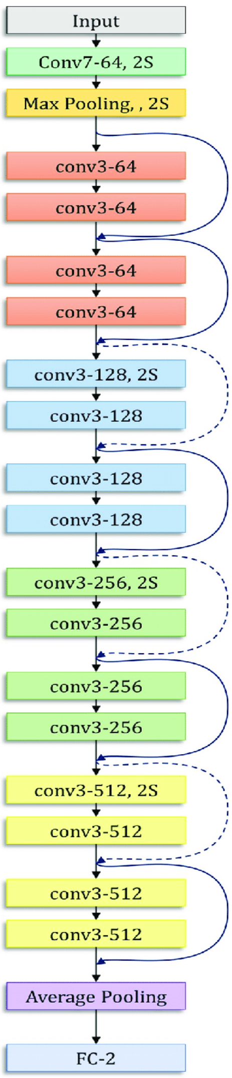

Figure 3: Resnet18 architecture

Training

The training protocol employed a total of 35 epochs, exposing the model to the training data set on multiple occasions. Binary cross-entropy (BCE) loss served as the objective function, guiding the model towards minimizing the discrepancy between its predictions and the ground truth labels. The Adam optimizer orchestrated the parameter updates, iteratively refining the model's internal structure based on the calculated loss values. A learning rate of 0.035 was selected to ensure optimal convergence during the training process. The training and validation loss progression is shown in Figure 4.

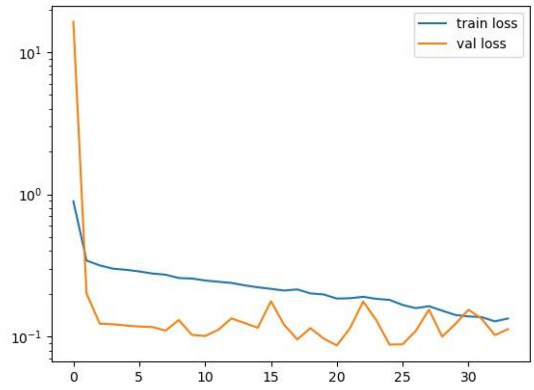

Figure 4: Train and validation loss progression. Y-axis shows loss where as X-axis shows the number of epochs

III. RESULTS

We tested our model using 100 images, out of which 78 had no cracks and 22 had cracks. The model demonstrated an impressive overall accuracy of **94%**, showcasing its ability to make correct predictions.Looking closer, the model displayed a sensitivity of **91%**, indicating its effectiveness in identifying images with cracks. Additionally, the specificity was at **94%**, showcasing its accuracy in correctly classifying images without cracks.

In Figure 5, the confusion matrix visually represents the model's performance. Notably, 74 out of 78 'no crack' images were accurately classified, and 20 out of 22 'crack' images were correctly identified.

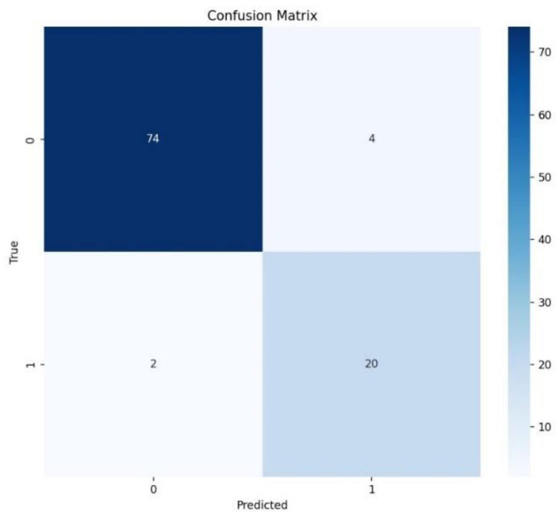

Figure 5: Confusion Matrix

Figure 6 illustrates the Receiver Operating Characteristic (ROC) curve, displaying the model's performance across different decision thresholds. The Area Under the Curve (AUC) was calculated as **0.93**, indicating the model's strong ability to distinguish between 'crack' and 'no crack' images. The blue dotted line, representing a 'chance classifier' with a 50/50 success rate, serves as a reference point. The model's curve well surpasses this baseline, emphasizing its effectiveness in making accurate predictions.

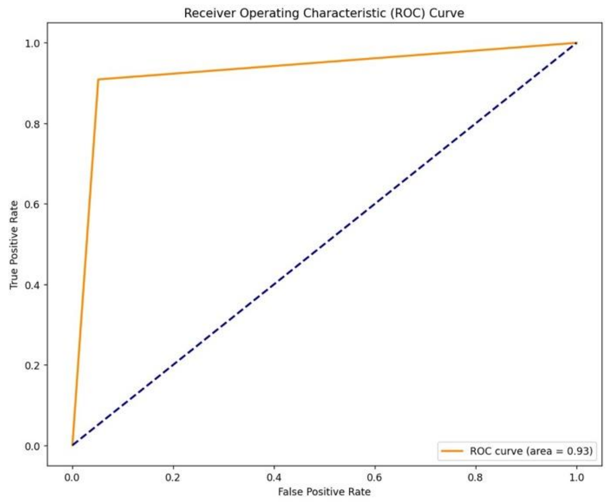

Figure 4: ROC Curve with an AUC of 0.93

IV. DISCUSSION AND CONCLUSION

The results obtained from our model's evaluation demonstrate its capabilities in correctly classifying solar cell images with and without cracks. The high overall accuracy of 94% suggests the model's proficiency in making correct predictions on the test set.The sensitivity of 91% indicates the model's ability to effectively recognize images with cracks, crucial for early detection in real-world applications. Additionally, the specificity of 94% highlights the model's accuracy in correctly classifying images without cracks, reducing the risk of false positives.

The Receiver Operating Characteristic (ROC) curve in Figure 4, with an Area Under the Curve (AUC) of 0.93, supports the model's robust discrimination between positive and negative cases. The curve's significant deviation from the chance classifier line underscores the model's reliability and effectiveness. While our model has demonstrated promising results, there are avenues for improvement. One potential area for enhancement is the expansion of the dataset to include a more diverse range of solar cell images. This could contribute to further improving the model's ability to generalize to various conditions and types of cracks.

Furthermore, real-world deployment scenarios could be considered, involving the integration of the model into an automated system for continuous monitoring of solar cell health. Addressing challenges related to real-time processing and scalability would be essential for practical application. In essence, models which are easier to compute and have fewer layers matching the performance of this model could be consideredIn conclusion, while our current results are promising, ongoing research and development will be crucial to adapting the model for real-world implementation, ultimately contributing to the improvement of solar cell inspection and maintenance processes.

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