Solar Panel Defect Detection Using Deep Learning

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***Abstract*—Solar energy is the most sustainable renewable energy, but the performance of solar panels is often reduced due to various faults like dust, snow, bird droppings, and physical or electrical damages. Manual inspection solar panel is labor-intensive and are prone to error. This paper presents a deep learning-based fault detection system that automatically identifies six types of solar panel surface conditions using convolutional neural networks (CNNs). Multiple pre-trained models—EfficientNetB0, ResNet50, InceptionV3, VGG16, and MobileNetV2—were trained and evaluated on a Kaggle dataset containing labeled solar panel images. Comparative analysis and ensemble averaging were performed to enhance overall accuracy.**

***Index Terms*—Solar energy, Deep learning, CNN, Fault detection, Image classification, Ensemble learning.**

I. Introduction

Solar panels convert sunlight into electrical energy and are sources of renewable energy infrastructures. However, environmental and physical factors can cause performance degradation and faults, including accumulation of dust, snow, bird droppings, and structural damage. These faults significantly reduce energy generation efficiency and can go undetected without proper monitoring systems. Traditional inspection methods rely on manual observation or infrared thermography, which are time taking, costly and are prone to human error. Recent advancements in deep learning and computer vision have enabled the automation of image-based fault detection with remarkable precision. This work aims to develop and evaluate convolutional neural network (CNN) models for solar panel fault detection.

II. Dataset

The dataset used was obtained from *Kaggle* [1] and consists of **869 labeled images** of solar panels under various environmental and operational conditions. It includes six classes:

Class	Number of Images
Bird-drop	191
Clean	193
Electrical-damage	103
Snow-covered	123
Dusty	190
Physical-damage	69

All images were scaled to 224×224 pixels and normalized. Data augmentation techniques including rotation, flipping, and brightness adjustment were applied to prevent overfitting.

III. Model Architecture

Five popular CNN architectures pre-trained on ImageNet [1], [2] were used for transfer learning:

- ResNet50: A 50-layer deep CNN,introduces residual connections to solve the problem of vanishing gradient.
- VGG16: A 16-layer CNN architecture which uses 3×3 convolutional filters stacked together captures fine image details
- InceptionV3: A 48-layer deep CNN built around parallel inception modules,uses multi-scale convolutions to capture different spatial features efficiently.
- MobileNetV2: A lightweight CNN with inverted residual blocks with bottlenecks and depthwise separable convolutions
- EfficientNetB0: A CNN that does compound scaling to achieve optimal performance.

Each model's top layers were replaced with custom dense layers tailored to six-class classification, followed by an activation layer.

IV. Model Training and Results

A. Binary Classification

1) Overview: In this stage, the dataset was reorganized into two primary categories: **Defective** and **Non-Defective**. The objective was to perform a high-level classification to determine whether a given solar panel image shows any fault or is in good condition. The defective class includes panels with physical damage, electrical damage combined whereas the non-defective class represents clean, dust, snow, and bird drop panels combined. In order to balance the classes, the non-defective class was divided into 4 batches of equal size. Then the 4 split balanced batches containing the defective class and a batch of non-defective class in each of the batches is subjected to train, test split. The split balanced batch's 70% of the data was used to train, 20% to validate, 10% to test.

2) Data Organization: The original dataset consisting of six classes was divided into:

- Class 0 — Defective (Electrical Damage, Physical Damage)
- Class 1 — Non-Defective (Clean, Dusty, Snow-Covered, Bird-drop)

All images were scaled to 224×224 pixels and augmented using rotation, flipping, and brightness variation to improve the performance of the model.

3) Training Configuration: Each model was trained using the following:

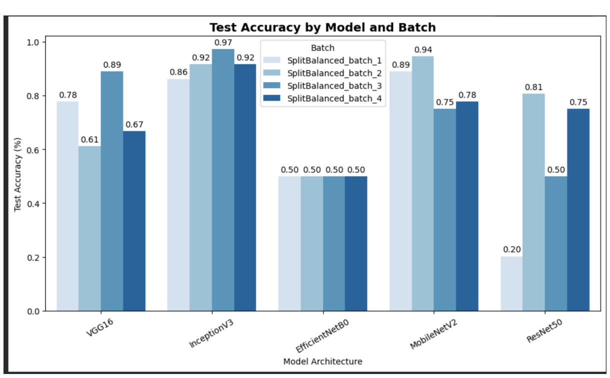
- Optimizer: Adaptive Moment Estimation
- Loss Function: Binary Cross Entropy
- Metric: Accuracy
- Batch Size: 32
- Image Size: 224×224
- Epochs: 10

Early stopping and model checkpoint were used to avoid overfitting and to keep the model that performed best during training. For every base model, the last layers were replaced with a GlobalAveragePooling2D layer, followed by a Dense layer with 128 units and ReLU activation, and an output layer with 1 unit and a Sigmoid activation function for binary classification.

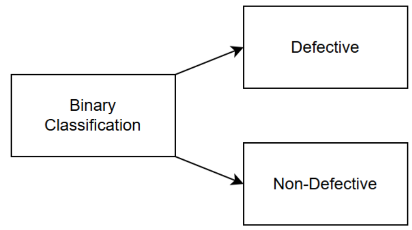
4) Results: The batch wise test and validation accuracies and the visualized plots are displayed below:

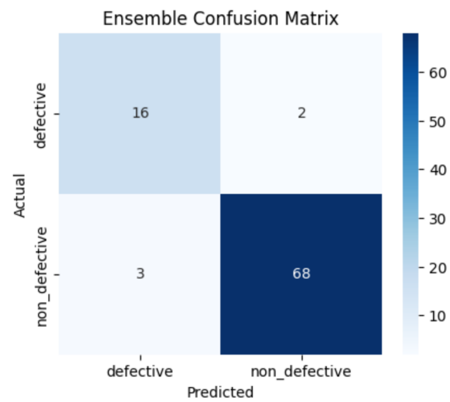
Batch	Model	Validation Accuracy (%)	Test Accuracy (%)
SplitBalanced_batch_1	VGG16	73.53	77.78
SplitBalanced_batch_1	InceptionV3	89.71	86.11
SplitBalanced_batch_1	EfficientNetB0	50.00	50.00
SplitBalanced_batch_1	MobileNetV2	82.35	88.89
SplitBalanced_batch_2	ResNet50	72.06	80.56
SplitBalanced_batch_2	VGG16	54.41	61.11
SplitBalanced_batch_2	InceptionV3	89.71	91.67
SplitBalanced_batch_2	EfficientNetB0	50.00	50.00
SplitBalanced_batch_2	MobileNetV2	83.82	94.44
SplitBalanced_batch_3	ResNet50	50.00	50.00
SplitBalanced_batch_3	VGG16	89.71	88.89
SplitBalanced_batch_3	InceptionV3	91.18	97.22
SplitBalanced_batch_3	EfficientNetB0	50.00	50.00
SplitBalanced_batch_3	MobileNetV2	73.53	75.00
SplitBalanced_batch_4	ResNet50	66.18	75.00
SplitBalanced_batch_4	VGG16	63.24	66.67
SplitBalanced_batch_4	InceptionV3	91.18	91.67
SplitBalanced_batch_4	EfficientNetB0	50.00	50.00
SplitBalanced_batch_4	MobileNetV2	70.59	77.78

Batch-wise Validation and Test Accuracy for Binary Classification Models



An ensemble model was made by taking the average of all these models and has acquired the accuracy of 92.33%.





B. *Binary Classification-Defective*

1) Overview: In this stage, the defective class was reorganized into two primary categories: **Physical-damage** and **Electrical-damage**. The objective was to perform a high-level classification to determine whether a given solar panel image shows physical or electrical damage. In order to balance the defective classes, the images were augmented and made of equal size. Then the augmented dataset is subjected to train test split. The split balanced batch's 70% of the data was used to train, 15% to validate, 15% to test.

2) Data Organization: The defective class is divided into:

- Class 0 — Electrical Damage
- Class 1 — Physical Damage

All images were scaled to 224×224 pixels and augmented using rotation, flipping, and brightness variation to improve the performance of the model.

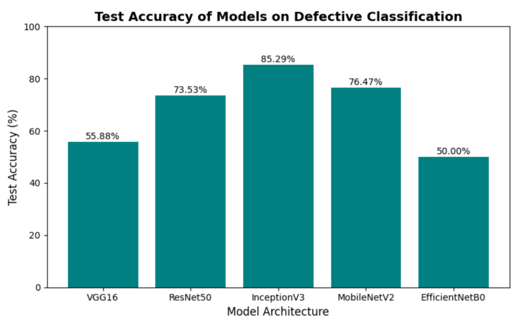
3) Training Configuration: Each model was trained using the following:

- Optimizer: Adaptive Moment Estimation with learning rate 1×10^{-4}
- Loss: Categorical Cross Entropy
- Metric: Accuracy
- Batch size: 32
- Image size: 224×224
- Epochs: 25 (with early stopping)

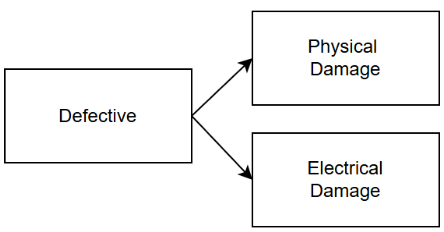
For the defective subset (Electrical vs Physical), transfer learning was applied with the base networks' weights frozen. The top of each model was replaced with a classification head consisting of a GlobalAveragePooling2D layer, a Dropout(0.4) layer for regularization, and a two-unit Dense output layer with softmax activation

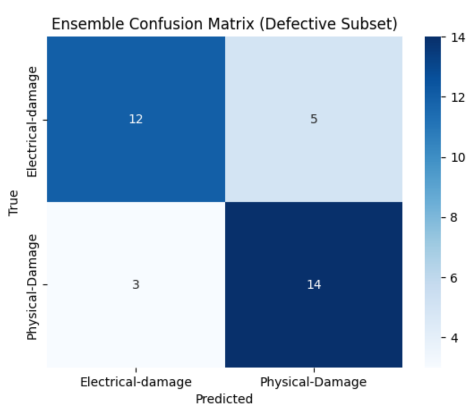
4) Results: The test accuracy of defective class models is shown below:

Model	Validation Acc. (%)	Test Acc. (%)
VGG16	83.33	55.88
ResNet50	70.00	73.53
InceptionV3	93.33	85.29
MobileNetV2	90.00	76.47
EfficientNetB0	50.00	50.00

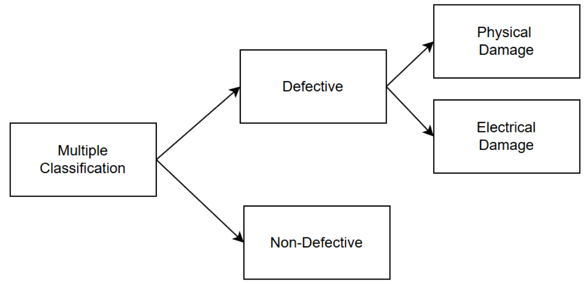


An ensemble model was made by taking the average of all these models and has acquired the accuracy of 76.47%.





Another ensemble model is made for the whole pipeline combined till now. The model can detect if a image is non-defective or defective, if defective then physical or electrical damage. This has achieved an accuracy of 73.33%.



C. Binary Classification-Nondefective

1) Overview: In this stage, the non-defective class was reorganized into two primary categories: **Clean** and **Non-clean**. The objective was to perform a high-level classification to determine whether a given solar panel image shows any clean or non-clean image. Inorder to balance the non-defective classes the images of non - clean class are splitted in batches of equal size. Then the split balanced batches of non - defective class and defective class dataset is subjected to train test split. The split balanced batch's 70% of the data was used to train, 15% to validate, 15% to test.

2) Data Organization: The defective class is divided into:

- Class 0 — Clean
- Class 1 — Non-clean(includes Dusty, Snow-Covered, Bird-drop)

All images were scaled to 224×224 pixels and augmented using rotation, flipping, and brightness variation to improve the performance of the model.

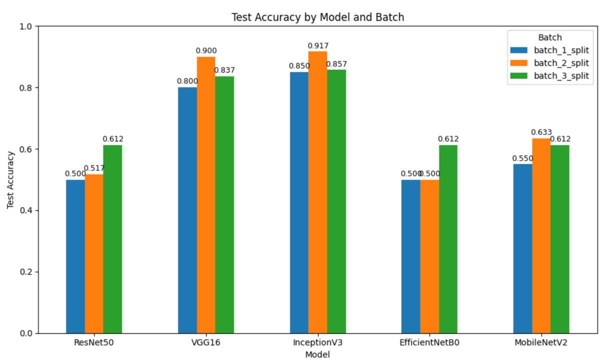
3) Training Configuration: Each model was trained using the following:

- Optimizer: Adaptive Moment Estimation with learning rate 1×10^{-4}
- Loss: Binary Cross Entropy
- Metric: Accuracy
- Batch size: 32
- Image size: 224×224
- Epochs: 25 (with early stopping monitoring)

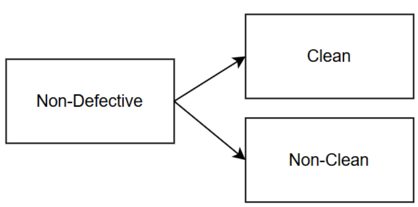
For the non-defective subset (Clean vs Non-clean), transfer learning was applied using ImageNet-pretrained base networks. Each models top was replaced with a binary classification head consisting of a GlobalAveragePooling2D layer, a Dropout(0.4) layer for regularization, and a single-unit dense output layer with a sigmoid activation function.

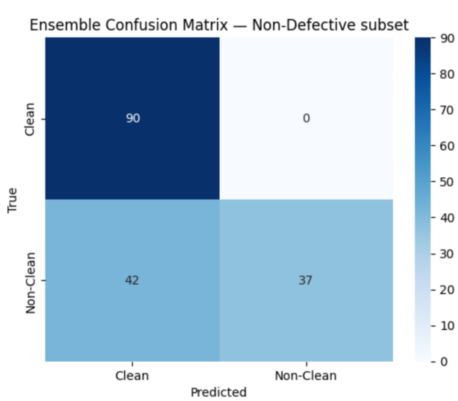
4) Results: The test accuracy of non-defective class models is shown below:

Batch	Model	Test Accuracy (%)
batch_1_split	EfficientNetB0	50.00
batch_1_split	InceptionV3	85.00
batch_1_split	MobileNetV2	55.00
batch_1_split	ResNet50	50.00
batch_1_split	VGG16	80.00
batch_2_split	EfficientNetB0	50.00
batch_2_split	InceptionV3	91.67
batch_2_split	MobileNetV2	63.33
batch_2_split	ResNet50	51.67
batch_2_split	VGG16	90.00
batch_3_split	EfficientNetB0	61.22
batch_3_split	InceptionV3	85.71
batch_3_split	MobileNetV2	61.22
batch_3_split	ResNet50	61.22
batch_3_split	VGG16	83.67

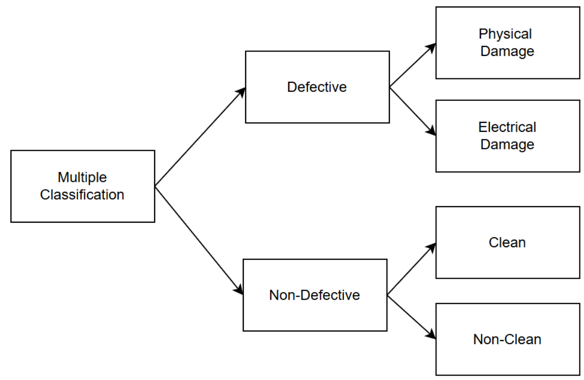


An ensemble model was made by taking the average of all these models and has acquired the accuracy of 75.15%.





Another ensemble model is made for the whole pipeline combined till now. The model can detect if a image is non-defective or defective, if defective then physical or electrical damage if non-defective then clean or non-clean. This has achieved an accuracy of 71.43%.



D. Multi Triple Classification

1) Overview: In this stage, the non-clean class was reorganized into three primary categories: **Snow**, **Bird-drop** and **Dust**. The objective was to perform a high-level classification to determine whether a given solar panel image shows snow, dust or bird-drop. In order to balance the non-defective, non-clean classes the images were augmented and made of equal size. Then the augmented dataset is subjected to train, test split. The split balanced batch's 70% of the data was used to train, 15% to validate, 15% to test.

2) Data Organization: The defective class is divided into:

- Class 0 — Bird-drop
- Class 1 — Dust
- Class 2 - Snow

All images were scaled to 224×224 pixels and augmented using rotation, flipping, and brightness variation to improve the performance of the model.

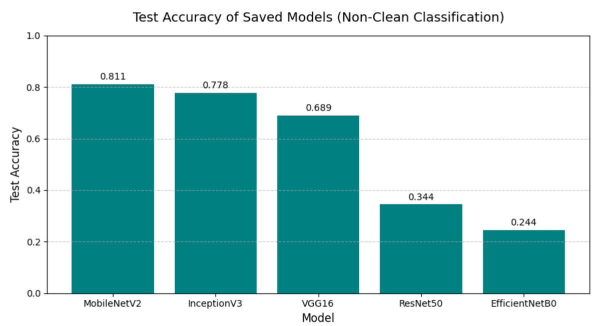
3) Training Configuration: Each model was trained using the following:

- Optimizer: Adaptive Moment Estimation with learning rate 1×10^{-4}
- Loss: Categorical Cross Entropy
- Metric: Accuracy
- Batch size: 32
- Image size: 224×224
- Epochs: 25 (with early stopping)

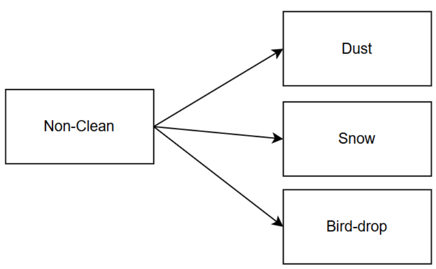
For the non-defective, non-clean subset (Snow vs Dust vs Bird-drop), transfer learning was applied with the base networks' weights frozen. Each model's top was replaced with a classification head consisting of a GlobalAveragePooling2D layer, a Dropout(0.4) layer for regularization, and a two-unit Dense output layer with a softmax activation.

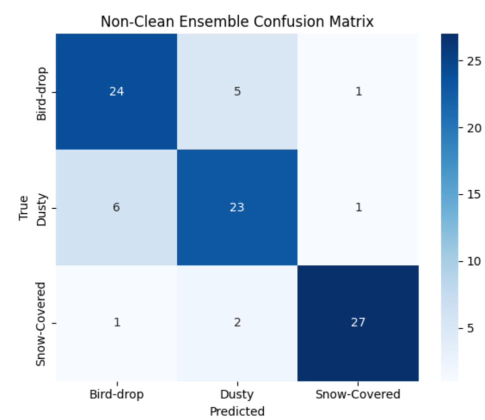
4) Results: The test accuracy of non-defective, non-clean class models is shown below:

Model	Test Accuracy (%)
EfficientNetB0	24.44
InceptionV3	77.78
MobileNetV2	81.11
ResNet50	34.44
VGG16	68.89

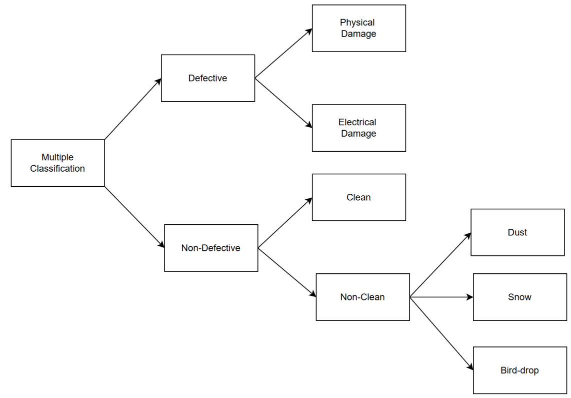


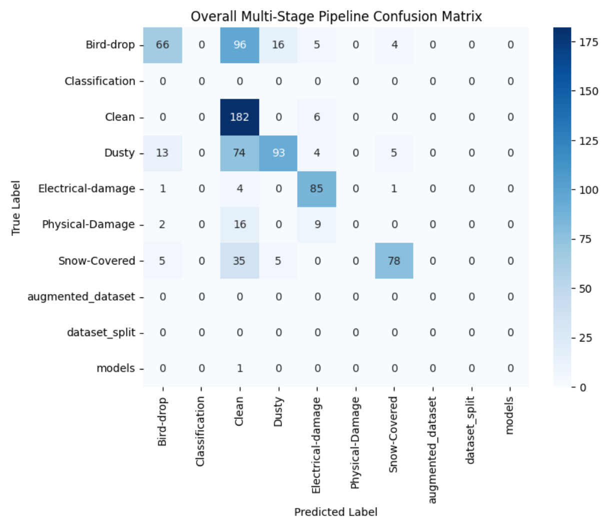
An ensemble model was made by taking the average of all these models and has an accuracy of 82.22%.





Another ensemble model is made for the whole pipeline combined till now. The model can detect if a image is non-defective or defective, if defective then physical or electrical damage. This has achieved an accuracy of 57.93%.





E. Multi six Classification

1) Overview: In this stage, the dataset is in six primary categories: **Physical-damage**, **Electrical Damage**, **Clean** and **Dust**, **Snow** and **Bird-drop**. The objective was to perform a high-level classification to determine whether a given solar panel image shows any of 6 categories. Inorder to balance the classes all the classes are augmented and made of equal size. Then the augmented is subjected to train test split. The split balanced batch's 70% of the data was used for training, 20% for validation, 10% for testing.

2) Data Organization: All images were scaled to 224×224 pixels and augmented using rotation, flipping, and brightness variation to improve model performance.

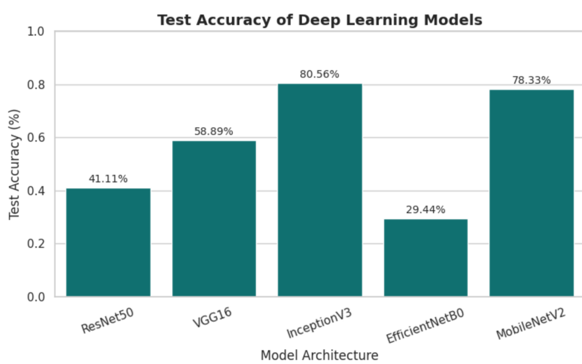
3) Training Configuration: Each model was trained using the following:

- Optimizer: Adaptive Moment Estimation
- Loss Function: Binary Cross Entropy
- Metric: Accuracy
- Batch Size: 32
- Image Size: 224×224
- Epochs: 10

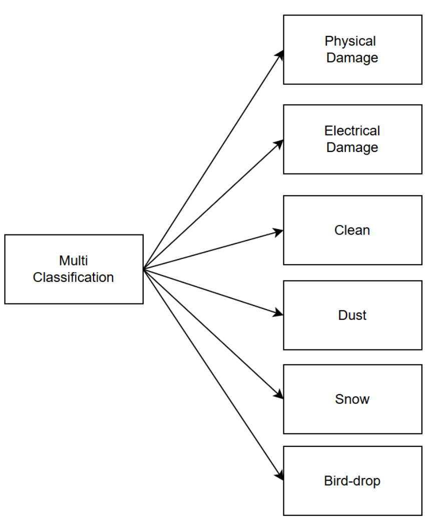
Early stopping and model checkpoints were used to prevent overfitting and to save the best-performing model. For each base model, the last layers were replaced using a GlobalAveragePooling2D layer, then a Dense layer with 128 neurons and ReLU activation, followed by an output layer with a single neuron and Sigmoid activation for classification tasks.

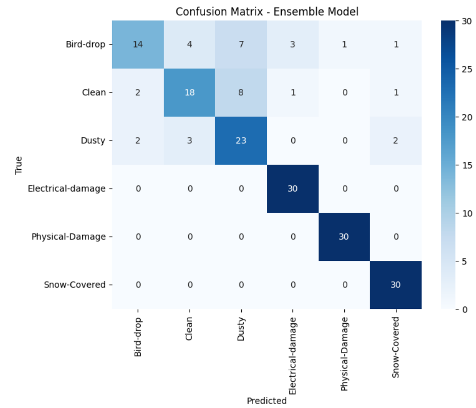
4) Results: The batch wise accuracies are displayed below:

Model	Test Accuracy (%)
ResNet50	41.11
VGG16	58.89
InceptionV3	80.56
EfficientNetB0	29.44
MobileNetV2	78.33



An ensemble model was made by taking the average of all these models and has an accuracy of 80.56%.





Acknowledgment

The authors would like to thank the Department of Computer Science and Engineering at IIIT-Vadodara for providing the support for this project. Special thanks to the faculty mentor Dr. B. Venkata Phani Krishna for valuable guidance and feedback throughout the project. We also thank Kaggle for providing the solar panel image dataset for public use which is used in this study.

References

[1] R. G. Rohith, D. S. Manish, R. N. A. Rahul, A. U. Dhavale, and R. R. John, “SparkNet—A Solar Panel Fault Detection Deep Learning Model,” *IEEE Access*, vol. 13, pp. 45678–45689, Apr. 2025, doi: 10.1109/ACCESS.2025.3564714.

[2] M. Abdelsattar, A. Abdelmoety, M. A. Ismeil, and A. Emad-Eldeen, “Automated Defect Detection in Solar Cell Images Using Deep Learning Algorithms,” *IEEE Access*, vol. 13, pp. 1234–1246, Jan. 2025, doi: 10.1109/ACCESS.2024.3525183.

[3] Kaggle, “Solar Panel Images Clean and Faulty Images ,” Available: https://www.kaggle.com/datasets/pythonafroz/solar-panel-images, accessed: Sep. 2025.