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Detecting Dust on Solar Panels using Deep Learning Models with Explainable AI Visualization

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Abstract:

Dust accumulation on solar panels is a well-known factor that reduces energy production and, if left unaddressed, can significantly affect system efficiency. Early and accurate detection of dust is therefore essential for effective maintenance and sustained power generation. This study presents an automated approach for identifying dust on solar panel using deep learning–based image classification. Two convolutional neural network (CNN) architectures, Xception and VGG16, were evaluated to assess their effectiveness in this task. To improve model robustness and generalization, an extensive preprocessing pipeline was applied to the dataset. The experimental results demonstrate that the Xception model achieved superior performance, reaching a classification accuracy of 98.82%, while the VGG16 model attained an accuracy of 93.49%. Beyond performance evaluation, this work emphasizes model interpretability. The integrated gradients method was employed to generate visual explanations of the models' predictions, highlighting image regions that contributed most to the classification outcomes. These visual interpretations provide valuable insight into the decision-making process and enhance confidence in the results. Overall, the findings indicate that deep learning offers a reliable solution for automated solar panel monitoring, reducing reliance on manual inspection. Moreover, incorporating interpretability techniques improves transparency and supports practical deployment. This study contributes to renewable energy maintenance research and lays the groundwork for intelligent systems that integrate automated detection, cleaning strategies, and predictive maintenance to enhance the long-term efficiency of solar power installations.

Keywords: CNN, Dust, Solar panels.

1. Introduction

The heavy reliance on fossil fuels responsible for about 80% of global energy use has led to an urgent push for renewable and sustainable energy solutions. Among the alternatives explored, solar energy stands out due to its abundance and renewability. Solar photovoltaic (PV) systems are expected to see significant growth, potentially reaching an installed capacity of 8519 GW by 2050. At that point, solar could supply roughly 25% of global electricity demand, becoming the second-largest energy source after wind [1]. Solar PV technology is an effective method for harnessing solar energy by converting sunlight into direct current electricity using PV cells. These cells serve as the fundamental components of solar power systems, where sunlight is directly transformed into electrical energy. To achieve the desired power output, multiple PV cells are interconnected in series and parallel configurations, forming solar panels [2]. Modelling is the initial step in studying the behaviour and performance of a PV panel within a simulated environment. To thoroughly evaluate its efficiency, it's essential to develop a precise model of the PV system, especially due to its relatively low power output and limited efficiency. An accurate and dependable PV panel model also enables better forecasting of energy generation from solar power plants under different environmental conditions [3]. The electricity output of PV cells is closely tied to the strength and yearly duration of solar radiation. Since these factors vary across different regions of the world, certain areas are identified as more favorable for solar energy generation. Typically, regions with high solar intensity and extended sunlight hours such as deserts and semi-arid zones offer the greatest potential. However, these promising areas are also highly susceptible to dust accumulation, which can settle on solar panel surfaces and significantly reduce their efficiency [4]. When dust settles on solar panels, it blocks sunlight, raises cell temperatures, and causes electrical resistance, all of which contribute to reduced power production. Research shows that energy losses from dust buildup typically range between 3% and 5% globally, reaching over 30% in dry and dusty regions—resulting in substantial financial losses each year. Regular cleaning is essential, as dust reduces system efficiency, increases energy loss, and leads to higher maintenance costs and time demands [5].

Typically, the standard approach to dealing with dust build up on solar panels involves routine cleaning, which can be both expensive and environmentally taxing. As a result, there is a growing need for effective methods to detect and manage dust early, ensuring optimal performance of PV systems while making efficient use of resources. Traditionally, manual visual inspections have been the primary means of identifying dust and dirt on PV modules. However, advancements in technology are leading to the increased use of intelligent image processing and sensor-based remote monitoring systems to enhance detection accuracy and efficiency. Deep learning techniques, in particular, offer reliable capabilities for identifying and categorizing dust particles on solar panels [6].

Deep learning has gained significant popularity in recent years, largely driven by the rapid expansion of big data. It continues to evolve, offering advanced capabilities across various machine learning tasks. Deep learning has notably enhanced progress in areas like object detection, image super-resolution, and image recognition. In fact, its performance has recently surpassed human-level accuracy in tasks such as image classification [7]. Despite their strong performance, deep learning models are often difficult to interpret. With vast numbers of parameters and no clear connection to real-world features, understanding how they make decisions remains a major challenge. As a result, the need for clearer and more interpretable AI systems is gaining growing attention [8].

This study reconnoitrers an approach that uses CNNs to detect dust on solar panels through image analysis. To achieve reliable performance and build trust in the model's predictions, integrated gradients technique is applied to interpret which regions of the image influence the model's decisions. This level of interpretability aims to improve transparency and understanding. In addition, the expected outcomes of this approach may help reduce reliance on manual inspections and enhance the efficiency of maintenance processes. The following sections of this study are structured as follows: First, a review of previous studies relevant to the topic is presented. This is followed by a description of the proposed method and the procedures adopted in conducting the study. Next, the main findings are presented and discussed in detail. Finally, the paper concludes with the key findings of the study, outlines its main limitations, and suggests directions for future work aimed at further improvement and development.

2. Related Works

Recent research has increasingly focused on automated methods for monitoring PV systems, especially for detecting dust, which significantly affects energy output. Traditional methods like manual checks and routine cleanings are often inefficient and expensive. Advances in deep learning have led to more accurate and scalable image-based detection techniques, with many studies utilizing pre-trained models for classification tasks.

UYSAL [9] utilized an open-source dataset of clean and dusty solar panels, applied data augmentation to address size and imbalance issues, and evaluated four CNN models—including MobileNetV1 and ResNet variants—trained with two different optimizers. Prova [10] developed a deep learning approach that combined InceptionV3, VGG16, and a custom CNN model to tackle the problem of dust detection on solar panels despite limited labeled data. To strengthen the training process and increase model reliability, data augmentation methods were applied to expand the dataset. Sefer, and Kaya [11] employed several deep learning models—such as EfficientNet, ResNet, MobileNet, VGG, and others—for binary classification of solar panels as clean or dirty. To improve accuracy, top-performing models were combined using an ensemble voting approach, which achieved strong results, highlighting its potential to improve solar panel maintenance and support sustainable energy efficiency. Shao et al. [12] presented a modified Adam optimizer designed for dust detection on solar panels. Tested across various models like ResNet-18, VGG-16, and MobileNetV2, the enhanced algorithm demonstrated improved performance, emphasizing its potential to enhance the accuracy of dust detection and support more efficient solar panel maintenance. Li, and Wang [13] proposed a hybrid deep learning model, UTran-ResNet50, for precise classification of dust levels on solar panels. By combining ResNet50 with Transformer architecture, the model captures both local and global features. It also incorporates an attention U-Net to minimize recognition errors and a positional attention module to boost feature detection accuracy. Onim et al. [14] introduced a new image dataset of clean and dusty solar panels and tested it with various state-of-the-art classification models. In addition, a custom CNN model called SolNet was proposed, tailored for dust detection. The researchers highlighted the potential to expand the dataset for multiclass classification and improve SolNet's performance through hyperparameter optimization. Alatwi et al. [15] concentrated on rapid dust detection in solar panel images to enhance cleaning efficiency and reduce energy loss from surface dust. They utilized 20 advanced pre-trained deep learning models to extract features from the images, which were then used to train and assess four different support vector machine variants. Their aim was to determine the most accurate model combination for classifying dusty panels using a public dataset.

Recent research on dust detection increasingly utilizes deep learning due to its powerful feature extraction capabilities. Traditional methods have struggled to cope with environmental variability; however, modern approaches using complex neural networks and other deep

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models have improved accuracy and reliability. These models have been applied to both image and sensor data, and techniques such as transfer learning help overcome data limitations. However, challenges remain in generalizing models across diverse conditions, handling limited data, and enabling real-time implementation. Furthermore, ensuring that model decisions are explainable and transparent using explanatory methods remains crucial, especially in security-sensitive or operational environments where trust and accountability are key.

3. Methodology

The methodological framework, outlined in Figure 1, consists of a series of structured stages aimed at constructing an effective dust detection pipeline for PV systems.

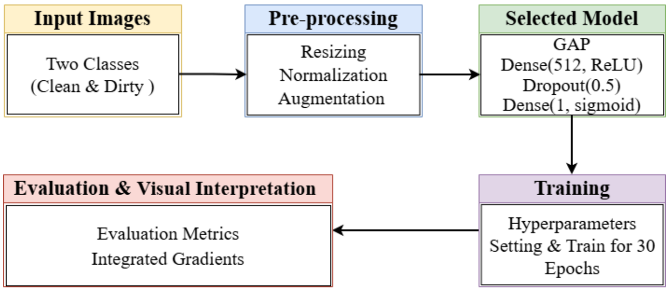

Figure 1: Method overview

The study employed an image dataset of clean and dusty solar panels obtained from Kaggle [16], originally compiled by Onim et al. [14]. The dataset contains 842 images, including 502 clean and 340 dusty samples, classified based on visible dust on panel surfaces. Sample images from both classes are shown in Figure 2.

Figure 2: Dataset sample images

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Prior to model training, the images underwent pre-processing to improve quality and ensure compatibility with deep learning models. The dataset was divided into training and testing sets using an 80:20 ratio, with 20% of the training data further allocated for validation. All images were resized to 224×224 pixels and normalized. To enhance generalization, data augmentation was applied to the training set as demonstrated in Figure 3, including zooming (20%), contrast adjustment, and rotations up to 20°. Augmented images are created prior to training and stored as additional files in the dataset, resulting in a permanent increase in dataset size. During training, both the original and the augmented images are utilized. Details of the dataset distribution and augmented samples are provided in Table 1. The test set was kept unchanged to allow unbiased performance evaluation.

Table 1 Dataset statistics

Set	Clean	Dirty	Sum
Train	401	272	673
Augmentations	1203	816	2019
Test	101	68	169
Sum	1705	1156	2861

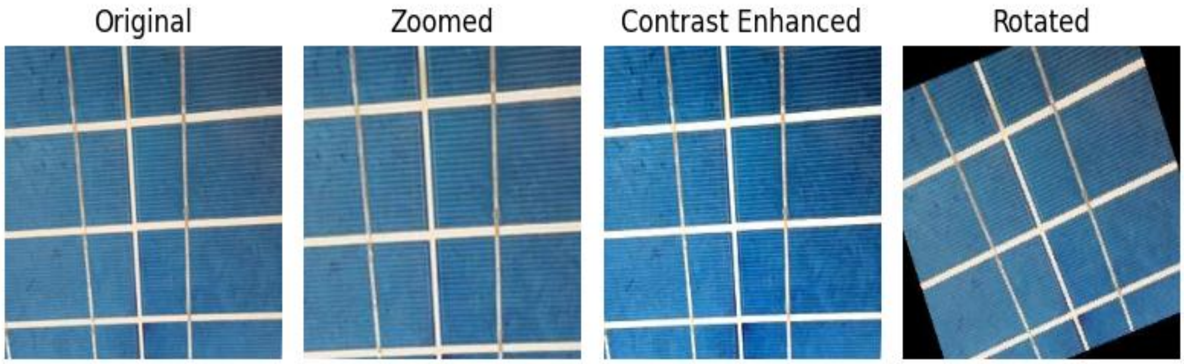

Figure 3: Implemented augmentation aspects

Two pre-trained CNN, VGG16 [17] and Xception [18], were adopted for binary dust classification. Both models utilized ImageNet weights, with convolutional layers frozen. Figure 4 presents a diagram of the two models employed in this research, highlighting the adaptation layers incorporated within them. A Global Average Pooling (GAP) layer was added, followed by a dense layer with 512 neurons and ReLU activation, a dropout layer (0.5), and a sigmoid output layer.

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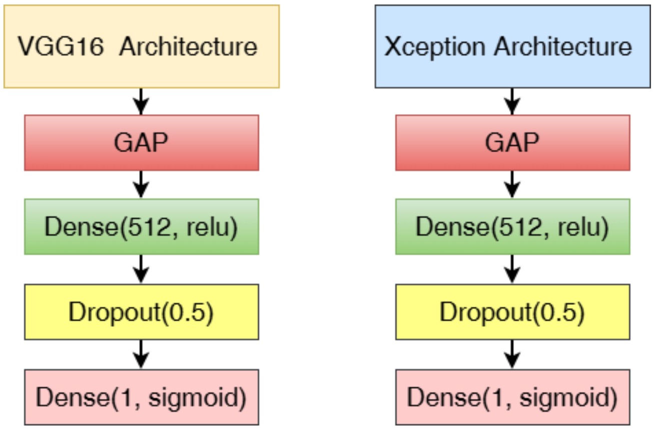

Figure 4: Models used and their adaptation layers

The models were trained using identical hyperparameters as listed in Table 2 and evaluated using standard performance metrics.

Table 2 Hyperparameters setting

Parameter	Batch Size	Initial Learning Rate	Optimizer	Loss	Epochs
Set	16	0.0001	Adam	Binary Cross-entropy	30

The model's effectiveness was measured using common metrics, with their corresponding mathematical formulas presented as follows [19]:

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN} \tag{1}$$

$$Precision = \frac{TP}{TP + FP} \tag{2}$$

$$Recall = \frac{TP}{TP + FN} \tag{3}$$

$$F1 - score = \frac{2TP}{2TP + FP + FN} \tag{4}$$

In the task of detecting dust on solar panels, model performance is evaluated using standard classification metrics based on four outcomes: true positives (TP), true negatives (TN), false positives (FP), and false negatives (FN). Here, TP refers to dusty panels correctly identified as dusty, while TN represents clean panels accurately classified as clean. FP denotes clean panels that the model incorrectly labels as dusty, and FN indicates dusty panels that are mistakenly classified as clean. These values provide a basis for calculating key performance indicators, which collectively reflect the model's effectiveness in distinguishing between clean and dusty conditions.

Finally, model decisions were analysed using integrated gradients [20] technique to identify image regions influencing classification outcomes. This interpretability step provides insight into the features associated with dust detection and supports the development of an effective and reliable solar panel monitoring system.

4. Results and Discussion

The performance results of both models are summarized in Table 3, providing a clear comparison of key evaluation metrics.

Table 3 Performance results

Metrics	VGG16	Xception
Accuracy	0.9349	0.9882
Precision	0.9385	0.9877
Recall	0.9263	0.9877
F1-score	0.9314	0.9877

The performance comparison between the VGG16 and Xception models demonstrated a clear advantage in favour of the Xception architecture for the binary classification task of dust detection on solar panels. VGG16 achieved a strong score accuracy of 93.49%, while Xception significantly outperformed it with an accuracy of 98.82%. This indicated that Xception was more effective in correctly classifying both clean and dusty panels across the dataset utilized. The precision, which indicates the proportion of correctly identified positive predictions among all positive predictions made, VGG16 recorded a value of 93.85%, while Xception reached an impressive 98.77%. This higher precision value for Xception implies fewer false positives, meaning the model was highly reliable in identifying dusty panels without misclassifying clean ones.

Recall, or sensitivity, which reflects the model's ability to correctly identify actual positive cases (dusty panels), was 92.63% for VGG16 and 98.77% for Xception. The Xception model demonstrated superior performance, showing that it was more consistent in detecting all instances of dust, thus minimizing false negatives.

Finally, the F1-score, which is the harmonic mean of precision and recall and offers a balanced view of model performance, was 93.14% for VGG16 compared to 98.77% for Xception. This reinforces the conclusion that Xception not only maintains a strong balance between precision and recall but also provides a more robust and reliable performance overall.

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While VGG16 shows solid results and is a proven architecture for image classification tasks, the Xception model clearly excels in all evaluated metrics. This indicated that Xception is more suitable for the specific task of dust detection on solar panels, providing higher accuracy, better precision and recall, and a stronger overall performance as reflected by the F1-score.

In addition, Figure 5 illustrates the confusion matrices for the two models evaluated in this study. These matrices offer a clear view of each model's classification performance on the test dataset, indicating the alignment between predicted and true labels. Presenting the matrices side by side allows for a direct comparison, revealing both the strengths of each model and the specific classes where misclassifications are more frequent.

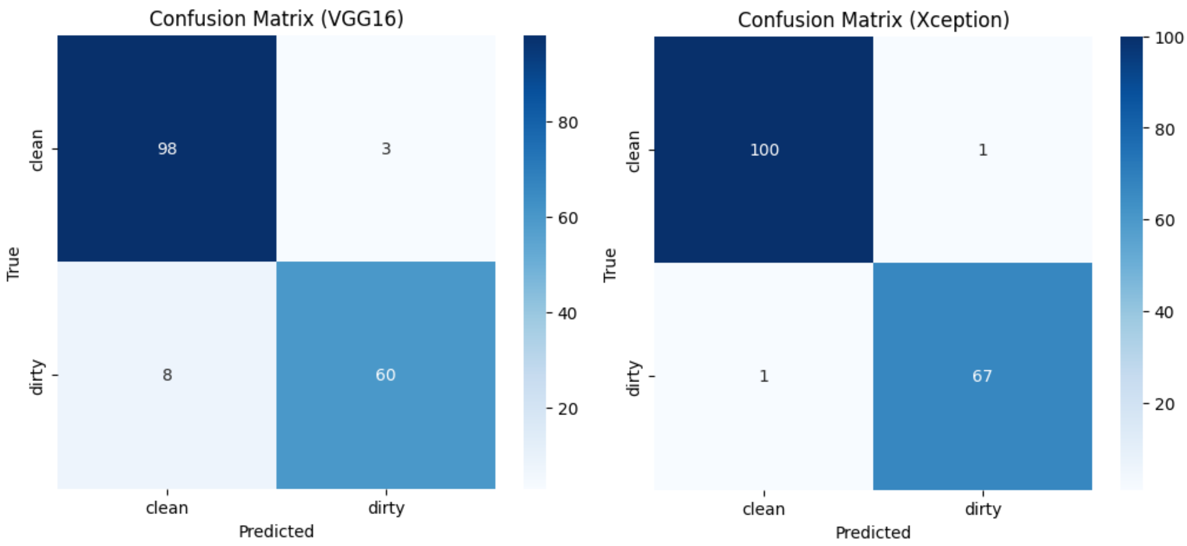

Figure 5: Classification confusion matrices for both models

As shown in Figure 5, the confusion matrices of the VGG16 and Xception models demonstrate how each model classifies clean and dirty solar panel images. The matrices indicate that both models perform effectively in distinguishing between clean and dusty panels, although subtle differences are observed in their accuracy and the distribution of classification errors. For the VGG16 model, 98 out of 101 clean images were correctly classified, while 3 were misclassified as dirty. In the case of dirty images, 60 were correctly identified, but 8 were mistakenly predicted as clean. This indicates that VGG16 has a slightly higher tendency to misclassify dirty panels as clean, which could affect the reliability in detecting contamination.

In contrast, the Xception model demonstrates improved performance. All but one clean image was correctly identified, and only a single dirty image was misclassified as clean. With 67 correct predictions for dirty panels and just 1 error, Xception shows a better balance between identifying clean and dirty images. This suggests that the Xception model is more robust and precise in distinguishing dust accumulation, reducing the likelihood of false negatives in practical applications.

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Comparing the two models, it is clear that Xception outperforms VGG16 in both overall accuracy and the ability to correctly identify dirty panels, which are often the more critical cases in solar panel monitoring. While both models achieve high accuracy for clean panels, the reduced misclassification rate in Xception makes it a more reliable choice for real-world deployment. The side-by-side presentation in Figure 5 effectively highlights these differences, providing a clear visual comparison of each model's strengths and weaknesses.

Integrated gradients method as illustrated in Figure 6 was applied to the best-performing model, (Xception model), to visualize the regions influencing its predictions. Figure 6 presents a solar panel through three distinct visual formats: the raw image, an integrated gradients map, and a composite overlay. In the original image, one can observe visible dust accumulation, especially concentrated in the lower-left section. The integrated gradients visualization, generated using the Xception model, highlights areas deemed most influential in the model's decision-making process.

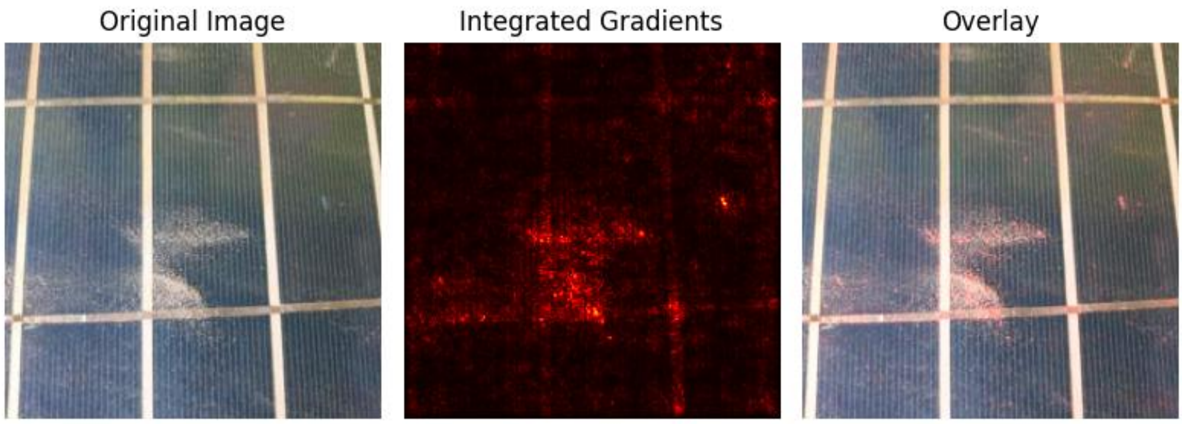

Figure 6: Integrated gradients visualization

Notably, these highlighted regions correspond closely to the dusty portions seen in the original image, indicating the model's sensitivity to such imperfections. The overlay merges this attribution map with the original photograph, providing a clear visual alignment between the regions of interest identified by the model and the actual surface contamination. This strongly supports the model's ability to accurately localize and prioritize areas affected by dust on the solar panel.

5. Conclusion

This study investigated the use of deep learning methods to detect dust accumulation on photovoltaic panels, aiming to provide both accurate classification and interpretable results. Among the two architectures considered, the Xception model consistently demonstrated

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superior performance compared to VGG16, achieving higher classification accuracy and establishing itself as a dependable choice for this application. To enhance the transparency of the models' predictions, integrated gradients were applied to identify the image regions that most strongly influenced the network's decisions, thereby providing clearer insights into the factors driving classification outcomes and increasing confidence in the model's behaviour.

While these findings are encouraging, several limitations should be acknowledged. The dataset utilized in this study was relatively small, which may restrict the broader applicability of the results, despite the use of data augmentation to partially mitigate this constraint. Additionally, relying exclusively on integrated gradients may not fully capture the complexity of model interpretability, suggesting the need for complementary explainable AI approaches. Future work should aim to incorporate larger and more diverse datasets, evaluate a broader range of deep learning architectures, and explore multiple explainable AI techniques to further enhance both predictive performance and interpretability. Such efforts would not only strengthen the reliability of the models but also provide more comprehensive insights into the factors influencing dust detection on solar panels.

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