Automated Anomaly Detection and Localization in Solar Panels Using Deep Learning Models

MSc Research Project
Artificial Intelligence

Muhammad Usama
Student ID: X23240636

School of Computing
National College of Ireland

Supervisor: Anderson Augusto Simiscuka

National College of Ireland
Project Submission Sheet
School of Computing

Student Name:	Muhammad Usama
Student ID:	X23240636
Programme:	Artificial Intelligence
Year:	2024
Module:	MSc Research Project
Supervisor:	Anderson Augusto Simiscuka
Submission Due Date:	12/12/2024
Project Title:	Automated Anomaly Detection and Localization in Solar Panels Using Deep Learning Models
Word Count:	6456
Page Count:	21

I hereby certify that the information contained in this (my submission) is information pertaining to research I conducted for this project. All information other than my own contribution will be fully referenced and listed in the relevant bibliography section at the rear of the project.

ALL internet material must be referenced in the bibliography section. Students are required to use the Referencing Standard specified in the report template. To use other author's written or electronic work is illegal (plagiarism) and may result in disciplinary action.

Signature:	
Date:	12th December 2024

PLEASE READ THE FOLLOWING INSTRUCTIONS AND CHECKLIST:

Attach a completed copy of this sheet to each project (including multiple copies).	☐
Attach a Moodle submission receipt of the online project submission, to each project (including multiple copies).	☐
You must ensure that you retain a HARD COPY of the project, both for your own reference and in case a project is lost or mislaid. It is not sufficient to keep a copy on computer.	☐

Assignments that are submitted to the Programme Coordinator office must be placed into the assignment box located outside the office.

Office Use Only	
Signature:	
Date:	
Penalty Applied (if applicable):	

Automated Anomaly Detection and Localization in Solar Panels Using Deep Learning Models

Muhammad Usama
X23240636

Abstract

Fault detection and localization in photovoltaic (PV) panels is a critical step in ensuring the efficiency and reliability of solar power systems. This research focuses on automating the process by applying advanced deep learning techniques, combining anomaly detection and fault localization in a comprehensive two-tier architecture. The system focuses on three key components: detecting anomalies, localizing faults, and evaluating the performance of the methodologies. For anomaly detection, the VGG19 model with transfer learning and fine-tuning was applied, achieving a training accuracy of more than 95% and a validation accuracy of more than 83%. For fault localization, the YOLOv8s model was used, which effectively localizes the faulty areas in the PV panels. The performance of these models was evaluated based on precision, accuracy, and robustness in real-world scenarios. The results show the system's ability to significantly reduce manual inspection efforts, enhance fault detection accuracy, and improve the operational efficiency of PV installations. This research shows the potential of integrating classification and localization techniques in building intelligent monitoring systems for solar energy applications.

Keywords: Anomaly Detection, Fault Localization, VGG19, YOLOv8s, Photovoltaic Panels, Deep Learning, Transfer Learning, Solar Energy Monitoring

1 Introduction

As a result of the global movement shifts towards the utilization of renewable energy, solar energy has become one of the main sources of clean and renewable energy that is very important in the realization of the United Nations sustainable development goals, elimination of carbon emissions that cause climate change impacts and meeting the growing global population energy demands. Since the solar panels are the main products utilized in the solar energy systems, have received enormous demand in the last few years across the word. This growth is enabled by installation of these systems in residential rooftops, mid-large commercial applications as well as utility scale solar powering farms. There were increased installations of the solar panels in 2024 compared to the previous year's installations,(Graham and Fulghum, 2024) and primarily based on expert data, the installations are expected to skyrocket in future years. But this has also led to new focal issues as to how to maintain the efficiency and longevity of solar panels.

However, several issues are still coming up when trying to meet the intended performance as well as reliability of the PV systems. It also the fact that dust, snow, damages, electrical issues, and bird droppings reduce the efficiency of the panels. The previous method of inspection and maintenance was not reliable and slow because these were manual and could not address situation where there were many solar power plants. Due to all these issue, it is very important to make computerized techniques to control the solar panels and their use while minimizing unnecessary downtime.

This project, titled *"Solar Panel Automated Anomaly Detection and Localization Using Deep Learning"*, addresses these challenges in the following ways. The system uses the VGG19 CNN for anomaly classification and YOLOv8 for fault detection localization. Solar panels are categorized into six classes—clean, dust, snow, damage, electrical problem, and bird droppings—and reflect the exact coordinates of each problem by placing bounding boxes around the problematic areas. This dual approach enables precise maintenance that enhances operation while minimizing losses in plants and other installations.

This is why the present study matters: previous approaches are insufficient, and the need for this information is evident. The techniques employed in the past were relatively simple, slow, and far from accurate or relied on manual sweeps incapable of recognizing or analyzing these issues on large sets of data. Although research has been conducted for creating models based on weather data or thermal imaging to detect degrading panels (Spajić et al., 2024), such approaches do not necessarily provide information on localizaing the faulty areas. Similarly, other fault detection technologies already in use in their own fields such as infrastructure monitoring and industrial defect detection. Increaing solar energy demands also need the advanced fault detection technologies for the panel monitoring, showing the versatility of enhanced methodologies. CNNs, among deep learning models, have revolutionized image-based anomaly detection and brought scalability and accuracy.

This work further extends these improvements by utilizing the feature extraction functionality of the VGG19 model and applying the real-time object detection performance of YOLOv8s. On the detection aspect, a high-level feature extractor VGG19 is used to classify the panel condition through extended visual segmentation, while the localization aspect makes use of the efficient object detection algorithm YOLOv8s to identify specific coordinates of the faults observed on the panel. Real-world performance will be assessed using accuracy, IoU, and mAP, while the system's quality will be tested across different environmental and operational contexts.

1.1 Research Objective

The main objective of this project is to automate anomaly detection and fault localization processes in photovoltaic (PV) panels using deep learning techniques. By using VGG19 for classification and YOLOv8s for localization, the system aims to improve the accuracy and scalability of solar panel monitoring, ultimately increasing maintenance efficiency and reducing operational downtime in large-scale solar energy systems.

1.2 Research Question

This study addresses the following research question:

"To what extent an automated classification and localization techniques improve the monitoring and maintenance of solar panels by providing accurate detection and localization of various anomalies?"

1.3 Paper Structure

This paper is structured as follows: Section 2 reviews the related work in the field of solar panel anomaly detection and localization. Section 3 describes the Methodology for both Anomaly detection and Fault Localization. Section 4 outlines the Design Specifications, including the use of VGG19 for anomaly detection and YOLOv8 for fault localization. Section 5 provides all the details on the implementation of the proposed system. Section 6 presents the evaluation and results, showcasing the model's performance. Section 7 discusses the findings, limitations, and practical implications of the study. Lastly, Section 8 concludes the study and proposes future directions for enhancing solar panel monitoring systems.

This project is set on automating the methods of anomaly detection and fault localization, leading to the improvement of solar panel monitoring and maintenance. The Main aim is to address the scalability challenges of a continuously advancing solar energy industry while maintaining the effectiveness and functionality of renewable energy systems.

2 Related Work

This section highlights the various different studies related to the current research and provides a foundational understanding of photovoltaic (PV) systems, data analysis approaches, and statistical learning methodologies. Additionally, it identifies the research gap addressed by this study.

2.1 Deep Learning for Anomaly Detection in Solar Panels

Machine learning has emerged as an important component of anomaly detection techniques in solar panels, providing accurate results with the minimal human intervention. Traditional methods, such as manual inspection or basic AI algorithms, often fail to analyze large scale datasets or adapt to varying environmental conditions. This subsection presents several recent works employing deep learning for anomaly detection in solar panels.

(Khedkar et al., 2024) Proposed a VGG16-based deep learning model for classifying solar panels into six categories: ideas related to the clean, dusty, snowy, bird-dropping, implantation, physical as well as electrical distortion. By using transfer learning, the training accuracy achieved was 95% and the validation accuracy was 82%. But the study outlined some limitations including shading and lighting while noting that more advancements continue to be made in automated solar panel monitoring.

(Bommes et al., 2021) Proposed a pseudo–anomaly detection method for the photovoltaic (PV) module infrared images with the supervised contrastive learning with the k–Nearest Neighbor (k–NN) classifier. The system oversolved domain shift and new fault detection problems, yielding AU ROC values between 73.3% and 96.6%. Consequently, this research demonstrates the feasibility of contrastive learning for anomaly detection in PV plants leading to scalable and automated maintenance.

(Shaik et al., 2024) Proposed an extended version of AUNet for boundary detection and damage segmentation in solar panels involving an ASPP module. The model obtained 98% of segmentations and 95% of Mean IoU. Classification using the five different levels of damage was done with a 98% classification accuracy achieved through transfer learning using VGG19. Specifically, this study focussed on the ability of the system in monitoring solar farms via unmanned aerial vehicles UAV.

(Nabti et al., 2022) Focused on predictive maintenance solutions for PV panels by analyzing soiling effects and optimizing cleaning strategies. By using machine learning algorithms, the study proposed integrating intelligent sensors and AI frameworks for efficient maintenance, reducing operational costs in large-scale installations.

(Pathak and Patil, 2023) Investigated preprocessing techniques for fault detection in thermal images, achieving a peak IoU of 0.54 for single-cell hotspots. The study emphasized the importance of preprocessing in enhancing image quality and fault localization accuracy.

Recent development of deep learning has enabled the establishment of dependable methods for identifying defects within printed circuit board (PCB) products. In a strong and complete framework described by (Bhattacharya and Cloutier, 2022) we used Single Stage Object Detection algorithm to classify the manufacturing defects of PCB shortly with highly valid outcome. Their proposed method is higher than other high-performing models, like YOLOv5m and Faster R-CNN-ResNet50, by reaching higher mAP from a low-resolution image from 94.9% from higher previous techniques up to 98.1%, a 3.2% enhancement. This framework combines a transformer-based model and can sufficiently concurrently apply CNNs and multi-hierarchical feature fusion to increase the detector's accuracy for the identification and positioning of defects. Besides, their method also decreases computational cost; it is three times less number of parameters than more models, therefore, it is likely to be applied to real time industry. Thus the study also provides urgency to integrate deep learning techniques in AOI for improving multi-defect-free models manufacturing.

2.2 Object Detection Techniques for Fault Localization

Deep learning has also been applied effectively for fault localization in solar panels.

(Duan and Ma, 2024) Proposed a UAV-based system using a thermal camera and GPS for real-time fault detection with an improved YOLOv3-tiny model. The system achieved a mean average precision (mAP) of 96.5%, demonstrating its suitability for challenging environments.

(Di Tommaso et al., 2022)Developed object detection models with YOLOv2 and ResNet50 for feature extraction, achieving a detection accuracy of 93%. The study highlighted the importance of varied training data in improving model efficiency for solar facility management.

(Han et al., 2021) Utilized UAVs with thermal cameras and improved YOLOv3-tiny models for efficient fault detection in extreme environments. The system provided actionable insights for maintaining PV systems in inaccessible regions.

In the paper related to RA et al. (2024), the smart solar panel monitoring system using machine learning and CNNs is devised for damage detection and real-time monitoring of the parameters. The framework combines image processing, IoT, and embedded systems to observe porosity including cracks, dust, or heat, and perform automatic maintenance with a Raspberry Pi Arduino, and ESP32. The real-time monitoring of voltage and current along with incorporating effective dust cleaning mechanism prolong the efficiency, availability, and durability of the solar panels. Such IoT connectivity in the cloud allow for data aggregation as a key to integrated sustainable energy production, and new approach to maintenance.

According to the research work of (Jia et al., 2024), there is an improved approach for detecting the defects of Photovoltaic (PV) modules by improving the performance of the VarifocalNet model. The researchers offered a solution to the challenge of determining the defects such as cracks, scratches and black cores that are so devastating to the PV module's performance and reliability. Main innovations include: presenting new bottleneck modules which introduce depth and receptive field into the network while keeping the size of the feature map small to enhance accuracy. The intermediate layer interactor is integrated into the feature pyramid network's detection head to facilitate further feature interaction by means of dynamic convolution; in addition, a new regression loss enhances the estimates for the bounding box regression. Experimentation on PVEL-AD dataset reveals that the proposed approach achieves better accuracy and almost similar speed as compared to other techniques to provide viable solution for identifying PV module defects.

As demonstrated in the paper by (Shen et al., 2024), an improved YOLOv5 model known as PCBA-YOLO is developed to solve the problem of defects in Printed Circuit Board Assemblies. The major alterations include replacing the first network components with the spatial pyramid pooling module with cross-stage partial structure (SPPCSPC) in an attempt to improve the combination of features, and a large kernel convolutional module (RepLKNet) used to increase receptive fields. Furthermore, the loss function was updated from original to SIoU to yield better performances and convergence rate. The study also developed a new dataset, called PCBA-DET, comprising 4000 images and 8 types of defect labels. Experiments demonstrated that the result accuracy of the proposed model was higher than YOLO-based models; mAP@0.5 reached 97.3% and the frame rate was 322.6 FPS for applying the model to industrial-level scenarios.

2.3 Need for Automated Solar Panel Fault Management

Automated solar panel fault management is required because conventional methods of inspecting the faults are not efficient enough. This project introduces a framework based on VGG19 and YOLOv8, enabling dual functionality: fault prediction, anomaly detection and fault localization. The categorization of panel conditions and the accurate determination of the precise location of abnormalities contribute to the improvement of maintenance methods, minimization of working interruptions, and great scalability.

This paper by (Shaikh et al., 2017) will endeavour to explore further and ask if and why solar energy is feasible and necessary as a green electricity produced from sunlight. To begin this discussion, it notes that solar energy is sufficient and can meet the global energy demands given estimations that the earth receives sufficient solar energy in one hour to power the world for a whole year. Photovoltaic energy is targets as global and inexhaustible electric power source for investor, commercial and residential applications with clean electricity from sunlight. It also concerns working principles of solar energy systems, types, and use of solar panels This is among other things that makes the review both timely and relevant. They have also discussed on the opportunities for solar energy including something like cost, sustainability and availability of solar energy over the fossil energy. In addition, it's aimed at illustrating the progress in photovoltaic technology to enhance the efficiency of the conversion and reducing the cost of energy conversion and discussing the growth of importance of solar energy with the view of addressing the challenges resulting from the exhaustion of non-renewable energy sources and negative environmental impact. Thus, to increase their efficiency, proper fault detection and fault localization, as the key part of solar panels, used for energy production, are crucial. This analysis of how photovoltaic panels are maintained reveals that fault management is an important aspect of maintaining solar energy systems as it helps to produce optimum results while increasing the longevity of the panels and minimising their downtime.

2.4 Significance of Fault Detection and Localization in Solar Panel Systems

Fault detection and especially localization are extremely important and it is best underscored by the study by (Sohail et al., 2023). Applying U-Net and LinkNet models with electroluminescence imaging, their work extracted accurate defect segmentation and classification. It guarantees the right maintenance approach and increases the lifespan of the PV modules and makes it possible to achieve sustainable energy solutions.

3 Methodology

This section outlines the research method employed, data preprocessing, data augmentation techniques, model architecture and fine-tuning, evaluation matrix, and types of results obtained. The approach for this study is twofold, based on the two corresponding steps of fault classification and fault localization.

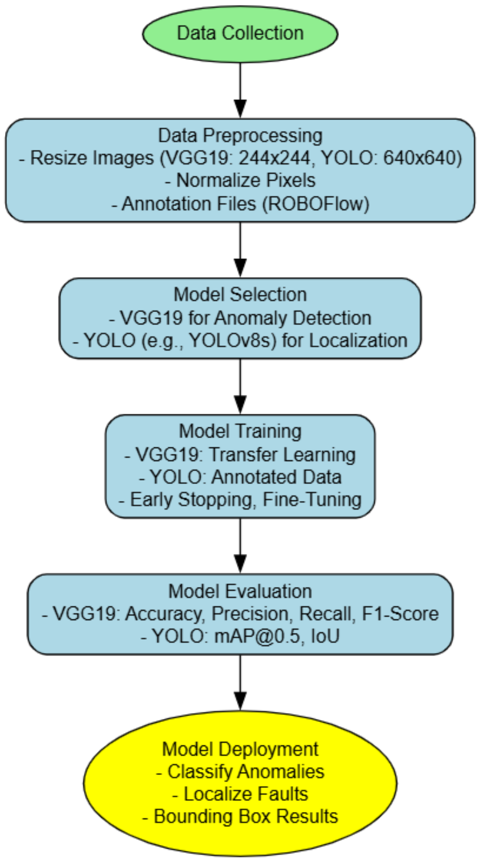

Figure 1: Research Methodology of PV Panel Anomaly detection and Localization

3.1 Data Collection

The dataset for this project was obtained from Kaggle with a total of 869 image files of photovoltaic (PV) panels. This data set can be accessed through this link:kaggle Dataset Link. These images were divided into six distinct classes, representing different conditions of solar panels: Bird-drop, Clean, Dusty, Electrical-damage, Physical-Damage, and Snow-Covered. This dataset is sourced because of its variety of anomalies and normal conditions, ensuring comprehensive training and evaluation of the system.

In the first part of the project, which is about anomaly detection, the dataset contained only labeled images. These images were then further split into training, validation, and test sets to be used with the VGG19 model to categorize the solar panels into the aforementioned six categories.

For the second part of the project, YOLO V8s was used to perform fault localization, and bounding box annotations were needed to train the YOLO models. Nevertheless, the dataset imported from Kaggle did not contain any annotation files. Therefore, all the annotation files were created manually, one by one, using the ROBOFlow application. Each image was uploaded to ROBOFlow, and bounding boxes were carefully drawn around the anomalies in each image. The annotated data was exported in the desired YOLO format, generating a .txt file for each image. These annotation files contained the class labels and the coordinates of bounding boxes that were used to train the YOLO models in order to localize the faults. The manually created annotation files are stored on Google Drive and can be accessed using the following link: Annotation Files.

3.2 Data Preprocessing

3.2.1 For Anomaly Detection

The dataset is balanced across all classes, and it is resized to 244x244 pixels to match the input requirement for the VGG19 model. Additionally, pixel values were normalized using the `vgg19.preprocess_input` function of TensorFlow to match the pixel values of model-trained weights.The VGG19 model employed transfer learning, through which the model reuses the weights from ImageNet, while allowing the model to focus on the anomaly detection task. A global average pooling layer and a dense layer were added to the model to classify the six solar panel conditions effectively. For the purpose of building and training the models accurately, the dataset was divided into 80% for training and 20% for validation purposes, ensuring that the data subset selected for each is distinct and thorough to cover all possibilities of anomaly detection.

Figure 2: PV Panel Dataset

3.2.2 For Anomaly Localization

For the anomaly localization task, bounding box annotation was needed for training the YOLO model. These annotations were generated manually, one by one with the help of the RoboFlow application. Images were loaded, and bounding boxes were drawn around each anomaly. The annotations were saved in YOLO format, which contains class labels and the desired anomaly coordinates of the bounding boxes.

The images and their corresponding annotations were then split into the training set, validation set, and the test set. Figures were also scaled at runtime in order to fit YOLO input dimensions of 640×640 pixels as required. The above steps were taken to enhance the structure of the dataset and make it ready for use in the YOLO model for the localization of faults.

3.2.3 Label Preparation

Bounding box annotations were created manually for all images using the ROBOFlow application. All these images were uploaded on the ROBOFlow platform, and bounding boxes were drawn around the anomalies in the images with their class labels tagged appropriately. These annotations were then exported in YOLO format with bounding box dimensions in the format of the respective class ID, x_{center}, y_{center}, width, and height.

In the YOLO format, four classes were used for model training:

- Physical Damage (index 0)
- Electrical Damage (index 1)
- Bird Drop (index 2)
- Snow Covered (index 3)

To create a YOLO-compatible data structure, it was decided to split the dataset into training, validation, and test sets. A separate folder was maintained for image files and another for the label files. These are some examples from the annotation files:

```
0  0.2703125 0.44140625 0.31875 0.38515625
1  0.225 0.57421875 0.38671875 0.44375
```

```
2  0.5421875 0.62421875 0.18046875 0.165625
3  0.80390625 0.61953125 0.3703125 0.45
```

4 Design Specifications

4.1 Anomaly Detection Using VGG19

More specifically, deep CNNs of the VGG19 type were used in this study for anomaly identification in solar photovoltaic panels, which was based on a pre-trained model that employs the ImageNet database. Leveraging transfer learning, the pre-trained weights of VGG19 were used, and the top layers were replaced to classify six anomaly classes: Bird drop, clean, dusty, electrical, physical and snowy.

To adapt the model, some modifications were made, including adding a global average pooling layer, a dropout layer (rate: 0.3) to avoid overfitting and one fully connected dense layer for classification into the six classes. Adam optimizer with a learning rate of 0.0001 was used for the optimizer with the sparse categorical cross-entropy loss function. The data was divided into training and validation sets with an 80:As for random samples, 20:1 ratio was employed, but random sampling in batches of 32 was used to improve variance. Another method known as the early stopping method was used to check validation loss and halt training if it hadn't improved after three iterations. The next level of training was performed while thawing the deeper layers of VGG19 with a lowered learning rate of 0.0001 was applied in order to get the greatest possible level of the model's performance and prevent it from being overtrained.

4.2 Anomaly Localization Using YOLO Models

The YOLO V8s model, a modified version of YOLO, was used for anomaly localization because of its suitability for real-time object detection and for identifying defective area on the solar panels using the annotation files of the bounding boxes. The model was started with the weight file `tolov8s.pt` to make use of transfer learning, which facilitated quicker convergence and better localization.

Bounding box annotations were manually created using the RoboFlow application, labeling anomalies into four classes: Physical damage, electrical damage, bird drop, and snow covered. These annotations are in YOLO annotations format where all the images co-ordinates of the bounding boxes and the classes labels provided are used to train the YOLOv8s model. The data was divided into training, validating and test datasets. The training phase of the model was performed for 60 epochs and the training process took 0.060 hours. The YOLOv8s model trained with the 168 layers 11,127,132 parameters and 28.4 GFLOPs during validation was able to detect the anomalies effective with the help of bounding boxes class labels and confidence scores.

5 Implementation of Anomaly Detection and Localization Models for PV Panels

The following sub-sections show the practical process of above described anomaly detection and localization models that are used in this project. Anomaly detection was done using VGG19 architecture and YOLOv8s for fault localization.

5.1 Setup and Configurations

The project was developed on a Windows 10 computer equipped with a 2.40GHz 11th Generation Intel Core i5 processor and 16GB RAM. Model training and experimentation were conducted using Jupyter Notebook Pro, which provided access to High RAM configurations for handling computationally intensive tasks.

5.2 Anomaly Detection Using VGG19

The dataset was categorized into six distinct classes: Bird-drop, Clean , Dusty , Electrical damage , Physical damage, and Snow covered. These classes were extracted and indexed using the directory structure of the dataset, ensuring compatibility with the model's training process as shown in the following table.

Index	Classes
0	Electrical-damage
1	Snow-Covered
2	Dusty
3	Bird-drop
4	Physical-Damage
5	Clean

Table 1: Classes with Corresponding Indices

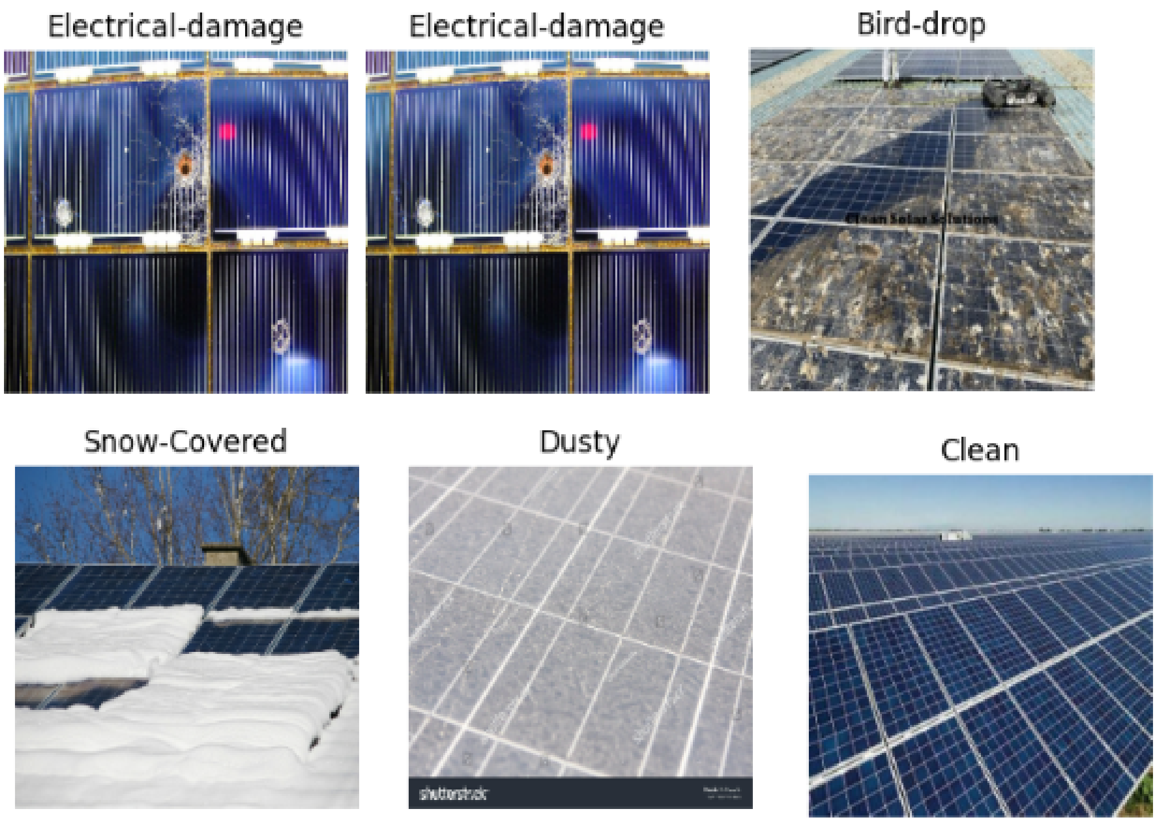

Figure 3: For Anomaly Detection

To load the dataset the method `image_dataset_from_directory()` provided in TensorFlow was used. Thus the whole dataset was used to create training (80%) and the validation (20%) set. The image size was reduced to 244×244 pixels.

Second, VGG19 was embarked on using `tf.keras.applications.VGG19` with weights being set to 'imagenet'. Some of the ignore layers were set to True and the inclusion of the top layers were set to False to enable augmentation for this particular type of anomaly detection. The input shape was made to match the resized images of 244 × 244 pixels and contained 3 color channels, and the layers of the base model were frozen (`trainable=False`) to perform transfer learning in the initial stage.

The architecture of the VGG19 model is summarized where all the layers that have been used, the total numbers of trainable parameters and the non trainable parameters are indicated. Base models were only fitted to prevent modifying the inherent features and new layers for the classification of six PV panel conditions were implemented.

Layer (type)	Output Shape	Param #	Connected to
input_layer_1 (InputLayer)	(None, 244, 244, 3)	0	-
get_item (GetItem)	(None, 244, 244)	0	input_layer_1[0][0]
get_item_1 (GetItem)	(None, 244, 244)	0	input_layer_1[0][0]
get_item_2 (GetItem)	(None, 244, 244)	0	input_layer_1[0][0]
stack (Stack)	(None, 244, 244, 3)	0	get_item[0][0], get_item_1[0][0], get_item_2[0][0]
add (Add)	(None, 244, 244, 3)	0	stack[0][0]
vgg19 (Functional)	(None, 7, 7, 512)	20,024,384	add[0][0]
global_average_pooling2d (GlobalAveragePooling2D)	(None, 512)	0	vgg19[0][0]
dropout (Dropout)	(None, 512)	0	global_average_poolin…
dense (Dense)	(None, 90)	46,170	dropout[0][0]

Total params: 20,070,554 (76.56 MB)
Trainable params: 46,170 (180.35 KB)
Non-trainable params: 20,024,384 (76.39 MB)

Figure 4: VGG199 Model Summary

Preprocess the images using TensorFlow's `vgg19.preprocess_input()` function to normalize pixel values and align them with the pre-trained weights of VGG19. The base model is initialized with weights pre-trained on *ImageNet*, except for the last layer. Additional layers include a global average pooling layer, a dropout layer (rate: 0.3), and a dense layer for six-class classification: *Bird-drop*, *Clean*, *Dusty*, *Electrical-Damage*, *Physical-Damage*, and *Snow-Covered*. Now, let's create this model by setting the optimizer up to be Adam with the learning rate being 0.001, while the loss function needs to be sparse categorical cross entropy. The model was trained for 20 iterations using both the Adam optimizer and the training sample. The EarlyStopping callback was used to track the validation loss, it set $'p$ to 03 to prevent overfitting. If the performance was not higher after three epochs, training was stopped and the best weights wer used. This approach made it possible to facilitate the training process while continuing to work with high quality models.

Finally, the final optimization, the fine-tuning technique as known was employed in the enhancement of the existing trained model. By using the command `base_model.trainable = True` the layers of the base model were unfrozen, and the base model is able to fine-tune pre-trained weights. To overcome from the problem of overfitting, all layers up to 14 layers were trained whereas all the remaining layers were made non-trainable. This approach made it possible to focus completely on the goal of the specific task to which the model is assigned, while at the same time, retaining the positive aspects of the learned features during pretraining. An architecture of a new model summary after fine–tuning is normally displayed to show the new changes.

Model: "functional"

Layer (type)	Output Shape	Param #	Connected to
input_layer_1 (InputLayer)	(None, 244, 244, 3)	0	-
get_item (GetItem)	(None, 244, 244)	0	input_layer_1[0][0]
get_item_1 (GetItem)	(None, 244, 244)	0	input_layer_1[0][0]
get_item_2 (GetItem)	(None, 244, 244)	0	input_layer_1[0][0]
stack (Stack)	(None, 244, 244, 3)	0	get_item[0][0], get_item_1[0][0], get_item_2[0][0]
add (Add)	(None, 244, 244, 3)	0	stack[0][0]
vgg19 (Functional)	(None, 7, 7, 512)	20,024,384	add[0][0]
global_average_pooling2d (GlobalAveragePooling2D)	(None, 512)	0	vgg19[0][0]
dropout (Dropout)	(None, 512)	0	global_average_poolin…
dense (Dense)	(None, 90)	46,170	dropout[0][0]

Total params: 20,070,554 (76.56 MB)
Trainable params: 14,205,018 (54.19 MB)
Non-trainable params: 5,865,536 (22.38 MB)

Figure 5: Model Summary wiht Fine-tunning

After fine-tuning, the model was recompiled with a reduced learning rate of 0.0001 to refine its performance. It was then trained for an additional 20 epochs with Early Stopping monitoring the validation loss to prevent overfitting and ensure optimal performance. The model achieved an accuracy of 83% on the validation dataset, successfully classifying anomalies across six classes.

5.3 Anomaly Localization Using YOLOv8

Annotations of the PV panel dataset were done using the RoboFlow application. Each image was uploaded, and bounding boxes were manually drawn around anomalies. The annotations were exported in YOLO format, including normalized coordinates: `class_id`, `x_center`, `y_center`, `width`, and `height`. Figure 2a shows an example annotated image and its corresponding annotation file.

Figure 6: PV Panel Image with its Annotation file

In order to prepare the datasets for the use in the YOLOv8 model, the requisite folder structure was constructed, in which four main folders were created with the distinguishing characteristic that the training and testing set folders also contained subdirectories name images and labels.

In order to evaluate the quality of the collected data a consistency check was performed to make sure that for each image there was an annotation file with the same name. When training the model, or when validating or testing, the code ensured that certain files are missing, for example, was an image and its corresponding annotation file. If for instance there were labels that did not have images, or images which did not have labels, then the specifics were printed to correct them. This was important to make sure the dataset was in the right format which is ideal for YOLOv8 training.

Training, validation and test images and their corresponding jpg annotation files were read using open source computer vision library. Each image was then matched with its corresponding annotation file, which included YOLO format annotations: class ID, x_center, y_center, width, and height are the five parameters in the regressive model. Finally if an annotation file was missing or in an improper format they got a warning and the image was excluded. The suggested approach enabled one to perform a necessary preprocessing of the dataset to prevent disruptions in either training or evaluating the YOLO model.

It has a training sets and validation set in which the data was divided into directories of images as well as their annotations. Class indices were detected from the annotations, ensuring they matched the expected classes: The classifications are Physical-Damage (0), Electrical-Damage (1), Bird-Drop (2), and Snow-Covered (3). Therefore, a `data.yaml` file was developed in which to specify the paths and the class names. The YOLOv8 model was used for this study and it was trained using the file `yolov8s.pt` with 60 epochs and a batch size of 16 with images of 640 x 640 pixels for effective localization of faults.

In addition, the YOLOv8 model achieved fault identification and localization for the photovoltaic panels. It was also able to correctly detect areas as containing abnormalities inclusive of physical and electrical damages, bird dropping, and snowy regions. While the precsion and recall metrics showing the need for the improvements, so after all, model localize the fault very efficiently

6 Evaluation and Results

6.1 Anomaly Detection Evaluation

Due to the anomaly detection problem, four key indicators of the model's performance – accuracy, precision, recall, and F1-score –were utilized. These metrics were calculated for each of the six classes: Bird-drop, Clean, Dusty, Electrical-Damage, Physical-Damage, and Snow-Covered allows the understanding of the model's performance characteristics of how well it is or is not working in each of the different types of anomalies. In order to better understand the effectiveness of the classifier, we constructed a confusion matrix that showed the correct classification as well as the misconceptions of classes. The training accuracy was gotten to 96%, while the validation accuracy was around 84% which affirmed that the current model has some of the best generalization capacity to other unseen data. For both the training and validation curves, one could clearly observe that the model had learned all the features that it required, in order to classify the anomalies successfully.

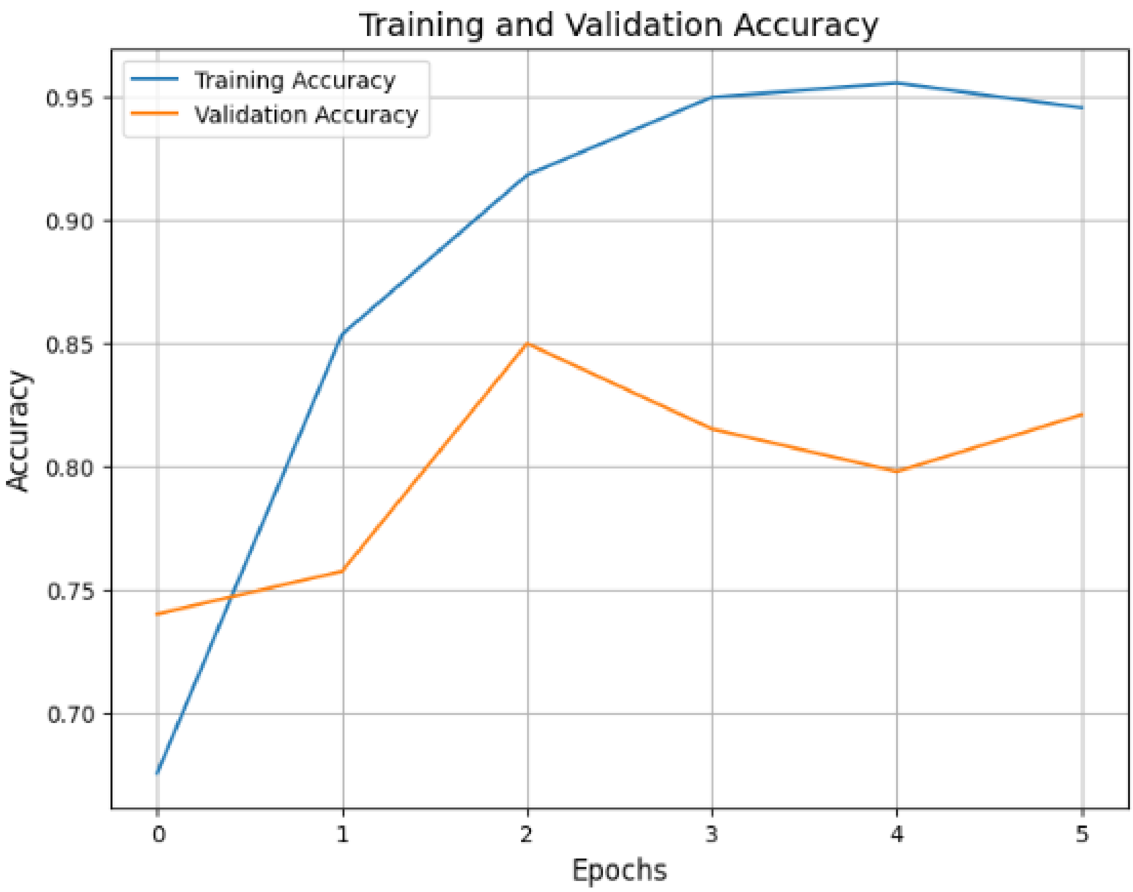

Figure 7: Evaluation Curves

Furthermore, analyzing the average IoU on a per-class-base showed that the proposed model had good performance in recognizing Clean and Dusty panels, but Electrical-Damage and Bird-drop classes are not easy to be tackled, which leads the relative poor precision and recall of these classes. As such there is a requirement for potential dataset augmentation or fine-tuning to enhance the capability to identify these anomalies. Thus, the evaluation metrics and the graphs do support that the VGG19 model is effective in detecting anomalies in photovoltaic panels to be used for monitoring systems in practice.

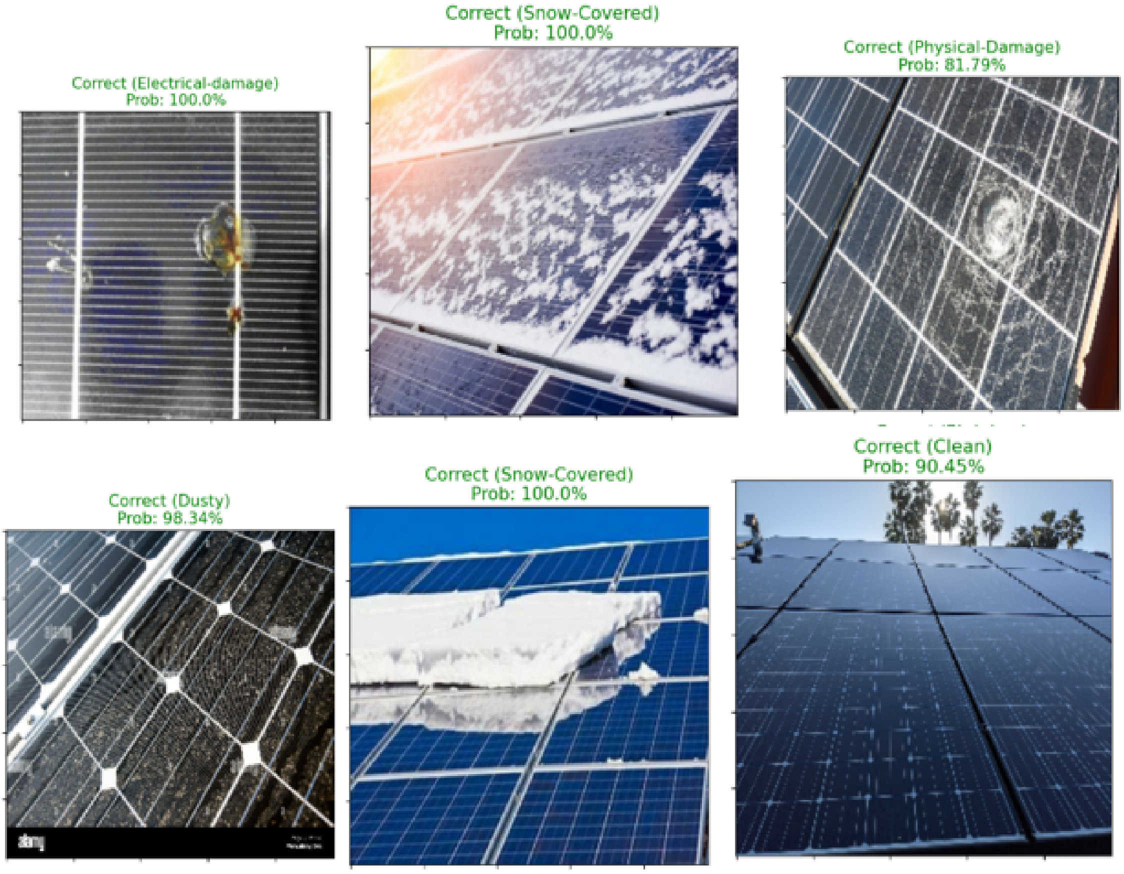

Figure 8: Results for Anomaly detection

Model	Techniques Used	Accuracy (%)
VGG16	Without Augmentation	67
RSNet	Data Augmentation	50
VGG16	Data Augmentation	75
VGG16	Data Augmentation + Transfer Learning	79
VGG19	Transfer Learning + Fine-Tuning	**96 (Train)** / 84 (Validation)

Table 2: Evaluation Results of Different Models on the Same Dataset

The comparison of models tested on the same dataset produced different performance results depending on the methods used. The baseline VGG16 model exhibits an accuracy of around 67%, and the model we developed using the RSNet architecture with data augmentation got just 50%, presumably because it lacked the ability to process the variability introduced due to augmentation. An example of augmentation is shown below, and using data augmentation increased the accuracy of the VGG16 model to 75%.

By using transfer learning, the models VGG16 increased it's to around 79% with the pre-existing concept of knowledge being useful for generalizing the dataset.

The highest accuracy was given by the VGG 19 model with transfer learning and fine-tune training set to 96 % training accuracy and 84 % validation accuracy. The reason for this improvement is that the architecture used by VGG19 is deeper and includes convolutional layers that can learn more complex features, much more so than the features the exact original layers can learn. Therefore, VGG19 outperforms others by keeping a balance between both the accuracy and robustness helping make it the best model for this dataset.

6.2 Anomaly Localization Evaluation

The YOLOv8s model was evaluated based on its ability to localize anomalies by predicting bounding boxes for four classes of damage: Physical-Damage, Electrical-Damage, Bird-Drop, and Snow-Covered. In the evaluation process, objectification stressed the model's ability to detect and pinpoint unusual regions in PV panel images accurately. When interpreting the outcomes, a qualitative analysis revealed that, the model achieved the intended goal of localizing anomalies through the use of bounding boxes with class labels and corresponding confidence levels. Although performance of a model can be measure by precision and recall, the interest was on the practical capacity of the model in identifying multiple anomalies potential under different environment and working conditions.

By doing a qualitative as well as a quantitative assessment of the bounding box predictions we found that the model was "seeing" a set of fault regions that are crucial for effective maintenance. Therefore, these results confirm the possibility of using the YOLOv8s model as a scalable real-time anomaly detection and localization technique for PV panel monitoring systems.

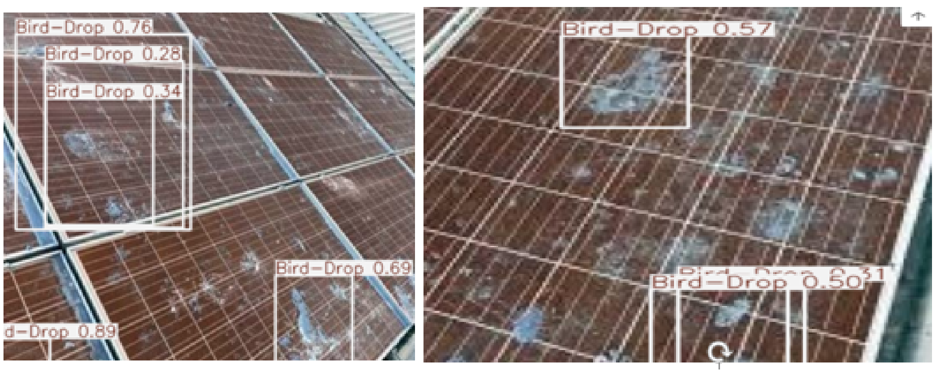

Figure 9: Bird-Drop Anomaly Localization

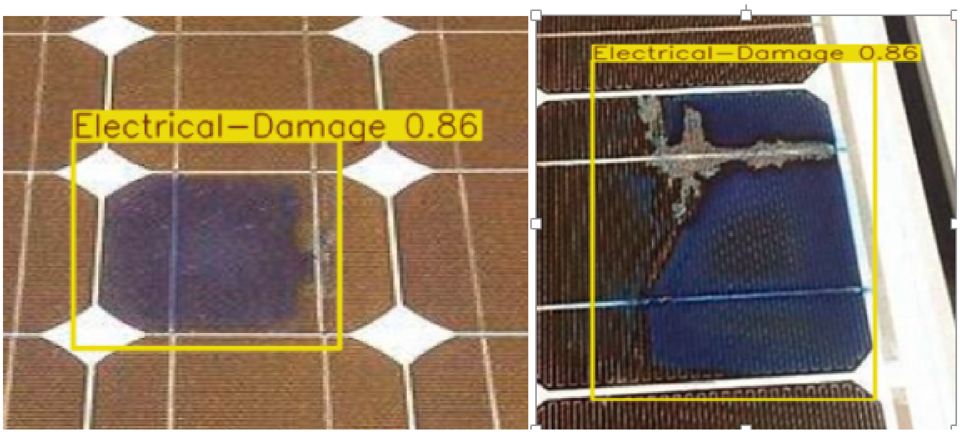

Figure 10: Electrical Damage Localization

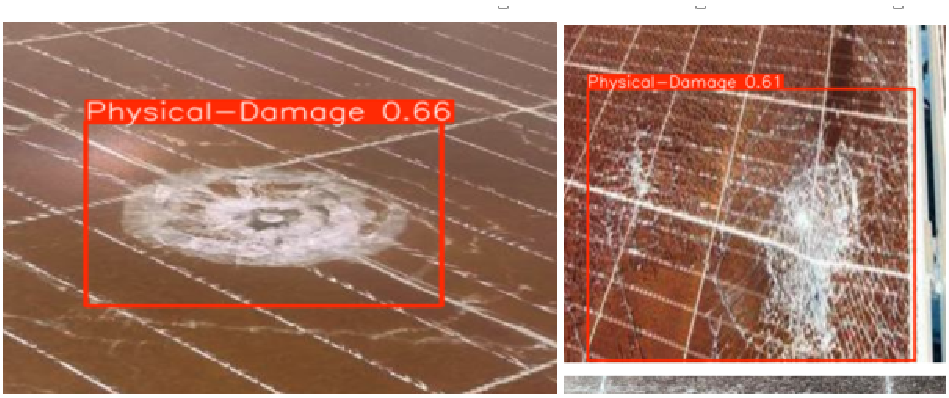

Figure 11: Physical Damage Localization

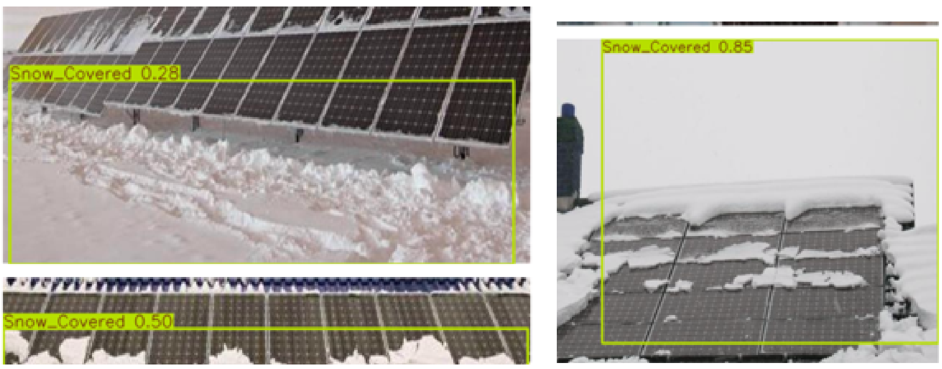

Figure 12: Snow-Covered

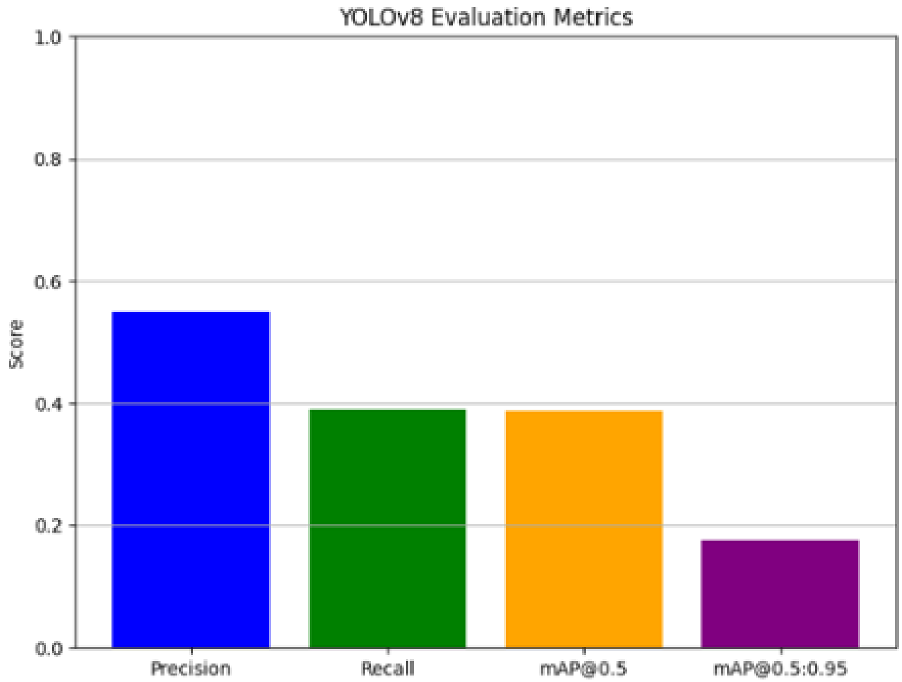

Figure 13: Evaluation Results for YOLO V8s

Model	**Classes**	**mAP@50 (%)**
YOLOv8s	Physical Damage Only	75
YOLOv8s	All Classes (Electrical,physical,snow,BD)	60

Table 3: Evaluation Results of YOLOv8s Model for Fault Localization on PV Panels

The fault localization task employed the YOLOv8s model for detecting and categorizing defects affecting photovoltaic (PV) panels. First, the model was trained on only one class—physical damage—and got the result of mAP@50 = 75% that proves that presented approach can localize and identify the physical faults. Nonetheless, when the model was trained with all the four classes – physical damage, electrical damage, snow-covered, and bird drop – the mAP@50 was only 60 percent.

It is equally important to note that performance lowers with the multiple classes in the dataset than with the single class because of the complexity of handling the classes, unclear data, and manual annotation errors. These issues aggravate the difficulties with the construction of a high-quality dataset that balances failures and aetiologies for fault localization tasks. Nevertheless, these manoeuvres give the YOLOv8s model direction for enhancing fault localisation through better annotation methods and augmentation data set.

7 Discussion

From the aforementioned findings validating proof of concept, there was progress regarding the automation of anomaly detection and localization of photovoltaic (PV) panels utilizing deep learning. Regarding the anomaly detection the training accuracy of the VGG19 model was 95% and the validation accuracy was 83%. This performance makes a point for using transfer learning, where setting the weights of VGG19 has enabled the extraction of outstanding features. In comparison to previous research work, for instance, one study that employed VGG16 model with 81% validation accuracy, this work obtained higher classification accuracy with the help of VGG19. The higher accuracy proves the possibility of the higher effectiveness of using the deeper architecture along with the wanted preprocessing. For the purpose of anomaly localization, the YOLOv8 model provided fruitful results in terms of localizing faulty areas on PV panels through enclosing such areas by bounding boxes. But this part of the project was a little problematic because bounding box annotations that were compiled manually were not very consistent. There were certain annotations that were not in the required format by YOLO and therefore such files were deleted from the dataset. As a result, the model was trained from a relatively small dataset perhaps constraining it. Nevertheless, we demonstrated YOLOv8's ability to localize anomalies across various classes such as Physical-Damage and Electrical-Damage confirming its effectiveness for real-time fault identification.

Even though the VGG19 has a good generalization, few anomaly classes were slightly poor including Electrical-Damage and Bird-Drop because of the lack of data. Likewise, the YOLOv8 model will be useful in terms of scalability in applications, but there is still room for enhancement in terms of annotation standards and the enlargement of the dataset for presentation optimization yet as pertains to localization.

All in all, the outcomes of this study show that deep learning can be utilized to solve the most significant problems in solar panel maintenance. Future work could be based on increasing the size of available data, the use of more complex architectures, such as EfficientNet, for anomaly detection or using automated tools for better quality annotations for the localization task.

8 Conclusion

This study aimed to adapt a practical approach, which defines the state of the art in anomaly detection and fault localization on photovoltaic, (PV), towards accomplishing the essential maintenance challenges of solar energy systems. To achieve this, the project applied two way approach. The first part of the above work implemented the use of the VGG19 model for anomaly detection with the highest training accuracy at 95 % and validation of 83 % compared to a similar work that was done on the VGG16 model with only 81 % validation accuracy. It also extends evidence to suggest that the deeper architectures, paired with transfer learning, are apt for classification tasks. The model successfully categorized PV panels into six anomaly classes: Clean, Dusty, Bird-drop, Electrical-Damage, Physical-Damage, and Snow-Covered are six classes that give a robust way of anomaly detection.

The second phase of the project was based on the anomaly localization of the faulty area with the help of the YOLOv8 model for bounding the faulty area on the panels. The model proposed was able to detect anomalies in the real-time application, however, issues such as variation in manual labelling and less samples also put a dampen on the performance. Nonetheless, the evaluations also reveal several problems of the model, such as noisy labels and inaccurate class boundaries, which indeed reflects weaknesses of the model being designed for scalable solar panel monitoring Although some issues mentioned above are existed, the model indeed illustrates its potential in localizing the faults from different classes, including the Physical-Damage, Electrical-Damage, Bird-

Drop, and Snow-Covered classes.

From this work, it has been shown that computer vision can be employed on solar panel maintenance with both classifying and localizing approaches. Nevertheless, it was revealed that there are several issues to be predicated as its limitations. The quality and quantity of the annotated dataset influenced the rate of YOLOv8 model performance, and some classes, birds drop, etc. had a downside because of the lack of large data.

The prospect of future work includes the extension of the dataset with more readings; disciplinary annotation checks with the help of AI tools; and the testing of different architectures, such as EfficientNet for the detection of anomalies. Further, domain specific features including thermal imaging required to detect electrical faults can be incorporated to improve the accuracy of the system.

References

Bhattacharya, A. and Cloutier, S. G. (2022). End-to-end deep learning framework for printed circuit board manufacturing defect classification, *Scientific Reports* **12**: 12559.

Bommes, L., Hoffmann, M., Buerhop-Lutz, C., Pickel, T., Hauch, J., Brabec, C., Maier, A. and Peters, I. M. (2021). Anomaly detection in ir images of pv modules using supervised contrastive learning, *arXiv preprint arXiv:2112.02922* .
URL: *https://arxiv.org/abs/2112.02922*

Di Tommaso, A., Betti, A., Fontanelli, G. and 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* .

Duan, R. and Ma, Z. (2024). A method for detecting photovoltaic panel faults using a drone equipped with a multispectral camera, *ISPRS Annals of the Photogrammetry, Remote Sensing and Spatial Information Sciences, Volume X-1-2024, ISPRS TC I Mid-term Symposium*, ISPRS, Changsha, China, pp. 59–65.
URL: *https://doi.org/10.5194/isprs-annals-X-1-2024-59-2024*

Graham, E. and Fulghum, N. (2024). Solar's record breaking growth in 2024, *Technical report*, Ember. Published under a Creative Commons ShareAlike Attribution Licence (CC BY-SA 4.0).
URL: *https://ember-climate.org/data/data-tools/china-solar-exports/*

Han, S. H., Rahim, T. and Shin, S. Y. (2021). Detection of faults in solar panels using deep learning, *2021 International Conference on Electronics, Information, and Communication (ICEIC)*, IEEE, pp. 1–4.
URL: *https://doi.org/10.1109/ICEIC51217.2021.9369744*

Jia, Y., Chen, G. and Zhao, L. (2024). Defect detection of photovoltaic modules based on improved varifocalnet, *Scientific Reports* **14**: 15170.
URL: *https://www.nature.com/articles/s41598-024-66234-3*

Khedkar, V., Kadam, K., Shetty, A., Rastogi, U. and Chavhan, P. G. (2024). Multiclass solar panel classification based on surface anomalies using vgg16, *International Journal of Intelligent Systems and Applications in Engineering* **12**(3): 3833–3842.
URL: *https://www.ijisae.org*

Nabti, M., Bybi, A., Chater, E. A. and Garoum, M. (2022). Machine learning for predictive maintenance of photovoltaic panels: cleaning process application, *E3S Web of Conferences* **336**: 00021.
URL: *https://doi.org/10.1051/e3sconf/202233600021*

Pathak, S. P. and Patil, S. A. (2023). Evaluation of effect of pre-processing techniques in solar panel fault detection, *IEEE Access* **11**: 72848–72860.
URL: *https://doi.org/10.1109/ACCESS.2023.3293756*

RA, N. K., R, S., R, R. and Venkatesh, R. J. (2024). Smart solar panel monitoring system, *International Conference on Electrical Electronics & Communication Technology (ICEECT'24)*, Vol. 6, PERI Institute of Technology, pp. 722–724.
URL: *https://irjedt.periit.ac.in/ICEECT24*

Shaik, A., Balasundaram, A., Kakarla, L. S. and Murugan, N. (2024). Deep learning-based detection and segmentation of damage in solar panels, *Automation* **5**: 128–150.
URL: *https://doi.org/10.3390/automation5020009*

Shaikh, M. R. S., Waghmare, S. B., Labade, S. S., Fuke, P. V. and Tekale, A. (2017). A review paper on electricity generation from solar energy, *International Journal for Research in Applied Science & Engineering Technology (IJRASET)* **5**(IX): 1884–1890. ISSN: 2321-9653; IC Value: 45.98; SJ Impact Factor: 6.887.
URL: *https://www.ijraset.com*

Shen, M., Liu, Y., Chen, J., Ye, K., Gao, H., Che, J., Wang, Q., He, H., Liu, J., Wang, Y. and Jiang, Y. (2024). Defect detection of printed circuit board assembly based on yolov5, *Scientific Reports* **14**: 19287.
URL: *https://www.nature.com/articles/s41598-024-70176-1*

Sohail, A., Islam, N. U., Haq, A. U., Islam, S. U. and Park, J. (2023). Fault detection and computation of power in pv cells under faulty conditions using deep-learning, *Energy Reports* **9**: 4325–4336.
URL: *https://doi.org/10.1016/j.egyr.2023.03.094*

Spajić, M., Talajić, M. and Mršić, L. (2024). Using cnns for photovoltaic panel defect detection via infrared thermography to support industry 4.0, *Business Systems Research* **15**(1): 45–66. JEL classification: Q42, Q55, Q56. Paper type: Review article. Received: 28 Jun 2024, Accepted: 17 Aug 2024. Acknowledgement: Supported by Project 101104579, AI-powered Next Generation of VET (AI4VET4AI), ERASMUS-EDU-2022-PEX-COVE.