Defect Detection in Solar Panels

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***Abstract*—The increasing global energy consumption, driven by population growth and technological advancements, highlights the urgent need for reliable, cost-effective, and sustainable renewable energy sources. Solar energy emerges as a viable solution to address these challenges, particularly through the use of photovoltaic (PV) panels, which convert solar radiation into electricity. However, these panels are prone to various environmental defects that must be identified and addressed promptly to maintain their efficiency and durability. This study examines the types of faults in PV panels, its supervision and the benefits of identifying faults. The study utilizes solar panel images dataset. Image processing, deep learning and object detection techniques are used for defect detection. The purpose of the proposed approach is to automate the detection process.**

***Index Terms*—solar panels, fault detection, PV panels, defect detection, image processing**

I. Introduction

Solar energy has emerged as a crucial alternative to conventional energy sources, particularly in remote areas like deserts and mountains where grid connectivity is challenging and costly. Many countries have adopted solar power to reduce reliance on fossil fuels and provide electricity to isolated regions. However, the occurrence of defects in photovoltaic (PV) panels, such as cell breakage, oxidation, delamination, and electrical component failures, can lead to significant issues like hotspots, overheating, and even fires. These defects often manifest as hotspots where the photovoltaic effect ceases, causing local overheating and potentially leading to destructive outcomes such as cell or glass cracking, solder melting, and solar cell degradation.

Traditional inspection methods, including visual inspection and I–V curve tracing, are often impractical for large-scale or remote installations due to their high cost, time consumption, and the need to halt energy production. In contrast, recent advancements in thermal imaging and artificial intelligence (AI) offer promising non-destructive, efficient, and accurate solutions for defect identification. Thermal imaging captures infrared radiation emitted by solar panels, allowing for the visualization of temperature variations associated with defects. AI algorithms, such as convolutional neural networks (CNNs) and support vector machines (SVMs), process thermal images to identify and classify defects based on their unique thermal signatures.

The integration of thermal imaging with AI algorithms enables automated detection and analysis of various types of defects, including cracks, delamination, hotspots, and corrosion, without the need for manual intervention. Key advantages of these technologies include rapid inspection speeds, high accuracy, and compatibility with large-scale solar installations. However, the effectiveness of AI-based methods relies heavily on the quality of network training, which requires a large number of high-quality image samples. Despite this challenge, the combination of thermal imaging and AI presents a significant advancement in the field of PV panel defect detection, offering a viable solution for condition monitoring in large-scale solar power plants.

Thus this study evaluates various morphological preprocessing methods using image processing techniques to prepare the dataset. Further, it also uses deep learning and transfer learning based approaches for classification of the images. The further paper is divided into sections covering the existing related works, the implemented methodologies, the results and the limitations we faced in the work.

II. Related works

The global photovoltaic (PV) industry is rapidly expanding due to growing energy demands and the limitations of fossil fuels. However, solar cell defects pose a significant challenge to PV system efficiency, leading to interruptions in electricity generation. This study proposed in paper[1] is a novel system for defect detection in solar cells, optimized for low-computation devices. The approach combines K-means clustering, MobileNetV2, and Linear Discriminant Analysis (LDA) to classify solar cell images and build detection models for each cluster, differentiating defective from non-defective cells. The system was evaluated on a benchmark electroluminescence (EL) image dataset, consisting of 2,426 images from 44 monocrystalline and polycrystalline panels. Using five fold cross-validation, metrics like accuracy, recall, precision, and F1-score were employed to assess performance, with the method achieving high accuracy compared to recent studies. The methodology proposed by the authors of paper[2] is an automatic multi-stage model using YOLOv3 and computer vision techniques to detect panel defects in aerial images captured by UAVs. The model processes both thermographic and visible images, detecting various defects and providing data-driven maintenance strategies. It performs well across different PV systems, achieving over 98% AP@0.5 for panel detection and strong performance detecting hotspots (AP@0.4: 88.3%) and visible anomalies (mAP@0.5: 70%). The model

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also estimates defect severity and soiling coverage, offering efficient and accurate inspections. Additionally, an analysis of YOLOv3's output scales reveals their impact on detection performance, contributing to improved system reliability and maintenance scheduling. The research carried out in the paper[3] includes a comprehensive review of thermal imaging and AI techniques, focusing on their integration for detecting and classifying defects such as cracks, delamination, hotspots, and corrosion. Thermal imaging captures infrared radiation to visualize temperature variations linked to defects, while AI algorithms, including convolutional neural networks (CNNs) and support vector machines (SVMs), process these thermal images to identify and classify defects based on unique thermal signatures. The authors of [4] introduce a U-Net neural network for image segmentation, enhancing image processing efficiency in solar panel defect detection. Condition monitoring and fault diagnosis utilize contour features from the 'masks' of true color infrared images, which reduce interference and improve reliability. A dataset of 295 infrared images from PV panels was created, with masks generated using LabelMe software. The dataset was augmented with mirroring, flipping, and cropping to expand the sample size for training. The U-Net was trained on 1,852 infrared and mask images, achieving a segmentation accuracy of 95.2%. Four criteria—contour area, perimeter, aspect ratio, and the ratio of contour area to the outer rectangle area—were developed for fault characterization. The combination of the U-Net and a Decision Tree classifier yielded a diagnostic accuracy of 99.8%, positioning this approach as an effective tool for PV panel condition monitoring. The research conducted in paper[5] brings out two innovative models: (i) a computer vision model that estimates the spatial distribution of solar PV deployment across neighborhoods using satellite images, and (ii) a machine learning (ML) model predicting this distribution based on 43 factors. The computer vision model, utilizing Faster Regions with Convolutional Neural Network (Faster R-CNN), achieved a mean Average Precision (mAP) of 81% for solar panel identification and 95% for roof detection. Analyzing 652,795 satellite images from Colorado, the study found that approximately 7% of households had rooftop PV systems, covering about 2.5% of roof areas by early 2021. Among 16 predictive models, XGBoost emerged as the best, explaining roughly 70% of the variance in rooftop solar deployment. Similarly in the study conducted by the authors of the paper[6] they aim to enhance image classification in the industry by employing advanced convolutional neural network (CNN) architectures and an ensemble of CNNs to detect micro-cracks in electroluminescence (EL) images of PV modules. Transfer learning is utilized to alleviate the need for large training datasets, enabling satisfactory performance on smaller, more practical datasets. Pre-trained models, including VGG-16, VGG-19, Inception-v3, Inception-ResNet50-v2, ResNet50-v2, and Xception, were individually evaluated before being combined through an ensemble method. This approach improved accuracy while minimizing reliance on a single model. The ensemble method achieved the highest accuracies of 96.97% for monocrystalline panels and 97.06% for polycrystalline panels. In paper [7] VGG-16 deep neural network model was employed to identify electrical hotspots using transfer learning. The model was developed by augmenting infrared thermographic images and leveraging pre-trained ImageNet weights of the VGG-16 architecture, incorporating global average pooling instead of traditional fully connected layers, along with a softmax output layer. The model utilized the categorical cross-entropy loss function and was optimized using the Adam optimizer with a learning rate of 0.0001, alongside several variants of the Adam optimization algorithm. Evaluation on a test infrared thermographic (IRT) image dataset demonstrated a remarkable accuracy of 99.98% in identifying electrical hotspots, outperforming similar studies. The study in paper[8] employs Grid Search cross-validation (GSCV) with five folds to optimize hyperparameters for both DL and ML models. Various performance metrics, including Adjusted R^2, Normalized Root Mean Square Error (NRMSE), Mean Absolute Deviation (MAD), Mean Absolute Error (MAE), and Mean Square Error (MSE), are utilized to evaluate the algorithms. Results reveal that the CNN-LSTM model outperforms nine other DL models with an Adjusted R^2 score of 0.984 while gradient-boosting regression ranks as the top ML method with an Adjusted R^2 score of 0.962 among six competing models. Additionally, explainable AI techniques like SHAP and LIME are used to interpret the results. In paper[9] the study emphasizes the critical need for condition monitoring in large solar power plants, particularly focusing on the challenge of analyzing individual strings or panels. It highlights that most faults in solar panels arise as hotspots caused by increased internal resistance. Various image processing techniques implemented in MATLAB were employed to detect these hotspots. The Hough transform technique proved effective in swiftly locating hotspots on thermal images of metal plates. Testing revealed that aged panels exhibited more hotspots due to heightened internal resistance compared to new panels. The quality of thermal images was assessed using conventional metrics, and the results demonstrated a high correlation coefficient through ANOVA analysis. Additionally, experimental validation confirmed that older panels produced lower power output than their newer counterparts. The research carried out in the paper[10] evaluates the feasibility of using Unmanned Aerial Vehicle (UAV) technology for solar panel fault detection, proposing a reliable, economical, and fast method. The UAV inspected solar panels at a solar farm, utilizing an infrared camera and a high-definition (HD) lens to capture images. Infrared images were transmitted for analysis, revealing three health conditions: normal operation, abnormal situations, and ambiguous cases. MATLAB image analysis was employed to assess panel health. The results indicate that UAVs effectively and efficiently capture thermal images to detect various faults, providing a fast, low-cost solution that can identify defects undetectable by visible light, thus aiding maintenance personnel in preventing solar module failures. The methodology followed in this paper[11] focuses on using ResNet50, a convolutional neural network (CNN), for computer vision tasks like image classification, object detection, and image segmentation. Datasets from Kaggle and DEWA Solar PV Plants will be utilized, undergoing steps such as data preprocessing, cleaning, organization, augmentation, and feature extraction. The goal is to build and train a high-performance model that accurately predicts defects in solar panels through a rigorous training, validation, and testing process. The process conducted by the authors of the paper[12] included examining 44 PV panels across four arrays, conducting per-pixel analysis to correlate snow coverage with performance indicators. Two PV selection methods were compared: Direct Selection (DS) and Perspective Transformation (PT), showing deviations between 0.1% and 7.35% of the panel area. Energy production estimates revealed that the lowest average energy output was 0.0368 kWh/panel for DS and 0.0395 kWh/panel for PT, attributed to an 84.1% uncovered PV ratio. Neural networks demonstrated a strong correlation between input/output pairs, achieving an average R-value of 0.9, which validated the effectiveness of deep learning methods. Additionally, uncertainty analysis indicated that area detection error increased with higher snow deposition rates (from 1.8% to 3.7%), suggesting that employing remote monitoring via deep learning could enhance energy production performance.In the research conducted in the paper[13]image processing techniques, including thresholding, erosion/dilation, and edge detection, were utilized to detect cracks and damages in solar panels. The solar panel images were thoroughly inspected to identify Regions of Interest (ROIs) for focused analysis. These image-processing steps enabled the identification of both the PV panels within the array and the specific damaged areas on those panels. To ensure accuracy, partial panels located at the edges of the images were excluded during processing. Overall, these techniques effectively pinpoint cracks and damages in solar panels within a PV array. The experiment carried out in the paper[14] elaborates on an image processing method to detect dust and dirt on photovoltaic panels, addressing the issue of reduced power generation efficiency caused by debris and the limitations of manual detection. The method employs various image processing techniques, including image enhancement, sharpening, filtering, and mathematical morphology-based closing operations, to highlight the target for recognition. To tackle uneven image binarization due to inconsistent illumination, histogram equalization is applied, enhancing image contrast and detail by expanding the dynamic range of pixel gray levels. The dirt area on the panel is identified by calculating its proportion to the total image area, with areas exceeding a specified threshold classified as faults. Additionally, the study integrates an improved A* path planning algorithm for UAV-based detection, significantly enhancing efficiency, reducing operation and maintenance costs, and improving the overall maintenance of photovoltaic units.This study in paper[15] evaluates two methods for detecting solar panels in thermal images captured by UAVs, particularly in complex backgrounds. The first method employs classical techniques, including edge detection, segmentation, SVM classification, and post-processing, achieving a precision of 0.997, recall of 0.970, and F1 score of 0.983. The second method utilizes deep learning with pre-processing steps, resulting in a precision of 0.996, recall of 0.981, and F1 score of 0.989. Notably, the deep learning method's post-processing step reduces false positives by over 60%, significantly enhancing panel detection. Future work aims to correct lens distortions, optimize the method for ortho mosaics, integrate geographic information for power lines, and combine panel detection with failure detection algorithms.The research conducted in this paper[16] brings to light a novel drone-based system for enhanced photovoltaic (PV) diagnostics, comprising three main steps: locating solar panels, detecting anomalies, and identifying the root causes of these anomalies. Utilizing a region-based convolutional neural network (CNN) for anomaly detection, the system achieves a high true positive rate of over 90% and a low false positive rate of 2-3% on a dataset of nearly 9,000 panels. The integration of RGB and thermal camera data is essential for effectively identifying and diagnosing defects. Experiments conducted across six different PV sites in Italy, Spain, and Japan showcase the system's superior performance compared to existing state-of-the-art methods, significantly enhancing accuracy and reliability while reducing the time required for manual inspections. The paper in [17] presents an efficient Real-Time Multi Variant Deep Learning Model (RMVDM) designed to detect and localize various defects in photovoltaic panels, including spotlight effects, cracks, dust, and micro-cracks. The image dataset undergoes preprocessing through the Region-Based Histogram Approximation (RHA) algorithm, followed by feature extraction using the Gray Scale Quantization Algorithm (GSQA). The extracted features are trained with a multi-layered deep learning model that incorporates different classes of neurons, each designed to measure Defect Class Support (DCS). During the testing phase, input images undergo various operations, and the model outputs DCS values to identify and localize defects. Additionally, the method employs the Higher-Order Texture Localization (HOTL) technique for enhanced defect localization. The proposed model demonstrates high efficiency, achieving approximately 97% accuracy in defect detection and localization while maintaining lower time complexity. The paper[18] presents a computer vision solution for detecting solar panels in images using a feature vector that characterizes image portions captured with standard cameras, independent of lighting conditions. This method was tested on images from an operational photovoltaic plant, demonstrating its effectiveness and robustness. The findings aim to support subsequent efforts to optimize energy efficiency in solar energy systems. The authors of the paper[19], an algorithm that utilizes thermal image processing to extract features from operating PV cells. These features are then compared to those from healthy PV modules using Support Vector Machine (SVM) classification to determine whether modules are defective. The algorithm's effectiveness was experimentally validated by testing it with intentionally created faulty datasets, successfully identifying defective PV modules. The authors of the paper[20] proposed an algorithm to detect micro-crack defects in multicrystalline solar cells, addressing challenges posed by various image anomalies such as dislocation clusters and grain boundaries. The proposed method utilizes an improved anisotropic diffusion filter combined with advanced image segmentation techniques. Evaluated on a dataset of 600 electroluminescence images , the algorithm achieved an average sensitivity of 97%, specificity of 80%, and accuracy of 88% in detecting micro-cracks.

III. Methodology

A. Morphological Operations implemented on the incorporated dataset

1) Opening and Closing: The process of opening involves removing small objects from the foreground and placing them in the background. It is a compounded operation where erosion is succeeded by dilation. The process of closing includes filling the narrow holes in the foreground of the image. It is performed by the compounded operation of dilation succeeded by erosion.
2) Erosion and Dilation: The process of erosion and dilation brings about profound changes in the original image passed into the pipeline. Erosion tends to remove the pixels from the boundary thereby reducing the size of the image. Dilation tends to increase the image's boundary size, enlarging the image content.
3) Histogram Equalization: is performed on the set of images. It is done to improve the contrast by adjusting its pixel values based on its intensity histogram.
4) Canny Edge Detection is a multi-step algorithm that finds the edges in images and reduces the data that needs to be processed. It works on noise reduction by using a Gaussian filter to smoothen the image and reduce noise. It uses a higher and lower threshold to determine which pixels are edges and identify the edges and data to be processed.
5) Snow Patch Isolation Using Morphological Operations for Image Segmentation: In this methodology, the goal is to isolate snow patches from a given image using morphological operations. First, the input image is converted to grayscale and then blurred using a Gaussian filter to reduce noise. A binary thresholding technique is applied, where pixels above a certain intensity value (200 in this case) are set to 255 (white), representing potential snow regions. To refine the segmentation, a morphological opening operation is performed, which involves erosion followed by dilation using a 5x5 kernel. Erosion helps to eliminate small noise, while dilation restores the size of the snow patches.
6) Thermal Image Segmentation and Region Detection Using Intensity Thresholding and Contour Analysis: Contour refers to a curve or boundary that outlines the continuous regions of pixels in an image with similar intensity values. It is used to identify and delineate the boundaries of specific areas of interest, such as hot spots, in thermal images based on intensity thresholds. In this methodology, thermal image analysis is performed to detect regions with specific intensity values, typically corresponding to areas of interest such as hot spots. A histogram of the grayscale image is first generated to analyze the distribution of pixel intensities, helping to determine an appropriate threshold for segmentation. The image is then converted to grayscale and smoothed using a Gaussian filter to reduce noise. A binary mask is created by thresholding the smoothed image, isolating pixel intensities within a predefined range (222 to 255), which highlights the regions of interest. Contours of the identified areas are extracted, and only those with an area greater than a specified threshold (150 pixels) are retained to avoid noise.

B. Transfer Learning

1) VGG16 is a deep convolutional neural network created by Oxford's Visual Geometry Group, known for its 16 layers (13 convolutional and 3 fully connected layers). Its simplicity lies in using small 3x3 convolution filters and 2x2 max-pooling layers. This design helps VGG16 learn effective feature representations while keeping the architecture straightforward. Due to its strong performance on large datasets like ImageNet, it's often used for transfer learning.
2) MobileNetV3 Small is a lightweight, efficient neural network architecture tailored for mobile and edge devices. It employs depth-wise separable convolutions, significantly reducing the number of parameters and computational load compared to traditional CNNs. This design incorporates non-linear activation functions and squeeze-and-excitation modules to enhance performance while maintaining a low computational footprint. Its advantages include quick inference, reduced model size, and low power consumption, making it ideal for real-time applications on resource-constrained mobile devices.
3) EfficientNetB0 is a convolutional neural network designed for efficient image classification, balancing accuracy and computational cost. It uses a unique compound scaling method to uniformly increase the network's depth, width, and resolution, resulting in better performance with fewer parameters than traditional models. The architecture integrates mobile inverted bottleneck convolutions and squeeze-and-excitation blocks to enhance feature representation and efficiency. This model excels by providing state-of-the-art accuracy while keeping computational demands low, making it perfect for use on resource-limited devices like mobile phones and edge systems. EfficientNetB0 is widely favored for tasks that require high efficiency without sacrificing performance.
4) DenseNet, or Densely Connected Convolutional Network, is a neural network architecture where each layer is directly connected to every other layer in a dense manner. This means that every layer receives inputs from all previous layers, promoting more

efficient gradient flow, better feature reuse, and a reduction in the number of parameters compared to traditional convolutional networks. DenseNet employs dense blocks interconnected by transition layers, which enhance learning and feature extraction across different levels. Its major advantage is mitigating the vanishing gradient problem, improving feature propagation, and achieving high accuracy with fewer parameters. This makes DenseNet both efficient and highly effective for various deep learning tasks.

In this project, we leverage various pre-trained models for image classification. The chosen model is loaded without its top layers, focusing on the convolutional and pooling layers to extract features from the input images. These features are then passed through a Global Average Pooling (GAP) layer to reduce dimensionality and a Dropout layer to prevent overfitting. The number of units in the final Dense layer matches the number of target classes. The model is compiled using the Adam optimizer and Sparse Categorical Crossentropy loss, which is ideal for multi-class classification. EarlyStopping monitors validation loss and halts training when no further improvement is seen, helping to avoid overfitting.

IV. Dataset

A. Source 1

In this study, we utilized a dataset of 885 images, sourced from the internet (Kaggle), which exhibited a slight class imbalance. The dataset is categorized into several classes based on the condition of the solar panels as shown in Figure 1 and Table 1. This categorization aids in training and evaluating the model's ability to accurately identify and classify different types of anomalies on solar panels.

Class	Explanation	No. of images in the class
Clean	unblemished panels	194
Bird drop	panels with bird droppings	192
Electrical damage	panels exhibiting electrical issues	104
Physical Damage	panels with physical impairments	70
Snow Covered	panels covered by snow	124
Dusty	panels affected by dust	191

Fig. 1. Classification dataset

B. Source 2

Additionally, we incorporated a second dataset, sourced from Roboflow, which consists of 536 thermal images of PV cells containing hotspots. This dataset provides crucial thermal

Fig. 2. Sample images from the dataset

imaging data, enhancing the diversity of our defect detection approach. The sample images from this dataset are shown in Figure 2

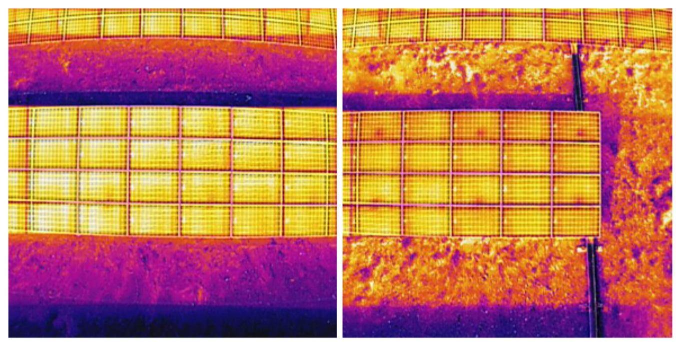

Fig. 3. Sample thermal Images of solar panel from the dataset used for hotspot localization

V. Results

The morphological operations conducted before training the models under various classifiers highlight certain key results that need to be elucidated:

In the above scenario, it is observed that the process of erosion tends to reduce image clarity, and loss of content from the image is observed. In contrast, dilation gives a more clear image and is easier to extract features from.

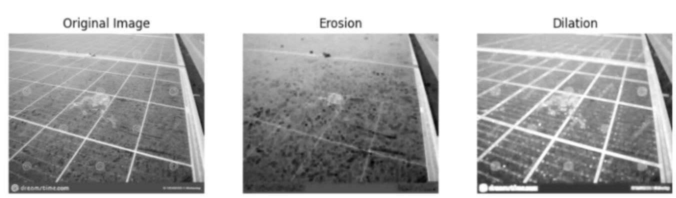

Fig. 4. Impact of Erosion and Dilation on the Input image

In this research, closing gives a more clear and feature-intensive image compared to opening where image details get blurred.

This input image after passing through histogram equalization tend to output a more contrasted image for further processing.

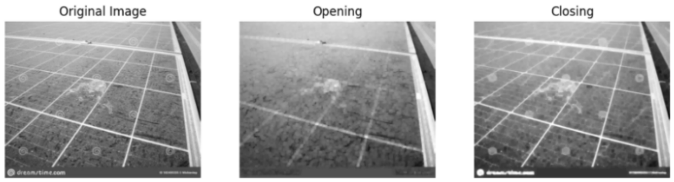

Fig. 5. Impact of Opening and Closing Operations

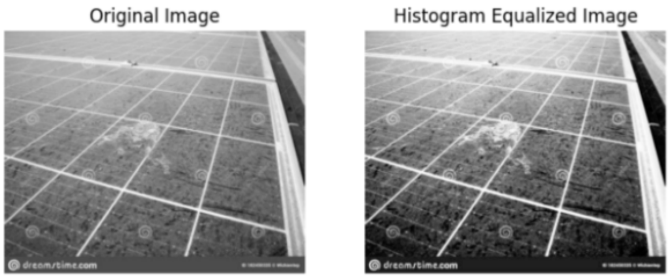

Fig. 6. Histogram Equalization of the Input Image

It uses a higher and lower threshold to determine which pixels are edges and identify the edges and data to be processed.

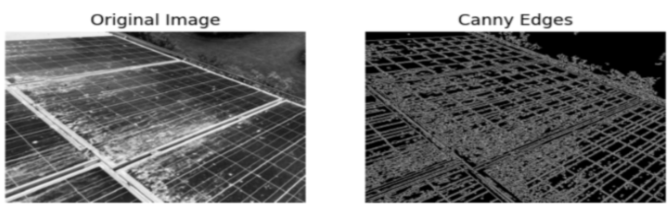

Fig. 7. Canny Edge Detection

The result of snow segmentation is a binary image highlighting the snow-covered areas, which is then displayed alongside the original image for comparison. This process effectively isolates snow patches as shown in Figure n, making it useful for applications such as snow coverage analysis.

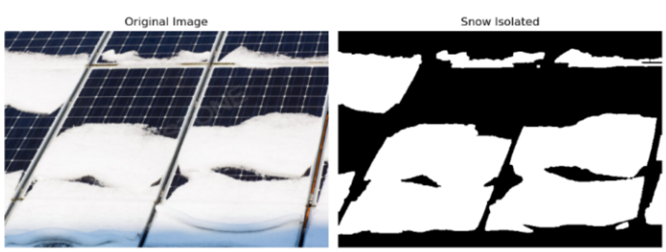

Fig. 8. Binary thresholding based snow segmentation on solar panels

On a solar panel, the presence of hotspots indicates the presence of defects. Thus localizing, identifying and localizing them using contouring provides information about the presence and scale of defects. These contours are drawn on the original image with a green outline, providing a clear visual indication of the detected regions. This combined approach of histogram analysis, thresholding, and contour detection as shown in Figure n enables effective segmentation and visualization of significant features in thermal images.

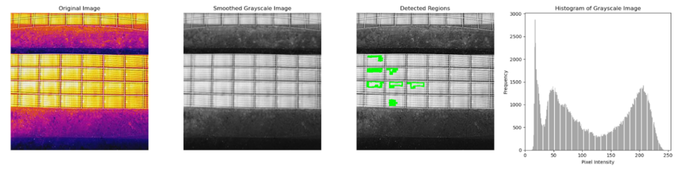

Fig. 9. Defect localization using intensity thresholding and contour localization

After conducting detailed research with multiple CNN networks, it is observed that DenseNet has a higher accuracy of 0.92 compared to the other models implemented. The DenseNet tends to give high accuracy due to the avoidance of vanishing gradient problems and feature propagation and hence offers higher accuracy compared to the other models implemented.

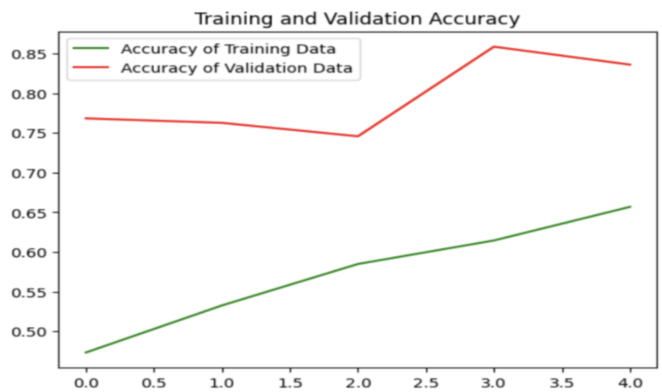

Fig. 10. Accuracy of Classification under VGG 16

Fig. 11. Accuracy under EfficientNet

VI. Limitations

A. Shadow Removal

In this project, we implemented image preprocessing to remove shadows cast on solar panels, aiming to prevent misclassification and improve dataset accuracy. This involved using

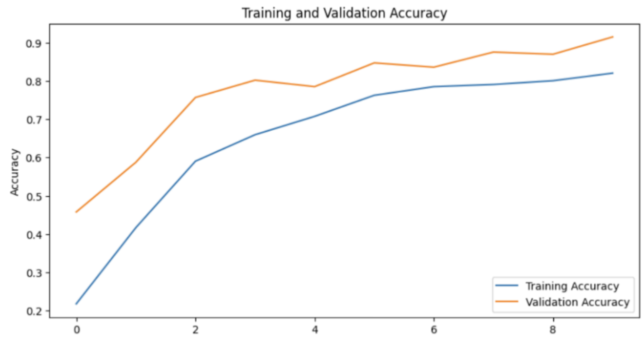

Fig. 12. Accuracy under DenseNet

S.No	Model	Accuracy (in %)
1	Dense Net	92
2	Efficient Net	86
3	VGG16	76
4	CNN model from scratch	67

Fig. 13. Compiled Accuracies of various models

K-means clustering to segment images into three regions based on color, utilizing the Lab color space to separate luminance (brightness) from chrominance (color). First, the image was reshaped into a 2D pixel array, and K-means clustering with three clusters was applied, representing the background, solar panel, and shadow regions. The shadow region was identified by selecting the cluster with the lowest average luminance in the L channel. To reduce shadow visibility, the luminance of pixels in the shadow cluster was enhanced by increasing their brightness. However, this method can struggle with varying lighting conditions or backgrounds with similar colors to the shadow region, leading to inaccurate segmentation. Consequently, the algorithm might mistakenly classify parts of the background or panel as shadows, causing inconsistencies in the final enhanced image. Figure 15 illustrates how this method sometimes only enhances part of the shadow due to variations in shadow intensity across the panel.

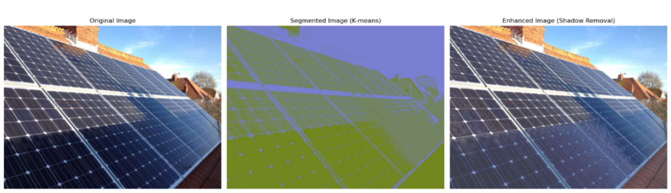

Fig. 14. Shadow elimination using K-means clustering

B. Glare Removal

A method is designed to reduce glare in images through a combination of grayscale conversion, thresholding, and inpainting. Initially, the image is converted to grayscale, and regions with high brightness indicating glare are marked with a binary mask. Inpainting then blends these masked glare areas with surrounding pixels using the Telea inpainting algorithm, aiming to diminish glare by blending it into the background. However, this method may have limitations. Non-uniform glare can complicate mask creation, and complex backgrounds may lead to artifacts during inpainting. Excessive glare can hinder the algorithm's ability to reconstruct original textures, and varying lighting conditions can make thresholding less effective. Despite these challenges, the method offers a basic solution for glare reduction. Figure n shows how the method is able to reduce glare to a very limited extent only.

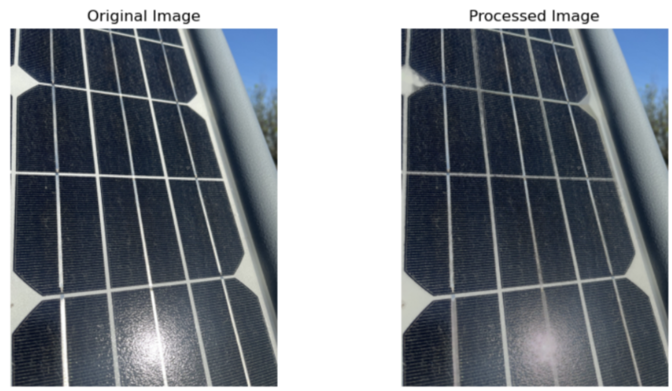

Fig. 15. Glare reduction using inpainting

VII. Conclusion

This study researches advanced image processing and deep learning techniques for image classification and segmentation. Morphological operations like opening and closing refined image regions by removing noise or filling gaps, while histogram equalization enhanced contrast. Canny edge detection identified edges efficiently using higher and lower thresholds to process data accurately. For snow patch isolation, grayscale conversion, Gaussian filtering, binary thresholding, and morphological operations resulted in a binary image highlighting snow-covered areas. This binary output, displayed alongside the original image, effectively isolated snow patches, proving valuable for snow coverage analysis. In transfer learning, models like VGG16, MobileNetV3, EfficientNetB0, and DenseNet were compared. VGG16 is known for simplicity and robustness, MobileNetV3 excels in lightweight efficiency for mobile applications, and EfficientNetB0 achieves a balance between accuracy and computational cost. DenseNet emerged as the top performer, achieving 0.92 accuracy in multi-class classification by leveraging effective feature propagation, better gradient flow, and avoiding vanishing gradient issues. The integration of image processing techniques with pre-trained CNNs demonstrates a powerful framework for accurate and efficient image classification and segmentation, with applications ranging from environmental monitoring to real-time mobile-based solutions.

References

[1] El-Rashidy, M.A. (2022). An efficient and portable solar cell defect detection system. Neural Computing and Applications, 34, 18497–18509. https://doi.org/10.1007/s00521-022-07464-2. Published: June 18, 2022.

[2] Di Tommaso, A., Betti, A., Fontanelli, G., Michelozzi, B. (2022). A multi-stage model based on YOLOv3 for defect detection in PV panels based on IR and visible imaging by unmanned aerial vehicle. Renewable Energy, 193. https://doi.org/10.1016/j.renene.2022.04.046
[3] Umar, S., Qureshi, M.S., Nawaz, M.U. (2024). Thermal imaging and AI in solar panel defect identification. *International Journal of Advanced Engineering Technologies and Innovations*, 1(3), 73.
[4] Wang, X., Yang, W., Qin, B., Wei, K., Ma, Y., Zhang, D. (2022). Intelligent monitoring of photovoltaic panels based on infrared detection. Energy Reports, 8, 5005-5015. https://doi.org/10.1016/j.egyr.2022.03.173.
[5] Kim, S.Y., Ganesan, K., Söderman, C., et al. (2023). Spatial distribution of solar PV deployment: an application of the region-based convolutional neural network. EPJ Data Science, 12, 25. https://doi.org/10.1140/epjds/s13688-023-00399-1.
[6] M. R. Rahman, S. Tabassum, E. Haque, M. M. Nishat, F. Faisal and E. Hossain, "CNN-based Deep Learning Approach for Micro-crack Detection of Solar Panels," 2021 3rd International Conference on Sustainable Technologies for Industry 4.0 (STI), Dhaka, Bangladesh, 2021, pp. 1-6, doi: 10.1109/STI53101.2021.9732592.
[7] Ukiwe, E.K., Adeshina, S.A., Jacob, T. et al. Deep learning model for detection of hotspots using infrared thermographic images of electrical installations. Journal of Electrical Systems and Information Technology 11, 24 (2024). https://doi.org/10.1186/s43067-024-00148-y.
[8] El-Shahat, D., Tolba, A., Abouhawwash, M. et al. Machine learning and deep learning models based grid search cross-validation for short-term solar irradiance forecasting. J Big Data 11, 134 (2024). https://doi.org/10.1186/s40537-024-00991-w.
[9] Kirubakaran, V., Preethi, D. M. D., Arunachalam, U., Rao, Y. K. S. S., Gatasheh, M. K., Hoda, N., Anbese, E. M. (2022). Infrared thermal images of solar PV panels for fault identification using image processing technique. The Scientific World Journal, 2022, Article ID 6427076. https://doi.org/10.1155/2022/6427076
[10] Liao, K. C. and Lu, J. H. (2020). Using Matlab real-time image analysis for solar panel fault detection with UAV. Journal of Physics: Conference Series, 1509, 012010. The 10th Asian-Pacific Conference on Aerospace Technology and Science The 4th Asian Joint Symposium on Aerospace Engineering (APCATS'2019 / AJSAE'2019), 28-31 August 2019, National Chiao Tung University, Hsin Chu, Taiwan. https://doi.org/10.1088/1742-6596/1509/1/012010
[11] AlMarzooqi, H. (2023). Defect Detection of Photovoltaic Panels by Image Processing. Rochester Institute of Technology.
[12] Zhang, X., Araji, M. T. (2023). Snow loss modeling for solar modules using image processing and deep learning. Sustainable Energy, Grids and Networks, 34, 101036. https://doi.org/10.1016/j.segan.2023.101036.
[13] Patel, A.V., McLauchlan, L., Mehrubeoglu, M. (2024). Defect Detection in PV Arrays Using Image Processing. Department of Electrical Engineering and Computer Science, Texas AM University-Kingsville, Kingsville, Texas, USA
[14] Hu, X., Du, Z. Wang, F. Research on detection method of photovoltaic cell surface dirt based on image processing technology. Sci Rep 14, 16842 (2024). https://doi.org/10.1038/s41598-024-68052-z
[15] Vlaminck, M., Heidbuchel, R., Philips, W., Luong, H. (2022). Region-Based CNN for Anomaly Detection in PV Power Plants Using Aerial Imagery. Sensors, 22(3), 1244. https://doi.org/10.3390/s22031244.
[16] M. Zhang and L. Yin, "Solar Cell Surface Defect Detection Based on Improved YOLO v5," in IEEE Access, vol. 10, pp. 80804-80815, 2022, doi: 10.1109/ACCESS.2022.3195901.
[17] Prabhakaran, S., Uthra, R. A., Preetharoselyn, J. (2023). Deep learning-based model for defect detection and localization on photovoltaic panels. Computer Systems Science Engineering, https://doi.org/10.32604/csse.2023.028898.
[18] S. Salamanca, P. Merchán and I. García, "On the detection of solar panels by image processing techniques," 2017 25th Mediterranean Conference on Control and Automation (MED), Valletta, Malta, 2017, pp. 478-483, doi: 10.1109/MED.2017.7984163.
[19] Natarajan, K., Bala, P.K., Sampath, V. (2020). Fault Detection of Solar PV System Using SVM and Thermal Image Processing. International Journal of Renewable Energy Research (IJRER), 10(2).
[20] Anwar, S.A., Abdullah, M.Z. Micro-crack detection of multicrystalline solar cells featuring an improved anisotropic diffusion filter and image segmentation technique. J Image Video Proc 15, (2014). https://doi.org/10.1186/1687-5281-2014-15