Automating the detection of surface defects on solar panels in Zambia

by

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&

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Submitted to the Department of Computing and Informatics
in partial fulfilment of the requirements for the degree of
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Abstract

The increasing adoption of solar photovoltaic (PV) systems has created a growing need for effective methods of monitoring and maintaining solar panels to ensure reliable energy generation. PV panels can experience various defects and surface conditions, including bird droppings, dust accumulation, electrical damage, and physical damage, which can reduce their performance and, in some cases, lead to further damage if not detected and addressed in time. Conventional inspection methods often rely on manual visual inspection, which can be time-consuming, labour-intensive, and difficult to scale as the number of solar installations increases.

This project presents the development of an automated solar photovoltaic panel defect detection and classification system using deep learning and computer vision. The system employs two image classification models based on the ResNet18 convolutional neural network architecture. The first model performs binary classification to distinguish between healthy and faulty solar panels, while the second model classifies faulty panels into four defect categories:

bird-drop, dusty, electrical-damage, and physical-damage.

The proposed system provides a practical approach to supporting solar panel inspection by reducing dependence on manual identification of visible defects and enabling faster preliminary assessment of panel conditions. The project demonstrates how deep learning and computer vision can be applied to support the maintenance and monitoring of photovoltaic systems, with potential relevance to the continued development of solar energy infrastructure in Zambia and other African countries.

Project Supervisor: Dr. Lighton Phiri and Dr. Steven Mudenda
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List of Abbreviations

AI	Artificial Intelligence
API	Application Programming Interface
DL	Deep Learning
GUI	Graphical User Interface
IEEE	Institute of Electrical and Electronics Engineers
ML	Machine Learning
UNZA	University of Zambia

Chapter 1

Introduction

Solar energy is becoming increasingly important to Zambia's electricity sector and to the broader African energy transition. Zambia has historically relied heavily on hydropower, making electricity generation vulnerable to variations in water availability. Consequently, the country has increasingly looked towards solar photovoltaic (PV) technology as a means of diversifying electricity generation and improving energy security. This transition is already evident in the development of large-scale solar projects, including the commissioning of a 100 MW grid-connected solar plant in Chisamba in 2025.

The growing adoption of solar energy is not unique to Zambia. Across Africa, solar PV is increasingly being deployed in utility-scale, commercial, residential and off-grid applications. The continent possesses substantial solar resources, yet hundreds of millions of people continue to lack reliable access to electricity. At the same time, declining technology costs have made solar PV increasingly competitive as an electricity-generation technology in many African countries.

As the number of photovoltaic installations increases, maintaining the performance and reliability of solar panels becomes increasingly important. Solar panels are continuously exposed to environmental and physical conditions that can result in defects or contamination, including dust accumulation, bird droppings, electrical faults and physical damage. If such conditions are not detected and addressed, they can reduce the effectiveness of photovoltaic systems and potentially increase maintenance requirements.

Conventional inspection methods commonly rely on visual examination by technicians. However, manually inspecting large numbers of panels can be time-consuming and labour-intensive. This creates an opportunity for artificial intelligence and computer vision techniques to support automated solar panel inspection.

Deep learning-based image classification provides a potential solution by allowing computer systems to learn visual patterns associated with different panel conditions. In

this project, this approach is applied to develop two models: a binary classifier for distinguishing healthy panels from faulty panels and a multiclass classifier for identifying specific fault categories.

The development of such a system is particularly relevant in Zambia and other African countries where solar deployment is increasing and efficient maintenance of photovoltaic infrastructure will become increasingly important. The project therefore seeks not only to demonstrate the application of deep learning to solar panel inspection, but also to produce a practical software system through which the developed models can be accessed.

1.1. Background of the Study

In solar farms and homes, solar photovoltaic panels are exposed to environmental conditions throughout their operational lifetime. These conditions can result in different types of defects or surface conditions that affect panel performance. Among the conditions considered in this project are bird-drop, dust, electrical damage and physical damage.

1.1.1 Solar Panel Defects

Bird-drop refers to contamination caused by bird droppings deposited on the surface of a solar panel. Such contamination can obstruct sunlight from reaching portions of the photovoltaic cells and may contribute to uneven operation of the panel.

Dust is another common form of contamination. Dust particles can accumulate on the surface of photovoltaic panels and reduce the amount of solar radiation reaching the cells. The effect can be particularly significant in areas where panels are exposed to dry and dusty environmental conditions.

Electrical damage refers to visible defects associated with electrical components or electrical-related failures in photovoltaic panels. These defects can affect the electrical performance of a panel and may require technical inspection.

Physical damage includes visible structural or surface damage to the panel, such as cracks or other forms of physical deterioration.

The presence of these conditions makes regular inspection important for maintaining photovoltaic systems.

1.1.2 Computer Vision and Image Classification

Computer vision enables computer systems to extract useful information from digital images. In the context of solar panel inspection, images can be analyzed automatically to identify visual characteristics associated with different panel conditions.

Image classification is a machine learning task in which an input image is assigned to one of a predefined set of classes. In this project, image classification was used at two levels. The binary model classified images into Healthy and Faulty, while the multiclass model classified faulty panel images into Bird-drop, Dusty, Electrical-damage and Physical-Damage.

1.1.3 Deep Learning for Image Classification

Deep learning has become widely used for image classification because deep neural networks can learn visual features directly from image data. Convolutional Neural Networks (CNNs), in particular, are designed to process image data and learn patterns such as edges, textures, shapes and higher-level visual features.

This project uses ResNet18, a convolutional neural network architecture based on residual learning. A pretrained ResNet18 model was used as the foundation for both classification tasks. The final classification layer was modified to produce the required number of classes.

1.2. Problem Statement

The increasing adoption of solar photovoltaic (PV) technology has created a growing need for effective inspection and maintenance of solar panels to ensure reliable and sustained energy generation. Solar PV panels are exposed to environmental and physical conditions that can result in visible defects and surface conditions such as bird droppings, dust accumulation, electrical damage, and physical damage. These conditions can affect the performance of photovoltaic modules and, in some cases, contribute to further damage if they are not identified and addressed in time. For example, bird droppings can cause partial shading of a PV module, resulting in reduced power output and the formation of hot spots that may damage the module. Sisodia and Mathur (2019) reported power losses of up to approximately 23.8% under the specific experimental conditions investigated in Western Rajasthan.

Despite the increasing deployment of solar PV systems, the identification of such defects commonly relies on manual inspection or specialised inspection techniques. Manual visual inspection requires personnel to examine panels individually, making the process time-consuming and labour-intensive, particularly when dealing with large numbers of panels. It may also be difficult to maintain consistent identification of different defect types when inspections are performed repeatedly or across large solar installations. Although techniques involving thermal imaging, infrared cameras and unmanned aerial vehicles have demonstrated their usefulness in photovoltaic inspection, such approaches may require specialised equipment and additional operational resources.

The problem is therefore the lack of an accessible automated system capable of identifying whether a solar PV panel is faulty and subsequently determining the type of visible defect from an image. Without such a system, preliminary defect identification remains dependent on human inspection, which can limit the speed and scalability of solar panel monitoring and maintenance.

1.3. Aim of the Study

To develop an image-based deep learning system for automated detection and classification of solar panel defects and integrate the trained models into a deployable software application.

1.4. Project Objectives

I. Collect and prepare a dataset of solar panel images representing healthy and faulty conditions.

II. Preprocess and analyze the image dataset to prepare it for deep learning-based classification.

III. Develop a binary classification model capable of distinguishing between healthy and faulty solar panel images.

IV. Develop a multiclass classification model capable of identifying different types of solar panel defects.

V. Evaluate the performance of the developed models using appropriate evaluation metrics, including accuracy, precision, recall, F1-score and confusion matrices.

VI. Develop a user application that allows users to submit solar panel images for automated defect detection.

VII. Develop a Fast API backend to provide an API for communication between the application and the trained machine learning models.

VIII. Deploy the backend and frontend to make the developed system accessible as a working application.

1.5. Project Scope

This project focuses on the development of an automated solar photovoltaic (PV) panel defect detection and classification system using deep learning and computer vision. The system is designed to analyse images of solar PV panels and identify visible conditions that may indicate a faulty panel.

The scope of the project covers the following areas:

1.5.1. Solar PV Image Dataset

The project uses a publicly available PV panel defect image dataset obtained from Kaggle. The dataset used in the implementation contains 762 images representing five categories: Clean, Bird-drop, Dusty, Electrical-damage, and Physical-Damage. The Clean category is used to represent healthy panels, while the remaining four categories represent faulty conditions.

1.5.2. Binary Defect Detection

The first stage of the system involves developing a binary image classification model using ResNet18. The model determines whether an uploaded solar panel image represents a healthy or faulty panel.

1.5.3. Fault Classification

For images identified as faulty, a second ResNet18-based model is used to classify the visible defect into one of four categories:

- Bird-drop
- Dusty
- Electrical-damage
- Physical-Damage

The project therefore focuses on visible image-based defects that can be identified from the appearance of the solar panel.

1.5.4. Model Development and Evaluation

Both models are developed using PyTorch and trained using image data prepared through resizing, augmentation and normalization. The models are evaluated using independent test datasets and performance measures including accuracy, precision, recall, F1-score, classification reports and confusion matrices.

1.5.5. Application Development

The trained models are integrated into an application that allows a user to submit an image of a solar panel for analysis. The application consists of a React Native frontend and a FastAPI backend. The backend receives the image, processes it using the trained models, and returns the predicted panel condition and, where applicable, the identified defect category.

1.5.6. System Deployment

The developed system is deployed to demonstrate its practical usability. The FastAPI backend is deployed using Render, while the application frontend is deployed using Vercel.

1.5.7. Scope Limitations

The project is limited to image-based detection of the four selected visible defect categories.

It does not cover:

- Prediction of the electrical power output or efficiency of an individual panel.
- Real-time physical monitoring using sensors.
- Thermal or infrared image analysis.
- Drone or UAV-based inspection.
- Automatic physical cleaning or repair of panels.
- Diagnosis of defects that cannot be reliably identified from the provided image.
- Prediction of the remaining useful life of a solar panel.
- Large-scale solar-farm asset management or maintenance scheduling.

Therefore, the project primarily demonstrates the feasibility of using deep learning and computer vision to provide automated preliminary identification of visible solar PV panel defects through an accessible software application

Chapter 2

Literature Review

2.1 Introduction

The increasing deployment of solar photovoltaic (PV) technology has created a growing need for effective methods of monitoring, inspecting, and maintaining photovoltaic systems. This is particularly relevant in Africa, where solar energy has considerable potential to improve electricity access and support the development of national energy systems. The International Energy Agency (IEA) reported that approximately 600 million people in sub-Saharan Africa lacked access to electricity as of 2024 [1]. Africa also possesses substantial solar resources, and solar PV has become one of the least-cost sources of electricity generation in many parts of the continent [2].

Solar photovoltaic capacity in Africa has increased substantially. According to the International Renewable Energy Agency (IRENA), Africa's installed solar PV capacity increased from approximately 1.79 GW in 2015 to 14.29 GW in 2024 [3]. This expansion highlights the growing importance of maintaining the performance and reliability of photovoltaic installations.

As photovoltaic installations expand, effective inspection methods become increasingly important. Conventional inspection approaches can require considerable time and human effort, particularly when examining large solar installations. Consequently, research has investigated computer vision, image processing, thermal imaging, unmanned aerial vehicles (UAVs), and artificial intelligence techniques for detecting and classifying PV panel defects. Barraz et al. [4], for example, reviewed deep learning and image-processing approaches for photovoltaic inspection, including the use of RGB and thermal images and UAV-based inspection workflows.

This chapter reviews existing research on solar energy development, common solar panel defects, conventional inspection techniques, image-based inspection, UAV-assisted inspection, and artificial intelligence-based defect classification. It also

examines the limitations of existing approaches and identifies the research gap addressed by the present study, which focuses on using deep learning to classify solar panel images as healthy or faulty and to identify categories of visible defects.

2.2 Solar Energy Development in Zambia

Zambia has historically relied heavily on hydropower for electricity generation. However, droughts and reduced water availability have exposed the vulnerability of this dependence, contributing to electricity shortages. The Government of Zambia has therefore pursued diversification of the national energy mix, including increased investment in solar photovoltaic (PV) generation [5].

The Ministry of Energy's project status report dated 28 November 2025 lists several completed solar projects, including the 100 MW Chisamba I Solar PV Plant and the 25 MW Mailo I Solar PV Plant in Serenje. The report also identifies commercial and industrial solar PV installations, demonstrating the expansion of solar generation beyond utility-scale power plants [6].

The Ministry's subsequent press statement, dated 30 November 2025, reported that 347 MW of new electricity generation capacity had been completed and that projects with a combined capacity of 2,510 MW were under construction. The projects under construction included the 50 MW Mansa Solar PV project, alongside other solar and non-solar generation developments [7]. These figures demonstrate the scale of Zambia's broader electricity-generation expansion, although they should not be interpreted as solar capacity alone.

The expansion of solar generation is particularly important in the context of Zambia's vulnerability to drought-related reductions in hydropower output. The International Monetary Fund reported that the severe 2024 drought significantly affected hydropower generation and increased the need to diversify electricity supply through alternative sources, including solar energy [8].

As solar infrastructure expands, maintaining the reliability and performance of photovoltaic installations becomes increasingly important. Efficient inspection methods

can help identify visible defects and support maintenance decisions, particularly as the number and scale of installations increase. This provides a relevant context for developing deep learning-based systems that classify solar panel images as healthy or faulty and identify categories of visible defects.

2.3 Solar Energy Development in Africa

The importance of solar energy extends beyond Zambia. Africa possesses substantial renewable energy resources, including significant solar potential, while simultaneously experiencing a large electricity-access deficit [9].

The International Energy Agency (IEA) estimates that approximately 600 million people in Africa lack access to electricity. At the same time, investment in clean energy has increased, with solar photovoltaic (PV) technology becoming the least-cost source of power in many African countries. The IEA reported that private-sector clean-energy investment in Africa increased from approximately USD 17 billion in 2019 to almost USD 40 billion in 2024 [10].

The International Renewable Energy Agency (IRENA) reported that Africa's installed solar PV capacity reached approximately 14.3 GW in 2024, compared with approximately 1.8 GW in 2015 [11].

The growth of decentralised solar systems is also important. The IEA reported that off-grid systems accounted for more than half of new electricity connections in sub-Saharan Africa in 2022, highlighting the role of solar home systems and other decentralised technologies in extending electricity access beyond conventional grid infrastructure [12].

Therefore, the increasing deployment of solar systems across Africa creates opportunities to improve energy access and increases the importance of reliable monitoring, inspection, and maintenance technologies.

2.4. Solar Photovoltaic Panel Defects

Photovoltaic (PV) modules are exposed to environmental conditions, mechanical stresses, and electrical operating conditions throughout their service life. These factors can contribute to defects, degradation, and failures that affect module reliability and power output [13], [14].

Common PV panel defects and performance-related conditions include:

- Dust and surface soiling
- Bird droppings
- Physical damage and cracks
- Cell degradation
- Electrical faults
- Hotspots
- Partial shading
- Corrosion
- Delamination
- Manufacturing defects

Dust, bird droppings, and other forms of surface soiling can reduce the amount of sunlight reaching the photovoltaic cells, thereby affecting energy generation [15]. Physical damage, including cracks in solar cells or breakage of the front glass, can compromise module integrity and may contribute to electrical losses. Other failures, such as corrosion, delamination, and defective electrical connections, can also affect the reliability and performance of PV modules [13], [14].

Hotspots are localised regions of elevated temperature that can develop when cells or parts of a module experience abnormal electrical conditions. They may be associated

with partial shading, damaged cells, soiling, or faulty electrical connections. If sufficiently severe or persistent, hotspots can contribute to further module damage and degradation [14].

Different inspection techniques are used to identify these problems. Visual inspection and RGB imaging can reveal certain visible defects, such as surface soiling, bird droppings, and physical damage. Thermal imaging can identify temperature abnormalities associated with some electrical and operational faults, while electroluminescence imaging can reveal cell cracks and other defects that may not be clearly visible in ordinary photographs [13].rather than directly measuring electrical performance or diagnosing every possible PV module failure.

Understanding the characteristics of these defects is important for developing automated inspection systems. In this study, the classification task focused on identifying healthy and faulty solar panel images and further classifying faulty images into bird-drop, dusty, electrical-damage, and physical-damage categories. The system therefore addressed image-based defect classification

2.4.1 Effects of Dust on Photovoltaic Panels

Dust accumulation on solar photovoltaic (PV) panels reduces the amount of solar radiation reaching the photovoltaic cells, potentially lowering their power output. The extent of the reduction depends on factors such as the amount of deposited dust, particle composition, humidity, and environmental conditions. Research reviewed by the authors of [16] demonstrates that dust accumulation can significantly affect PV-panel performance, although the magnitude of the effect varies between studies and operating conditions.

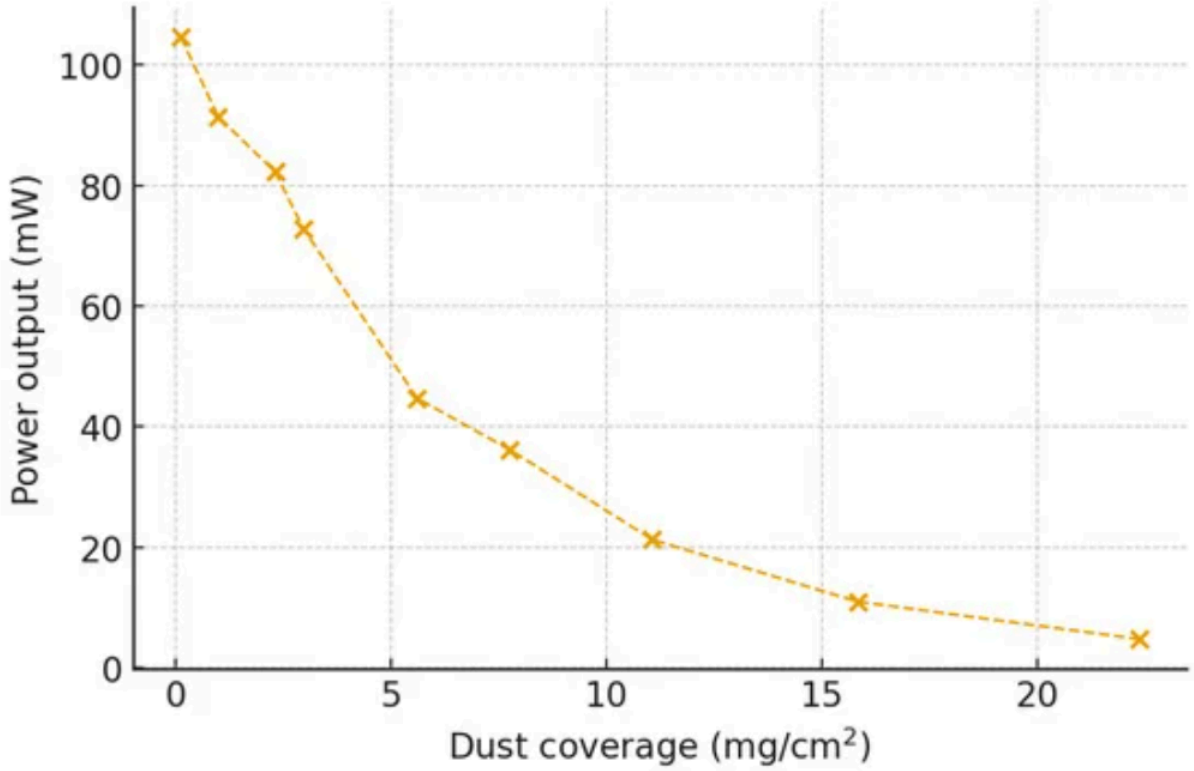


Figure 1: Power output versus dust coverage on a lab-scale solar panel.

The effects of dust accumulation demonstrate the importance of identifying visible surface contamination during solar-panel inspection and maintenance. In this project, dust was one of the four defect categories targeted by the multiclass image-classification model. The model was designed to identify dusty panels from RGB images, providing an initial indication of visible surface contamination. It did not directly measure the resulting power loss or efficiency reduction.

2.4.2 Effects of Bird Droppings on Photovoltaic Panels

Bird-dropping deposition is an important form of soiling that can negatively affect the performance of photovoltaic (PV) modules. Unlike general dust deposition, which tends to form a relatively continuous layer over the module surface, bird droppings can produce localised areas of partial or complete shading. This reduces the amount of solar radiation reaching the cells underneath the affected region and can consequently reduce the electrical output of the module. Sisodia and Mathur [17] describe bird

droppings as an environmental contamination source that can significantly restrict light transmission through the transparent surface of a PV module.

The effect of bird droppings is particularly important because the resulting shading is non-uniform. When a portion of a PV module is shaded while other cells remain illuminated, the affected cell may become reverse-biased and behave as a load rather than a power-generating element. This can cause electrical power to be dissipated as heat within the affected region, potentially producing a hotspot. Prolonged or severe hotspot formation may contribute to cell damage and other module failures. Dorobantu et al. [18] reported that the temperature of a bird-dropping-contaminated area increased from approximately 27.8 °C on a clean surface to 37.5 °C. Chaudhary and Chaturvedi [19] also reported temperatures of approximately 49 °C in areas affected by bird droppings and cement deposits, under an ambient temperature of 39 °C.

Figure 2: Effect of partial shading caused by bird dropping on a photovoltaic module.

The magnitude of the effect is not constant and depends on factors such as the amount and spatial distribution of the droppings, rainfall, and the inclination of the PV module. In the Western Rajasthan study, the highest observed power loss reached

approximately 23.8% at a horizontal tilt angle during March, whereas losses were approximately 1% during the monsoon period, when rainfall naturally cleaned much of the module surface [17]. The researchers also examined the influence of module inclination. At low inclinations between 0° and 25°, the reported power loss was approximately 14.2%. Between 25° and 60°, power losses remained relatively stable at approximately 6.2–6.5%, while at inclinations above 60°, losses increased again, reaching approximately 9.7% [17].

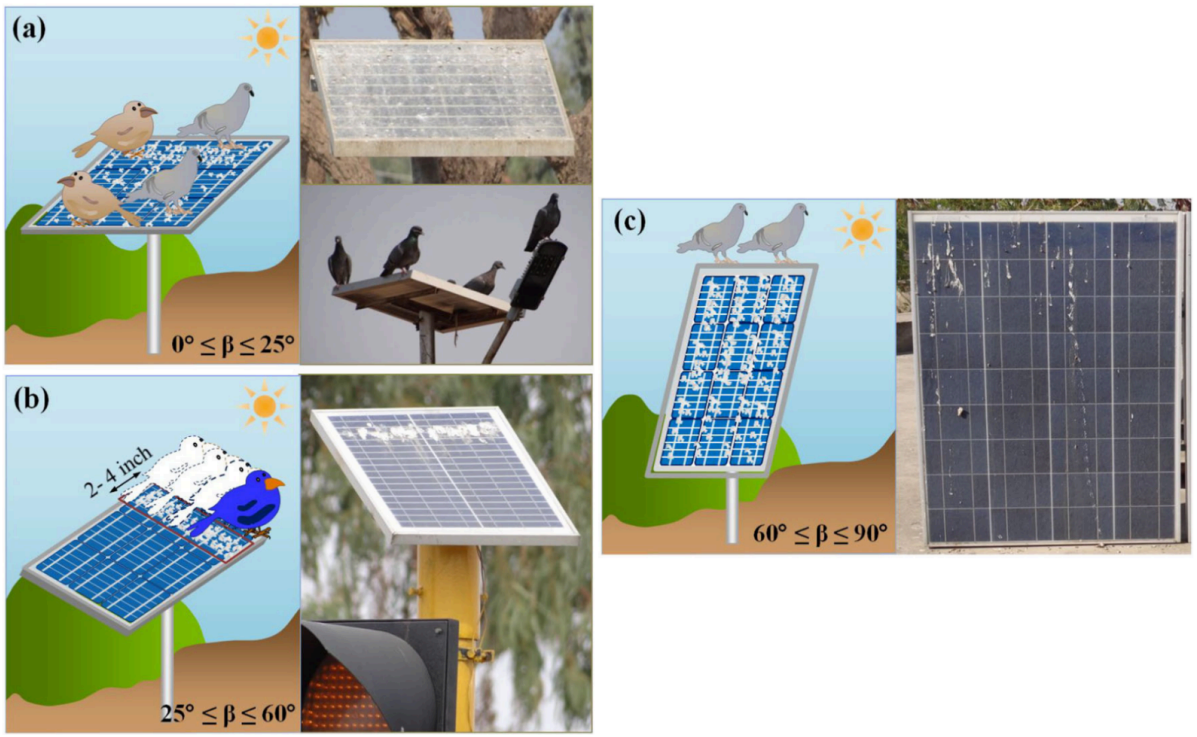


Figure 3: Bird-dropping deposition patterns on PV modules at different tilt angles.

The study also found substantial reductions in light transmittance through contaminated glass surfaces. Between October and March, average transmittance reductions were approximately 27–31% for inclinations between 0° and 25°, 13–15% for inclinations between 25° and 60°, and 18–24% for inclinations between 60° and 90° [17]. These findings demonstrate that bird-dropping deposition is not merely a cosmetic issue but can measurably affect the optical and electrical performance of PV modules.

Therefore, timely identification of bird-dropping contamination can contribute to effective PV system maintenance by allowing affected modules to be identified before prolonged shading and associated thermal effects lead to further performance degradation. This provides a motivation for automated visual inspection systems capable of identifying bird-dropping defects from panel images. In this project, bird-dropping contamination was one of the four defect categories targeted by the multiclass image-classification model. The model was designed to identify visible bird-dropping contamination from RGB images; it did not directly measure the resulting power loss or temperature increase.

2.4.3 Effects of Cracks on Photovoltaic Panels

Physical damage, particularly cracking of solar cells, is an important concern in the reliability and performance of solar photovoltaic (PV) modules. Cracks can develop due to mechanical stress during manufacturing, transportation, installation, and operation. Depending on their characteristics and location, cracks may disconnect parts of a solar cell from electrical conduction, potentially reducing the active area available for power generation. However, the presence of a crack does not necessarily result in a substantial reduction in electrical performance, as the impact depends on the nature and extent of the damage [20], [21].

Dhimish et al. [20] investigated the impact of cracks on PV power performance using electroluminescence (EL) measurements to examine possible faults in PV modules. The researchers applied statistical tests, including the t-test and F-test, to determine whether cracks significantly affected power generation. Their proposed approach identified 60% of the cracks that significantly affected the total power generated by the examined modules. This finding highlighted the difficulty of determining the electrical consequences of physical damage through crack identification alone.

Similarly, Papargyri et al. [21] reviewed experimental and numerical investigations of microcracks in crystalline silicon photovoltaic cells. Their review examined the origins of cracks, the factors contributing to their development, and their effects on the mechanical integrity and electrical characteristics of PV modules. The authors

observed that cracks do not always cause substantial performance degradation, indicating that the relationship between visible or detected cracks and electrical power loss is not straightforward.

These studies demonstrate the importance of identifying physical damage while recognising that image-based defect detection does not, by itself, establish the electrical severity of the damage. In the present study, physical damage was treated as one of the defect categories in the multiclass classification model. The model classified solar panel images into bird-drop, dusty, electrical-damage, and physical-damage categories using RGB images. It was designed to identify the visible defect category rather than estimate the power loss or electrical performance associated with a crack.

2.5 Conventional Solar Panel Inspection

Traditional photovoltaic inspection commonly involves visual examination and electrical or thermal measurements.

Visual inspection can identify visible conditions such as dirt, bird droppings, cracks and physical damage. However, manual inspection can become time-consuming when large numbers of panels are installed.

Thermal and infrared inspection provides another approach because temperature variations can reveal abnormalities that may not be immediately visible in conventional photographs.

However, inspection of large photovoltaic farms presents challenges because hundreds or thousands of panels may need to be examined. This creates a need for inspection approaches that can cover large areas efficiently while reducing the amount of manual analysis required.

2.6 UAV-Based Solar Panel Inspection

Liao and Lu (2021) investigated the use of an unmanned aerial vehicle equipped with both infrared and visible-light cameras to detect solar module faults. Their system transmitted images from the UAV to a ground station, where image-processing

techniques were applied. The proposed process included grayscale conversion, filtering, three-dimensional temperature representation, probability-density analysis and cumulative-distribution analysis [22].

The researchers conducted field experiments involving both large-scale solar farms and smaller solar installations. Their results demonstrated that infrared imaging could be used to identify abnormal regions and estimate the proportion of defective areas. The authors reported that the approach could reduce inspection time and provide maintenance personnel with information useful for determining whether cleaning or further maintenance was required.

One important contribution of this study is its demonstration that combining UAVs with infrared imaging can provide a faster alternative to completely manual inspection. However, the approach primarily relies on thermal characteristics and image-processing/statistical techniques, rather than a deep-learning image-classification model designed to classify multiple visual defect categories.

2.8 UAV Thermal Imaging for Photovoltaic Hotspot Detection

Pruthviraj et al. (2023) investigated UAV-based thermal inspection of a 55 MW solar field in southern India. A thermal camera mounted on a UAV was used to capture images of the photovoltaic installation. The researchers created an orthomosaic representation of the solar field and used thermal information to identify defective panels and hotspots [5].

The study identified 232,934 solar panels and automatically indicated 2,481 defective panels. The identified defects were associated with factors including manufacturing failure, ageing, shading, soiling, dust and extreme weather conditions.

The researchers reported that UAV-based thermal inspection could provide substantial time savings when compared with conventional thermographic inspection. They also reported hotspot-mapping accuracy of up to approximately 97% using their image-visualization and thermal-analysis approach.

The study demonstrates the scalability of aerial inspection and the usefulness of thermal imaging for large photovoltaic installations. However, the approach requires specialized UAV and thermal-imaging equipment, together with suitable environmental and operational conditions for thermal inspection. The researchers themselves identify factors such as flight height, camera resolution, solar irradiance, camera angle, wind and environmental conditions as important considerations for successful inspection.

This creates an opportunity for alternative approaches based on ordinary RGB images and deep-learning classification, particularly where specialized thermal equipment may not be readily available.

2.9 Artificial Intelligence and Computer Vision for Solar Panel Inspection

Artificial intelligence and computer vision provide an alternative approach to conventional inspection by allowing computers to learn visual characteristics associated with different panel conditions.

Rather than manually defining every characteristic of a defect, deep-learning models can learn relevant features from labelled images during training. This makes image classification particularly suitable for applications where different defect categories have visually distinguishable characteristics.

A solar panel inspection system based on computer vision can therefore be designed to receive an image of a panel and produce a classification indicating its condition.

In the context of this project, this concept is implemented at two levels:

- Binary classification — determining whether an image represents a healthy or faulty panel.
- Multiclass classification — determining which type of fault is present in a faulty panel.

This two-stage approach differs from systems that focus exclusively on hotspot detection or thermal anomaly mapping.

2.10 Deep Learning and ResNet for Image Classification

Convolutional Neural Networks (CNNs) are widely used for image classification because they can automatically learn hierarchical visual representations from images.

Early layers of a CNN can learn relatively simple visual features such as edges and textures, while deeper layers can learn more complex patterns and structures. This makes CNNs suitable for recognizing visual differences between various solar-panel conditions.

This project uses ResNet18, a residual convolutional neural network architecture. ResNet introduces residual connections that allow information to pass through multiple network layers more effectively, helping to address difficulties associated with training deeper neural networks.

Rather than training the network entirely from random initialization, the project used a pretrained ResNet18 and modified its final classification layer for the required number of classes. This approach is commonly referred to as transfer learning, where knowledge learned from a larger image dataset is adapted to a new classification task.

For the binary classifier, the final layer was modified to produce two outputs which are;

Healthy and Faulty.

For the multiclass classifier, the final layer was modified to produce four outputs:

Bird-drop, Dusty, Electrical-damage and Physical-Damage.

2.11 Research Gap

The reviewed studies demonstrate that automated photovoltaic inspection is an active area of research. UAV-based thermal imaging has demonstrated the ability to inspect large solar farms and identify hotspots and defective cells efficiently. Similarly, image-processing approaches have demonstrated the potential to reduce inspection time and support maintenance decisions.

However, several gaps remain.

First, many existing approaches rely on specialized thermal cameras, UAV platforms and aerial data collection. Such equipment can increase the cost and technical requirements associated with deploying the system.

Second, some approaches primarily identify thermal anomalies or hotspots, rather than directly classifying visually identifiable defect categories.

Third, there is limited emphasis in the reviewed work on developing an end-to-end software application that combines deep-learning classification with a user-facing application and remotely accessible API.

Finally, there is a need for approaches that are relevant to the practical context of developing countries such as Zambia, where solar deployment is expanding and cost-effective inspection technologies could become increasingly valuable.

2.12 Proposed Contribution of the Study

This project addresses the identified gap by developing an image-based deep-learning solar panel defect detection system using ordinary solar panel images.

Unlike approaches that depend primarily on UAV-mounted thermal cameras, the developed system uses RGB images and a pretrained ResNet18 architecture.

The project implements a two-stage classification approach:

Stage 1: Binary Classification

The first model determines whether the solar panel is:

- Healthy
- Faulty

Stage 2: Multiclass Classification

For panels identified as faulty, the second model determines whether the defect is:

- Bird-drop
- Dusty
- Electrical-damage

- Physical-Damage

The models were evaluated using independent test datasets. The binary classifier achieved 96.52% test accuracy, while the multiclass classifier achieved 90.70% test accuracy.

Furthermore, rather than stopping at model development, the trained models were integrated into a software application. A React Native frontend was developed and connected to a FastAPI backend responsible for receiving images and performing model inference. The backend was deployed using Render, while the frontend was deployed using Vercel.

This combination of deep-learning classification, application development and cloud deployment provides a practical implementation of an automated solar-panel inspection system.

Chapter 3

Methodology

3.1 Overview of the Methodology

The project followed a CRISP-DM model development process consisting of Business understanding, dataset preparation, image preprocessing, dataset splitting, model development, model training, model evaluation, application development and system deployment.

The overall workflow can be represented as shown in the diagram below:

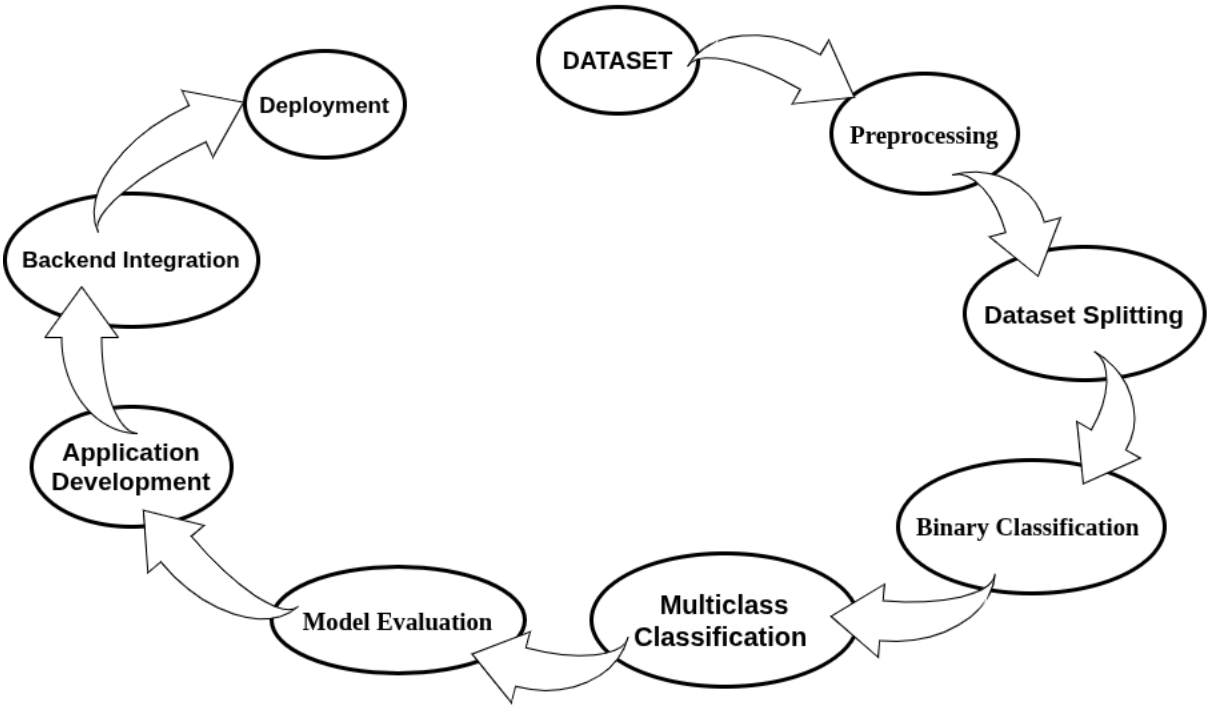


Figure 4: Summary of methodology workflow

3.2 Dataset Preparation

The project used a solar panel image dataset from Kaggle containing 762 images distributed across five classes [23]:

Table I. Kaggle Dataset Distribution

Class	Number of images
Bird drop	207
Dusty	190
Clean	193
Electrical damage	103
Physical damage	69
Total	762

The Clean class represented healthy solar panels, while the remaining four classes represented faulty conditions.

A dataframe was created to associate each image with its corresponding class and file path. The images were then prepared for use with PyTorch.

3.3. Image Preprocessing

Because the original images had different dimensions and colour-channel formats, preprocessing was applied before they were supplied to the neural network.

The images were converted to RGB format and resized to 224×224 pixels, which corresponds to the input size used by ResNet18.

For the training data, data augmentation was applied using:

- Random horizontal flipping with a probability of 0.5
- Random rotation within ± 10 degrees
- Conversion to tensors
- ImageNet normalization

Validation and test images were resized and normalized without random augmentation. This ensured that validation and test evaluation was performed on consistent image representations.

3.4.Dataset Splitting

The dataset was divided into training, validation and test sets.

For the binary classifier, the 762 images were divided into:

- **Training**: 533 images
- **Validation**: 114 images
- **Testing**: 115 images

For the multiclass classifier, the clean class was excluded because the purpose of this model was to identify the specific type of fault. This resulted in 569 faulty images distributed across four classes.

The multiclass dataset was divided into:

- **Training**: 398 images
- **Validation**: 85 images
- **Testing**: 86 images

The class distribution of the multiclass training set was:

Table II. Distribution of Multiclass training set

Class	Training images
Bird-drop	145
Dusty	133
Physical damage	48
Electrical damage	72

An intersection check was performed between the three datasets. The results were:

Train ∩ Validation = 0

Train ∩ Test = 0

Validation ∩ Test = 0

This confirmed that no image was shared between the training, validation and test sets.

3.5. Binary Classification Model

The first model was developed as a binary classifier whose purpose was to determine whether a solar panel image was healthy or faulty.

The classes were mapped as:

Healthy = 0

Faulty = 1

A pretrained ResNet18 model was used as the base architecture. The original final classification layer, which was designed for 1,000 ImageNet classes, was replaced with a fully connected layer having two outputs.

The resulting architecture therefore produced two class predictions: Healthy and Faulty.

The model was trained using:

- **Model**: Pretrained ResNet18
- **Output classes**: 2
- **Loss function**: CrossEntropyLoss
- **Optimizer**: Adam
- **Learning rate**: 0.0001
- **Weight decay**: 0
- **Batch size**: 32
- **Training epochs**: 10

During training, the model was evaluated against the validation set after each epoch. The model achieving the highest validation accuracy was saved as the best model rather than simply using the model from the final epoch.

3.7 Multiclass Classification Model

After developing the binary classifier, a second model was developed to identify the specific type of fault present in a faulty solar panel.

The Clean class was excluded from this stage, leaving four classes:

- Bird-drop
- Dusty
- Electrical-damage
- Physical-Damage

The class labels were mapped as follows:

Table III. Multiclass Class Label Distribution

CLASS	VALUE
Bird-drop	0
Dusty	1
Physical-Damage	2
Electrical-damage	3

A fresh pretrained ResNet18 was again used as the base model. The final classification layer was replaced with a linear layer containing four outputs:

Linear(in_features=512, out_features=4)

The model was trained using:

- **Model**: Pretrained ResNet18
- **Output classes**: 4
- **Loss function**: CrossEntropyLoss
- **Optimizer**: Adam
- **Learning rate**: 0.0001
- **Weight decay**: 0
- **Batch size**: 32
- **Training epochs**: 10

During model development, additional optimization experiments were conducted, including data augmentation, dropout and class-weighted loss. However, these experiments did not outperform the original configuration.

3.8 System Architecture and Design

3.8.1 Use Case Diagram

The use case diagram illustrates the interactions between the user and the proposed solar photovoltaic (PV) defect classification system. It identifies the main functions that the user can perform and shows how the system supports the identification of solar panel defects from uploaded images.

The user begins by uploading an image of a solar panel to the system. The binary classification model then analyses the image and classifies the panel as either healthy or faulty. If the panel is classified as faulty, the multiclass classification model identifies the defect category as bird droppings, dust, electrical damage, or physical damage. The system then presents the classification result to the user.

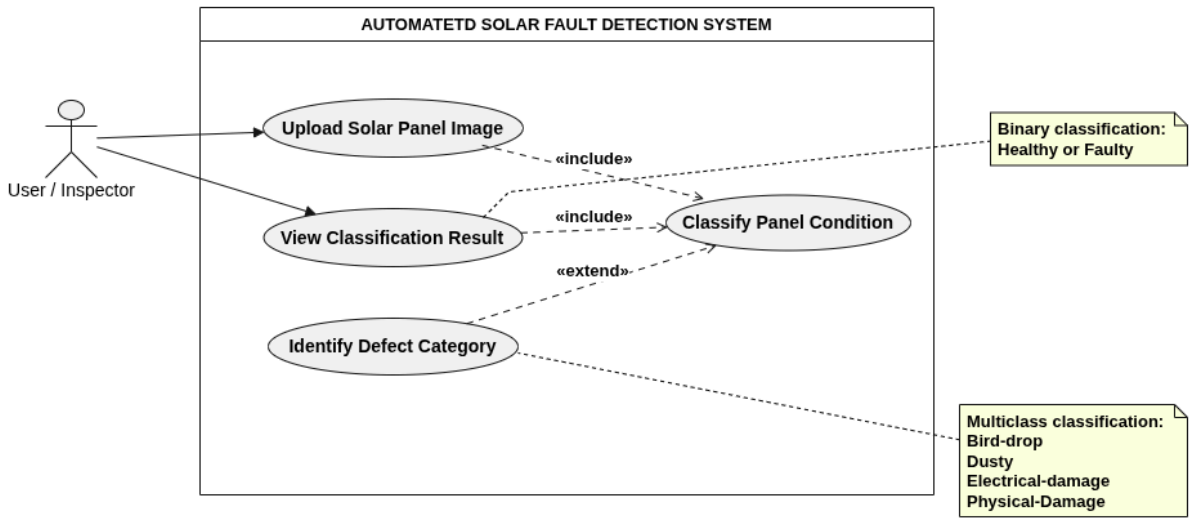


Figure 5: Use Case Diagram of the Proposed Solar PV Defect Classification System.

The diagram represents the main interaction between the user and the proposed system. Image upload provides the input required for classification, while the binary model determines the initial condition of the panel. The multiclass model is used when a faulty panel is detected, allowing the system to provide a more specific defect

classification. This two-stage approach separates the initial healthy-or-faulty decision from the identification of the particular defect category.

The use case diagram defines the intended functionality of the system and provides a basis for its subsequent design and implementation. It focuses on image-based defect classification and does not represent direct measurement of electrical output, thermal inspection, or automated physical maintenance of the solar panel.

3.8.2 Application Development

After the machine learning models were developed and evaluated, they were integrated into a software application to provide a practical interface for users.

3.8.2.1 Frontend

The application frontend was developed using React Native. The frontend provides the user interface through which a solar panel image can be submitted for analysis and the classification result can be presented to the user.

The application communicates with the backend through HTTP requests rather than directly accessing the machine learning model.

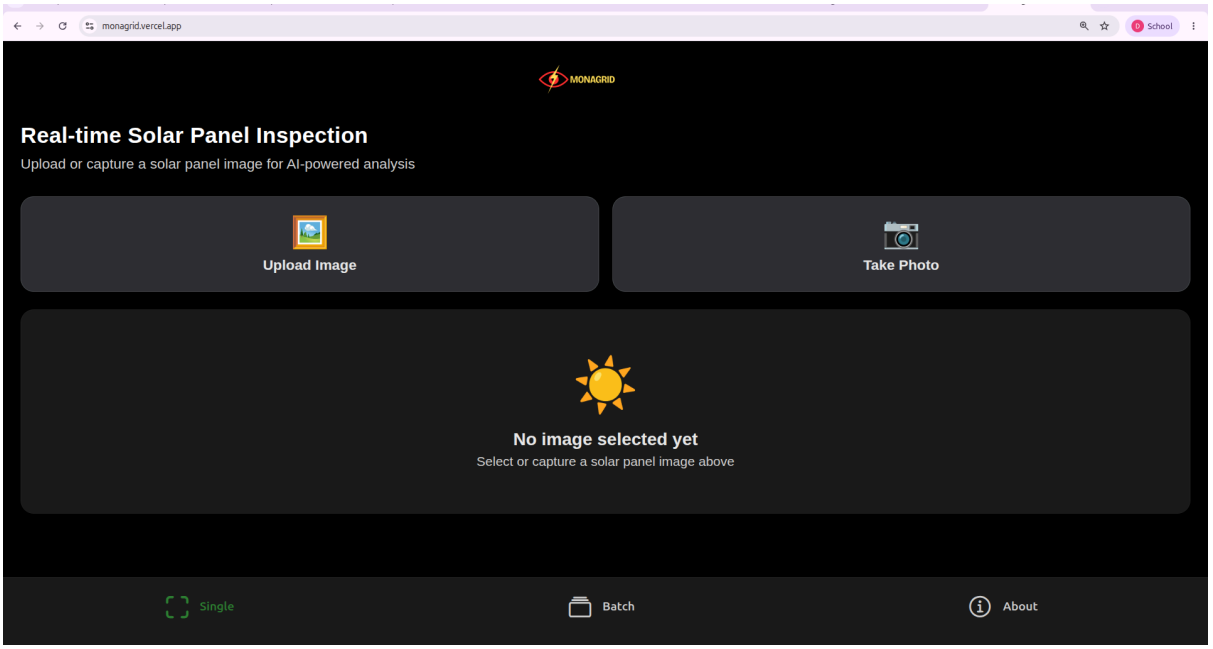


Figure 6: frontend UI.

3.8.2.2 Backend

A FastAPI backend was developed to provide the API layer between the frontend and the machine learning models.

The backend is responsible for:

- Receiving the solar panel image from the frontend.
- Processing the uploaded image.
- Preparing the image in the format required by the model.
- Loading/running the trained classification model.
- Obtaining the model prediction.
- Returning the prediction to the frontend through an API response.

This architecture separates the user interface from the machine learning functionality and allows the models to be accessed through a defined API.

3.9 System Deployment

The completed system was deployed using cloud-based hosting services.

The FastAPI backend was deployed on Render, allowing the API and machine learning inference functionality to be accessed remotely.

The frontend was deployed using Vercel, providing a publicly accessible deployment of the application's frontend.

The resulting architecture can therefore be summarized as:

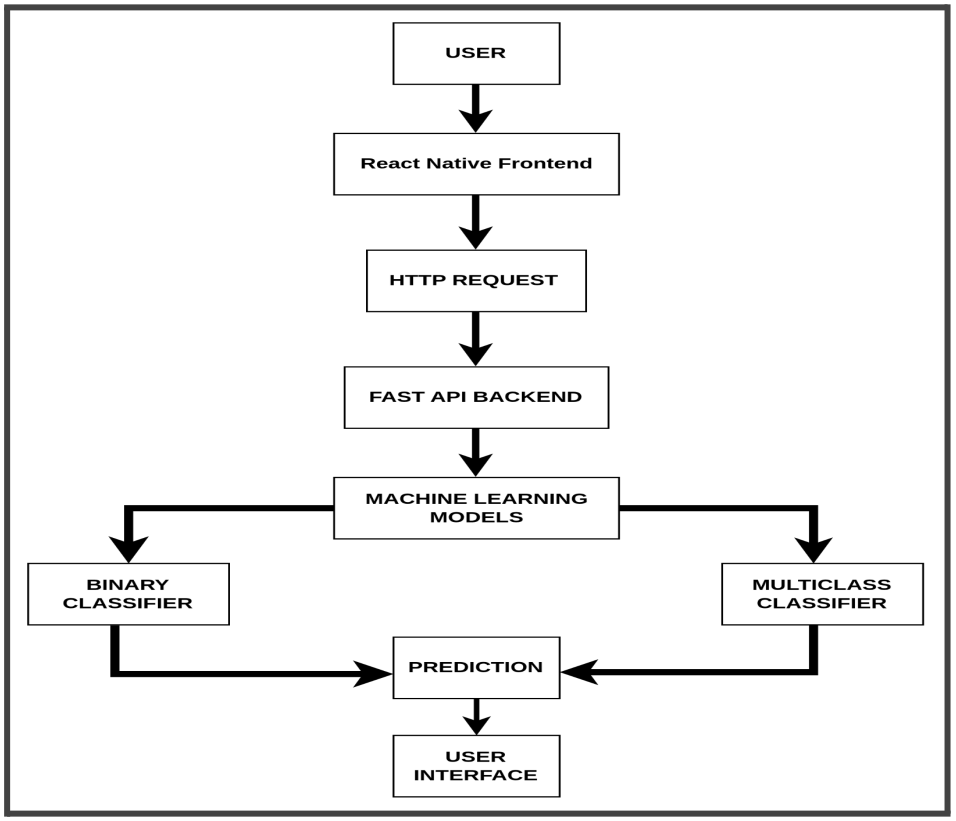


Figure 7: Summary of the system architecture

This approach allowed the machine learning models developed during the project to move beyond experimentation in Google Colab and become part of an operational software system.

Chapter 4

Evaluation

7.1 Introduction

This chapter evaluated and discussed the results presented in Chapter Six. The evaluation examined the effectiveness of the binary and multiclass ResNet18 models, considered the types of classification errors they produced, and assessed the extent to which the experimental findings addressed the project's technical objectives.

The discussion focused on the quantitative model results and their implications for image-based solar PV panel defect classification. It also considered the limitations of the dataset and the extent to which the results supported the potential use of the proposed system as an aid to preliminary defect identification.

7.2 Evaluation Framework

The models were evaluated using accuracy, precision, recall, F1-score, test loss, and confusion matrices. These measures were used because each described a different aspect of classification performance.

Accuracy measured the proportion of test images classified correctly. Precision measured the proportion of predictions for a particular class that were correct, while recall measured the proportion of actual images belonging to that class that were correctly identified. The F1-score combined precision and recall into a single measure. Confusion matrices provided a detailed account of the categories that were correctly and incorrectly predicted.

For the binary model, particular attention was given to the faulty class because a faulty panel classified as healthy represented a missed defect in the context of image-based inspection. For the multiclass model, evaluation focused on how consistently the model distinguished the four defect categories.

The evaluation was based on the recorded experimental results from the models' respective test datasets. It did not treat model accuracy as proof of complete diagnostic capability, since the models were trained to classify image categories rather than measure the full electrical condition of a PV panel.

7.3 Evaluation of Binary Classification Performance

The binary classification model achieved 93.04% test accuracy, correctly classifying 107 of the 115 test images. This result demonstrated that the model distinguished between healthy and faulty images in most cases.

The faulty class achieved a precision of 96.43%, indicating that most images predicted as faulty were actually labelled faulty in the test dataset. Its recall was 94.19%, showing that the model correctly identified 81 of the 86 faulty images. The faulty-class F1-score of 95.29% reflected the balance between these two measures.

Despite this performance, the confusion matrix revealed five false-negative predictions, in which faulty images were classified as healthy. This was a significant limitation because such a prediction could cause a panel displaying a visible defect to be overlooked if the classification were used to guide further inspection. The model also produced three false-positive predictions, classifying healthy images as faulty.

The healthy class achieved a recall of 89.66% and a precision of 83.87%. These values showed that the model identified most healthy images correctly but also assigned some faulty images to the healthy category and some healthy images to the faulty category.

The binary model therefore met the technical aim of distinguishing between healthy and faulty images with a high overall test accuracy. However, its false-negative predictions demonstrated that the model was not error-free and that overall accuracy alone could not establish the reliability required for operational inspection.

7.4 Evaluation of Multiclass Classification Performance

The multiclass model achieved a test accuracy of 90.70%, correctly classifying 78 of the 86 test images. Its weighted-average F1-score of 90.67% indicated that its overall precision and recall remained well balanced when the number of test examples in each class was considered.

The model's strongest recall was recorded for Dusty at 96.55%. It correctly identified 28 of the 29 dusty images. This indicated that the model was effective at identifying the dusty category within the test dataset. However, its precision of 87.50% showed that some images predicted as dusty belonged to other categories.

Electrical-damage achieved the highest precision at 93.33%, but its recall was 87.50%. The model correctly identified 14 of the 16 Electrical-damage images, while one was classified as Dusty and one as Physical-Damage. These errors demonstrated that the model did not consistently distinguish every electrical-damage image from the other defect categories.

Bird-drop achieved a precision of 93.10% and a recall of 87.10%. The confusion matrix showed that three Bird-drop images were classified as Dusty and one as Electrical-damage. Physical-Damage achieved precision and recall of 90.00%, with nine of its ten test images correctly classified.

The macro-average F1-score of 90.53% showed that the model maintained a similar overall level of performance when all four classes were given equal weight. The weighted-average F1-score of 90.67% was slightly higher, reflecting the weighting of classes according to their representation in the test dataset.

These results indicated that the multiclass model was able to distinguish between the four defect categories for most test images. Nevertheless, the remaining errors showed that its predictions were not consistently correct for every defect type.

7.5 Analysis of Misclassifications

The confusion matrices provided insight into the main classification errors made by the models.

For the binary model, the most important error was the classification of five faulty images as healthy. These false negatives indicated that the model sometimes failed to identify visible defects represented in the test dataset. The three healthy images classified as faulty represented false positives, which showed that the model could also flag images that belonged to the healthy category.

For the multiclass model, the errors were distributed across several defect categories. Bird-drop images were sometimes classified as Dusty or Electrical-damage, while one Dusty image was classified as Bird-drop. Electrical-damage images were confused with Dusty and Physical-Damage, and one Physical-Damage image was classified as Bird-drop.

These errors may have reflected similarities in the visual features of the images. For example, the appearance of dirt, surface deposits, and other visible marks may overlap depending on the image and the defect's appearance. However, the confusion matrices alone did not establish the precise cause of each misclassification.

The class distribution was another consideration. The multiclass dataset contained fewer Electrical-damage and Physical-Damage images than Bird-drop and Dusty images. The corresponding test supports were 16 and 10 images, respectively. Performance estimates for these classes were therefore based on fewer test examples than those for Bird-drop and Dusty.

The error analysis suggested that future improvements should focus on expanding the dataset, reviewing misclassified examples, and improving the representation of visually similar defect categories. The binary model would particularly benefit from measures that reduce the number of faulty images classified as healthy.

Chapter 5

Results

6.1 Introduction

This chapter presented the experimental results of the binary and multiclass solar photovoltaic (PV) panel defect classification models. The binary model achieved a test accuracy of 93.04%, while the multiclass model achieved a test accuracy of 90.70%. The results are presented using confusion matrices, precision, recall, F1-scores, and test loss.

6.2 Binary Classification Results

The binary classification model achieved an accuracy of 93.04%, correctly classifying 107 out of 115 test images.

The model correctly classified 26 healthy images and 81 faulty images. Three healthy images were incorrectly classified as faulty, while five faulty images were incorrectly classified as healthy.

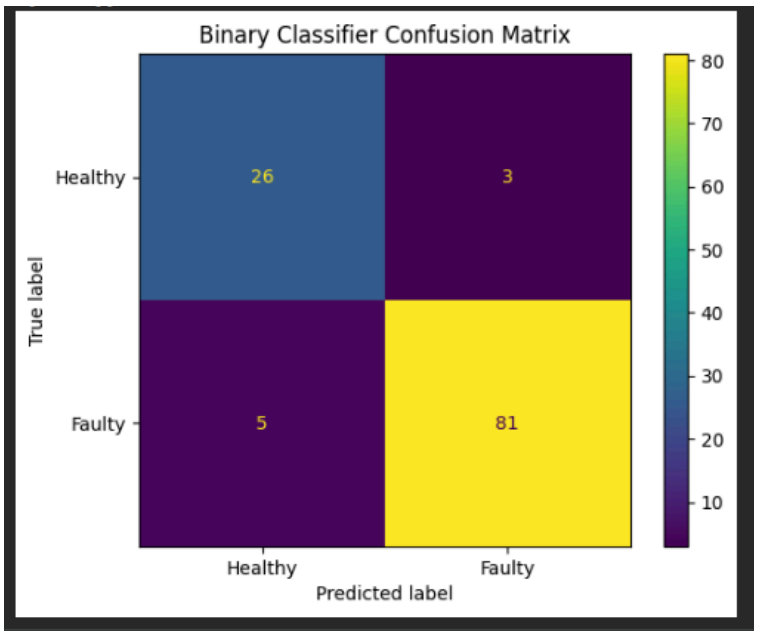


Figure 8. Confusion matrix for the Binary Classifier

Table IV. Evaluation results of the binary classification model

Class	Precision	Recall	F1-Score
Healthy	83.37%	89.66	86.67
Faulty	96.43	94.19	95.29

The faulty class achieved a precision of 96.43%, recall of 94.19%, and F1-score of 95.29%. The healthy class achieved a precision of 83.87%, recall of 89.66%, and F1-score of 86.67%.

6.3 Multiclass Classification Results

The multiclass classification model achieved a validation accuracy of 87.06% and a test accuracy of 90.70%, with a test loss of 0.2236.

Table V: Multiclass classification model performance

Evaluation measure	**Result**
Validation accuracy	87.06%
Test accuracy	87.06%
Test Los	0.2236
Correct test predictions	78
Incorrect test predictions	8
Total test images	86

The model correctly classified 27 Bird-drop images, 28 Dusty images, 14 Electrical-damage images, and nine Physical-Damage images. Eight test images were incorrectly classified.

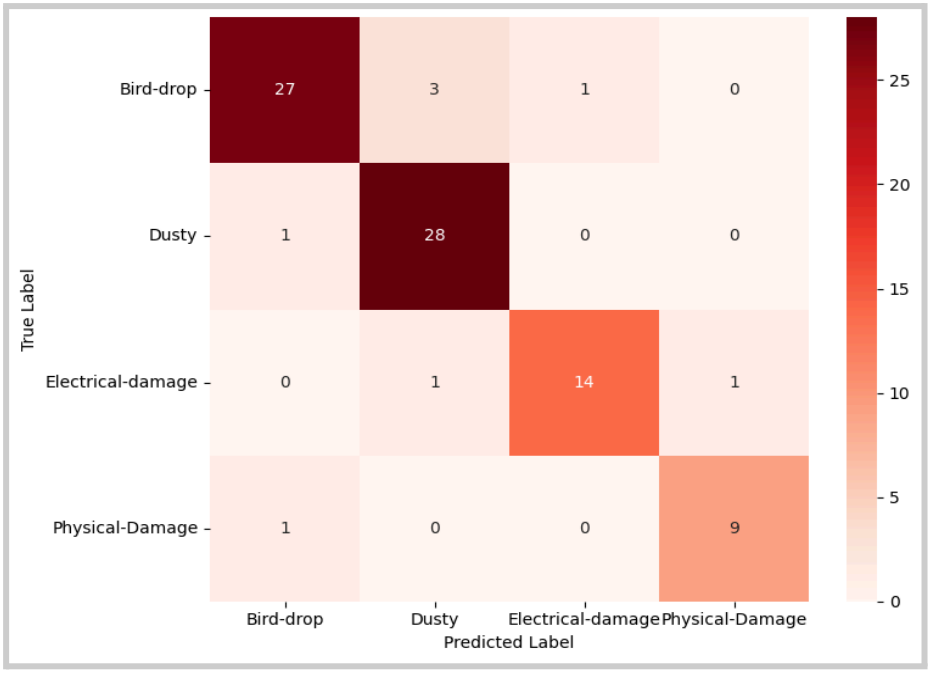


Figure 9: Confusion matrix for the multiclass classifier

The Dusty class achieved the highest recall at 96.55%, while Electrical-damage achieved the highest precision at 93.33%. The macro-average F1-score was 90.53%, and the weighted-average F1-score was 90.67%.

Table VI: Multiclass Classification model evaluation results

Class	Precision	Recall	F-Score	Support
Bird-drop	0.9310	0.8710	0.9000	31
Dusty	0.8750	0.9655	0.9180	29
Electrical damage	0.9333	0.8750	0.9032	16
Physical damage	0.9000	0.9000	0.9000	10
Macro Average	0.9098	0.9029	0.9029	86
Weighted Average	0.9090	0.9070	0.9070	86

6.4 Summary of Results

Table VII: Summary of classification results

Model	Classification task	Test accuracy	Key performance result
Binary classifier	Healthy versus faulty	93.04%	Faulty-class F1-score: 95.29%
Multiclass classifier	Four defect categories	90.70%	Weighted-average F1-score: 90.67%

The binary model correctly classified 107 of 115 test images, while the multiclass model correctly classified 78 of 86 test images. Both models achieved test accuracies above 90%. The confusion matrices nevertheless showed that each model produced eight incorrect predictions on its respective test dataset.

Chapter 6
Discussion

6.1 Introduction

This chapter discussed the findings from the development and evaluation of the deep learning-based solar PV panel defect classification system. It interpreted the performance of the binary and multiclass ResNet18 models, considered their relevance to solar panel inspection, and discussed the project's contributions and limitations.

The discussion focused on the quantitative results obtained from the test datasets. It also considered the practical implications of image-based defect classification and the distinction between identifying a visible defect in an image and determining the actual electrical or operational condition of a PV panel.

6.2 Interpretation of Findings

The binary classification model achieved 93.04% test accuracy, demonstrating that the trained network could distinguish between healthy and faulty panel images in most cases. This finding supported the use of convolutional neural networks for learning visual differences between the two categories.

The confusion matrix provided a more detailed understanding of the binary model's performance. Of the 86 faulty images in the test dataset, 81 were correctly classified and five were incorrectly classified as healthy. The model therefore achieved a faulty-class recall of 94.19%. This result was important because a missed defect may prevent a panel from being flagged for closer inspection.

The three healthy images incorrectly classified as faulty also demonstrated that the model could produce false alarms. In a practical inspection workflow, such predictions could lead to additional manual checks of panels that did not display the defect categories represented in the dataset. The model's performance therefore involved a balance between identifying faults and avoiding incorrect classifications.

The multiclass model extended the classification task by identifying four defect categories. Its test accuracy of 90.70% and weighted-average F1-score of 90.67% indicated that it was able to distinguish between the selected categories for most test images. The model achieved its highest recall for Dusty images, at 96.55%, while Bird-drop and Electrical-damage each had lower recall values of 87.10% and 87.50%, respectively.

The confusion matrix indicated that some Bird-drop images were classified as Dusty or Electrical-damage. This pattern suggested that visual similarities between certain images could affect the model's predictions. Dust accumulation, bird droppings, and physical surface marks may produce overlapping visual features, depending on the appearance of the panel and the conditions under which the image was captured. The model's errors showed that these categories were not perfectly separable using the dataset and training approach employed.

The Physical-Damage category achieved an F1-score of 90.00%. Although this result was encouraging, it was based on a test support of only ten images. The result therefore needed to be interpreted in the context of the relatively small number of test examples available for this class.

Taken together, the findings demonstrated that the models learned useful image features for PV panel classification. They also showed that the quality and breadth of the dataset, the visual differences between defect types, and the consequences of individual prediction errors were important considerations when interpreting model performance.

6.3 Comparison with Existing Work

Research in photovoltaic inspection has investigated several approaches to identifying defects and performance-related problems. Conventional inspection methods rely on human observation and specialised diagnostic procedures. Other approaches use thermal imaging, unmanned aerial vehicles, image processing, and machine learning to support the identification of panel abnormalities.

Thermal inspection can help reveal temperature-related anomalies that are not necessarily visible in ordinary RGB images. Image-based deep learning, by contrast, learns visual patterns from labelled examples and can classify images according to the categories represented in its training data. These approaches address related but different aspects of PV inspection.

The present project focused on RGB-image classification using ResNet18. Its binary model classified images as healthy or faulty, while its multiclass model distinguished four visible defect categories. The results demonstrated that this approach could achieve test accuracies above 90% on the respective datasets used in the experiments.

However, a direct numerical comparison with other studies would require consideration of differences in datasets, image acquisition conditions, class definitions, train-test splitting procedures, and evaluation methods. The accuracy values obtained in this project were therefore interpreted as evidence of performance on the project's own test datasets rather than proof that the models outperformed other published approaches.

The project also differed from inspection systems that depend on thermal imagery or aerial data because it concentrated on classification from ordinary panel images. This provided a relatively accessible approach to visible-defect identification, although it did not provide the additional diagnostic information that may be obtained from thermal sensors or other specialised inspection equipment.

6.4 Contributions of the Project

The project made several contributions to the application of deep learning to solar PV panel inspection.

First, it developed a binary classification model that distinguished healthy panels from faulty panels. The model achieved 93.04% test accuracy, demonstrating the feasibility of using a ResNet18-based classifier for the initial identification of visible panel defects.

Second, the project developed a separate multiclass classification model for four categories of defects: bird-dropping, dust accumulation, electrical damage, and physical damage. The model achieved 90.70% test accuracy and a weighted-average F1-score of 90.67%. This extended the classification task beyond the general identification of faulty panels to the categorisation of specific visible defects.

Third, the project evaluated the models using several complementary metrics. The use of confusion matrices and class-specific precision, recall, and F1-scores provided a more detailed account of performance than overall accuracy alone. This analysis identified the categories and error types that could benefit from further improvement.

Fourth, the project established a software architecture intended to make image-based classification accessible through an application interface and a backend inference service. This architecture provided a pathway for presenting model predictions through software rather than requiring users to interact directly with the underlying model code.

Collectively, these contributions demonstrated how deep learning models could form part of a software-based approach to preliminary solar panel defect identification.

6.5 Limitations and Implications

Despite the encouraging experimental results, the project had several limitations.

6.5.1 Dataset Size and Class Distribution

The dataset used for the experiments contained 762 images across five original categories. The multiclass task used 569 images after the Clean category was excluded. The number of examples varied across the defect categories, with Electrical-damage and Physical-Damage represented by fewer images than Bird-drop and Dusty.

A limited number of examples may restrict the range of visual variations learned by a model. Additional images showing different defect sizes, severities, panel types, and environmental conditions would help improve the representativeness of the dataset.

6.5.2 Dependence on Image Quality

The models relied on visual information contained in the input images. Image resolution, lighting, shadows, viewing angle, camera distance, and obstruction could affect the appearance of a defect. Consequently, a model trained on one collection of images might not achieve the same performance when presented with images captured under substantially different conditions.

6.5.3 Classification Scope

The system was designed to classify visible defects rather than perform a complete technical assessment of a solar PV installation. Its predictions did not establish the actual electrical output, power loss, remaining useful life, or precise physical condition of a panel. In particular, the Electrical-damage class represented a category learned from labelled images; the model did not independently measure electrical characteristics or confirm internal electrical faults.

The system also did not replace thermal imaging, electrical testing, or expert inspection. Its intended role was to support preliminary identification of visible abnormalities rather than provide a definitive diagnosis of all PV panel faults.

6.5.4 Generalisation

The reported results were based on the project's available dataset and test splits. They did not establish equivalent performance across all PV installations, geographical areas, panel technologies, or image acquisition environments. Further evaluation using independent datasets would be needed to determine how well the models generalised beyond the images used in this project.

6.5.5 Interpretation of Model Performance

The binary model's 93.04% accuracy and the multiclass model's 90.70% accuracy provided useful summaries of their test performance. However, the confusion matrices demonstrated that both models still made incorrect predictions. The binary model incorrectly classified five faulty images as healthy, while the multiclass model confused some defect categories.

These errors were relevant to the potential use of the system in inspection workflows. Model predictions would need to be interpreted with an understanding of their limitations, particularly where missing a defect could have operational consequences. A prediction should therefore be treated as an indication from an image classifier rather than conclusive proof of a panel's condition.

6.6 Chapter Summary

This chapter discussed the results of the binary and multiclass classification experiments and considered their implications for solar PV panel inspection. The binary model achieved 93.04% test accuracy, while the multiclass model achieved 90.70% test accuracy and a weighted-average F1-score of 90.67%.

The findings demonstrated the potential of ResNet18 for classifying healthy and faulty panels and identifying four categories of visible defects. The confusion matrices also revealed errors that could affect practical use, particularly the misclassification of faulty images as healthy and the confusion between visually similar defect categories.

The project contributed two evaluated image-classification models and a software architecture intended to make their predictions accessible through an application. Its limitations included the size and class distribution of the dataset, dependence on image quality, and the restricted scope of RGB-image classification. These findings informed the conclusions and recommendations presented in Chapter Eight.

Chapter 7

Conclusion

In this study, we developed deep learning models for the classification of solar photovoltaic panel defects using ResNet18. The first model classified panel images as either healthy or faulty, achieving an accuracy of 93.04%, while the second model classified faulty panels into bird-drop, dusty, electrical-damage, and physical-damage categories, achieving an accuracy of 90.70%. These results demonstrated the potential of deep learning to support the identification and classification of visible solar panel defects. However, some misclassifications remained, particularly where faulty panels were classified as healthy or where different defect categories shared similar visual characteristics. The study was limited by the size and distribution of the available dataset and by its reliance on RGB images, which did not provide a complete assessment of the electrical condition of a solar panel. Further improvements through the use of larger and more diverse datasets, alternative model architectures, and additional diagnostic information could strengthen the accuracy and reliability of the proposed system. Although the initial focus of this research was the classification of solar panel defects, the same approach could be extended to other forms of solar panel inspection and maintenance, contributing to the development of accessible intelligent tools for supporting solar energy systems in Zambia and beyond.

Appendices

APPENDIX A: INDIVIDUAL CONTRIBUTION STATEMENT

A.1 Project and Group Information

Item	Details
Project Title	Automating the detection of surface defects on solar panels in Zambia
Student Name	DONALD MAZOLE
Computer Number	2021479374
Supervisor	Dr. Lighton Phiri
Group Size	2
Group Members	• Donald Mazole • Emmanuel Kafunda

A.2 Overall Group Project

The project focuses on developing a deep learning-based system for classifying solar photovoltaic (PV) panel images to support the identification of healthy panels and common panel defects. The system uses image classification techniques to analyse images and produce predictions that may assist users in identifying panels that require further inspection.

The overall aim is to develop a system that first determines whether a solar panel is healthy or faulty and, where a panel is classified as faulty, identifies the likely defect category. The project uses convolutional neural network techniques, specifically ResNet18, to perform binary and multiclass image classification.

The system is intended to provide an accessible software-based approach to preliminary solar panel defect identification. It is not intended to replace professional inspection, electrical measurements, or specialised diagnostic procedures.

A.3 Individual Role and Responsibilities

The following responsibilities describe the machine learning and image-classification work associated with the project. Retain only those responsibilities that accurately represent the work personally undertaken.

No.	Area of Responsibility	Description
1	Dataset preparation	Organising the downloaded solar panel image dataset into the appropriate categories for the classification tasks.
2	Machine learning development	Developing and training ResNet18-based binary and multiclass classification models using PyTorch in Google Colab.
3	Model evaluation	Evaluating the trained models using test accuracy, confusion matrices, precision, recall, F1-scores, and test loss where applicable
4	Technical documentation	Documenting the dataset, model configurations, experimental procedures, evaluation results, and limitations of the classification approach.

A.4 Detailed Individual Contribution

My contribution to the project focused on the data preparation, development, training, and evaluation of deep learning models for solar PV panel defect classification.

I worked with a dataset obtained from Kaggle that contained 762 images distributed across five categories: Bird-drop, Clean, Dusty, Electrical-damage, and Physical-Damage. I used the downloaded dataset version for the experiments conducted in this project.

For the binary classification task, I treated images in the Clean category as healthy panels and combined the remaining four categories into the faulty class. The resulting dataset was divided into training, validation, and testing sets containing 533, 114, and 115 images, respectively.

I developed a ResNet18-based binary classification model using PyTorch. The model was configured to produce two output classes: Healthy and Faulty. I trained the model using the Adam optimiser with a learning rate of 0.0001 and evaluated its performance on the test set.

For the multiclass classification task, I excluded the Clean category and used the remaining 569 images to classify four defect categories: Bird-drop, Dusty, Electrical-damage, and Physical-Damage. The data was divided into training, validation, and testing sets containing 398, 85, and 86 images, respectively. I developed a second ResNet18-based model with four output classes to perform this classification task.

I evaluated the multiclass model using test accuracy, test loss, a classification report, and a confusion matrix. I also examined alternative model configurations involving dropout, weight decay, and class weighting and compared their performance with the baseline model.

The evaluation results were documented and used to discuss the models' classification performance, including the types of errors made and the differences in performance across defect categories.

A.5 Individual Deliverables

No.	Deliverable	
1	Prepared image dataset	Organised the downloaded 762-image dataset into the categories required for binary classification and prepared the four defect categories for multiclass classification.
2	Binary classification model development	Developed and trained a ResNet18-based model to classify solar panel images as Healthy or Faulty.
3	Multiclass classification model development	Developed and evaluated a ResNet18-based model to identify Bird-drop, Dusty, Electrical-damage, and Physical-Damage categories.
4	Model evaluation results	Generated and documented classification metrics, confusion matrices, and test results for the developed models.

A.6 Contribution to the Main System or Research Output

My principal contribution to the project was the development and experimental evaluation of the machine learning component. This included the preparation of image data, implementation of two ResNet18 classification models, model training, comparison of model configurations, and interpretation of evaluation results.

The binary model provides the first classification stage by distinguishing healthy panels from faulty panels. The multiclass model provides a more detailed classification stage for images belonging to the four faulty categories.

The models were evaluated as separate classification experiments. Their intended use in a complete application involves an image submission interface and a backend service that processes images and returns classification results. Any frontend, backend, integration, or deployment work completed by other group members should be acknowledged here, where applicable.

A.7 Individual Implementation and Technical Work

The technical work associated with my contribution involved Python, PyTorch, Google Colab, image dataset preparation, and ResNet18-based image classification.

For the binary classification model, I configured the network to output two classes. For the multiclass model, I configured the network to output four defect categories. The multiclass label mapping used in the experiments was Bird-drop = 0, Dusty = 1, Electrical-damage = 2, and Physical-Damage = 3.

The models were trained and evaluated using separate training, validation, and testing subsets. The validation data supported model selection, while the test data was used to assess the selected model's classification performance.

The binary model achieved a test accuracy of 93.04%. The multiclass model achieved a test accuracy of 90.70% and a test loss of 0.2236. These results represent performance on the project's held-out test sets and should not be interpreted as guaranteed performance on images collected under different real-world conditions.

The intended application architecture consists of a React Native mobile interface and a FastAPI backend. The backend is intended to receive images, preprocess them, invoke the classification models, and return predictions. This architecture should be described as planned unless implementation and integration have been verified.

A.8 Individual Testing and Evaluation Contribution

My contribution to testing and evaluation focused on assessing the classification performance of the developed machine learning models.

For the binary model, the test set contained 115 images. The model correctly classified 107 images, producing a test accuracy of 93.04%. Its confusion matrix was:

Actual class	Predicted Healthy	Predicted Faulty
Healthy	26	3
Faulty	5	81

For the multiclass model, the test set contained 86 images. The model correctly classified 78 images, producing a test accuracy of 90.70%. Its confusion matrix was:

Actual class	Bird-drop	Dusty	Electrical-damage	Physical-Damage
Bird-drop	27	3	1	0
Dusty	1	28	0	0
Electrical-damage	1	28	0	0
Physical-Damage	1	0	0	9

I also reviewed the class-level precision, recall, and F1-scores to assess performance beyond overall accuracy. The results indicated that the model's performance varied across classes, making the confusion matrices and class-level metrics important for interpreting its strengths and limitations.

The evaluation described here concerns the machine learning experiments. It does not imply that field testing, formal user acceptance testing, or usability evaluation was conducted.

A.9 Collaboration with Other Group Members

The project involves multiple components that may include requirements analysis, system design, image classification, user interface development, backend implementation, testing, and documentation.

My contribution was focused on the machine learning experiments and their evaluation. Where other group members contributed to the application interface, backend services, system design, requirements, or other project components, their work should be acknowledged according to their actual responsibilities.

The intended connection between the classification models and the application requires an interface through which an image can be submitted and a backend through which the model prediction can be returned. Any shared implementation, integration, or troubleshooting activities should be identified here based on the work actually undertaken by each group member.

A.10 Contribution Summary

My contribution to the project centred on developing and evaluating two deep learning models for solar PV panel image classification. I prepared the image categories for the two classification tasks, implemented ResNet18-based models using PyTorch, trained the models, and analysed their test performance.

The binary model achieved 93.04% test accuracy, while the multiclass model achieved 90.70% test accuracy. The results were used to assess the models' ability to distinguish healthy panels from faulty panels and to classify four types of defects.

Any jointly completed work, including system design, application integration, and shared documentation, should be distinguished from work undertaken primarily by other group members. The final statement should reflect the actual division of responsibilities within the project.

A.11 Estimated Contribution

Project Activity	Individual Contribution (%)	Collaborative Contribution (%)
Problem Analysis	50	50
Literature Review	100	100
System/Research Design	50	50
Implementation/Development	100	100
Testing and Evaluation	70	70
Documentation	80	80
Other: Dataset Preparation	50	50

A.12 Statement of Authorship and Contribution

I confirm that the contribution described in this statement accurately represents the work that I personally undertook as part of the project. I have identified collaborative work and have not knowingly claimed the work of another group member as my own.

Student Name: _____DONALD MAZOLE_____

Computer Number: _____2021479374_____

Signature: _____

Date: _____19/10/2026_____

A.13 Supervisor Verification

I confirm that, to the best of my knowledge, the contribution described above is consistent with the student's participation in the project.

Supervisor Name: _____

Signature: _____

Date: _____

APPENDIX B: USER MANUAL / INSTALLATION GUIDE

B.1 Introduction

This appendix describes the intended operation and technical setup of the solar PV defect classification system. The system is designed to accept a solar panel image, classify it as healthy or faulty, and, where the image is classified as faulty, predict the likely defect category.

The classification component comprises two ResNet18-based deep learning models developed using PyTorch. The intended application architecture uses a React Native frontend and a FastAPI backend.

B.2 System Requirements

The intended system requires the following components:

- A compatible computer or mobile device for accessing the application.
- A React Native development environment for building and running the mobile application.
- Python for running the backend service.
- FastAPI for providing the backend API.
- PyTorch for loading and executing the trained models.
- The saved model weights and any associated preprocessing configuration required for inference.
- Compatible image-processing libraries and dependencies.
- A network connection when the frontend communicates with a separately hosted backend.

B.3 Intended Installation Procedure

- 1. Obtain the project source code and the required model files.
- 2. Install the dependencies specified for the backend environment.
- 3. Configure the backend to locate the saved binary and multiclass model weights.
- 4. Configure the image preprocessing procedure to match the input requirements used during model training.
- 5. Start the FastAPI backend in the configured Python environment.
- 6. Configure the React Native application to communicate with the correct backend API address.
- 7. Start the mobile application using the appropriate React Native development workflow.
- 8. Submit a test image and verify that the application displays the response returned by the backend.

These steps describe the intended setup procedure. They should not be presented as a record of a successful installation or deployment unless the steps have been carried out and verified.

B.4 Intended System Usage

The intended workflow for a user is as follows:

1. Open the application.

2. Select or capture an image of a solar PV panel.

3. Submit the image for classification.

4. Allow the backend to validate and preprocess the image.

5. Obtain the binary model's prediction.

6. If the image is classified as healthy, display the healthy classification.

7. If the image is classified as faulty, pass it to the multiclass classification stage to predict the likely defect category.

8. Display the faulty classification and predicted defect category to the user.

The predicted category is an automated image-based assessment and should not be treated as a definitive engineering diagnosis.

B.5 Limitations

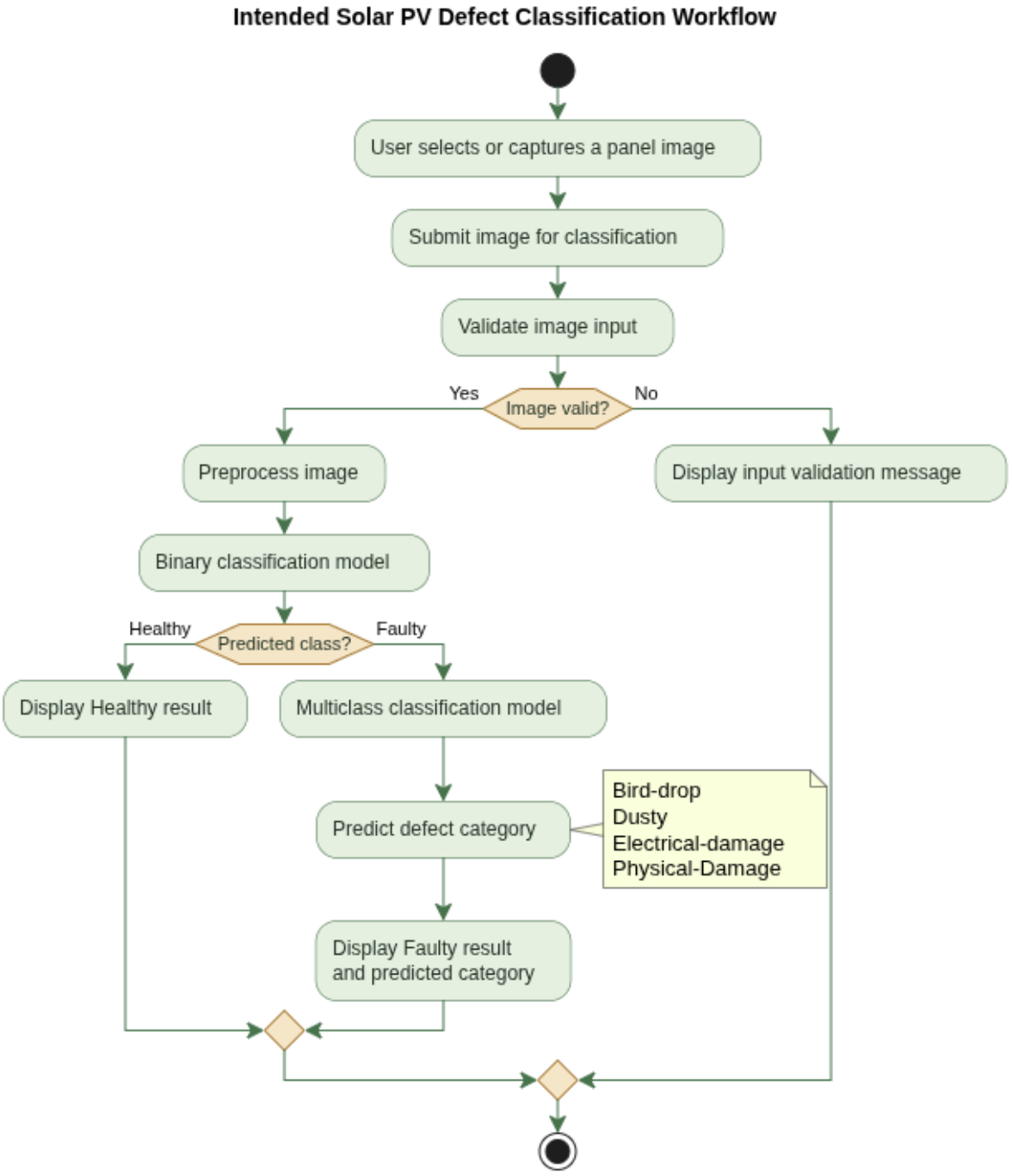
The system is designed for image-based classification. Its output depends on the quality and characteristics of the submitted image and the data used to train the models. It does not directly measure a panel's electrical output, voltage, current, temperature, or remaining service life. It also does not perform physical repairs.

The intended application workflow and deployment configuration remain subject to implementation and verification where these activities have not yet been completed.

ADDITIONAL SYSTEM DESIGNS / DIAGRAMS

C.1 Intended System Workflow

The activity diagram below represents the intended sequence of operations, from image submission to the classification result. It distinguishes the binary classification stage from the multiclass defect classification stage.



C.3 Intended Classification Model Structure

The project uses two ResNet18-based classification models. The first model has two output classes, Healthy and Faulty. The second model has four output classes corresponding to Bird-drop, Dusty, Electrical-damage, and Physical-Damage.

The models were trained and evaluated as separate experiments. Their sequential use within the application represents the intended classification workflow and should not be interpreted as evidence of completed application integration.

Bibliography

[1] International Energy Agency, *Financing Electricity Access in Africa*, Paris, France: IEA, 2025. [Online]. Available: https://www.iea.org/reports/financing-electricity-access-in-africa

[2] International Energy Agency, *Africa Energy Outlook 2022*. Paris, France: IEA, 2022. [Online]. Available: https://www.iea.org/reports/africa-energy-outlook-2022

[3] International Renewable Energy Agency, *Renewable Capacity Statistics 2025*. Abu Dhabi, United Arab Emirates: IRENA, Mar. 2025. [Online]. Available: https://www.irena.org/Publications/2025/Mar/Renewable-capacity-statistics-2025

[4] Z. Barraz, I. Sebari, K. Ait El Kadi, and I. Ait Abdelmoula, *Towards a holistic approach for UAV-based large-scale photovoltaic inspection: A review on deep learning and image processing techniques*, *Technologies*, vol. 13, no. 3, Art. no. 117, Mar. 2025, doi: 10.3390/technologies13030117.

[5] Ministry of Energy, *The Integrated Resource Plan (IRP)*, Government of the Republic of Zambia. [Online]. Available: https://www.moe.gov.zm/irp/. [Accessed: Oct. 23, 2026].

[6] Ministry of Energy, *Pipeline and Complete Projects: Projects Completed as at 28 November 2025*. Lusaka, Zambia: Government of the Republic of Zambia, 2025. [Online]. Available: https://www.moe.gov.zm/wp-content/uploads/2025/11/PROJECTS-AS-AT-28-NOVEMBER-2025.pdf.

[7] Ministry of Energy, *Status of Zambia's Energy Project Pipeline*, press statement, Nov. 30, 2025. [Online]. Available: https://www.moe.gov.zm/wp-content/uploads/2025/11/Press-Statement-Status-of-Zambias-Energy-Project-Pipeline.pdf.

[8] International Monetary Fund, *Zambia: Sixth Review Under the Extended Credit Facility Arrangement, Request for a Waiver of Nonobservance of a Quantitative Performance Criterion, and Financing Assurances Review*, IMF Country Report No. 26/021. Washington, DC, USA: IMF, Jan. 2026. [Online]. Available: https://www.imf.org/-/media/files/publications/cr/2026/english/1zmbea2026001-source-pdf.pdf.

[9] International Energy Agency (IEA), *Africa Energy Outlook 2022*. Paris, France: IEA, 2022. [Online]. Available: https://www.iea.org/reports/africa-energy-outlook-2022

[10] International Energy Agency (IEA), "Africa," in *World Energy Investment 2025*. Paris, France: IEA, 2025. [Online]. Available: https://www.iea.org/reports/world-energy-investment-2025/africa

[11] International Renewable Energy Agency (IRENA), *Renewable Capacity Statistics 2025*. Abu Dhabi, United Arab Emirates: IRENA, Mar. 2025. [Online]. Available: https://www.irena.org/Publications/2025/Mar/Renewable-capacity-statistics-2025

[12] International Energy Agency (IEA), "Africa's electricity access planners turn to geospatial mapping," 2023. [Online]. Available: https://www.iea.org/commentaries/africas-electricity-access-planners-turn-to-geospatial-mapping

[13] International Energy Agency Photovoltaic Power Systems Programme (IEA PVPS), *Review of Failures of Photovoltaic Modules: Final*. IEA PVPS Task 13. [Online]. Available: https://iea-pvps.org/key-topics/review-of-failures-of-photovoltaic-modules-final/

[14] "Review of degradation and failure phenomena in photovoltaic modules," *Renewable and Sustainable Energy Reviews*, vol. 169, Art. no. 112160, 2022, doi: 10.1016/j.rser.2022.112160.

[15] J. G. Bessa, L. Micheli, F. Almonacid, and E. F. Fernández, "Monitoring photovoltaic soiling: Assessment, challenges, and perspectives of current and potential strategies," *iScience*, vol. 24, no. 3, Art. no. 102165, Mar. 2021, doi: 10.1016/j.isci.2021.102165.

[16] A. Abdessadak, H. Ghennioui, B. El Bhiri, N. Thirion-Moreau, M. Abraim, and S. Merzouk, "Assessing the effects of dust on solar panel performance: A comprehensive review and future directions," *Engineering Proceedings*, vol. 112, no. 1, Art. no. 9, 2025, doi: 10.3390/engproc2025112009.

[17] A. K. Sisodia and R. K. Mathur, "Impact of bird dropping deposition on solar photovoltaic module performance: A systematic study in Western Rajasthan," *Environmental Science and Pollution Research*, vol. 26, no. 30, pp. 31119–31132, 2019, doi: 10.1007/s11356-019-06100-2.

[18] L. Dorobantu, M. O. Popescu, C. L. Popescu, and A. Craciunescu, "The effect of surface impurities on photovoltaic panels," in *Proc. Int. Conf. Renewable Energies and Power Quality (ICREPQ'11)*, Las Palmas de Gran Canaria, Spain, Apr. 2011, pp. 621–624. doi: 10.24084/repqj09.405.

[19] A. S. Chaudhary and D. K. Chaturvedi, "Thermal image analysis and segmentation to study temperature effects of cement and bird deposition on surface of solar panels," *International Journal of Image, Graphics and*

Signal Processing, vol. 9, no. 12, pp. 12–22, Dec. 2017, doi: 10.5815/ijigsp.2017.12.02.

[20] M. Dhimish, V. Holmes, B. Mehrdadi, and M. Dales, "The impact of cracks on photovoltaic power performance," *Journal of Science: Advanced Materials and Devices*, vol. 2, no. 2, pp. 199–209, Jun. 2017, doi: 10.1016/j.jsamd.2017.05.005.

[21] L. Papargyri, M. Theristis, B. Kubicek, T. Krametz, C. Mayr, P. Papanastasiou, and G. E. Georghiou, "Modelling and experimental investigations of microcracks in crystalline silicon photovoltaics: A review," *Renewable Energy*, vol. 145, pp. 2387–2408, Jan. 2020, doi: 10.1016/j.renene.2019.07.138.

[22] K.-C. Liao and J.-H. Lu, "Using UAV to detect solar module fault conditions of a solar power farm with IR and visual image analysis," *Applied Sciences*, vol. 11, no. 4, Art. no. 1835, 2021, doi: 10.3390/app11041835.

[23] Afroz, "Solar Panel Images Clean and Faulty Images," *Kaggle*. [Online]. Available: https://www.kaggle.com/datasets/pythonafroz/solar-panel-images. [Accessed: Oct. 23, 2026].