Intelligent dust monitoring and cleaning optimization on photovoltaic panels

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ABSTRACT

Dust deposition on photovoltaic (PV) panels is a significant operational issue, often leading to power losses exceeding 15–30% in regions with high airborne particle concentrations. Although numerous studies have investigated either visual detection of dust or analytical estimation of performance loss, most approaches focus on a single task and provide limited practical insight for real-time maintenance. This work introduces a dual-task deep learning framework that simultaneously classifies dust severity and predicts the corresponding power loss from panel images. Five recent architectures vision transformer (ViT), swin transformer, GhostNet, DenseNet, and MobileNetV2 are employed as backbone feature extractors, with extracted embeddings processed by a multi-head multi-layer perceptron (MLP) combining shared representation learning with separate classification and regression outputs. The system is trained and evaluated on a real-world dataset of PV panels, and performance is assessed using accuracy and mean absolute error. DenseNet achieves the highest accuracy (94%) and lowest prediction error, while lightweight convolutional neural network (CNN) backbones demonstrate the best balance between precision and computational efficiency. By integrating hybrid processing and dual predictive capability, the proposed method offers a more comprehensive and deployable solution for automated PV monitoring compared to existing single-output approaches.

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1. INTRODUCTION

In recent years, renewable energy sources have gained significant global attention for their role in mitigating climate change, with photovoltaic (PV) systems emerging as a major contributor to sustainable power generation. However, the efficiency of PV panels is strongly affected by environmental conditions, particularly dust accumulation, which obstructs solar radiation and leads to measurable power losses [1]-[3]. PV modules consist of multiple p-n junction cells that convert photon energy into electrical current, and their behavior is commonly modeled using equivalent electrical circuits composed of a photocurrent source, diodes, and internal parasitic resistances. To accurately describe their behavior, equivalent circuit (as shown in Figure 1) models are commonly used, incorporating a current source (Iph), two diodes (ID1, ID2), and resistors Rs and Rsh to represent internal and leakage resistances [4]. The output current is expressed as:

$$I_{pv} = I_{ph} - I_{D1} - I_{D2} - \frac{V_D}{R_{sh}}$$

This model helps analyze PV electrical characteristics across various architectures monocrystalline, polycrystalline, dye-sensitized, and perovskite cells, including advanced types like PERC, HIT, and TOPCon. Their performance is strongly dependent on surface cleanliness, emphasizing the importance of regular inspection [5], [6].

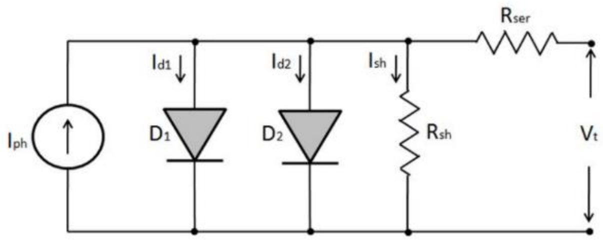

Figure 1. Equivalent electrical circuit of a solar panel

Dust accumulation is particularly problematic in arid and semi-arid environments where low rainfall prevents natural cleaning of the panels, resulting in reduced energy output, thermal hot spots, accelerated material degradation, and a shorter operational lifespan [7]-[9]. To mitigate these effects, recent research has investigated automated dust detection using deep learning. Onim *et al.* [10] proposed SolNet, a lightweight convolutional neural network (CNN) that outperformed AlexNet and visual geometry group (VGG) in classification tasks. Cruz-Rojas *et al.* [11] combined U-Net with extreme gradient boosting (XGBoost) and random forest (RF), achieving promising segmentation results. Cui *et al.* [12] used mask R-CNN to detect dusty areas with high precision on both real and synthetic datasets. Prova [13] demonstrated the capabilities of InceptionV3 for dust classification, while Oulefki *et al.* [14] introduced DeepSolarEye, reaching a dice coefficient of 92%. Alatwi *et al.* [15] proposed a low-cost solution based on DenseNet-169 coupled with support vector machine (SVM), suitable for edge deployment.

Further studies also report high performance. Bassil *et al.* [16] compared several CNN architectures including VGG and MobileNet, while Mohammed and Alawi [17] leveraged EfficientNet for dust detection with excellent results. He *et al.* [18] and Shah *et al.* [19] employed MobileNet and InceptionV3 respectively, with strong accuracy. Detection-oriented methods such as YOLOv8 Xie *et al.* [20], YOLOv3 Karakan *et al.* [21], and ensemble CNNs Sefer and Kaya [22] also demonstrated high precision. Shao *et al.* [23] achieved one of the highest reported accuracies through an improved MobileNet architecture.

Despite their effectiveness, many of these models are computationally intensive, which limits their real-time deployment on embedded or low-power devices. Moreover, existing studies generally focus on a single task either classification or segmentation without estimating the impact of soiling on actual power generation. To address these limitations, the present study introduces a novel dual-task deep learning framework capable of both dust-level classification and regression-based estimation of power loss. Five recent architectures vision transformer (ViT), swin transformer, GhostNet, DenseNet, and MobileNetV2 are employed exclusively as feature extractors, with their embeddings processed through a multi-head multi-layer perceptron (MLP). This design enables shared representation learning while performing two complementary tasks simultaneously.

This article is organized as follows: section 2 describes the proposed approach, detailing the experimental setup, datasets, and analytical methods used to assess the impact of dust accumulation on solar panel performance. In section 3 presents and analyzes the obtained results. Finally, section 4 concludes the study by summarizing the key findings and providing perspectives for future work aimed at improving dust detection and maintenance strategies to enhance PV system performance.

2. METHOD

To address both classification and regression tasks for PV panel monitoring, a hybrid deep learning framework was developed. It integrates multiple backbone networks for feature extraction with a lightweight MLP dual-head prediction module, enabling simultaneous classification of PV panel surface states (clean, dusty, soiled) and regression estimation of quantitative performance metrics, specifically power loss percentage and irradiance (see Figure 2). In the following section, the sequence of processing stages is presented in detail to describe the operation of the proposed algorithm.

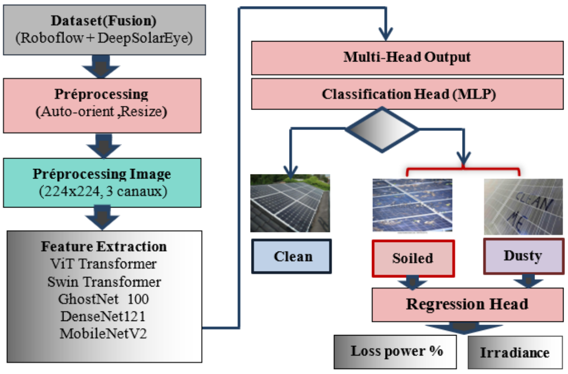

Figure 2. Hybrid deep learning architecture for PV panel health monitoring classification and regression

2.1. Dataset and preprocessing

Due to the absence of public datasets coupling both semantic labels and performance measurements, we opted to fuse two complementary datasets at the training level (shared backbone). The roboflow dataset (2,323 images) is used exclusively for classification (as shown in Figure 3), with the detailed splits being 1,619 for training, 469 for validation, and 235 for testing [24]. The DeepSolarEye dataset [25] is used exclusively for regression, leveraging the power loss (%) and irradiance values encoded in the filenames. For the latter, images were normalized to [0,1] and randomly split into training, validation, and test sets (following an 70:20:10 ratio). To prevent data leakage between the regression splits, we sanitized the DeepSolarEye filenames by removing timestamps and other non-essential metadata before proceeding with the random division. The test sets from both sources are strictly maintained separately, ensuring a valid and uncontaminated evaluation of the metrics.

Figure 3. Clean, dusty and soiled samples of solar PV panel

2.2. Comparative evaluation of backbone networks

To establish a robust and deployable system for PV panel health monitoring, a critical step involved the comparative evaluation of several leading deep learning backbone networks. The selection criteria were multidimensional, focusing not only on classification and regression accuracy but also on model complexity and suitability for deployment on resource-constrained embedded systems. The chosen models span both CNN architectures (DenseNet, MobileNetV2, GhostNet) and the more recent transformer-based models (ViT, swin transformer), allowing for a comprehensive assessment of feature extraction capabilities for PV surface analysis. Extracted features are globally pooled and fed into the dual-head MLP for joint classification and regression.

2.2.1. ViT
ViT divides 224×224 images into 16×16 patches, embeds each patch into a 768-dimensional vector, and processes them through 12 transformer encoder layers. The [CLS] token is used as the feature representation. ViT was employed as a frozen feature extractor.

2.2.2. Swin transformer
Swin-tiny uses window-based self-attention with a shifting mechanism to capture local and global context. It outputs 768-dimensional features after four hierarchical stages, mean-pooled before MLP input. Swin provides a scalable trade-off between accuracy and computational cost.

2.2.3. GhostNet
Generates compact 1,280-dimensional feature vectors using efficient operations, enabling high-speed inference with minimal memory footprint—ideal for real-time embedded deployment.

2.2.4. DenseNet121
Connects each layer to all subsequent layers to maximize feature reuse and gradient flow, improving extraction of fine-grained dust patterns.

2.2.5. MobileNetV2
Employs depthwise separable convolutions and squeeze-and-excitation modules to produce 1,280-dimensional features efficiently, balancing speed and representation quality [26].

2.3. MLP dual-head prediction
Globally pooled backbone features are fed into two MLP heads simultaneously:
- Classification head: predicts PV panel surface state (clean, dusty, soiled). Evaluated using accuracy, precision, recall, and F1-score.
- Regression head: predicts power loss percentage and irradiance. Metrics include mean square error (MSE), root MSE (RMSE), and R^2. Outputs are reported in physically interpretable units, and error distributions are analyzed to ensure dataset comparability.

This dual-head design allows joint learning of qualitative and quantitative degradation aspects.

2.3.1. Training and hyperparameters
All backbone layers were frozen, and only the MLP heads were trained. The hyperparameters used for training are summarized in Table 1. Evaluation was conducted on both datasets to ensure unbiased performance. This configuration allows reproducible training while focusing computational resources on the MLP heads for efficient dual-task learning.

Table 1. Hyperparameters for MLP heads training

Parameter	Value
Backbone layers	Frozen (Only MLP heads trained)
Optimizer	Adam
Learning rate	1×10^{-4}
Batch size	32
Number of epochs	Model-dependent
Data augmentation	Random horizontal flip, small rotations (±15°), brightness/contrast jitter
Random seeds	Fixed for reproducibility

3. RESULTS AND DISCUSSION
This study proposes a multi-task learning framework for PV panel assessment, simultaneously performing surface condition classification (clean, dusty, soiled) and regression-based estimation of power loss and irradiance. The system integrates pre-trained backbones ViT transformer, swin transformer, GhostNet_100, DenseNet121, and MobileNetV2 whose extracted visual features are processed by a dual-head MLP for joint learning.

3.1. Classification and regression performance
Table 2 presents the comparative performance of all evaluated models. For classification, DenseNet achieved the highest accuracy (94.00%), closely followed by GhostNet (93.47%), while transformer-based models, ViT (88.00%) and swin transformer (87.50%), exhibited lower performance. In terms of regression, GhostNet outperformed all models, with MSE=0.00214, RMSE=0.0462, MAE=0.0316, and R^2=0.8926,

demonstrating a favorable balance between predictive accuracy, model compactness (22M parameters), and computational efficiency. In contrast, transformer-based models, despite their higher complexity (up to 65M parameters), showed reduced regression performance ($R^2 \approx 0.65$). MobileNetV2 occupied an intermediate position, providing moderate accuracy and slightly less stable convergence. Importantly, these regression errors correspond to small deviations in predicted power loss percentages, indicating that the models can reliably estimate actual energy loss, which is critical for practical PV monitoring and maintenance decisions.

Table 2. Comparative performance of hybrid architectures for classification and regression tasks

Backbone	Vector dimension	Epoch	Classification accuracy (%)	MSE (%)²	RMSE (%)	MAE (%)	R²
ViT	768	65	88.00	0.01070	0.1035	0.0657	0.652
Swin	768	31	87.50	0.02289	0.1513	0.1228	0.653
GhostNet	1280	22	93.47	0.00213	0.0462	0.0316	0.893
DenseNet	1024	14	94.00	0.00321	0.0567	0.0370	0.881
MobileNetV2	1024	18	90.95	0.00302	0.0550	0.0390	0.875

Figure 4 illustrates training and validation convergence curves obtained with different backbones, Figures 4(a) and 4(b) show that GhostNet and DenseNet exhibit strong generalization with closely aligned curves, in contrast, Figures 4(c) and 4(d) indicate that ViT and swin transformer display pronounced overfitting, characterized by high training accuracy but lower validation performance and diverging loss curves. Finally Figure 4(e) shows that MobileNetV2 demonstrates moderate generalization, with minor oscillations in its validation curve, suggesting slower convergence and higher sensitivity to data fluctuations.

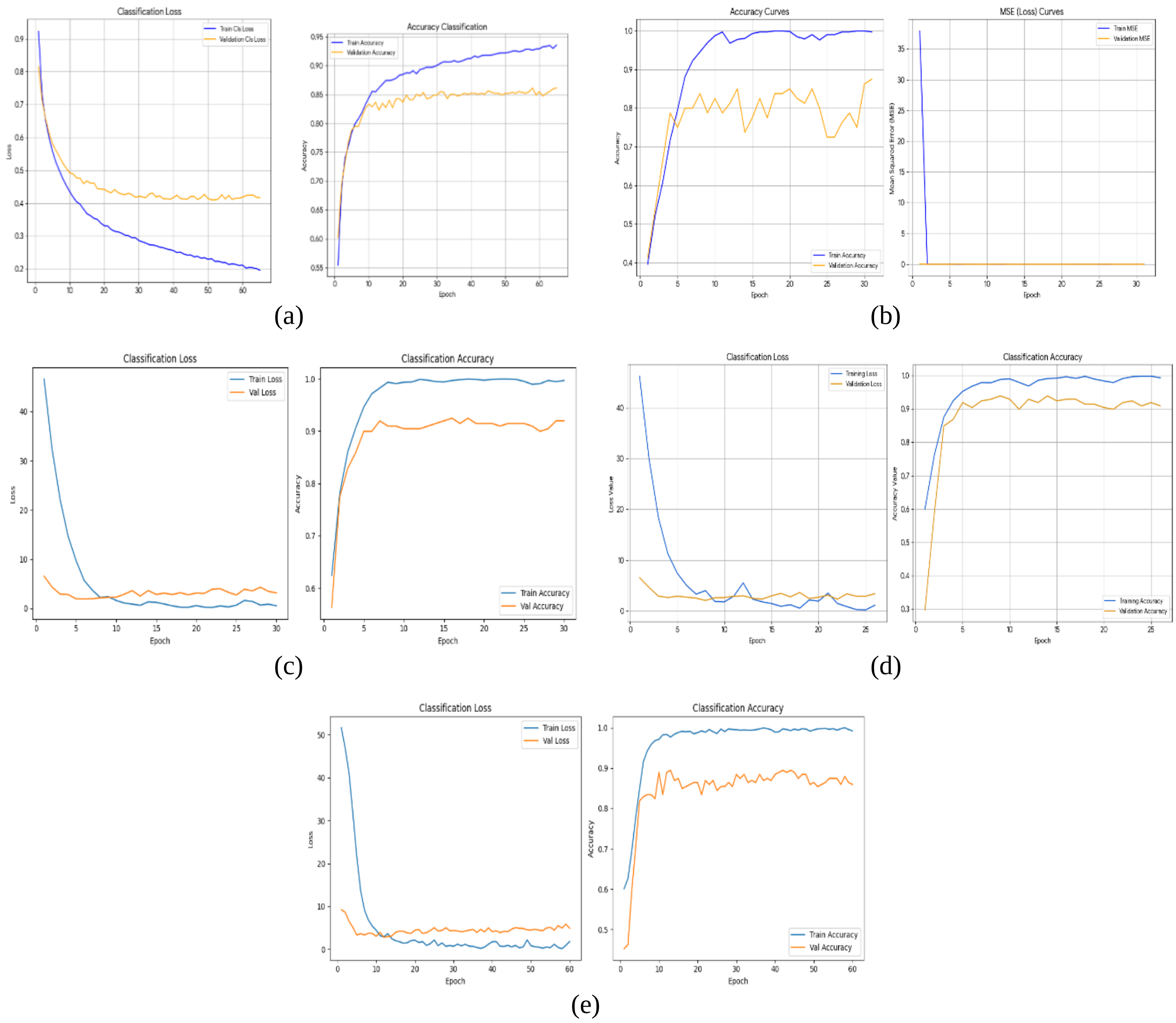

Figure 4. Convergence and generalization of classification models with various backbones: (a) ViT training and validation curves, (b) swin transformer training and validation curves, (c) GhostNet training and validation curves, (d) DenseNet training and validation, and (e) MobileNetV2 training and validation curves

Figure 5 presents the confusion matrices of the evaluated models. Figures 5(a) and 5(b) show that ViT and swin transformer exhibit notable confusion, mainly between clean and dusty classes. Figure 5(c) indicates that GhostNet provides balanced performance. Figure 5(d) shows that DenseNet achieves the highest accuracy with minimal confusion, while Figure 5(e) illustrates that MobileNetV2 suffers from higher misclassification rates.

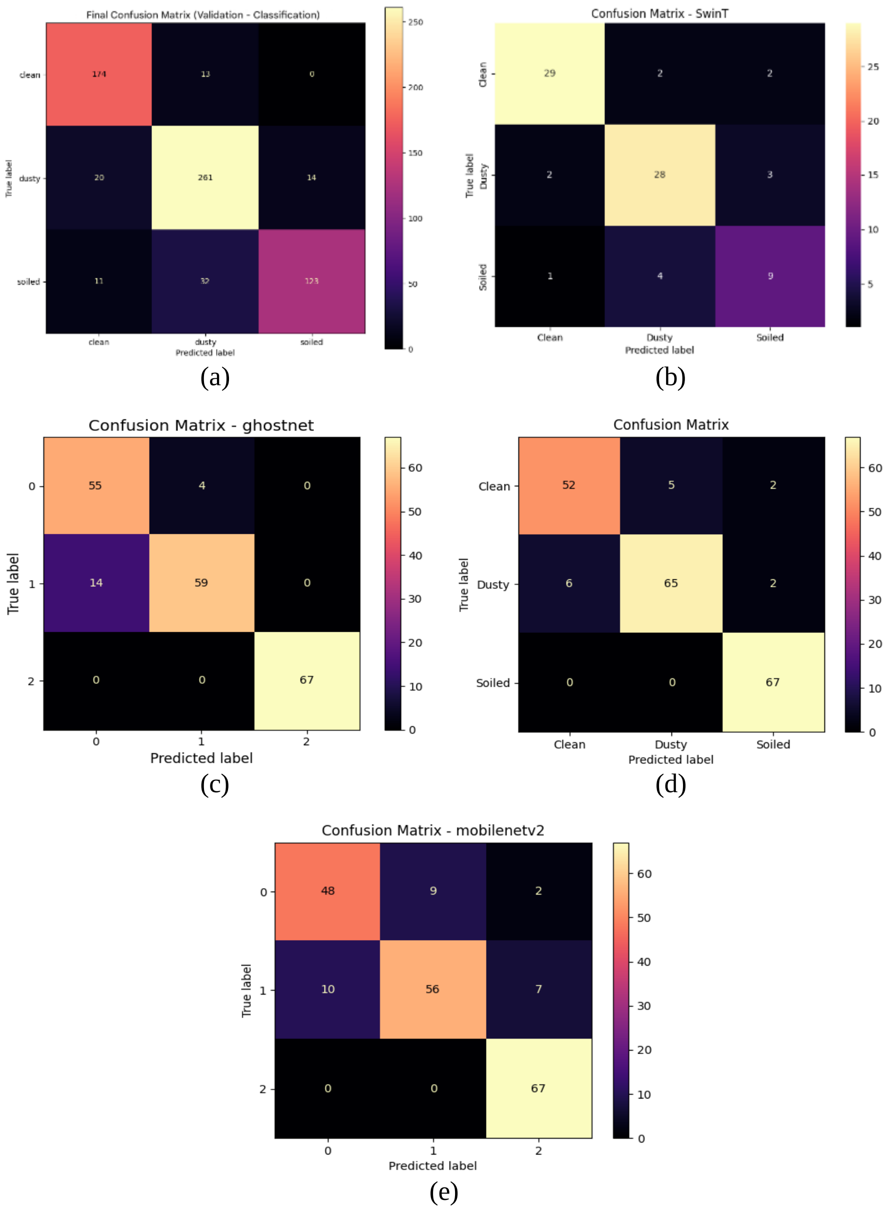

Figure 5. Final confusion matrix of various models: (a) ViT training, (b) swin transformer, (c) GhostNet, (d) DenseNet, and (e) MobileNetV2

The evaluation of regression performance, presented in Figure 6, demonstrates the superior efficiency of lightweight convolutional architectures compared to transformer-based models in estimating power loss (in %). GhostNet proved to be the top-performing backbone, achieving an RMSE of only 0.0021% and a near-perfect alignment of its predictions along the identity line (y=x), thereby confirming high fidelity and the absence of systemic bias. The DenseNet and MobileNetV2 models also showed excellent results (RMSE approx 0.003%). In contrast, ViT and swin revealed significantly lower performance, with notable dispersion (RMSE of 0.0107% for ViT) and weaknesses in modeling low-loss states. This suggests that the feature extraction mechanisms inherent to architectures optimized for local efficiency (such as GhostNet) are better suited for accurately quantifying the surface degradation of PV panels. These observations confirm that lightweight CNN-based architectures, specifically GhostNet and DenseNet, are particularly effective for dual-task scenarios, combining accurate dirt classification with reliable regression of PV performance metrics.

3.2. Comparison with existing literature

A comparative evaluation against previous approaches is presented in Table 3. Most prior studies focused on single-task models, either performing segmentation or classification of PV panel surfaces. Architectures such as InceptionV3, DenseNet-169, VGG, and MobileNet demonstrated effective dust detection but lacked quantitative regression outputs for performance degradation. Our proposed hybrid multi-task framework achieves a classification accuracy of 94%, surpassing many state-of-the-art models while simultaneously estimating power loss and irradiance. This dual-task capability provides a more comprehensive diagnostic of PV panel performance, supporting monitoring, maintenance planning, and solar energy optimization.

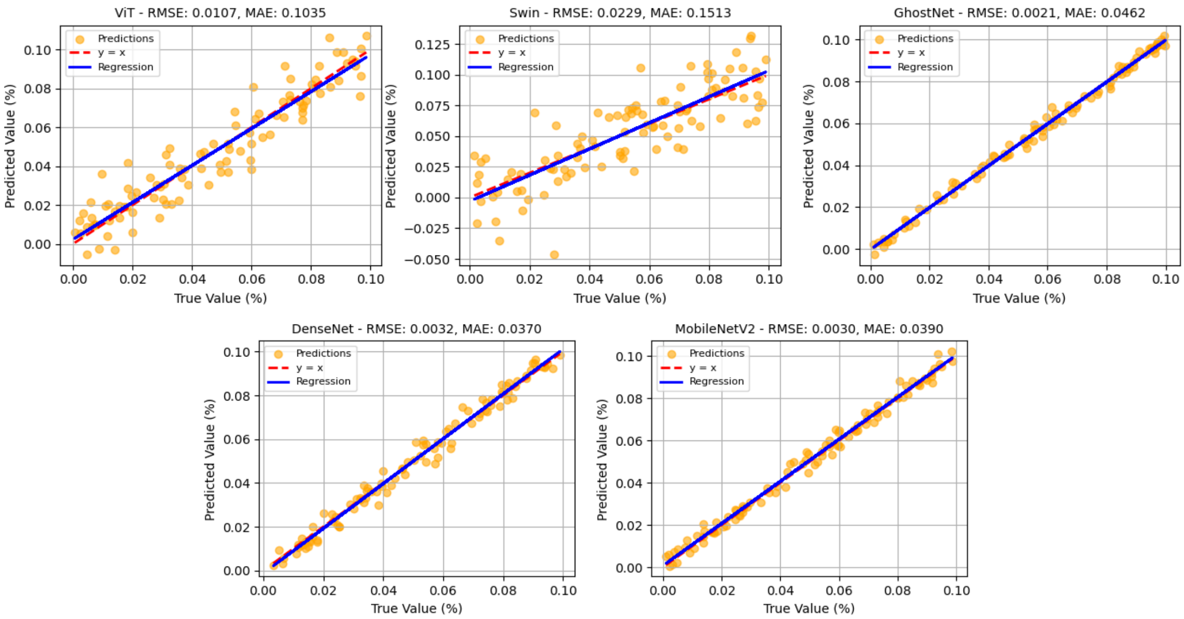

Figure 6. Comparison of regression performance (power loss %) of different backbone models on the test dataset

Table 3. Comparison of the accuracy of our proposed method with existing methods reported in the literature

Reference	Model (s) used	Method	Accuracy/mAP/IoU
Cruz-Rojas *et al.* [11]	U-Net, XGBoost, RF	Segmentation	89.38% IoU
Prova [13]	InceptionV3	Classification	93.10% accuracy
Oulefki *et al.* [14]	DeepSolarEye	Segmentation	92% dice
Alatwi *et al.* [15]	DenseNet-169 + SVM	Classification	86.8% accuracy
Bassil *et al.* [16]	VGG and MobileNet	Classification	89.8% accuracy
Shah *et al.* [19]	InceptionV3	Classification	92.34% accuracy
Our method	Vision transformer, swin transformer, DenseNet, GhostNet, MobileNetV2	Classification and regression	94% accuracy

4. CONCLUSION

This study presents a hybrid deep learning framework for dual-task PV panel assessment, integrating image-based dirt classification with regression-based estimation of power loss and irradiance. Unlike prior approaches that focus on either classification or regression, the proposed method simultaneously addresses both tasks using a multi-head MLP with multiple backbone feature extractors, providing a more comprehensive and deployable solution for real-time PV monitoring. GhostNet and DenseNet demonstrated superior accuracy, computational efficiency, and generalization, outperforming heavier transformer-based models.

While the framework shows promising results, limitations include reliance on a limited dataset, constrained environmental diversity, and short-term evaluation. Future work should address large-scale validation across diverse climatic conditions, longitudinal monitoring to capture temporal degradation patterns, incorporation of additional predictive tasks such as fault detection, and benchmarking against emerging architectures in real-world deployments. Overall, this framework offers a practical, data-driven solution for sustainable, efficient, and reliable solar energy management.

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AUTHOR CONTRIBUTIONS STATEMENT

This journal uses the Contributor Roles Taxonomy (CRediT) to recognize individual author contributions, reduce authorship disputes, and facilitate collaboration.

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Ali Kourtiche		✓		✓	✓	✓		✓	✓	✓	✓	✓	✓	
Santiago Felici-Castell								✓				✓	✓	
Mohammed El Amine Said			✓			✓					✓			
Rania Bouanani			✓			✓					✓			

C : **C**onceptualization
M : **M**ethodology
So : **So**ftware
Va : **Va**lidation
Fo : **Fo**rmal analysis
I : **I**nvestigation
R : **R**esources
D : **D**ata Curation
O : Writing - **O**riginal Draft
E : Writing - Review & **E**diting
Vi : **Vi**sualization
Su : **Su**pervision
P : **P**roject administration
Fu : **Fu**nding acquisition

CONFLICT OF INTEREST STATEMENT

Authors state no conflict of interest.

DATA AVAILABILITY

The data that support the findings of this study are openly available. The first dataset, “Solar Panel Dust and Soiling,” is accessible via Roboflow at https://universe.roboflow.com/amr-fph1m/solar-panel-dust-and-soiling/dataset/2. The second dataset, “DeepSolarEye,” is available on GitHub at: https://github.com/sudarsan13296/DeepSolarEye.

REFERENCES

[1] H. Ahmed, E. D. Barbulescu, M. Nassereddine, and O. Al-Khatib, “Internet of things important roles in hybrid photovoltaic and energy storage system: a review,” *International Journal of Electrical and Computer Engineering (IJECE)*, vol. 14, no. 6, pp. 6182–6194, Dec. 2024, doi: 10.11591/ijece.v14i6.pp6182-6194.

[2] A. S. Al-Ezzi and M. N. M. Ansari, “Photovoltaic solar cells: a review,” *Applied System Innovation*, vol. 5, no. 4, p. 67, Jul. 2022, doi: 10.3390/asi5040067.

[3] F. Uysal, “Dust detection on solar photovoltaic panels used in optoelectronics with convolutional neural network-based deep learning models,” *International Journal of Computational and Experimental Science and Engineering*, vol. 11, no. 1, pp. 873–878, Feb. 2024, doi: 10.22399/ijcesen.922.

[4] M. A. Hasan and S. K. Parida, “An overview of solar photovoltaic panel modeling based on analytical and experimental viewpoint,” *Renewable and Sustainable Energy Reviews*, vol. 60, pp. 75–83, Jul. 2016, doi: 10.1016/j.rser.2016.01.087.

[5] M. F. Mahmoud, A. T. Mohamed, R. A. Swief, L. A. Said, and A. G. Radwan, “Arithmetic optimization approach for parameters identification of different PV diode models with FOPI-MPPT,” *Ain Shams Engineering Journal*, vol. 13, no. 3, p. 101612, May 2022, doi: 10.1016/j.asej.2021.10.007.

[6] S. N. Vodapally and M. H. Ali, “A comprehensive review of solar photovoltaic (PV) technologies, architecture, and its applications to improved efficiency,” *Energies*, vol. 16, no. 1, p. 319, Dec. 2023, doi: 10.3390/en16010319.

[7] A. Elamim, S. Sarikh, B. Hartiti, A. Benazzouz, S. Elhamaoui, and A. Ghennioui, “Experimental studies of dust accumulation and its effects on the performance of solar PV systems in Mediterranean climate,” *Energy Reports*, vol. 11, pp. 2346–2359, Jun. 2024, doi: 10.1016/j.egyr.2024.01.078.

[8] K. Ilse *et al.*, “Techno-economic assessment of soiling losses and mitigation strategies for solar power generation,” *Joule*, vol. 3, no. 10, pp. 2303–2321, Oct. 2019, doi: 10.1016/j.joule.2019.08.019.

[9] R. Ding *et al.*, “Self-powered autonomous electrostatic dust removal for solar panels by an electret generator,” *Advanced Science*, vol. 11, no. 26, p. 2401689, May 2024, doi: 10.1002/advs.202401689.

[10] M. S. H. Onim *et al.*, "SolNet: a convolutional neural network for detecting dust on solar panels," *Energies*, vol. 16, no. 1, 2023, doi: 10.3390/en16010155.
[11] T. Cruz-Rojas, J. A. Franco, Q. Hernandez-Escobedo, D. Ruiz-Robles, and J. M. Juarez-Lopez, "A novel comparison of image semantic segmentation techniques for detecting dust in photovoltaic panels using machine learning and deep learning," *Renewable Energy*, vol. 217, 2023, doi: 10.1016/j.renene.2023.119126.
[12] Y. Cui *et al.*, "An exploratory framework to identify dust on photovoltaic panels in offshore floating solar power stations," *Energy*, vol. 307, 2024, doi: 10.1016/j.energy.2024.132559.
[13] N. N. I. Prova, "Improved solar panel efficiency through dust detection using the InceptionV3 transfer learning model," *8th International Conference on I-SMAC (IoT in Social, Mobile, Analytics and Cloud), I-SMAC 2024 - Proceedings*, pp. 260–268, 2024, doi: 10.1109/I-SMAC61858.2024.10714631.
[14] A. Oulefki, T. Trongtirakul, S. Agaian, S. Benbelkacem, and N. Zenati, "Multi-view VR imaging for enhanced analysis of dust accumulation on solar panels," *Solar Energy*, vol. 279, 2024, doi: 10.1016/j.solener.2024.112708.
[15] A. M. Alatwi, H. Albalawi, A. Wadood, H. Anwar, and H. M. El-Hageen, "Deep learning-based dust detection on solar panels: a low-cost sustainable solution for increased solar power generation," *Sustainability*, vol. 16, no. 19, p. 8664, Oct. 2024, doi: 10.3390/su16198664.
[16] J. Bassil, H. Noura, O. Salman, K. Chahine, and M. Guizani, "Deep learning image classification models for solar panels dust detection," in *2024 International Wireless Communications and Mobile Computing (IWCMC)*, May 2024, pp. 1516–1521, doi: 10.1109/IWCMC61514.2024.10592387.
[17] H. M. A. Mohammed and A. E. Ba Alawi, "CASolarNet: Channel Attention EfficientNet-based model for solar panel dust detection," in *2024 4th International Conference on Emerging Smart Technologies and Applications (eSmarTA)*, Aug. 2024, pp. 1–4, doi: 10.1109/esmarta62850.2024.10638876.
[18] H. He, C. Zhou, P. Yu, and X. Lu, "Research on a photovoltaic panel dust detection system based on improved Mobilenet algorithm," in *2024 IEEE 7th Advanced Information Technology, Electronic and Automation Control Conference (IAEAC)*, Mar. 2024, pp. 707–712, doi: 10.1109/IAEAC59436.2024.10503927.
[19] M. Shah, M. Joshi, P. Patel, N. Mevada, R. Baria, and M. Chauhan, "Improving solar power generation with InceptionV3 dust detection on the solar panel energy systems," in *2023 Third International Conference on Ubiquitous Computing and Intelligent Information Systems (ICUIS)*, Sep. 2023, pp. 448–456, doi: 10.1109/ICUIS60567.2023.00080.
[20] C. Xie, Q. Li, Y. Yang, L. Zhang, and X. Liu, "Research on a photovoltaic panel dust detection algorithm based on 3D data generation," *Energies*, vol. 17, no. 20, p. 5222, Oct. 2024, doi: 10.3390/en17205222.
[21] A. Karakan, Y. Oğuz, and A. Yönetken, "Detecting pollution in solar panels with deep learning," in *7th International Conference on Engineering Technology and Applied Sciences (ICETAS)*, 2024, pp. 19–24.
[22] T. Sefer and M. Kaya, "Detection of dust on solar panels with deep learning," *Kahramanmaraş Sütçü İmam Üniversitesi Mühendislik Bilimleri Dergisi*, vol. 27, no. 4, pp. 1451–1464, Dec. 2024, doi: 10.17780/ksujes.1493906.
[23] Y. Shao, C. Zhang, L. Xing, H. Sun, Q. Zhao, and L. Zhang, "A new dust detection method for photovoltaic panel surface based on Pytorch and its economic benefit analysis," *Energy and AI*, vol. 16, p. 100349, May 2024, doi: 10.1016/j.egyai.2024.100349.
[24] "Solar Panel Dust and Soiling Dataset," *Roboflow,* 2023. https://universe.roboflow.com/amr-fph1m/solar-panel-dust-and-soiling/dataset/1.
[25] S. Mehta, A. P. Azad, S. A. Chemmengath, V. Raykar, and S. Kalyanaraman, "DeepSolarEye: power loss prediction and weakly supervised soiling localization via fully convolutional networks for solar panels," in *Proceedings - 2018 IEEE Winter Conference on Applications of Computer Vision, WACV 2018*, Mar. 2018, vol. 2018-Janua, pp. 333–342, doi: 10.1109/WACV.2018.00043.
[26] M. Sandler, A. Howard, M. Zhu, A. Zhmoginov, and L. C. Chen, "MobileNetV2: inverted residuals and linear bottlenecks," in *Proceedings of the IEEE Computer Society Conference on Computer Vision and Pattern Recognition*, Jun. 2018, pp. 4510–4520, doi: 10.1109/CVPR.2018.00474.

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