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Detecting Dusty and Clean Photovoltaic Surfaces Using MobileNet Variants for Image Classification

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Abstract The effectiveness of three MobileNet variations—MobileNetV1, MobileNetV2, and MobileNetV3—in correctly classifying dusty and immaculate Photovoltaic (PV) surfaces is investigated. To maintain PV panels' efficiency and maximize energy production, precise detection of dust accumulation is crucial. The demand for automated solutions arises from the inefficiency and high labor costs of conventional inspection techniques. A dataset consisting of 400 images, with an equal number of clean and dusty PV surfaces, was used to ensure a fair representation of both groups. Prior to being divided into training and validation sets, the images underwent preprocessing and normalization. Subsequently, each variant of MobileNet underwent training and evaluation using this dataset. Performance indicators such as training accuracy, validation accuracy, F1-score, and loss values were assessed. MobileNetV1 demonstrated superior performance, with a training accuracy of 88.53%, validation accuracy of 91.25%, and an F1-score of 0.9114. MobileNetV3 exhibited the lowest performance, achieving a training accuracy of 59.90%, a validation accuracy of 61.87%, and an F1-score of 0.6115. The study's findings establish that MobileNetV1 is the optimal model for accurately identifying dusty and clean PV surfaces. The research illustrates the viability of using Deep Learning (DL) algorithms in PV maintenance, and choosing the most suitable algorithm for doing the task.

Keywords:. Deep Learning; Dust Detection; Image Classification; MobileNet Variants; Photovoltaic Surfaces.

1 Introduction

Photovoltaic (PV) systems are a crucial element of renewable energy technology. They turn sunlight into electricity by utilizing the PV effect in semiconductor materials [1]. Solar panels play a vital role in the generation of sustainable energy since they have the capacity to generate electricity from a renewable and unlimited source - the sun [2]. PV systems are being more and more utilized in both residential and industrial settings, making a substantial contribution to the decrease in greenhouse gas emissions and the reduction of reliance on fossil fuels [3].

The collection of dust on the surfaces of PV systems significantly reduces their efficiency and output [4]. Dust particles impede sunlight from reaching the solar cells, resulting in diminished power generation [5]. Extended dust deposition diminishes energy output and hastens the deterioration of PV systems, hence reducing their lifespan [4]. Consequently, preserving the cleanliness of PV surfaces is crucial for ensuring their best performance and durability.

Automated methods for dust detection and removal are essential to mitigate the considerable effect of dust on the efficiency of PV systems [6]. Conventional cleaning techniques are expensive, laborious, and may be unsuccessful, especially in extensive solar arrays [7]. Automated detection and cleaning solutions enhance maintenance consistency and efficiency, optimizing energy production and system longevity without necessitating operator intervention. These systems autonomously monitor dust levels and initiate cleaning operations by utilizing sensors, image processing algorithms, and artificial intelligence [7].

Precisely identifying dust collection on PV surfaces is essential for preserving efficiency and prolonging the system's operating lifespan. Contemporary methods depend significantly on manual inspections, which are laborious, time-consuming, and susceptible to human mistake [8]. These systems necessitate specialists to manually access and visually examine each panel,

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presenting difficulties for extensive installations or panels situated in remote areas [9]. Moreover, manual checks elevate maintenance expenses and subject workers to possible safety hazards [6].

In addition to human inspections, contemporary dust detection systems for PV panels encompass fundamental image processing techniques and sensor-based methodologies. Conventional image processing techniques frequently depend on manually specified features and basic thresholding, which can yield limited precision and are susceptible to inconsistencies due to fluctuating lighting conditions or the inclusion of additional pollutants [10]. Sensor-based techniques, including transmittance or reflectance measurements, provide real-time data on dust accumulation; nevertheless, they are expensive to install and maintain, especially in extensive solar farms. These sensors are susceptible to ambient influences, potentially resulting in erroneous readings [11]. These constraints highlight the necessity for more resilient, precise, and scalable dust detection techniques.

Progress in Deep Learning (DL) and Convolutional Neural Networks (CNNs), especially the MobileNet architecture, presents a viable resolution to these issues. CNNs can autonomously learn and extract pertinent information from photos, facilitating more precise and dependable classification of dusty versus clean PV surfaces. MobileNet, recognized for its computational efficiency and efficacy in picture classification, offers an optimal architecture for the development of scalable dust detection systems. The capacity of MobileNet variations to address the shortcomings of conventional approaches can enhance the efficacy of PV system performance maintenance.

The primary objective of this project is to build and assess image classification algorithms utilizing MobileNet variations for the detection of dust on PV surfaces. The main goal is to improve the precision and efficacy of dust detection relative to current techniques. The suggested method aims to provide a scalable and dependable solution for real-world applications by autonomously extracting pertinent information from photographs of PV panels, hence ensuring optimal performance and prolonged system longevity. This study emphasizes the innovation of employing MobileNet variations in this setting, demonstrating their role in enhancing PV system maintenance.

The outcomes of this study could transform maintenance procedures for PV installations. This study tackles the significant problem of efficiency decline caused by dust accumulation, contributing to the advancement of automated detection methods that can lessen the necessity for labor-intensive human inspections, decrease maintenance expenses, and enhance safety. Furthermore, the improved detection capabilities afforded by MobileNet versions may facilitate expedited cleaning interventions, ensuring that PV panels function at optimal efficiency, thereby increasing energy output from renewable sources.

This study's significant innovation is the utilization of MobileNet variations for the classification of clean and dusty PV surfaces. MobileNet's streamlined and efficient CNN design is ideally suited for this task, providing a compromise between high classification accuracy and minimal computing demands. The research illustrates the viability and benefits of utilizing sophisticated DL algorithms in PV maintenance, facilitating the development of more intelligent, automated systems that can be scaled for practical use.

This research paper is structured to provide a thorough examination of detecting dusty and clean PV surfaces using MobileNet variants for image classification. The Introduction sets the stage by highlighting the problem, current challenges, and objectives of the study. The Methodology section delves into the details of the research process, including data presentation, the Machine Learning (ML) algorithms used, and the evaluation metrics. Following this, the Results and Discussion section presents and analyzes the findings, offering insights into the model's performance and its implications. Finally, the Conclusion summarizes the key outcomes of the research and suggests directions for future work, ensuring a comprehensive understanding of the study's contributions and potential impact.

2 Methodology

2.1 Data Presentation

For this investigation, the study employed a dataset of 400 images of PV surfaces, with half of them being clean and the other half being dirty. Fig. 1 depicts the distribution of images in the two classes, with an equal number of images in each category. This ensures that the dataset used for training and evaluation is balanced.

The images in each category are visually shown in Fig. 2. Five clean PV surfaces are shown in the top row (marked in green), while five dusty surfaces are shown in the bottom row (marked in red). The dataset used in this study is better understood thanks to these images, which highlight the clear visual differences between the two groups. By keeping all sample images at the same square size of 224 by 224 pixels, uniformity in the visual presentation is achieved.

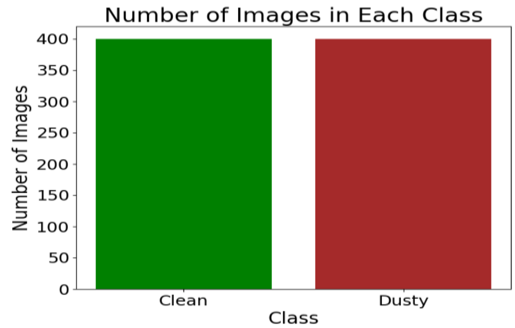

Fig. 1 Number of images in each class.

Fig. 2 Examples of clean and dusty PV surfaces.

2.2 ML Algorithms

This research classified PV surfaces as dusty or clean using a variety of ML methods. Data preprocessing, data partitioning, model design, model training, model assessment, prediction visualization, and reporting are the seven main parts of the workflow. Each part plays a crucial role in ensuring the accuracy and reliability of the final model. The flow is shown in Fig. 3.

The first step in the procedure is data preparation. In this phase, the study includes the necessary libraries and set up the setup. "Pandas", "numpy", "seaborn", "matplotlib", "tensorflow", and "glob" are the important Python packages. After setting up the environment, the study loads and do preprocessing on the data. The images in the dataset are divided into two categories: clean and unclean. After the photos are resized to a standard size of 224 by 224 pixels, labels are applied, designating clean images with a value of 0 and dusty images with a value of 1. Following loading and preprocessing, the data is split into several sets for validation and training. By guaranteeing that the model is trained on a certain subset of data and subsequently validated on a separate subset, overfitting is prevented and the model's ability to generalize to new, unidentified data is ensured.

Subsequently, the subsequent phase involves constructing the model. The foundation model the study utilizes is MobileNetV1, which is a pre-trained CNN. The selection of MobileNetV1 is based on its exceptional efficiency and accuracy in performing picture classification jobs. We incorporate custom dense layers and an output layer into the main model to tailor it to our particular classification task. Utilizing custom layers allows for the precise adjustment of the model's performance. Subsequently, the model undergoes training using the provided training data. Callbacks like "EarlyStopping" and "ReduceLROnPlateau" are used during training to avoid overfitting and maximize the Learning Rate (LR). The "EarlyStopping" technique terminates the training process when there is no further improvement in the validation loss. On the other hand, the "ReduceLROnPlateau" technique decreases the LR when a plateau in the validation loss is identified. The model undergoes training for a maximum of 100 epochs, with validation conducted at every epoch. Following the completion of training, the model is assessed by employing the validation data. The evaluation entails the computation of crucial measures, such as validation loss and accuracy, which offer insights into the model's performance on data that it has not been trained on. In order to more thoroughly evaluate the model's performance, the study employs visualizations to display its predictions on the validation set. This stage entails producing predictions for the validation images and then comparing them to the actual labels. Utilizing visualizations aids in comprehending the model's capabilities and limitations in differentiating between pristine and dirty surfaces.

The last step of the workflow entails producing comprehensive reports on the model's performance. This involves computing the F1-score, producing a classification report, and visualizing the confusion matrix. The classification report presents precise measurements of precision, recall, and F1-scores for each class, providing a thorough assessment of the model's efficacy. The confusion matrix provides a visual representation of the counts of True Positive (TP), True Negative (TN), False Positives (FPs), and False Negative (FN) predictions, aiding in the identification of specific areas where the model may be making incorrect classifications. The outlined procedure, depicted in the flowchart in Fig. 3, guarantees a methodical approach to constructing, training, and assessing the MobileNet variations for the classification of both clean and dusty solar surfaces. By adhering to this systematic procedure, the study may attain a sturdy and dependable model with a high level of accuracy in classification and the capacity to generalize well.

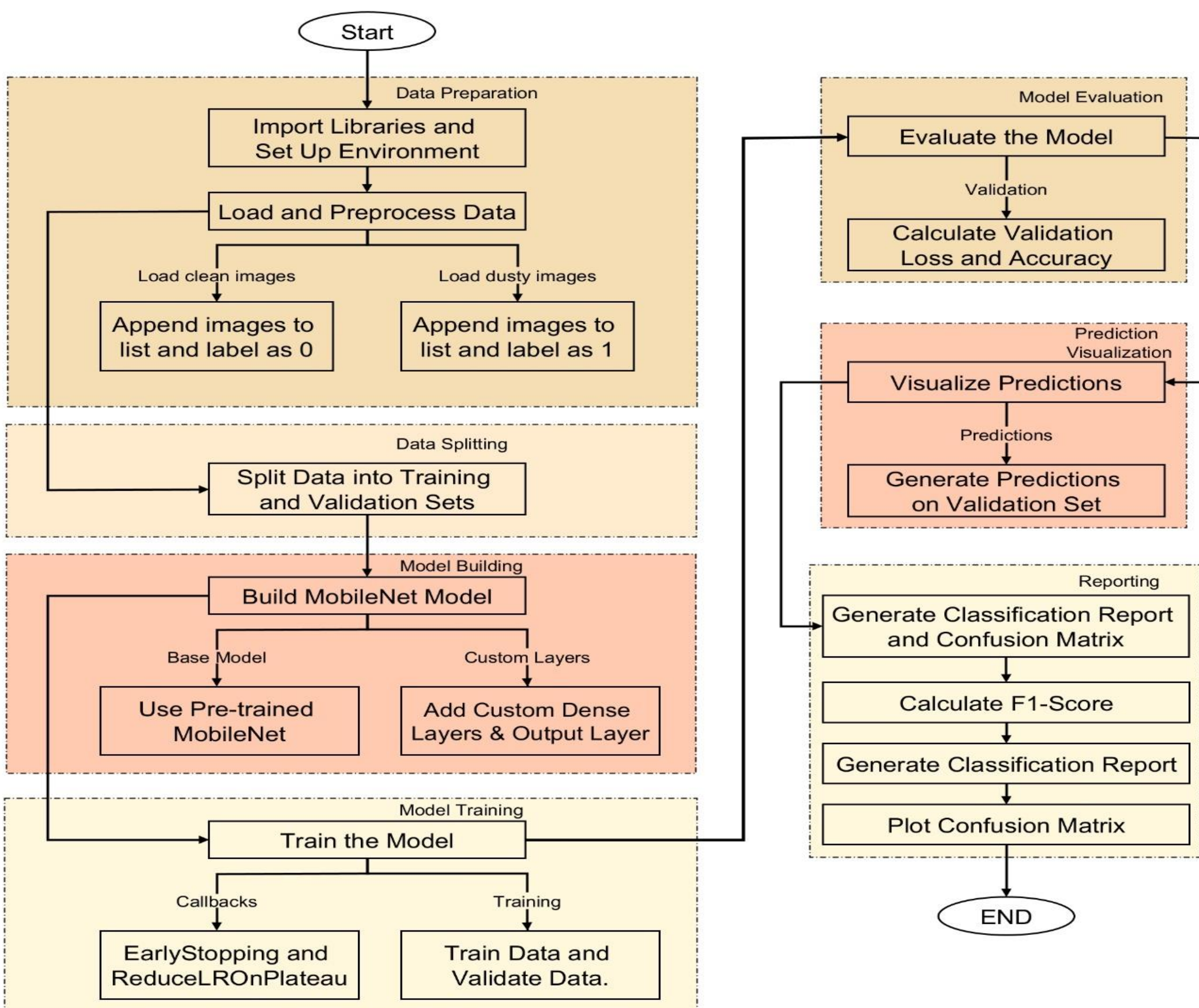

Fig. 3 Detailed workflow of the process using MobileNet versions for classifying clean and dusty PV surfaces.

Table 1 General comparison of MobileNetV1, MobileNetV2, and MobileNetV3.

Feature	MobileNetV1	MobileNetV2	MobileNetV3
Architecture	Original MobileNet architecture	Improved version with better performance and efficiency	Further optimized version with lightweight layers
Year of Release	2017	2018	2019
Depthwise Separable Convolution	Yes	Yes	Yes
Bottleneck Layers	No	Yes	Yes
Squeeze-and-Excitation Modules (SE Modules)	No	No	Yes
Inverted Residuals	No	Yes	Yes
Model Size	~17 MB	~14 MB	~10 MB
Floating Point Operations (FLOPs)	569 million	300 million	219 million
Use Cases	General purpose, mobile applications	Enhanced performance for mobile and edge devices	Optimized for speed and low-power applications
Pre-trained Weights Availability	Yes	Yes	Yes

Table 1 presents a thorough comparison of the three MobileNet variations, namely MobileNetV1, MobileNetV2, and MobileNetV3, emphasizing their structural characteristics and applications. MobileNetV1, which was announced in 2017, established a basis for reducing computational cost by utilizing depthwise separable convolutions, a novel technique that greatly decreased the amount of computing required compared to conventional convolutions. MobileNetV2, introduced in 2018, enhanced the existing design by integrating inverted residuals and linear bottlenecks, resulting in greater performance and economy. The model's size and processing requirements were greatly reduced in this version, making it more suitable for mobile and edge devices. The most current version, MobileNetV3, was released in 2019. It improved the architecture by using lightweight layers and SE Modules, which resulted in lower computation costs and smaller model sizes. Applications requiring fast speed and low power consumption are best suited with this version. Pre-trained weights are included in every one of these variants, which makes them simple to use in a variety of contexts, from general-purpose to highly optimized mobile ones. The enhancements described in Table 1 illustrate the progression and ongoing enhancement in efficiency and performance throughout the many versions of MobileNet [12-15].

2.3 Evaluation Metrics

To assess how well various MobileNet versions classified PV surfaces as dusty or clean, the study used a variety of assessment metrics in this study. Accuracy, precision, recall, F1-score, and confusion matrices are the primary performance metrics. These metrics provide a comprehensive understanding of the robustness and effectiveness of the models.

The ratio of accurately predicted instances to the total number of instances is used to compute accuracy, which serves as a gauge for the model's overall soundness [16]. It is described by Equation (1). Where TN stands for TNs, FP for FPs, FN for FNs, and TP for TPs.

The percentage of TP predictions among all positive forecasts is represented by precision. Understanding the model's performance is especially helpful when the cost of FPs is large [17]. Equation (2) illustrates the calculation of precision. Recall, which is often referred to as sensitivity or TP rate, quantifies the percentage of real positives that the model properly identifies [18]. When the cost of FNs is considerable, it matters. The definition of recall is given in Equation (3). The F1-score is a statistic that provides a balance between accuracy and recall, calculated as the harmonic mean of the two [19]. It is especially helpful for datasets that are unbalanced. The formula for the F1-score is given in Equation (4).

The confusion matrix offers a comprehensive breakdown of the model's performance by displaying the counts of TP, TN, FP, and FN predictions. It aids in comprehending the specific types of errors made by the model. The metrics and their corresponding equations provide a thorough evaluation framework for assessing the performance of the models in this study. By utilizing these metrics, the study can gain a better understanding of the strengths and weaknesses of each MobileNet variant in the task of classifying clean and dusty PV surfaces. [20-22].

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

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

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

$$F1 - Score = 2 \times \frac{Precision \times Recall}{Precision + Recall} \tag{4}$$

3 Results and Discussion

This section provides a comprehensive analysis of the results obtained from our investigation, which focused on the identification of dusty and clean PV surfaces. The study utilized MobileNet variations for image classification in our research. The performance of MobileNetV1, MobileNetV2, and MobileNetV3 was assessed using multiple measures, such as training accuracy, training loss, validation loss, validation accuracy, and F1-score. Furthermore, the performance of each model is visually shown using confusion matrices and accuracy/loss graphs.

Table 2 unequivocally shows that when it comes to training accuracy, validation accuracy, and F1-score, MobileNetV1 outperforms the other two versions. With a training loss of 0.48003, the MobileNetV1 model achieved a training accuracy of 88.53%. 91.25% was the validation accuracy, while the validation loss was 0.4077. The model has good performance in properly classifying both clean and dirty surfaces, as seen by its F1-score of 0.9114.

MobileNetV2 demonstrates strong performance with a training accuracy of 83.50%, a training loss of 0.6019, a validation loss of 0.5794, and a validation accuracy of 85.00%. The F1-score of 0.8481 demonstrates its dependable performance, albeit slightly inferior to MobileNetV1. MobileNetV3 exhibits the poorest performance in comparison, with a training accuracy of 59.90%, training loss of 0.7242, validation loss of 0.7216, and validation accuracy of 61.87%. The F1-score of 0.6115 indicates a restricted capacity to accurately differentiate between clean and dusty surfaces.

Table 2 Training and validation metrics for MobileNet variants.

Algorithm	Training Accuracy	Training Loss	Val Loss	Val Accuracy	F1
MobileNetV3	0.5990	0.7242	0.7216	0.6187	0.6115
MobileNetV2	0.8350	0.6019	0.5794	0.8500	0.8481
MobileNetV1	0.8853	0.4803	0.4077	0.9125	0.9114

Table 3 presents the comprehensive classification reports for the three MobileNet variations, highlighting precision, recall, and F1-score for both classes (clean and dusty). The classification data in Table 3 indicate the improved performance of MobileNetV1, with excellent precision, recall, and F1-scores for both clean and dirty classes. Specifically, MobileNetV1 attained a precision of 0.9000 for clean surfaces and 0.9200 for dusty surfaces, with matching recalls of 0.9300 and 0.9000, giving in an F1-score of 0.9100 for both classes. This high level of performance implies that MobileNetV1 is highly effective at correctly identifying both types of surfaces with low misclassification. MobileNetV2 likewise performs well, reaching precision of 0.8400 for clean surfaces and 0.8600 for dusty surfaces, with recalls of 0.8600 and 0.8400, respectively, yielding to an F1-score of 0.8500 for both classes. While somewhat lower than MobileNetV1, MobileNetV2 displays robust categorization capabilities. MobileNetV3 exhibits inferior performance across all classification parameters, achieving a precision of 0.6100 for clean surfaces and 0.6200 for dusty surfaces, recalls of 0.6400 and 0.6000, and resultant F1-scores of 0.6300 and 0.6100, respectively. The results suggest that there are considerable difficulties in appropriately categorizing the images, resulting in a decreased overall efficiency of MobileNetV3.

Table 3 Classification report for MobileNet variants.

Algorithm	Class	Precision	Recall	F1-Score	Support
MobileNetV3	Clean	0.6100	0.6400	0.6300	80
MobileNetV3	Dusty	0.6200	0.6000	0.6100	80
MobileNetV3	**Average**	**0.6200**	**0.6200**	**0.6200**	**160**
MobileNetV2	Clean	0.8400	0.8600	0.8500	80
MobileNetV2	Dusty	0.8600	0.8400	0.8500	80
MobileNetV2	**Average**	**0.8500**	**0.8500**	**0.8500**	**160**
MobileNetV1	Clean	0.9000	0.9300	0.9100	80
MobileNetV1	Dusty	0.9200	0.9000	0.9100	80
MobileNetV1	**Average**	**0.9100**	**0.9100**	**0.9100**	**160**

Fig. 4 displays the training and validation accuracy for the three variations of MobileNet throughout the training epochs. From the Fig. 4 it is evident that MobileNetV1 in Fig. 4(a) achieves the highest and most consistent validation accuracy, with a clear upward trend and minimal fluctuations. The training accuracy also demonstrates a steady increase, indicating the model's efficiency and stability in learning. MobileNetV2 in Fig. 4(b) performs well with a consistently rising validation accuracy, albeit with slight fluctuations. The training accuracy shows a steady upward trend, indicating effective learning. On the other hand, MobileNetV3 in Fig. 4(c) exhibits significant fluctuations in validation accuracy, suggesting instability and challenges in effectively learning the classification task. The training accuracy also displays instability, highlighting difficulties in model convergence.

Fig. 5 depicts the training and validation loss for the three variations of MobileNet throughout the training epochs. The loss curves in Fig. 5 highlight the superior performance of MobileNetV1. MobileNetV1 Fig. 5(a) exhibits a clear and consistent decrease in both training and validation losses, indicating effective learning and minimal overfitting. The convergence is smooth, indicating the model's robustness. MobileNetV2 Fig. 5(b) also demonstrates a steady decline in training and validation losses, although with more fluctuations compared to MobileNetV1. The convergence is satisfactory, but the model shows slightly higher validation loss towards the end. MobileNetV3 Fig. 5(c) displays higher and more irregular losses, which align with its lower classification performance. The significant fluctuations indicate difficulties in learning and model instability.

The confusion matrices in Fig. 6 exhibit the detailed performance of each model in differentiating between clean and dirty solar surfaces. MobileNetV1 Fig. 6(a) displays the maximum accuracy, with 74 clear images properly categorized as clean and just 6 misclassified as dusty. Similarly, 72 dirty images are correctly categorized as dusty with only 8 misclassified as clean. This matrix supports the model's high precision and recall, consistent with the metrics in Table 3. MobileNetV2 Fig. 6(b) similarly performs well, with 69 clean images correctly classified and 11 misclassified, whereas 67 dusty images are correctly classified and 13 misclassified. Although significantly lower in accuracy compared to MobileNetV1, it nevertheless displays robust classification ability. MobileNetV3 Fig. 6(c) exhibits reduced accuracy with considerable misclassifications. Only 51 clean images are accurately classified with 29 misclassified as dusty, while 48 dusty images are correctly classified with 32 misclassified as clean. The significant degree of misclassification underscores the constraints of MobileNetV3 in this particular task.

Ensuring proper maintenance of a PV cell is crucial in order to prevent possible issues and guarantee maximum performance. To ensure efficiency, it is crucial to regularly clean, examine for damage, and monitor system components. To ensure optimal energy production and system lifespan, it is crucial to maintain the PV cell in a pristine condition, free from dust, dirt, debris, and technical malfunctions. This will enable the cell to continually deliver the highest achievable power output [23-29].

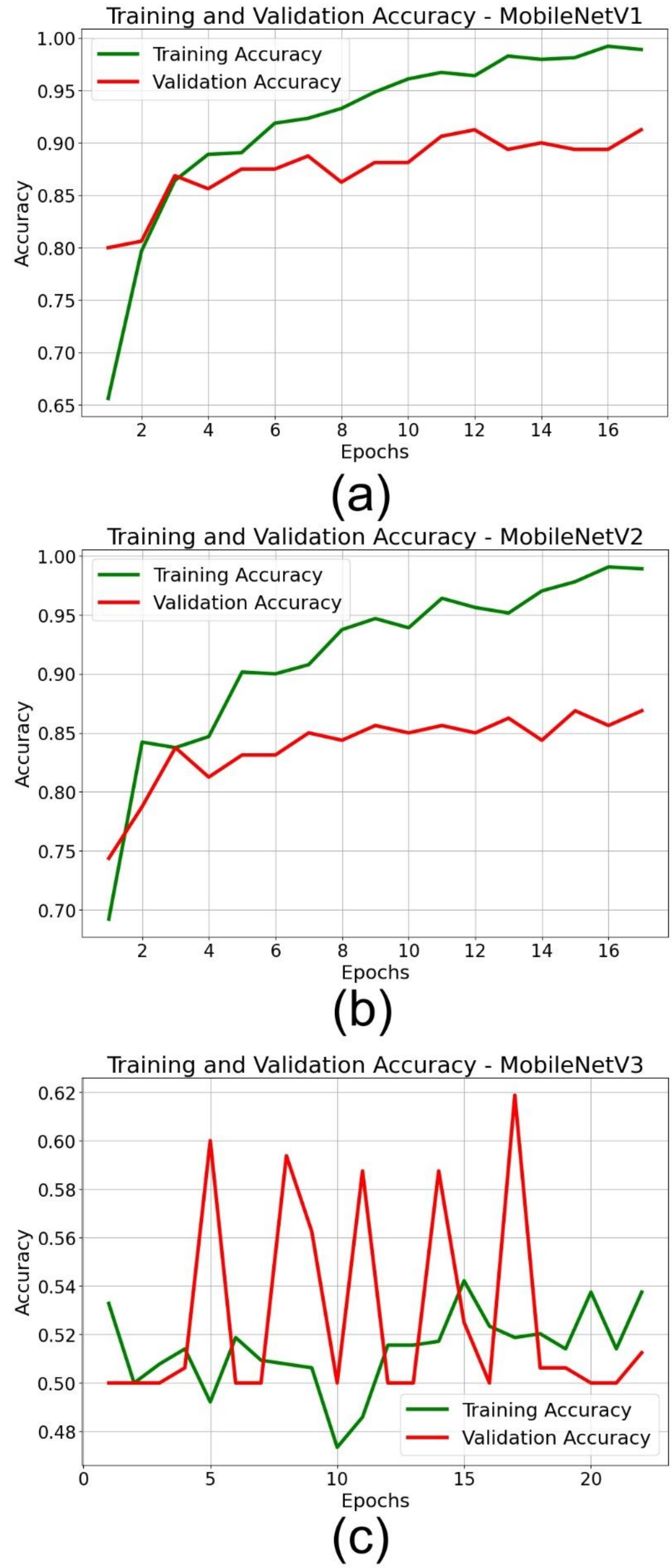

Fig. 4 Training and validation accuracy for (a) MobileNetV1, (b) MobileNetV2, and (c) MobileNetV3.

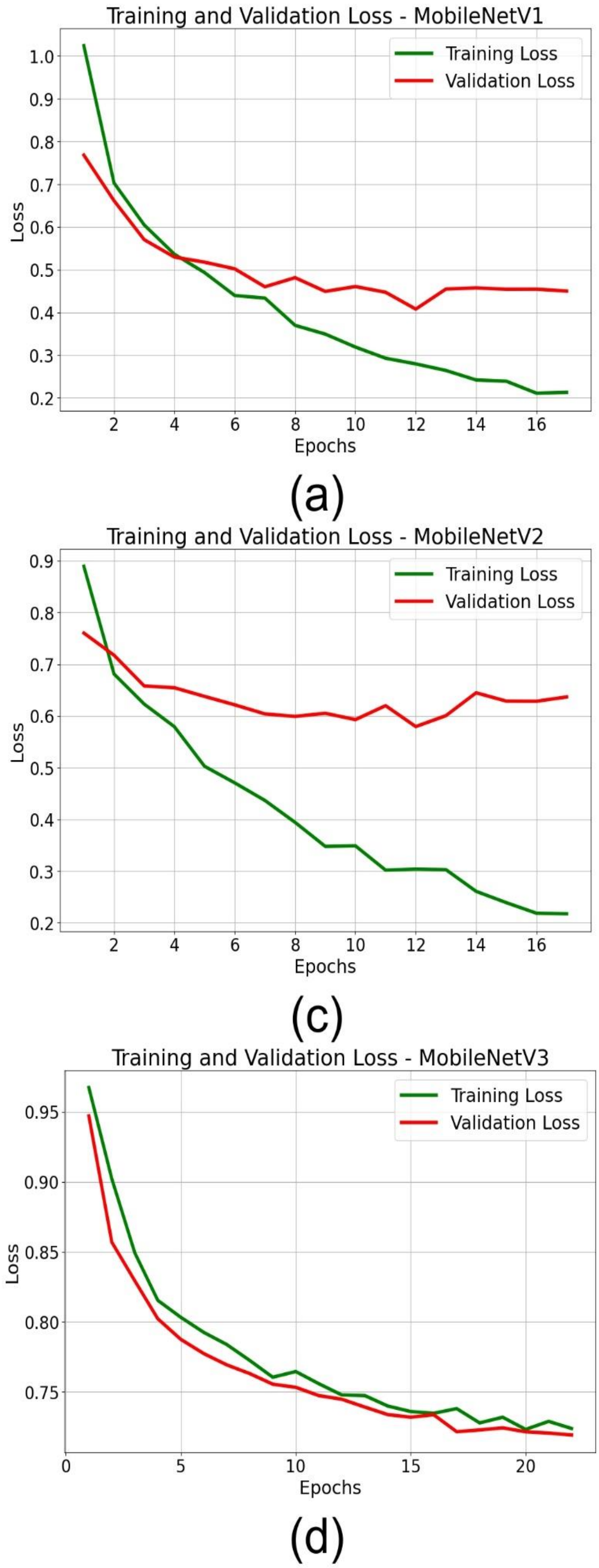

Fig. 5 Training and validation loss for (a) MobileNetV1, (b) MobileNetV2, (c) MobileNetV3.

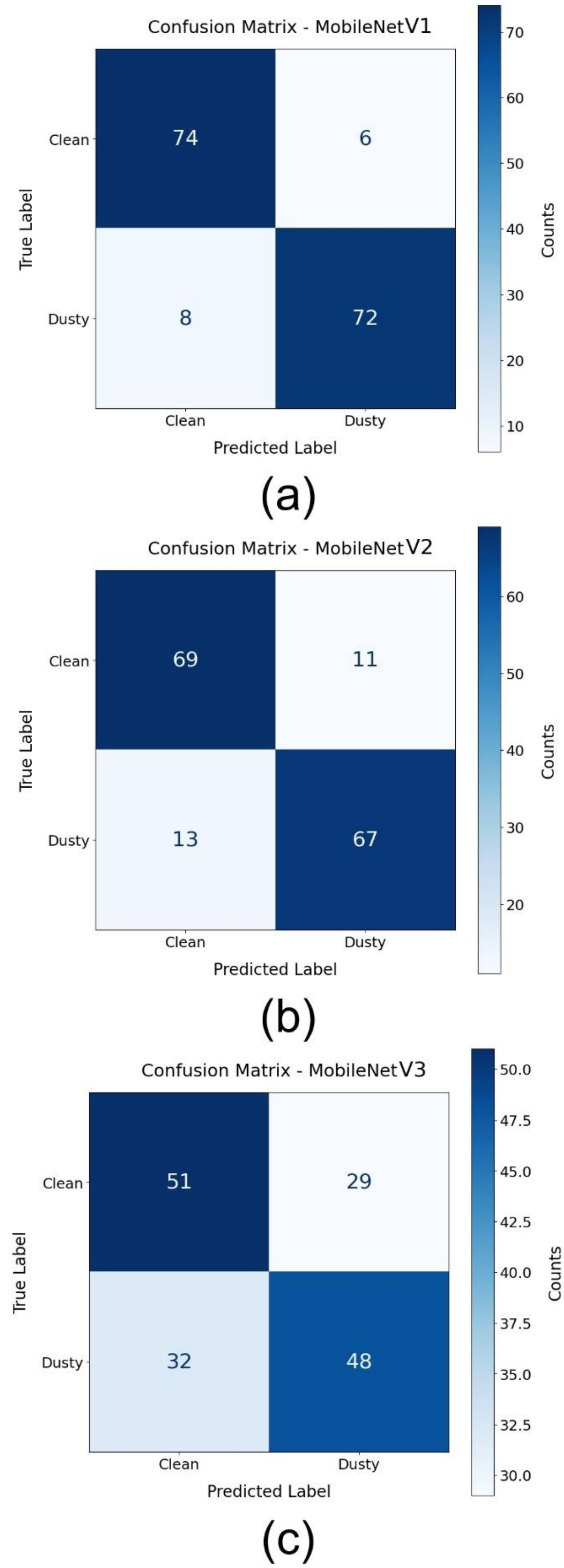

Fig. 6 Confusion matrices for (a) MobileNetV1, (b) MobileNetV2, and (c) MobileNetV3 on clean and dusty image classification.

4 Conclusion

The effectiveness of three MobileNet variants—MobileNetV1, MobileNetV2, and MobileNetV3—in correctly classifying PV surfaces as dusty or clean is examined in this research study. The research aimed to develop an automated and accurate method for detecting dust accumulation on solar panels, an essential task for maintaining the panels' overall performance and efficiency. To provide a fair representation of all categories, the 400 images in the dataset used for this analysis included an equal number of clean and dusty PV surfaces. To evaluate the efficacy of each MobileNet variation, the images were preprocessed and split into distinct training and validation sets. In the bulk of the measurements, MobileNetV1 outperformed the other two variations. MobileNetV1 demonstrated its robustness and great classification abilities by achieving the highest accuracy in both training and validation, as well as the best F1-score. With a competitive F1-score and good training and validation accuracy, MobileNetV2 showed promising performance. However, MobileNetV3 did not perform well, achieving much lower metrics, indicating limitations in its ability to accurately categorize the images. The test highlights MobileNetV1's outstanding performance, obtaining high recall and accuracy on both dirty and clean surfaces. Although it showed considerably poorer accuracy and recall than MobileNetV1, MobileNetV2 still performed well overall. Significant misclassifications by MobileNetV3 led to worse recall, F1-scores, and accuracy. Confusion matrices and the visual representations of the training and validation accuracy and loss curves provided more insight into the models' performance. The learning process of MobileNetV1 showed the greatest degree of consistency and stability, exhibiting smooth convergence in both accuracy and loss. However, MobileNetV3's poor classification performance was clearly related to its irregular learning patterns and a significant rise in validation loss. According to the research, MobileNetV1 performs better at identifying dusty and clean solar surfaces than the other two MobileNet versions. This system is a solid choice for automated inspection systems intended to maintain the efficiency of PV panels because of its excellent accuracy, precision, recall, and F1-score. To further improve the model's performance, future research may concentrate on refining the MobileNetV1 architecture or using fresh techniques for data augmentation. Furthermore, testing our method on large-scale and diverse datasets may confirm its applicability in real-world scenarios. In order to improve classification accuracy and robustness, further research may investigate the use of more complex DL models or hybrid approaches that combine several models.

Abbreviations

CNN	Convolutional Neural Network
DL	Deep Learning
FN	False Negative
FLOPs	Floating Point Operations
FP	False Positive
LR	Learning Rate
ML	Machine Learning
PV	Photovoltaic
SE Modules	Squeeze-and-Excitation Modules
TN	True Negative
TP	True Positive

CRediT authorship contribution statement

All authors have equally contributed to every facet of this research. Their joint efforts encompassed: Conceptualization; Data curation; Formal analysis; Funding acquisition; Investigation; Methodology; Project administration; Resources; Software; Supervision; Validation; Visualization; Roles/Writing - original draft; and Writing - review & editing.

Declaration of competing interest

The authors affirm that there are no conflicts of interest related to the publication of this paper. They disclose no competing financial interests or personal relationships that might appear to have influenced the findings presented in this work.

Data availability

The data from this study can be obtained by requesting it from the corresponding author.

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