# Predicting Dust Accumulation Patterns on Photovoltaic Panels Using Computer Vision.

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**Abstract**

Uneven dust accumulation on photovoltaic cells (PV) can significantly impact power generation efficiency by creating localized shading effects and hot spots. A single sandstorm is able to reduce the module power output by 20% and a PV module not cleaned for 6 months can suffer a power drop of more than 50% [2]. Hence, effective monitoring and timely maintenance of PV panels are essential to mitigate these effects and maintain optimal energy production. Traditional methods of dust detection and cleaning, such as periodic manual cleaning or sensor-based systems, not only waste manpower and water resources, but the efficiency is also low [4]. In contrast, deep learning techniques, such as transformers or Convolutional Neural Networks (CNNs), offer automated and scalable monitoring, are cost-efficient and can process diverse statistics (e.g., seasonal changes, sandstorms and so on). These techniques can identify dust distribution patterns, predict accumulation rates, and even recommend cleaning intervals based on real-time conditions. For example, SolNet, a CNN-based architecture, has shown good potential in identifying clean and dirty solar panels [23]. However, not much work has been done for the prediction of dust accumulation. Predicting dust accumulation, however, could allow resource and time-optimized maintenance schedules thus reducing the frequency of cleaning cycles [23]. This study seeks to develop a dust accumulation prediction model that enhances PV maintenance practices, boosting both efficiency and reliability in solar energy generation. The study evaluates dust accumulation prediction models for PV panels, comparing a Deep Residual Neural Network (DRNN) and Vision Transformer (ViT) in single-stage configurations. Results indicate that DRNN, especially with silver line removal, achieves high accuracy (MAE: 3.6130, MSE: 29.36, $R^2$: 0.9976) while ViT underperforms with high error metrics and low or negative $R^2$ values. The findings suggest that the based model offers a reliable and resource-efficient solution.

## 1. Introduction
### 1.1. Background

The United Arab Emirates (UAE) has made significant commitments to reduce carbon emissions and increase the use of renewable energy as part of its sustainability goals. Through the UAE Net Zero 2050 Strategy, the country aims to cut its carbon dioxide emissions by 70% and increase clean energy usage by 50% by 2050. This initiative aligns with global efforts to combat climate change and supports the UAE's ambition to be at the forefront of energy transition in the region and worldwide[18][19]. Solar energy is a key component of the UAE's strategy, as the country is home to some of the world's largest solar power projects, such as the Al Dhafra Solar PV Plant, which helps reduce millions of tons of CO2 emissions annually. Currently, solar energy contributes significantly to the UAE's clean energy capacity and is expected to play a crucial role in achieving the nation's sustainability goals[17]. However, one of the major challenges that affects the reliability and efficiency of solar panels in the UAE is dust accumulation. Dust can reduce the efficiency of solar panels by up to 50% in severe cases, making frequent cleaning necessary to maintain optimal performance. This requirement for regular cleaning increases operational costs, which can reach up to $1,000 per panel annually for large-scale installations [3]. Despite the UAE's advanced efforts in addressing dust accumulation on solar panels through the use of robotic cleaning systems, automated tools, anti-soiling coatings, and optimized panel mounting structures, there is still an opportunity to further enhance the efficiency and cost-effectiveness of solar energy maintenance. Existing solutions focus on reducing water usage and preventing manual labor, yet they do not leverage predictive capabilities to determine the optimal cleaning schedule.

Our research addresses this issue by proposing a machine-learning model that leverages deep residual neural networks, vision transformer models and drone-captured images to predict the level of dust accumulation on solar panels. By determining the optimal cleaning schedule based on real-time data, the project aims to reduce maintenance costs, enhance the efficiency and reliability of solar panels, and make solar energy a more competitive and sustainable option for the UAE. This innovative approach will not only support the UAE's sustainability goals but also provide a profitable solution for industries by minimizing unnecessary maintenance and maximizing energy output[4].

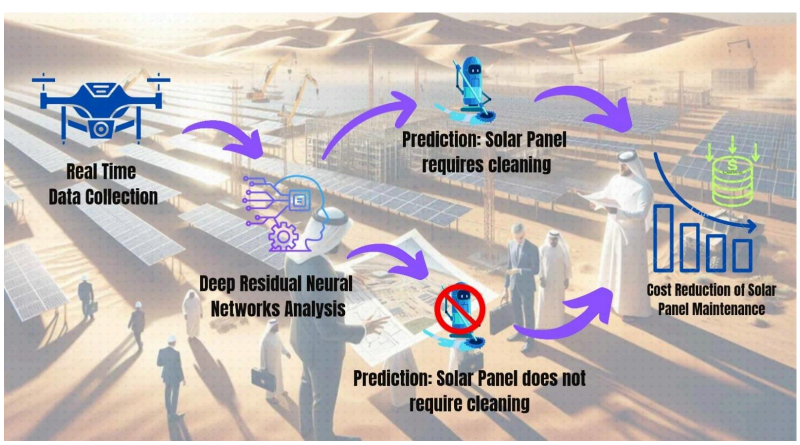



Fig 1. Overview of Dust Accumulation Pattern Prediction Project: The solution begins with real-time data collection via drones on dust accumulation on solar panels. This data is analyzed

using deep residual neural networks to predict whether the solar panels require cleaning. Based on these predictions, maintenance actions are determined. Ultimately, reducing operational costs.

## 1.2. Research Project Objectives

Given the significant impact of dust accumulation on solar panel efficiency and the high costs associated with frequent cleaning, this project aims to develop an innovative approach that combines advanced machine learning algorithms and real-time monitoring to optimize maintenance schedules. Dust build-up on solar panels not only reduces energy production but also leads to inefficiencies that, over time, can hinder the reliability and sustainability of solar energy systems. Through this approach, a data-driven solution will be given to improve the performance, reliability, and sustainability of solar energy systems in the UAE.

To achieve this, the project is structured into a series of objectives, divided into completed and planned goals. Each objective targets a unique aspect of the problem, from data collection and preprocessing to model development and evaluation. Together, these objectives contribute to innovative advancements in solar panel maintenance strategies and provide a sustainable blueprint for efficient and cost-effective energy solutions.

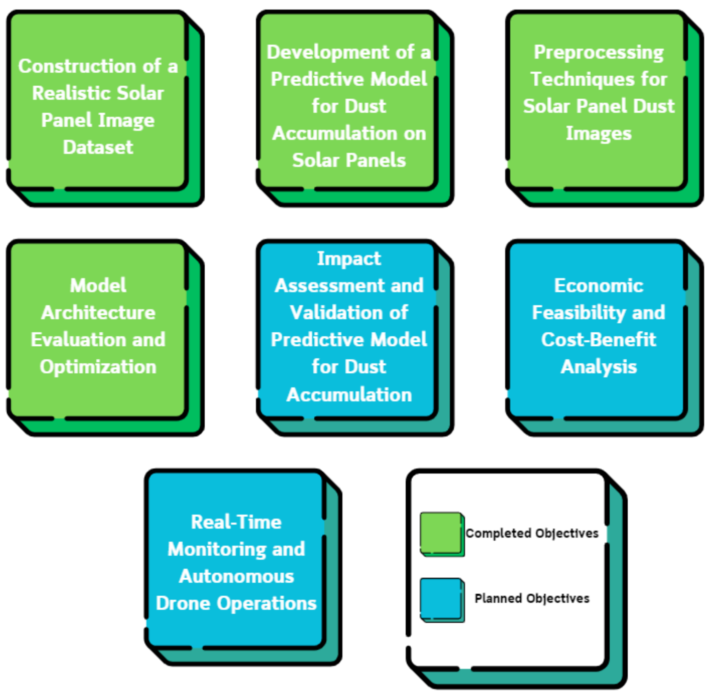



Fig 2. Overview of Completed and Planned Objectives of the Predictive Model for Dust Detection on Solar Panel Project Proposal.

### Completed Objectives

Dust accumulation prediction aims to improve the PV cell cleaning routine using Computer Vision techniques. By integrating fine-tuned transformer and residual neural network models, this project enhances prediction accuracy and supports more efficient maintenance practices.

The specific objectives are as follows:

- **Construction of a Realistic Solar Panel Image Dataset:** To construct a realistic and comprehensive image dataset for solar panel monitoring, capturing various dust accumulation scenarios that simulate real-world conditions, including variations in focal length, angle, and lighting, to ensure dataset robustness and variability.
- **Development of a Predictive Model for Dust Accumulation on Solar Panels :** To develop an advanced predictive model utilizing deep residual neural networks, capable of accurately estimating dust accumulation on solar panels from images captured by drones. This model will be trained on an extensive dataset of labeled images, allowing it to identify patterns linked to various dust accumulation levels and assess their impact on the energy efficiency of solar panels. This objective aims to create a robust, scalable solution that supports effective maintenance and optimization of solar energy systems by enhancing predictive accuracy.
- **Preprocessing Techniques for Solar Panel Dust Images:** To develop and implement advanced image preprocessing techniques that refine the dataset by removing image margins, eliminating internal white lines within the solar panels, and accurately identifying panel areas. These preprocessing steps are designed to help the model distinguish between dust and irrelevant visual features, thereby enhancing the accuracy of dust accumulation predictions.
- **Model Optimization:** To evaluate and select the most effective machine learning models by testing various architectures, such as deep residual networks and convolutional neural networks, on the developed dataset. This process aims to identify the optimal model architecture for accurate dust accumulation prediction, which will serve as the foundation for further enhancements and integration into the overall predictive framework.

**Planned Objectives**

Building on the foundations laid by completed objectives, the next step phase of the project is to focus on advancing model performance and improving real-time deployment capabilities. These objectives aim to expand the project's applicability by refining algorithms and ensuring that the project's outcomes are scalable and aligned with the needs of solar energy systems in the UAE.

- **Impact Assessment and Validation of Predictive Model for Dust Accumulation:** To implement and validate the model in real-world scenarios to evaluate its effectiveness in predicting dust accumulation and its effect on panel efficiency. This includes integration with drones and the creation of an automated monitoring system to conduct tests under different environmental conditions and seasons in the UAE. Establish partnerships with solar energy companies and research institutions to test the system at a large scale in commercial solar farms. This will help validate the model in real-world environments and gather insights for further refinement and scaling of the solution.
- **Economic Feasibility and Cost-Benefit Analysis:** To conduct a detailed cost-benefit analysis to evaluate the economic feasibility of the intelligent monitoring and cleaning system. This analysis will focus on comparing the costs of implementing and maintaining the system with the savings generated from improved solar panel efficiency, reduced water usage, and longer panel lifespan.
- **Real-Time Monitoring and Autonomous Drone Operations:** To develop a fully integrated system where drones autonomously navigate and capture images of solar panels according to pre-defined flight paths. The system will include real-time data transmission to the machine learning model, allowing for immediate analysis and actionable insights, such

as alerting maintenance teams when cleaning is required. This objective also includes the development of sustainability metrics to assess the environmental impact of the optimized cleaning strategy, including water usage reduction, energy savings, and extended lifespan of solar panels.

Each completed and planned objective builds on the previous one, ensuring a comprehensive research approach that addresses all aspects of the identified problem.

### 1.3. Previous Technologies: Literature

Dust accumulation on photovoltaic (PV) panels is a critical issue that significantly reduces efficiency by disrupting thermal balance and power generation, with potential efficiency losses reaching up to 50%, thereby increasing operational costs[18]. The United Arab Emirates (UAE) has taken significant measures to address the issue of dust accumulation on solar panels, utilizing advanced technological solutions to enhance the efficiency and lifespan of its solar energy installations. These initiatives are critical for maintaining high energy output and ensuring the long-term viability of solar power in the region's challenging environmental conditions. One of the primary solutions implemented in the UAE is the use of robotic cleaning systems. For instance, Noor Abu Dhabi, one of the largest single-site solar plants globally, employs a sophisticated dry-cleaning robotic system. The system comprises 1,430 robots that travel approximately 800 kilometers daily to clean over 3.3 million solar panels [12]. This approach eliminates the need for water, which is a critical consideration in arid regions, and minimizes manual labor costs and the risk of panel damage due to abrasive dust particles (Noor Abu Dhabi). In addition to robotic systems, automated cleaning solutions are widely deployed across various solar facilities in the UAE. These systems are equipped with robotic arms or brushes that traverse the surface of the solar panels to remove dust and debris.(SolarQuarter). Furthermore, the UAE has optimized its solar panel installations by implementing tilted mounting structures. These structures are designed to reduce dust accumulation by allowing rainwater to naturally wash away particles. The optimal tilt angle is determined based on geographic location and climatic conditions, which helps maintain better cleanliness and performance over time. [22]

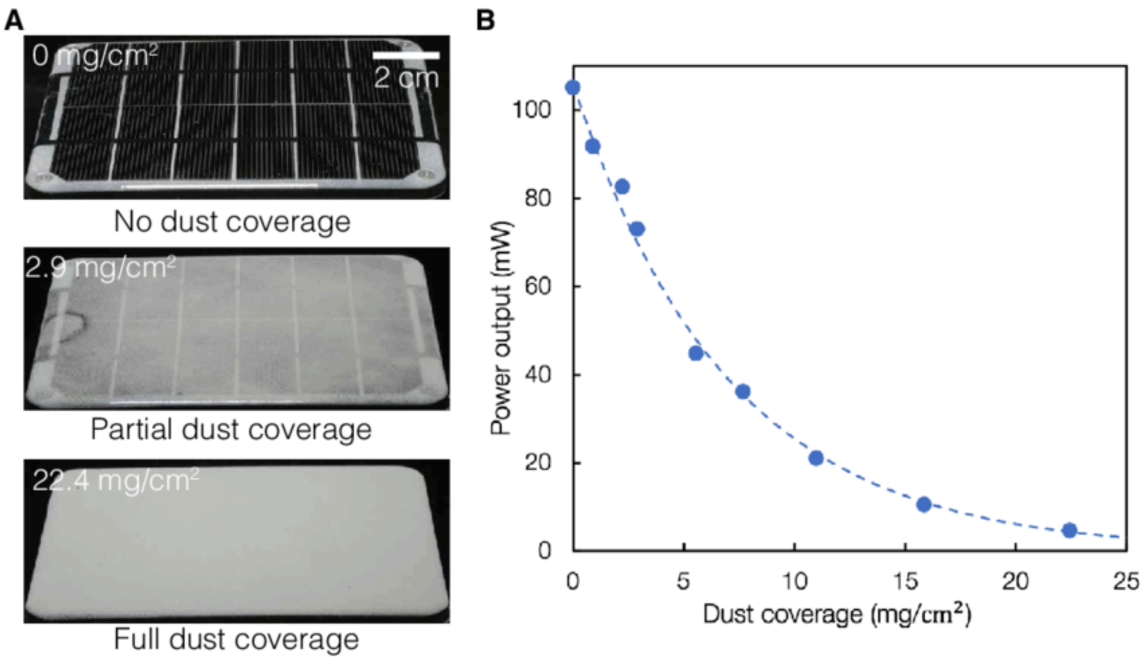


Fig 3. Impact of Dust on Solar Panel Performance [13]

In parallel to these mechanical and structural solutions, the UAE is actively leveraging artificial intelligence (AI) to enhance its solar energy systems. For example, the Dubai Electricity and Water Authority (DEWA)'s R&D Centre employs deep residual neural networks and other advanced AI models to improve the performance of photovoltaic panels. These models are used for load consumption analysis, expansion planning, and demand-side management, optimizing energy efficiency and reducing operational costs. Such initiatives align with the UAE's broader sustainable development goals and demonstrate the potential of AI to revolutionize solar energy management [8].

In addition, the literature emphasizes the potential of hybrid systems that merge physical sensor data with image-based techniques to offer a multi-modal solution for dust detection and measurement. For example, integrating information from sensors that measure particulate matter concentration and real-time imagery captured by drones can enable more precise assessments of dust density and distribution across solar farms. These hybrid systems can provide a more comprehensive dataset for model training and validation, thereby increasing the robustness and reliability of the predictive models used for maintenance scheduling.
One notable approach combines Long Short-Term Memory (LSTM) networks and convolutional neural networks (CNNs) to predict dust buildup and its impact on panel efficiency. These models have shown a marked improvement in predicting non-linear patterns of dust accumulation over time by leveraging time-series data and spatial features extracted from images. [5] Researchers have developed CNN-based frameworks that automatically classify dust density and differentiate between dust accumulation and other surface anomalies, such as cracks or shading. These models have been further enhanced by integrating time-series analysis using Recurrent Neural Networks (RNNs) or Long Short-Term Memory (LSTM) networks, which allow the system to track changes in dust patterns over time and predict future accumulation trends. This approach enables the identification of optimal cleaning intervals, reducing the frequency of unnecessary

cleaning and thereby lowering operational costs. Researchers have also examined the inclusion of environmental factors such as humidity, wind speed, and temperature variations to further enhance the predictive accuracy of these models.This multi-modal approach not only improves the accuracy of dust detection but also enables the prediction of cleaning schedules based on weather patterns and the specific environmental conditions of each installation site. [6]

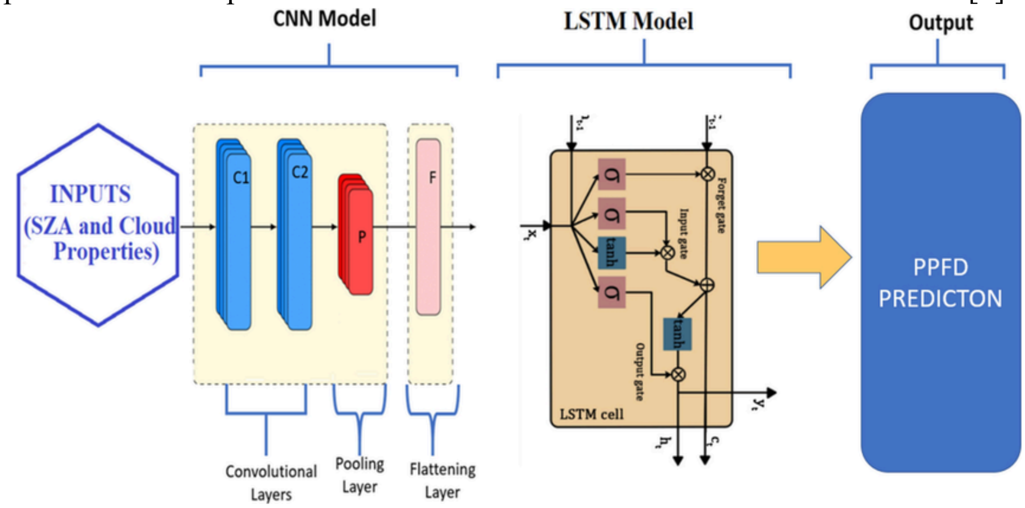



Fig 4. Hybrid Model CNN and LSTM [5]

However, despite these advancements, there remains a gap in the literature concerning the use of deep learning for optimizing cleaning schedules based on the predicted impact of dust on energy output. Current research primarily focuses on monitoring and detection, but few studies have delved into predictive maintenance strategies that leverage machine learning to determine the most cost-effective cleaning intervals. Addressing this gap, the proposed research aims to develop a machine learning framework that not only predicts dust accumulation but also integrates decision-making algorithms to optimize cleaning frequency and minimize operational costs. This approach will contribute to the existing body of knowledge by introducing a new perspective on predictive maintenance, particularly suited to the harsh environmental conditions of the UAE.[10]

Uneven dust accumulation is particularly problematic as it causes differential heating across the panel surface, which not only diminishes the service life of the panels but also introduces safety hazards. Methods for detecting dust, such as visual inspections and power output comparisons, often fall short in terms of accuracy and fail to meet the needs of modern PV systems. Even advanced methods like transmittance-based sensors, such as DustIQ, provide only localized measurements, while laboratory techniques involving manual assessment are error-prone and not scalable for large installations. Machine learning techniques offer a promising solution, utilizing image data and pattern recognition to enhance detection accuracy. Although support vector machines (SVMs) and convolutional neural networks (CNNs) have been applied in image analysis across various domains like agriculture and manufacturing, these approaches face limitations when generalized to PV systems. Deep Residual Neural Networks (DRNNs) address these challenges. An example of how DRNNs are a solution to the mentioned challenge consists of a technique that employs skip layers to improve feature learning and mitigate network degradation, enabling more precise detection of dust concentrations through advanced image processing. DRNNs excel in handling uneven dust distribution, incorporating techniques such as image correction, segmentation, and clustering to provide an accurate assessment of dust levels. These preprocessing methods, including perspective transformation and grid removal, are essential for refining detection accuracy. Furthermore, a novel multiscale error evaluation method, known as the "error loop," is employed to measure model performance through both absolute and relative errors, aiming to minimize operational costs.[10][16][5] Experimental validation has demonstrated that DRNNs outperform traditional methods like multi-layer perceptrons (MLPs) and SVMs, maintaining lower and more stable mean absolute error (MAE) as network depth increases, proving their suitability for large-scale deployment in PV systems. [10][16][5]

On the other hand, DRNNs are particularly effective for time-series forecasting and environmental data analysis, providing an edge in predicting the impact of dust accumulation on solar panels. Optimization techniques such as Bayesian Optimization (BO) and Random Search (RS) are crucial for fine-tuning hyperparameters, improving model efficiency, and enhancing predictive accuracy. BO, for example, efficiently explores hyperparameter spaces using probabilistic models. Effective data preprocessing methods, including normalization and feature selection through metrics like the Pearson relation coefficient, further enhance the learning capabilities of these models. Future improvements may focus on integrating additional environmental factors like shading and developing hybrid models that combine different ML algorithms (e.g., ANN + GPR) to boost accuracy, particularly when optimized with advanced techniques like BO. [10][16][5]

## 1.4. Community Impact, Innovation, or Industry Partnership

### 1.4.1 Community Impact: Strengthening Energy Security, Workforce Development, and Resource Sustainability in Local Communities

At a community level, the proposed research project enhances the UAE’s energy security, ensuring that the nation has a stable and reliable supply of clean energy and ensures the conservation of water resources and the reduction of carbon footprint. This, in turn, promotes energy independence, which can shield communities from global energy market fluctuations, leading to more affordable and sustainable energy solutions for residents and businesses. As the project advances, it will require a workforce with expertise in various fields, such as data science, drone technology, solar energy systems, and machine learning. By partnering with local universities, research institutions, and tech companies, the project can stimulate the development of new educational and training opportunities for the UAE workforce. This initiative has the potential to create new jobs in technology, engineering, and sustainable energy sectors, equipping local professionals with valuable, future-oriented skills that are increasingly in demand in the global job market. Moreover, this will promote a culture of innovation within the community, as young professionals are exposed to practical applications of AI and renewable energy solutions, preparing them for leadership roles in the UAE’s future green economy. As solar energy becomes more widespread, local communities will have greater control over their energy sources, leading to more resilient and sustainable communities. This shift also reduces dependence on external energy sources, creating a more self-sufficient energy ecosystem.

### 1.4.2 Innovation: Harnessing Advanced AI and Drone Technology for Optimized Solar Panel Maintenance

The proposed research introduces an innovative solution for solar panel maintenance by integrating Deep Residual Neural Networks (DRNN) and Vision Transformers (ViT) with real-time drone technology to predict dust accumulation. The use of DRNN enables multi-scale feature learning to detect intricate dust patterns, while ViT enhances image processing by capturing both local and global features of dust distribution on solar panels. This advanced machine learning approach allows for precise, real-time predictive maintenance, reducing operational costs. A key innovation is the ability to minimize unnecessary maintenance. The system's autonomous drones offer scalable, efficient monitoring of large solar farms, further enhancing the effectiveness of solar panel maintenance.This innovative approach not only improves the sustainability and efficiency of solar energy in the UAE but also has global applicability, making it a transformative solution for solar energy maintenance in arid regions worldwide. By reducing resource use, improving cost-efficiency, and leveraging advanced AI technologies, the project positions itself at the forefront of sustainable energy innovation.

### 1.4.3 Industry Partnerships: Collaboration with Solar Energy Operators, Drone Technology Providers, and AI Platforms for Enhanced Solar Panel Maintenance

Industry stakeholders, including solar energy companies, technology firms specializing in drone manufacturing, AI and machine learning platform providers, as well as environmental sustainability initiatives, can benefit significantly from collaborating on this project. The partnerships would not only enhance the technical capabilities of the proposed solution but also accelerate its commercialization and adoption across different regions. Solar energy companies stand to gain from the implementation of predictive dust accumulation models, in the form of joint pilots and deployment in solar farms. This collaboration can help solar operators in achieving their sustainability and profitability goals by offering a cost-effective, data-driven solution for maintenance scheduling. On the other hand, collaborating with drone technology providers would not only enhance the capabilities of the proposed system but also drive innovation in autonomous drone operations. For example, drone companies might integrate AI tools for other industries like agriculture or infrastructure management, while solar energy companies might explore further AI applications for energy storage or grid management. Through these partnerships, this research has the potential to generate value not only for the renewable energy sector but for various industries looking to harness the power of AI and automation.

## 2. Methodology

### 2,1. Our Solution

Our approach introduces an innovative model that uses the strengths of Deep Residual Neural Networks (DRNN) and Vision Transformers (ViT) to accurately predict dust accumulation on photovoltaic (PV) panels. This solution focuses not only on identifying the presence of dust but also on estimating its weight, which directly impacts the energy efficiency and operational costs of solar installations. By leveraging the multi-scale feature learning capabilities of DRNNs and the advanced image processing abilities of ViTs, our model captures intricate patterns of dust distribution that traditional models often overlook.

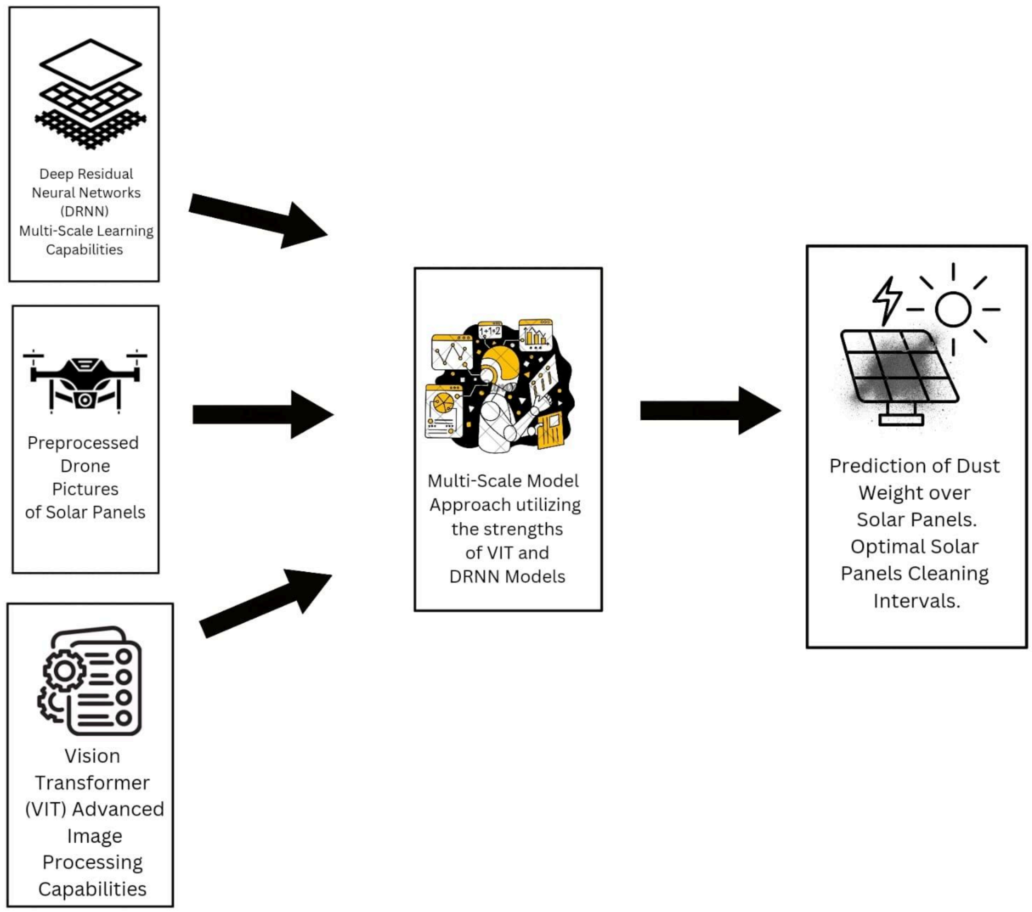



Fig 5. Machine Learning Model Proposal Overview

Unlike previous methods that primarily focused on binary classification (clean vs. dusty) or power output comparison, our approach emphasizes precise dust mass estimation through a two-stage training process. The model is initially fine-tuned to differentiate clean panels from dusty ones and then further trained to accurately predict the weight of accumulated dust using both image data and metadata (e.g., focal length). This integration of metadata into the model enables a more nuanced understanding of the visual patterns, leading to more precise and actionable predictions.

By combining advanced residual learning, transfer learning with pre-trained transformer models, and optimized image preprocessing techniques, our approach overcomes the limitations of prior models. It offers a scalable and efficient solution for real-time dust monitoring, ultimately enabling data-driven decisions for PV panel maintenance and energy optimization.

## 2,2. Project Workflow Overview

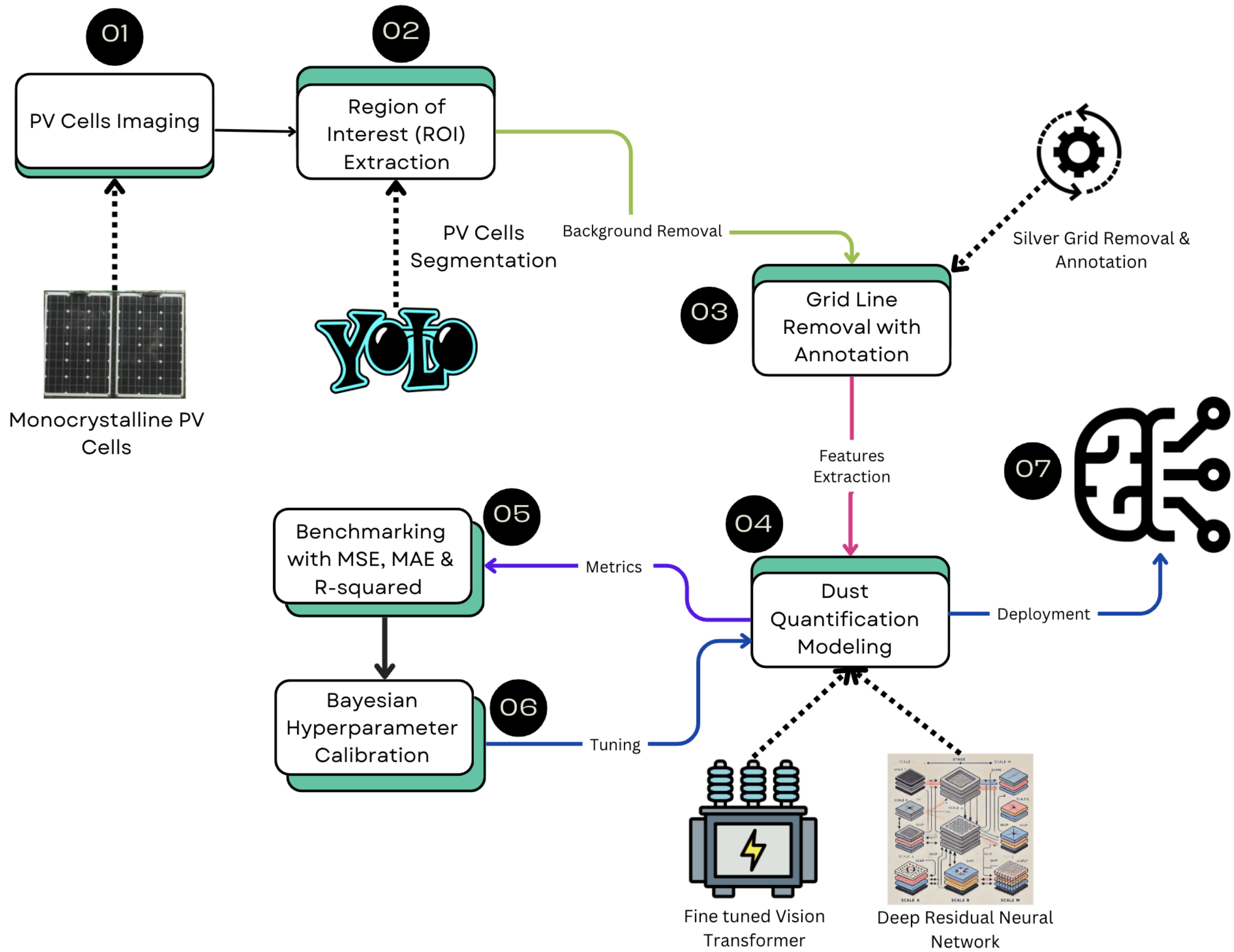



Fig 6. Workflow for PV panel soiling quantification using computer vision and deep learning models.

This project workflow illustrates the process for predicting dust accumulation on photovoltaic (PV) cells. The process begins with data acquisition capturing high-resolution images of monocrystalline PV cells. The phase of data collection is followed by the data generation phase which involves segmenting these images with YOLO and isolating the PV cells for precise analysis. Following segmentation, image processing cleans the data by removing silver grids and adding annotations, ensuring that the model focuses on dust-covered areas. Finally, two models — a fine-tuned Vision Transformer and a Deep Residual Neural Network (DRNN) — are fed with extracted visual features from precious steps to predict dust concentration. With extensive model optimization, the model is ready for deployment, enabling real-time dust monitoring on PV cells.

### 2.3 PV Cells Imaging

In our study, over 500 high-resolution images of dust accumulation on solar panels were initially captured to build a comprehensive dataset. However, during the initial stages of training, it was observed that the dust distribution on the photovoltaic (PV) cells was uneven. This inconsistency caused the model to misinterpret patterns, leading to inaccurate predictions or model hallucinations. To address this issue, the data collection process was refined by systematically controlling the weight of dust particles distributed on the PV cells. We collected images for two distinct weight ranges.

| ***Stages*** | ***Weight Range (in grams)*** | ***Dataset Size*** |
|---|---|---|
| 1 | 1 to 20 | 420 |
| 2 | 20 to 400 | 500+ |

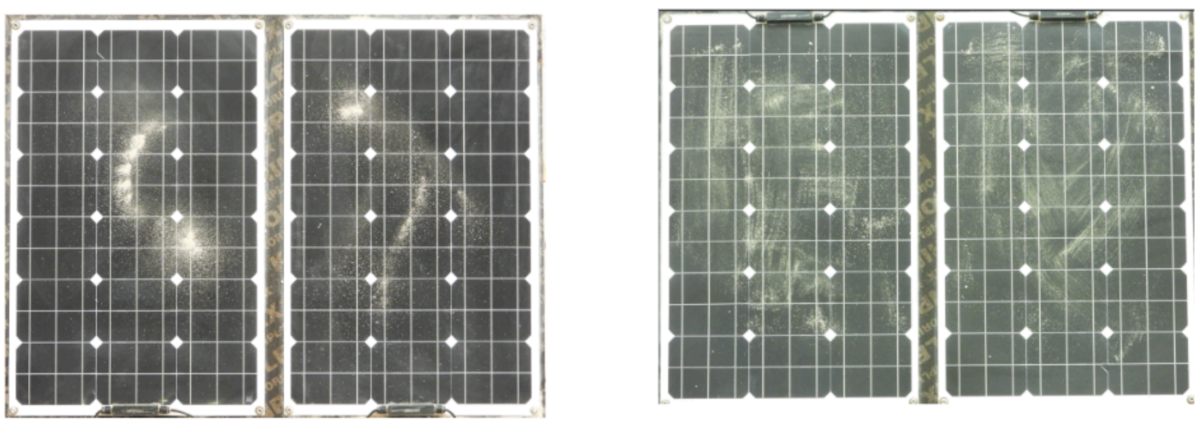


Fig 7. 5 grams of Dust on old and new previous dataset

Each stage was crucial in ensuring a more uniform dust distribution across the PV cells. For consistency and high optical zoom capability, a **Nikon P1000 camera** was used to capture the images. The focal length was adjusted between 24mm and 175mm to capture different perspectives of the dust accumulation.

For the refined dataset, dust accumulation was carefully distributed between 1g and 20g resulting in a total of **420 images**. This setup resulted in a total of 420 images, each representing a unique combination of dust weight and distribution pattern. In the dataset, each weight configuration was represented by 21 images, ensuring a balanced and comprehensive dataset. To capture various perspectives, images were taken with a camera focal length ranging from 24mm to 175mm. This variation in focal length adds depth to the dataset and helps the model to make accurate predictions for images of varying resolution. The table below summarizes the dust accumulation weight ranges and per-weight image configurations.

| ***SN*** | ***Weight (in grams)*** | ***Total images per weight*** | ***Weight Increment (in grams)*** |
|---|---|---|---|
| 1 | 1-20 | 21 | 1 |
| 2 | 25-100 | 21 | 5 |
| 3 | 110-200 | 21 | 10 |

| | | | |
|---|---|---|---|
| 4 | 220-400 | 21 | 20 |

### 2.4 Region of Interest Extraction

In the process of automating the identification and extraction of solar panels from images, a key step involved training a model to detect and isolate the solar panels from the surrounding background. To achieve this, the YOLO (You Only Look Once) algorithm, a state-of-the-art object detection model, was employed. YOLO is known for its fast and accurate object detection capabilities, making it an ideal choice for this task.

The training dataset for YOLO consisted of a large number of images featuring solar panels in various settings, angles, and lighting conditions. After rigorous training, the YOLO model achieved an accuracy rate of 99%, successfully detecting and identifying the coordinates of solar panels in the images with minimal false positives or negatives. This high level of accuracy was critical to ensure that the subsequent steps in the methodology were based on reliable data.

Once the YOLO model was trained, all the images used in the experimental setup were passed through the trained model. The model accurately identified the solar panels in each image, marking the coordinates for their precise location. This process ensured that only the solar panels were isolated from the broader image, eliminating any extraneous background elements that could interfere with the analysis.

Following the identification of the solar panels in the images, a Python script was developed to automate the cropping process. The script utilized the coordinates provided by the YOLO model to cut out the region of interest (the solar panels) from each image. This step ensured that all further experimentation and analysis were conducted solely on images containing the solar panels, without any background distractions. These cropped images were then used as the primary dataset for training and testing the machine learning models developed as part of the research proposal.

By automating the region of interest extraction using YOLO and Python, the methodology ensured precision, speed, and scalability in handling large datasets of solar panel images. This approach streamlined the process of data preparation, which is crucial for building accurate and efficient machine learning models in the next phases of the project.

### 2.5 Grid Line Removal With Annotation

Key preprocessing techniques were applied to enhance the quality of the dataset:

- **Silver lines removal**: The silver grid lines on PV cells are essential for conducting electricity. However, they can interfere with image analysis by creating visual obstruction. Hence, removing the silver grid from the images is critical to isolate the dust coverage on the surface of a PV cell. Thus, all the images in the dataset are passed through a preprocessing pipeline that consists of grayscale conversion, Gaussian blurring, and Canny edge detection to identify the grid lines. Additionally, morphological operations such as dilation and erosion are applied to make the edges continuous and eliminate noise. This step ensured that the model remained focused on the relevant soiling regions of the panel surfaces, avoiding the confusion caused by these grid-like features.

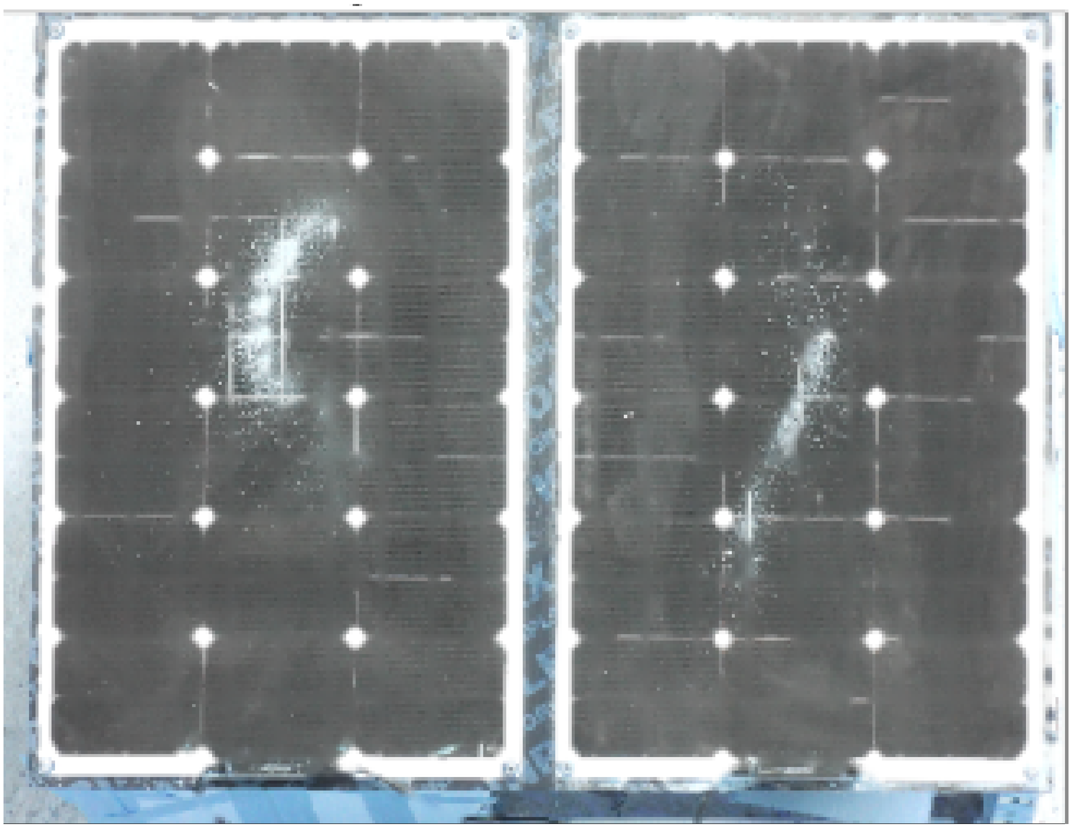


Fig 8. PV cell with silver lines removed.

- **Data augmentation**: Data augmentation is essential to increase the variety and volume of the training dataset, which in return improves the model's ability to generalize to unseen data. To address this, various conventional data augmentation techniques such as flipping, rotation, scaling, and brightness adjustment were applied to the PV cell images. This not only increases the dataset size but also helps the model learn from a diverse range of perspectives, lighting conditions, and orientations.
- **Edge detection:** The next step in image processing is edge detection. It is a vital method to identify features associated with dust accumulation on PV cells, such as the shape, texture, and distribution patterns of dust particles. Additionally, edge detection serves as a method to recognize if the model is hallucinating or not. In this project, instead of using traditional edge detection methods, a deep learning-based approach, the Korna model, was used for more precise and adaptive edge extraction. This deep learning-based edge detection helps ensure that only relevant edges are extracted from the dataset, thereby eliminating hallucinating edges created by dust patterns and boosting prediction accuracy.

**2.6 Dust Quantification Modeling**

In this study, we implemented multiple models to predict dust accumulation on photovoltaic (PV) panels. Our approach utilizes both Deep Residual Neural Networks (DRNN) and Vision

Transformers (ViT) to improve the accuracy of dust weight prediction from solar panel images. These methods allow for multi-scale feature learning and efficient handling of complex patterns such as dust accumulation.

Unlike existing models that primarily focus on dust detection or energy forecasting, our approach leverages **multi-scale feature learning** and **transfer learning** to optimize the cleaning and maintenance schedules of PV systems, directly reducing operational costs and improving energy efficiency. The use of ViT in a **two-stage training process**, where the model is fine-tuned first to classify clean versus dirty panels and then predict dust weight, introduces a novel application of **transformer-based models** in solar panel maintenance. This allows for more precise, data-driven decisions regarding when and how to clean panels, making our approach more actionable and scalable compared to traditional methods. By combining **advanced image preprocessing techniques** with residual learning and leveraging pre-trained models for enhanced efficiency, our proposal delivers a cutting-edge solution that not only addresses current limitations in dust detection but also offers a practical tool for **real-time operational improvements**.

### 2.6.1 Deep Residual Neural Network (DRNN)

The Deep Residual Neural Network (DRNN) model for dust accumulation prediction was configured with a 7-layer architecture, each layer comprising 64 neurons. To facilitate deeper network training, the model employed residual learning, introducing skip connections that enable the network to focus on learning subtle variations, or residuals, in dust accumulation patterns across the PV panel surfaces. Additionally, the DRNN incorporated a multi-scale learning configuration with 6 layers, allowing the network to process input data at various scales and capture both broad and fine-grained patterns of dust accumulation. The input to the model consisted of images of PV cells, while the output was a continuous variable predicting the dust weight on the panels. For training, the dataset was split into a 75-25% train-test ratio, with 75% allocated for training and 25% for testing. The training process used 2-3 attributes, including Image Name, Focal Length, and Dust Weight, to provide a comprehensive representation of each sample and improve model accuracy in predicting dust levels.

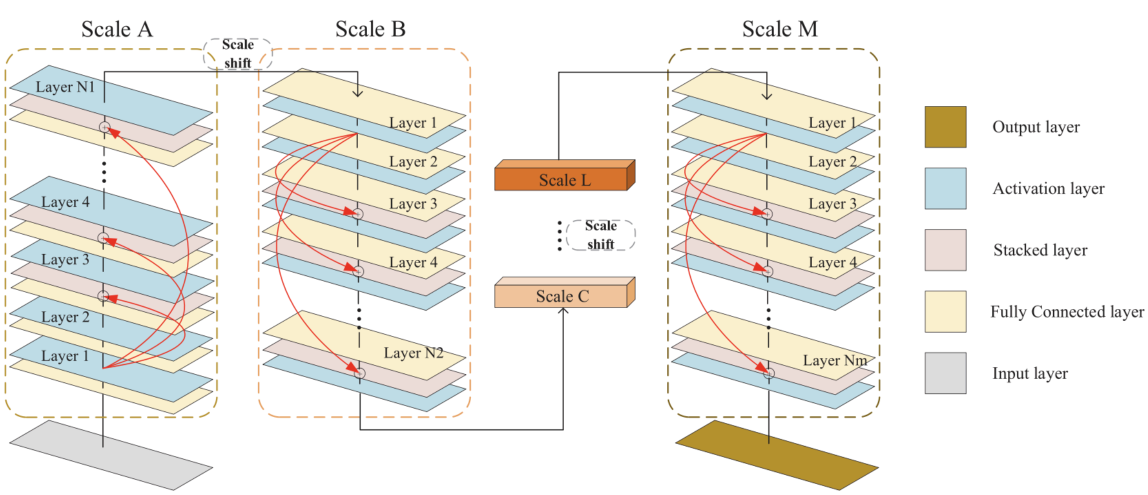


Fig 9. Model architecture of Deep Residual Neural Network [16]

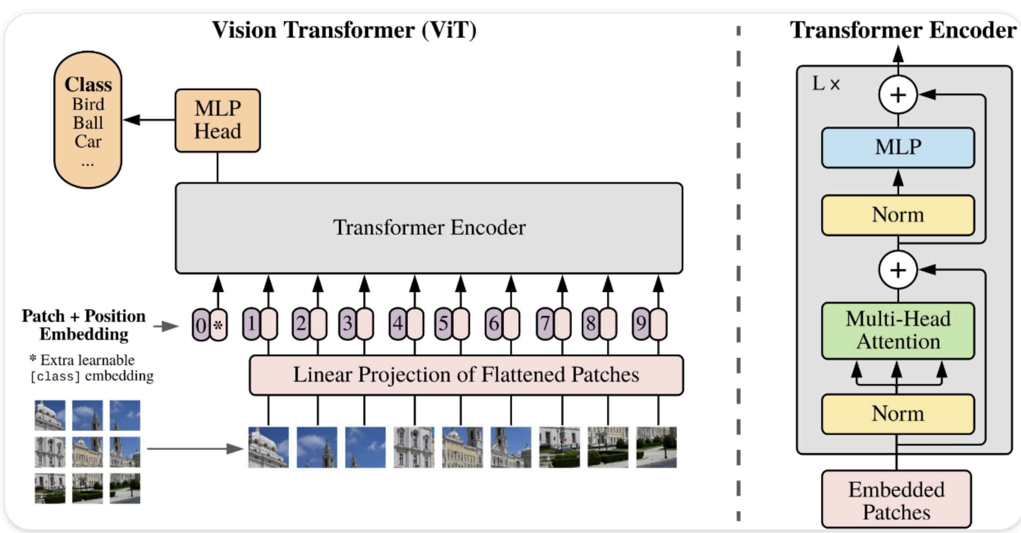
A series of convolutional layers were implemented to extract spatial features from the images. The CNN model featured three hidden layers, each followed by batch normalization and activation functions, which were key in stabilizing the learning process and improving the network's performance. In one configuration, convolution layers were combined with **residual connections**, and this model included 10 hidden layers. The residual connections enabled more efficient training by bypassing some layers and improving gradient flow during backpropagation.

### 2.6.2 Vision Transformer (ViT)

The ViT model, known for its ability to handle image-based tasks, was applied to predict dust accumulation using both image data and metadata (e.g., focal length and dust weight). The model was trained in a **Two-Stage Training Process**, which consists of the following steps:

a. **Stage 1**: Fine-tuning was performed to detect solar panels, and a pre-processing step was performed to distinguish panels that need dust accumulation evaluation.
b. **Stage 2**: After fine-tuning, the model was retrained specifically for dust weight prediction, where the input consisted of both image data and metadata (Image, Focal Length, and Dust Weight).

The ViT model leveraged **transfer learning**, utilizing pre-trained weights from a large-scale dataset, which were then fine-tuned for our specific dust weight prediction task. This approach allowed for more efficient feature extraction, particularly from the complex visual patterns in PV panel images.




ViT architecture. Taken from the original paper.

Fig 10. Model architecture of Vision Transformer (ViT) [21]

### Multi-Scale Feature Learning

For both DRNN and CNN models, multi-scale feature learning was employed to capture information at various spatial resolutions within the images. This was essential in predicting dust accumulation patterns, as dust coverage often varies across different regions of the PV panels.

**Convolutional Layer Stack**

Each convolutional layer in the CNN and DRNN models was followed by an activation function (e.g., ReLU) and batch normalization. This stack allowed the network to learn robust features from the images while minimizing the risk of overfitting.

**Regression Output Layer**

All models featured a regression output layer, designed to predict the continuous variable of dust weight. This is a critical aspect of the prediction task, as dust accumulation is a continuous measurement rather than a categorical classification.

**Transfer Learning**

The Vision Transformer (ViT) model used transfer learning by adopting a pre-trained model on a large dataset. This model was fine-tuned on our dust accumulation prediction task, which helped speed up convergence and improve accuracy. The transfer learning process allowed the model to leverage its pre-existing knowledge of image features and focus more effectively on the dust weight prediction task.

## 2.7 Benchmarking with MSE, MAE, and R squared, and Bayesian Hyperparameter Calibration

In this experiment, the Deep Residual Neural Network (DRNN), Convolutional Neural Network (CNN), and Vision Transformer (ViT) models were trained and tested on the same dataset of solar panel images, with the target variable being dust weight. The DRNN was designed to capture subtle variations in dust patterns using residual connections, while the CNN focused on spatial feature learning with and without residual connections. The ViT incorporated metadata (such as focal length) into its image-based predictions and utilized a two-stage training approach for better generalization.

To assess the model's performance, metrics such as Mean Squared Error (MSE), Mean Absolute Error (MAE), and R-squared ($R^2$) were used. These metrics were obtained after training the models with both the initial and extended datasets of solar panel images. The different configurations for each model included the CNN with and without residual connections, and ViT models with various configurations (image-only, image + focal length, and multi-stage).

Subsequently, Bayesian optimization was applied to fine-tune hyperparameters such as the number of neurons, DRNN scales, learning rate, and batch size. This process involved 50 trials to identify the optimal model configurations for each architecture, ensuring that the models could make accurate dust accumulation predictions across diverse solar panel images.

## 6. Experiments and Results.

### 6.1. Training and Test Loss Functions of DRNN and VIT models.

The results from our study reveal significant insights into the performance of the Deep Residual Neural Network (DRNN) and Vision Transformer (ViT) models for dust weight prediction.

Analyzing the training and test loss curves, the DRNN model demonstrated a rapid decrease in loss during the initial epochs, followed by gradual stabilization, indicating effective learning and generalization. In contrast, the ViT models, particularly in their multi-stage configurations, exhibited slower convergence rates and greater fluctuations in early epochs, highlighting the superior stability and efficiency of the DRNN in achieving lower final loss values. Inference outputs further validate the DRNN's predictive accuracy, as seen in test images of various dust weights, such as 5g and 20g. The model's predictions closely matched the actual values, showcasing its practical applicability and effectiveness in real-world scenarios where accurate dust weight predictions are essential for optimizing maintenance schedules.

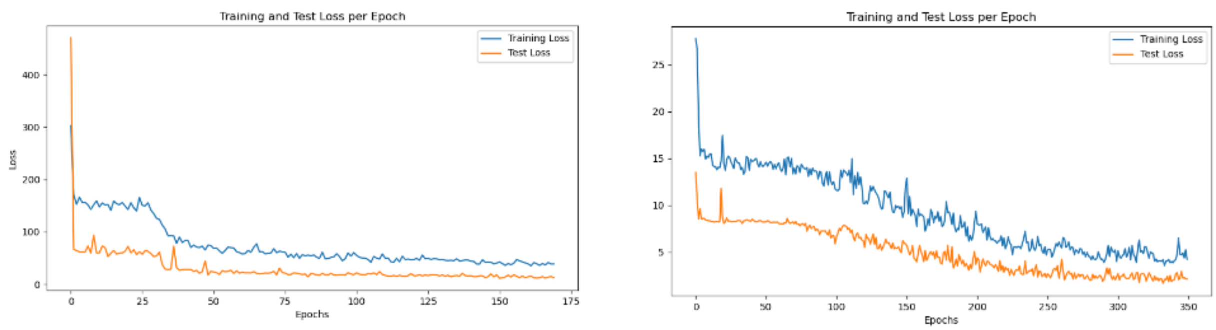



Fig 11. DRNN and VIT Training and Test Loss per Epoch Function

### 6.2. Mean Absolute Error (MAE), Mean Squared Error (MSE), and $R^2$ across the DRNN, CNN (with and without residual connections), and various ViT configurations

#### 6.2.1 Results for Initial Solar Panel Image Dataset with 1-20g of Dust

Following the analysis of the loss plots, a comparative study using key metrics—Mean Absolute Error, Mean Squared Error, and $R^2$—across the DRNN, CNN (with and without residual connections), and various ViT configurations (image-only, image + focal length, and multi-stage) revealed the DRNN's superior performance. The DRNN achieved the lowest MAE (1.2764 for training and 1.1531 for testing) and MSE (2.8222 for both), along with the highest $R^2$ score of 0.91, indicating its strong generalization capabilities. In contrast, the ViT models, particularly when using image-only data, showed higher error rates and lower $R^2$ values, underscoring the limitations of these approaches in comparison to the DRNN.

| | MAE (Train, Test) | MSE (Train, Test) | $R^2$ (Final, Max) |
|---|---|---|---|
| DRNN | 1.2764, 1.1531 | 2.8222, 2.8222 | 0.91, 0.91 |
| Conv | 2.5882, 2.5882 | 12.6548, 41.8291 | 0.60, 0.71 |
| Conv + Res | 3.4744, 4.5573 | 20.2248, 30.8364 | 0.36, 0.48 |
| ViT (Image) | 4.4018, 4.7898 | 28.3451, 31.6991 | 0.10, 0.20 |
| ViT (Image + FL) | 1.4774, 1.4063 | 3.6042, 3.2543 | 0.89, 0.91 |
| ViT (Multi-stage) | 4.7992, 4.7992 | 32.7244, 39.0586 | - |

Key observations from the study include the DRNN's effectiveness at predicting lower dust weights with high accuracy. However, as dust weights increased, the model's error margins grew, suggesting challenges in capturing the more complex patterns associated with heavier dust accumulation. This trend indicates a need for further refinement of the model to enhance its ability to process intricate features present in high dust weight scenarios. Moving forward, efforts focused on expanding the dataset and improving model robustness for higher dust weights by retaking images at specific weight intervals (e.g., [20, 200, 10], [200, 300, 20], [300, 400, 20]) and completing manual annotations to increase training data precision. Additionally, the ViT model was retrained using the original dataset during Stage 1 of its multi-stage training process to improve generalization. These steps are intended to strengthen the model's performance, particularly for situations involving heavy dust accumulation.

When evaluating the models using the [1-20]g dataset, the DRNN with silver lines removed achieved the best performance, showing a low Mean Absolute Error (MAE) of 1.1531 and a Mean Squared Error (MSE) of 2.8222 for the test set, along with an $R^2$ value of 0.91, indicating a strong correlation between predicted and actual values. The ViT models performed less effectively in comparison, with higher error rates and a negative $R^2$ value when silver lines were not removed, highlighting their challenges in generalization for dust weight prediction.

### 6.2.1 Results for Extended Dataset with higher Dust Weights at Specific Intervals

For the extended [1-400]g dataset, the DRNN continued to outperform other models, particularly when silver lines were removed, resulting in an MAE of 3.6130, an MSE of 29.3573, and an $R^2$ value of 0.9976. This suggests that the DRNN can effectively generalize to larger dust weight ranges. In contrast, the ViT models, both single-stage and multi-stage, struggled with higher error rates—up to an MAE of 84.3710—and displayed low or negative $R^2$ values, demonstrating difficulty in learning accurate predictions across the full weight range. Overall, the results illustrate that removing silver lines from the input images significantly improves model performance, and the DRNN consistently delivers superior accuracy compared to ViT configurations across both datasets.

| | *Silver Lines Removed?* | *Dataset* | *MAE (Train, Test)* | *MSE (Train, Test)* | *$R^2$* |
|---|---|---|---|---|---|
| *DRNN* | Yes | [1-20]g | 1.2764, 1.1531 | 2.8222, 2.8222 | 0.91, 0.91 |
| | No | [1-20]g | 1.3018, 1.2054 | 2.8445, 2.6103 | 0.9094, |
| *ViT (Single Stage)* | Yes | [1-20]g | 1.4774, 1.4063 | 3.6042, 3.2543 | 0.89, 0.91 |
| | No | [1-20]g | 4.8264, 5.4886 | 31.7661, 39.2798 | Negative |
| *ViT (Multi-stage)* | Yes | [1-20]g | 4.7992, 4.7992 | 32.7244, 39.0586 | - |

| | *Silver Lines Removed?* | *Dataset* | *MAE (Train, Test)* | *MSE (Train, Test)* | *$R^2$* |
|---|---|---|---|---|---|
| *DRNN* | Yes | [1-400]g | 3.6368, 3.6130 | 31.3577, 29.3573 | 0.9976 |
| | No | [1-400]g | 4.2813, 4.9100 | 42.4072, 65.7748 | 0.9968 |
| *ViT (Single Stage)* | Yes | [1-400]g | 87.4281, 84.3710 | 14948, 14120 | *Negative* |
| | No | [1-400]g | 82.3479, 75.9681 | 12045.6, 12426.6 | 0.0825 |
| *ViT (Multi-stage)* | Yes | [1-400]g | 70.6301, 68.9350 | 9255.98, 10159.49 | 0.2950 |

The best result for the DRNN, as shown in Fig 11, highlighted stable training and test loss curves over 350 epochs, confirming the model's ability to generalize well across the expanded dataset.

Fig 12. DRNN for 1-400g and Silver Lines Removed

### 6.3 Results of Bayesian optimization for hyperparameters

Additionally, Bayesian optimization was applied to fine-tune hyperparameters such as the number of neurons, DRNN scales, learning rate, and batch size. The optimization process included 50 trials, with ongoing efforts showing a reduction in loss from 68.366 to 44.822 as the number of neurons and scales were adjusted. The results visualization displayed a strong linear relationship between actual and predicted dust weights, further validating the model's predictive capabilities and its application potential for real-world PV panel maintenance scenarios.

| | # neurons | # scales | Learning Rate | Batch Size | Loss |
|---|---|---|---|---|---|
| Trials = 5 | 53 | 3 | 0.00485 | 16 | 68.366 |
| Trials = 50 (Ongoing ) | 38 | 4 | 0.00023 | 16 | 44.822 |

Table: Summary of results from Bayesian optimization for hyperparameters

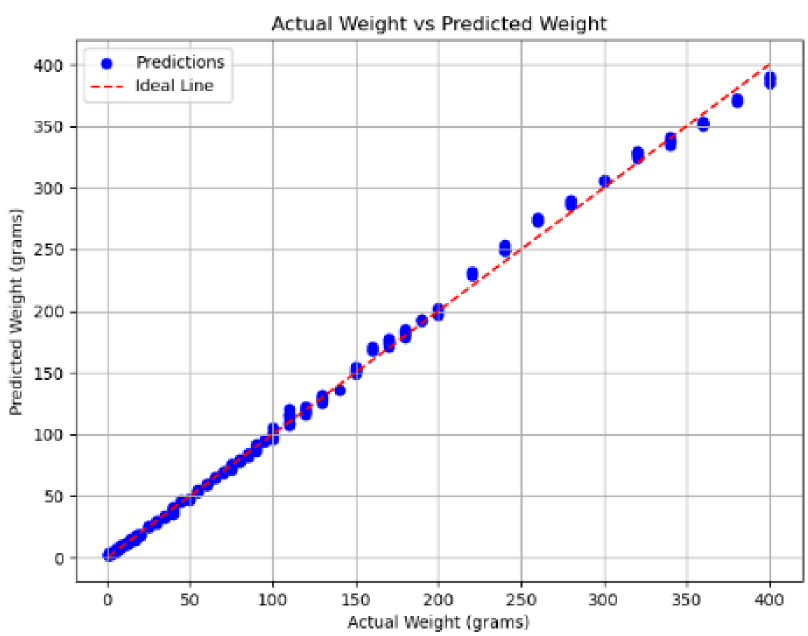



Fig 13. Predicted VS Actual Weight Plot (Images Used From Test Split)

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