EEET ECOLOGICAL ENGINEERING & ENVIRONMENTAL TECHNOLOGY

Ecological Engineering & Environmental Technology, 2025, 26(7), 216–226
https://doi.org/10.12912/27197050/205233
ISSN 2719–7050, License CC-BY 4.0

Received: 2025.05.01
Accepted: 2025.05.31
Published: 2025.06.15

Design and manufacturing of an intelligent dust detector for solar panels using artificial intelligence

Omar Elkhoundafi[1*], Azzedine Elmrabet[1], Rachid Elgouri[1]

[1] Laboratory of Advanced Systems Engineering, Ibn Tofail University, Kenitra, Morocco
* Corresponding author's e-mail: omar.elkhoundafi@uit.ac.ma

ABSTRACT

The goal of this research is to create an intelligent dust detection system for solar panels in order to improve their energy performance in the face of adverse environmental circumstances, particularly dust collection. The suggested system uses a camera module attached to a Raspberry Pi to take real-time photos of a 200 × 200 mm glass surface, imitating a solar panel. These photos are evaluated using a convolutional neural network (CNN) that can classify the surface's cleanliness. The technology detects dust buildup and sends out preventive maintenance reminders. With a classification accuracy of 94.53%, the model assures consistent dirt detection, assisting in maintaining optimal energy output, improving operating efficiency, and lowering maintenance expenses. From a practical aspect, the created solution provides an automated, cost-effective, and simply deployed instrument for monitoring the cleanliness of photovoltaic installations, particularly in locations prone to dust accumulation. This study is unique in that it uses an artificial intelligence-based approach to integrate dust detection into a predictive maintenance strategy, with one or more sensors placed near to the solar panels depending on the size of the installation. The findings emphasize the importance and promise of AI in the intelligent and sustainable management of renewable energy systems.

Keywords: dust accumulation, environmental factors, dust detection, PV module, artificial intelligence.

INTRODUCTION

Solar energy stands out as a promising renewable resource for addressing the global energy issue and mitigating climate change [Ma et al., 2014]. As a clean, sustainable, cost-free, and widely available alternative to fossil fuels [Hayat et al., 2019], it has enormous long-term advantages. Photovoltaic (PV) systems are known for their environmental friendliness and versatility. According to research, PV systems not only have the ability to meet global energy demand, but they are also expected to outperform all other energy sources over the next decade [Usman et al., 2020]. Furthermore, since power prices and installation and maintenance costs continue to climb, improving PV systems may help cut expenses and stimulate widespread national adoption [Ali et al., 2018; Khan et al., 2021]. Installing photovoltaic panels for domestic energy production can dramatically reduce annual carbon emissions, helping to reduce greenhouse gas output, which is a top objective on the United Nations' environmental agenda [Blum et al., 2021; Gołebiowska et al., 2021]. While the initial prices of equipment and installation remain relatively expensive, they are steadily dropping [Energy Informative, 2019; Yu et al., 2022; Zhang et al., 2020], driven by ongoing research focused at improving photovoltaic conversion efficiency in order to generate more power from the same quantity of solar energy [NREL, 2021].

However, photovoltaic power generation involves a number of obstacles, especially in terms of production, optimization, and maintenance [Thebault and Gaillard, 2021]. It is critical to understand that sun radiation is the most important environmental component influencing power generation. Furthermore, temperature, dust, humidity, wind, and shading have a substantial impact on PV conversion efficiency, affecting both current and voltage output, as well as the amount of exploitable PV energy [Nezamisavojbolaghi et al., 2023; Long et al., 2022]. It is generally known that dust buildup and contaminants reduce solar cell productivity. To remove accumulated dust, PV panels must be cleaned on a regular basis [Kazem et al., 2015; Dahham et al., 2023; Deepak and Malvi, 2023]. Dust deposition on photovoltaic panels is essentially determined by two factors: the qualities and types of dust—such as leaves, bird droppings, and soil particles—and changing weather conditions, which are frequently exacerbated by environmental pollution. Additionally, manufacturing and installation variables including as surface flaws, panel location, height, and orientation have a substantial impact on PV system performance. The physical, chemical, biological, and electrostatic aspects of dust all contribute to performance decline. Notably, settled dust particles encourage further accumulation by facilitating the adherence of fresh particles, resulting in ever thicker dust layers on panel surfaces [Shariah and Al-Ibrahim, 2023; Ghosh et al., 2019].

Furthermore, meteorological circumstances influence solar cell efficiency, with the impact varies by location. As a result, there is no uniform method for accurately determining the effect of dust on PV performance [Salim and Narayanan, 2020; Ma et al., 2019].

Researchers began exploring strategies to maximize energy extraction from renewable sources, primarily solar panels, several years ago. Abuqaauud and Ferrah [2020] describes a computer vision-based approach for detecting dust and debris on PV panels. Aji et al. [2023] uses camera technology to automatically detect dust buildup, with an average detection accuracy of 50.8%. As discussed by Alfaris [2023], an expert artificial intelligence (AI) system built on the MATLAB platform is used to do sophisticated prediction and data processing. The work in Ayyagari et al. [2022] provides an image classification system that uses neural networks to detect dirt on panels, achieving an accuracy of 96.54% by combining picture data with weather information. Bassil et al. [2024], a deep learning binary classifier model based on EfficientNetB7 is designed to discriminate between 'dusty' and 'clean' panels. Meanwhile, Bose et al. [2024] describes a novel technique that uses specular reflection to identify dust particles and trigger cleaning cycles as needed. Cruz-Rojas et al. [2023] compares three approaches to assessing panel condition via semantic segmentation: unsupervised learning, supervised with machine learning algorithms, and deep learning, with supervised models offering a good balance between performance and speed, while deep learning is more effective with unnormalized inputs. Elyanboiy et al. [2024] presents a global approach to intelligent fault detection in solar panels, applying artificial intelligence techniques, using YOLO-NAS for fault identification and OpenCV for dust coverage rate calculation. The results obtained with the YOLO-NAS model for fault detection show significant precision and recall values, reaching 0.96 and 0.89 respectively. [Gracia and Caroline, 2024], the image dataset of clean and dusty solar panels was applied to four state-of-the-art models, and the EfficientNetB0 model was then proposed to detect dust on solar panels, with an impressive accuracy rate of around 85.92%. Hassan et al. [2024] evaluates and compares existing dust control strategies, focusing on environmental, technical and economic perspectives. He et al. [2024] proposes a model combining feature extraction with MobileNet and a classifier to detect dust, achieving 94% accuracy. Karima et al. [2023] proposes an advanced image processing method, applied with Visual Studio, to differentiate between clean and dusty panels. Maity et al. [2020] focuses on an approach based on CNN to detect dust on solar panels and predict power loss due to dust accumulation. Mamdouh and Zaghloul [2024] used an innovative image processing and machine learning approach, with LSTM (long-term memory) and ANN (artificial neurons) models proving the most accurate at predicting output, with rates of 99.50% and 98.50% respectively. In Mohammed et al. [2018], an Arduino Uno microcontroller was used to regulate a wiper-based cleaning mechanism that was activated when the panel's output power fell below 50% of its nominal value. [Olorunfemi et al., 2023] describes a method for detecting and removing dirt from solar panels by combining TCS3200 color sensors and Arduino Uno components. In Pillai et al. [2023], a neural network with a back-propagation algorithm is used to estimate energy generation based on sensor-measured dust accumulation and sun irradiation. Saquib et al. [2020] uses image processing techniques to identify dust, with the dust % acting as an input parameter for the neural network model. Shah et al. [2023] the author used the InceptionV3 model to detect dust, achieving

92.34% accuracy on a dataset of 1,200 images of clean and dirty panels. In paper Shao et al. [2024] the author proposed an improved Adam algorithm, incorporating Warmup and cosine annealing techniques to optimize dust detection, overcoming the limitations of traditional Adam, tested on ResNet-18, VGG-16 and MobileNetV2. Keerthana and Hariharasudhan [2024] benchmarking showed that the Dense Net achieves 98% accuracy, outperforming the multilayer perceptron at 88%, the implementation uses a Raspberry Pi to validate results with real-time images, optimizing system efficiency. In Yadav et al. [2021] preliminary examination by visual inspection using a microscope is one of the least expensive and most easily accessible methods. Tunell et al. [2023], the authors present a method for identifying micro- and nanoparticles on nanostructured surfaces that combines electron microscopy and image processing techniques. This method overcomes the limits of optical microscopy by deleting periodic surface characteristics, which greatly improves particle detection. The approach detects 5.62 particles per 100 μm^2, compared to 0.63 particles using typical optical methods.

The goal of this research is to create and test an embedded, autonomous, and real-time system for detecting soiling on photovoltaic panels that incorporates a computer vision model into a Raspberry Pi. Despite substantial breakthroughs in AI-based detection, few studies have resulted in lightweight, low-cost solutions that can operate autonomously in real-world scenarios. This technology gap impedes the widespread deployment of intelligent preventative maintenance solutions. The major goal is to develop an embedded system that can automatically detect dust accumulation from on-site collected photos, activate alarms in the event of contamination, and ensure effective integration in real-world contexts. The main idea is that a CNN model trained on relevant photos may detect dirt with high enough accuracy to begin proactive cleaning measures, decreasing energy efficiency losses. By addressing this gap, the study helps to improve the operational management of photovoltaic installations.

MATERIALS AND METHODS

To validate the proposed AI-based dust detection system, an experimental setting was created to mimic real-world conditions. This section explains the hardware and software components, data gathering methods, and preparation steps taken to ensure high-quality model training. The system was meant to run independently, taking and analyzing photos to efficiently classify dirt collection on solar panels.

Dataset collection and preprocessing

To create our deep learning-based dirt detection algorithm, we used a sensor setup designed to mimic real-world conditions in a solar field. The sensor consists of a 200 × 200 mm glass screen mounted on an aluminum cube, which houses a Raspberry Pi camera, as illustrated in Figure 1. The camera takes photos of the glass surface to assess its cleanliness, which serves as an indicator of dirt deposition on adjacent solar panels. The sensor was programmed to record 80 photos every day for 15 days, ensuring that the dataset reflected variations in lighting conditions, weather effects, and dirt accumulation. This produced an initial dataset of 1.200 photos. We cleaned the data thoroughly to remove extraneous photos due to occlusions, reflections, or sensor malfunctions.

- removed photographs with low lighting conditions that could hinder model training,
- removed duplicate photos to reduce repetition.

Figure 1. Various components of the experiment

After cleaning, the final dataset consisted of 1.002 photos classified as follows:
- there are 235 photos of clean glass panels, which are a proxy for solar panels.
- 767 photos of a dusty glass panel, which represents unclean solar panels.

Figure 2 displays representative photos from the collection, illustrating clean and dirty glass panels captured by the sensor. Because the dataset was skewed (with more photos of dirty panels than clean panels), we used data augmentation techniques to increase model generalization and equalize the class distribution. The strategies included:
- random rotation (±15°) to imitate varied viewing angles,
- variable image orientation through horizontal flipping,
- adjusted contrast to reflect lighting conditions,
- use Gaussian noise injection to improve model robustness to real-world noise.

These preprocessing processes ensure that our model is trained on a broad and representative dataset, which improves its capacity to correctly categorize dirt accumulation in real-world solar field conditions.

Model architecture

The suggested CNN is intended to categorize photos recorded by the Raspberry Pi-based sensor unit, distinguishing clean from unclean solar panels. The architecture has a hierarchical structure, with convolutional layers capturing spatial features, pooling layers reducing feature map size, and dense layers performing classification tasks. The computational graph of the model, shown in Figure 3, depicts the sequential processing of input images using convolutional processes, activation functions, pooling layers, and fully connected layers. Furthermore, the picture depicts the gradient flow during backpropagation, which shows the weight updates and optimization processes involved in training. This architecture provides efficient feature extraction and categorization, making it well-suited for real-time deployment in solar panel monitoring systems

Training parameters

The model was developed using supervised learning on data collected from the deployed sensor unit. The training procedure was tuned with the following parameters:
- loss function: cross-entropy loss, ideal for binary classification,
- the Adam-based optimization technique was chosen for its flexible learning rate capabilities,
- empirical adjustment yielded a learning rate of 0.001,
- batch size: 32 to balance computational efficiency and stability,
- 50 epochs with early stopping based on validation loss to avoid overfitting,
- early stopping criteria: training was discontinued if validation loss did not improve after seven consecutive epochs.

To improve the model's generalization, methods for augmenting data such arbitrary rotation,

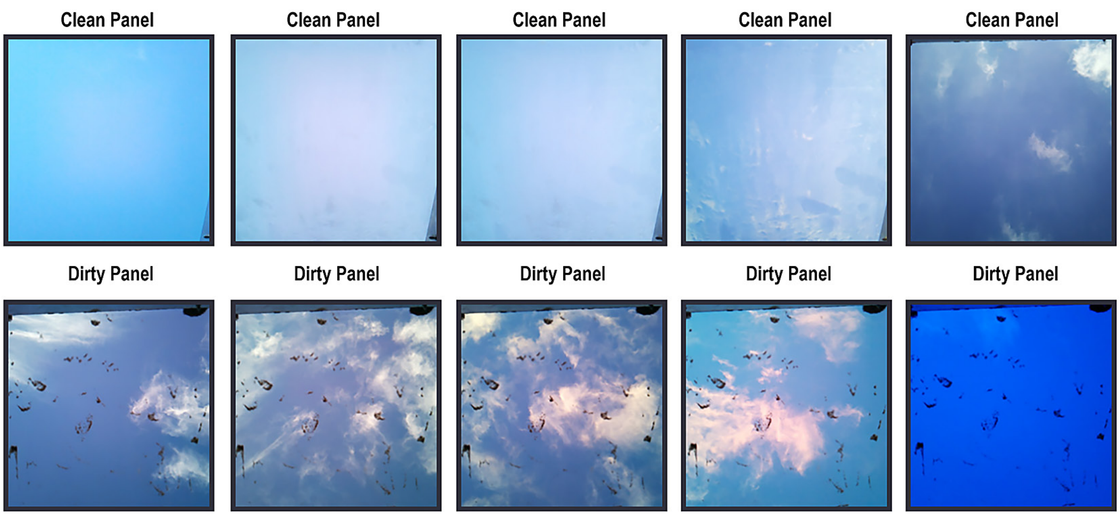


Figure 2. Sample images of clean and dirty panels from the dataset

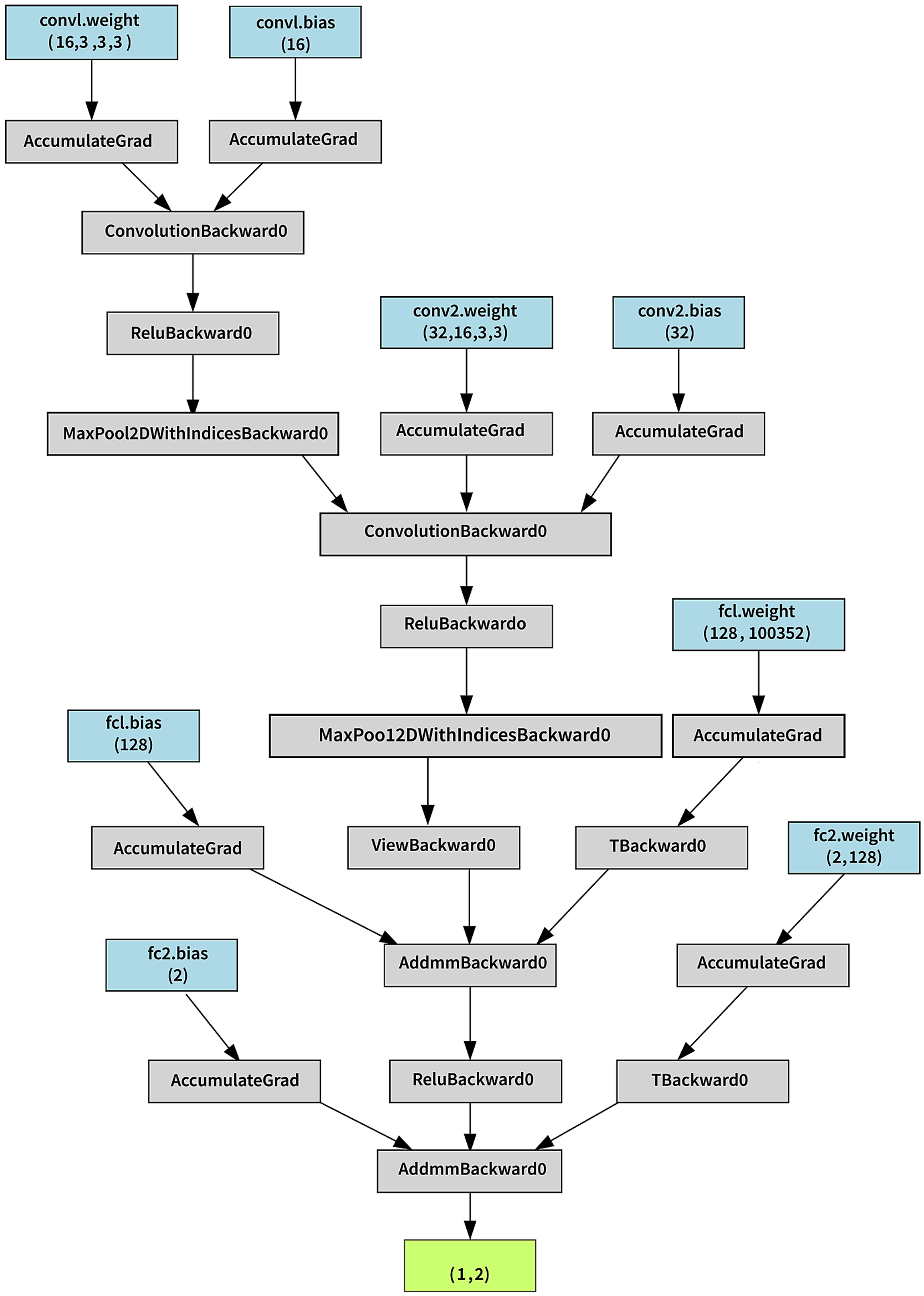


Figure 3. CNN model architecture for dirt detection

flipping, contrast modifications, and Gaussian noise injection were used.

Model evaluation parameters

To evaluate the model's performance, several main evaluation factors were considered:

- accuracy measures the model's overall categorization performance,
- precision: assesses the model's ability to recognize clean and dirty panels,
- recall: evaluates the model's sensitivity to identify dirt accumulation,

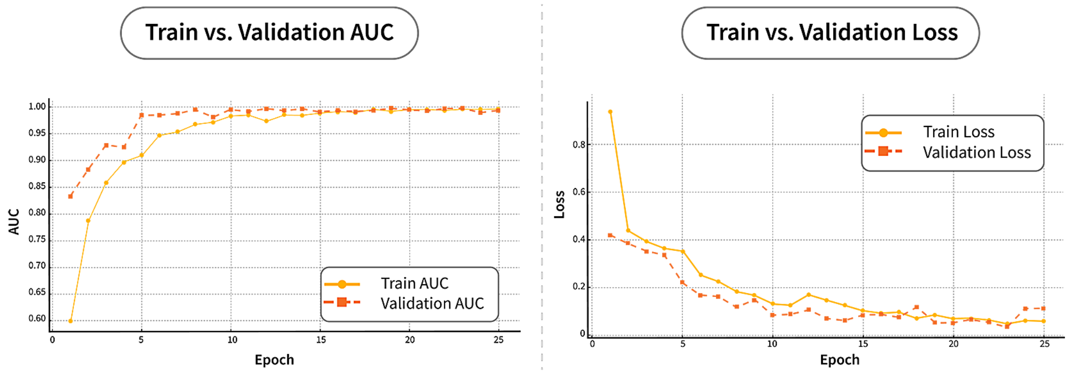


Figure 4. Training and validation loss and accuracy over epochs

- the F1-score provides a balanced assessment of precision and recall,
- confusion matrix analysis visualizes classification errors and evaluates the distribution of accurate and wrong predictions between classes.

The evaluation findings, including performance indicators and categorization analysis, will be detailed in the Results section. Before being used in solar field monitoring applications, the final trained model was tested against an independent test set to confirm its robustness and dependability.

Deployment

To enable real-time monitoring of dirt collection on solar panels, a Python-based deployment script for the Raspberry Pi and its camera module was created. The system gathers photos autonomously, infers using the trained CNN model, and sends alerts when dirt accumulation is identified. This strategy ensures proactive maintenance, which reduces efficiency losses caused by panel contamination. The deployed system follows a standardized operational sequence to allow automatic monitoring:

Image acquisition:

- the raspberry pi camera captures photographs of the 200 × 200 mm glass panel, indicating solar panel cleanliness.
- images are captured at predetermined times throughout the day to accommodate for changing lighting and environmental conditions.

Using the Trained CNN Model for Inference:

- preprocessing each acquired image (e.g., scaling, normalization, format standardization) to satisfy the trained CNN model input requirements.
- the CNN classifies images as clean or unclean using learned features from the dataset,

Automated decision and alert mechanisms:

- if the classification results show dirt accumulation, the system sends an email notice to the appropriate individuals.
- the message contains both the timestamp and the processed image, allowing the maintenance staff to verify the condition remotely.

This automated sensor deployment offers an effective, low-cost, and scalable alternative for keeping solar panels clean. By combining real-time inference with an automatic alert system, it allows for proactive intervention, optimizing solar energy production and lowering operational expenses.

RESULTS AND DISCUSSION

The performance of the proposed CNN-based dirt detection system was assessed after thorough training and validation. The model's effectiveness was evaluated using training accuracy, loss progression, and classification metrics computed on the validation set.

Training performance

The model was trained across 25 epochs, with training and validation loss monitored to ensure convergence. The training and validation accuracy improved consistently, demonstrating effective learning. Similarly, the training and validation losses dropped gradually, indicating stable optimization. The plots in Figure 4 show the loss and accuracy trends over epochs, demonstrating the model's convergence and performance stability.

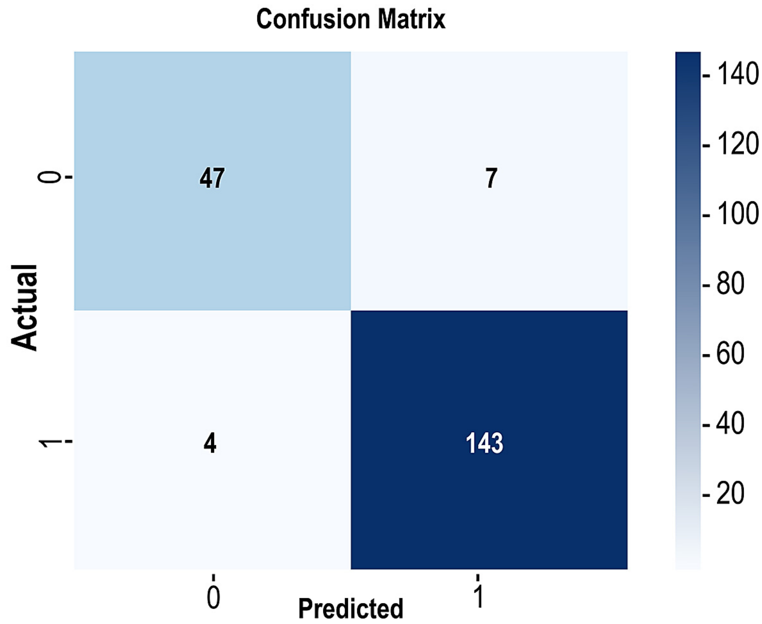


Figure 5. The model demonstrates strong performance, with minimal misclassifications between clean and dirty panel images

Confusion matrix analysis

The confusion matrix, displayed in Figure 5, offers information about the model's classification performance. It shows the number of correctly and incorrectly identified samples for each class.

Evaluation metrics

To quantify classification effectiveness, we computed standard performance metrics in Table 1. The results show high classification accuracy with a good balance of precision and recall, ensuring reliable detection of dirt accumulation on the sensor's glass panel.

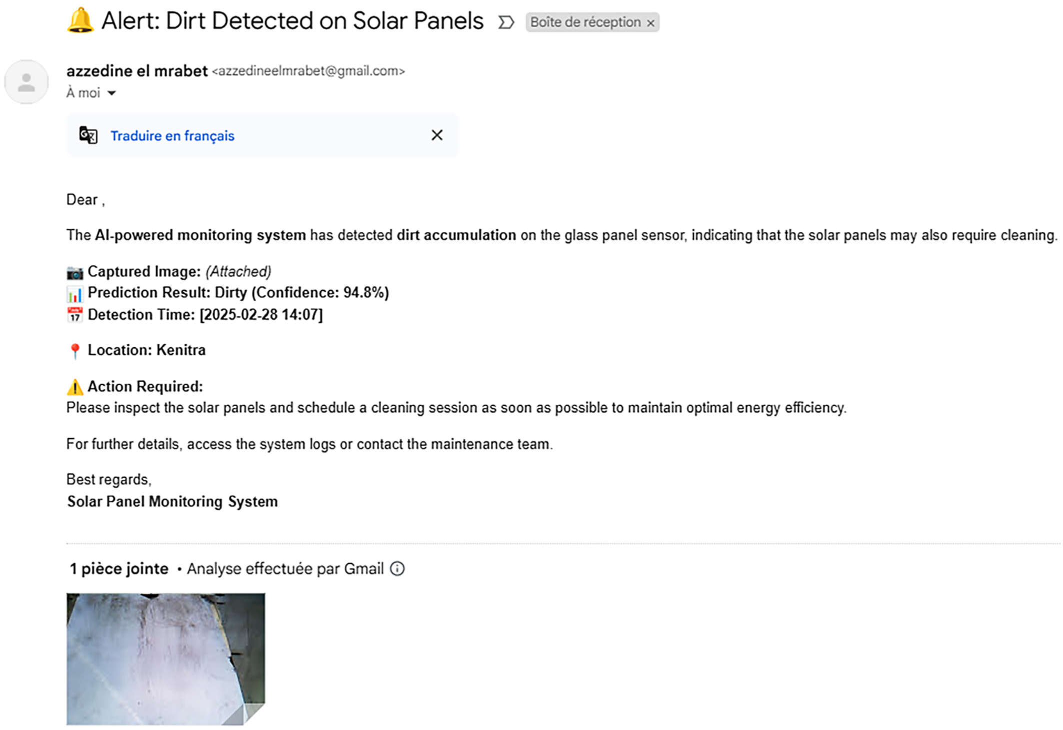
System test and prediction

A set of controlled experiments were carried out to validate the deployed system's real-world performance. Waiting for natural dust accumulation would be time-consuming, thus a manual dusting technique was established. The purpose was to imitate real-world situations and assess the system's capacity to detect dirt and issue appropriate alarms. To simulate real-world soiling, various small dust particles were manually put to the glass surface. Several test conditions were produced by adjusting the amount of dust to simulate light, moderate, and heavy contamination levels. The Python-based deployment script performed periodic image captures and used the SMTP (Simple Mail Transfer Protocol) approach to send automatic notifications via email. When the model recognized a filthy surface, the system generated and sent an email notification. The email included detection timestamps, captured images for inference, and classification results (Clean or Dirty) with confidence scores. The test results will be delivered in the form of an email notification, demonstrating the system's functioning and reliability in real-world scenarios.

Figure 6 shows a screenshot of an email notification, demonstrating the system's ability to detect dirt and relay alerts in real time:

Table 1. Model evaluation metrics summary

Metric	Value	Interpretation
Accuracy	94.53%	Overall correctness of predictions
Precision	0.9448	Ability to correctly classify clean and dirty panels
Recall	0.9453	Sensitivity to detecting dirt accumulation
F1-score	0.9448	Balance between precision and recall


🔔 Alert: Dirt Detected on Solar Panels Boîte de réception ×

azzedine el mrabet <azzedineelmrabet@gmail.com>
À moi

Traduire en français

Dear ,

The **AI-powered monitoring system** has detected **dirt accumulation** on the glass panel sensor, indicating that the solar panels may also require cleaning.

Captured Image: *(Attached)*
Prediction Result: Dirty (Confidence: 94.8%)
Detection Time: [2025-02-28 14:07]

Location: Kenitra

Action Required:
Please inspect the solar panels and schedule a cleaning session as soon as possible to maintain optimal energy efficiency.

For further details, access the system logs or contact the maintenance team.

Best regards,
Solar Panel Monitoring System

1 pièce jointe • Analyse effectuée par Gmail

Figure 6. Email notification received from the system

Table 2. Results from previous studies for comparison

Reference	Method used	Accuracy (%)
[23]	Camera technology	50.8
[29]	OpenCV for dust coverage rate calculation	89
[30]	EfficientNetB0 model	85.92
[32]	Improved mobilenet algorithm	94
[40]	InceptionV3 model	92.34
Current study	Neural network (CNN)	94.53

DISCUSSION

The results of this investigation reveal a considerable improvement in accuracy over existing methods as shown in Table 2. Camera-based technology [23] has the lowest accuracy of 50.8%, indicating low reliability for applications that require extensive investigation. The solution employing OpenCV for dust coverage rate estimation [29] achieves 89%, suggesting a considerable increase in automated image processing. However, deep learning models outperform these traditional methods. The EfficientNetB0 model [30] scores 85.92%, whereas InceptionV3 [40] scores 92.34%, demonstrating their efficacy in picture categorization and analysis. The updated Mobilenet algorithm [32] achieves 94%, approaching peak performance.

Unlike all existing technologies, which rely on reviewing photos of solar panels, our research offers a novel approach to enhancing dust detection. Rather of analyzing photographs of actual panels, we designed a custom sensor that mimics the shape and inclination of solar panels when placed alongside installations. This sensor detects dust accumulation automatically and alerts you when cleaning is required.

The new study, which employs a CNN, exceeds all previous approaches with a 94.53% accuracy, indicating the efficacy of CNN designs in enhancing image recognition and processing. This new technology encourages proactive maintenance by preventing energy losses caused by panel contamination, while also reducing the complexity and limitations associated with direct panel imaging. This performance improvement demonstrates how deep learning models, particularly CNNs, provide more robust and precise solutions for image processing applications, reducing errors and enhancing overall system efficiency.

CONCLUSIONS

This study demonstrates that the primary objective was met. The suggested system, which combines optical sensors and machine learning algorithms, allows for real-time monitoring and precise classification of the panels' cleaning status. The study's main innovation is attaining an average detection rate of 94.53% in just 21.59 seconds, which is a huge improvement over earlier methods, which were frequently slower or less accurate. This performance fills a significant vacuum in the research, as few studies have successfully combined high accuracy, low latency, and real-world applicability.

The proposed method not only reduces energy efficiency losses due by dust deposition, but it also lays the door for more cost-effective and sustainable photovoltaic system maintenance. Future study could focus on improving accuracy using more advanced deep learning approaches, as well as using weather predicting models to enhance automated cleaning schedules.

REFERENCES

1. Ma, T., Yang, H., Lu, L. (2014). Feasibility study of a stand-alone hybrid solar–wind–battery system for a remote island. *Applied Energy, 121*, 149–158. https://doi.org/10.1016/j.apenergy.2014.01.090
2. Hayat, M. B., Ali, D., Monyake, K. C., Alagha, L., Ahmed, N. (2019). Solar energy—A look into power generation, challenges, and a solar-powered future. *International Journal of Energy Research, 43*, 1049–1067. https://doi.org/10.1002/er.4252
3. Usman, Z., Tah, J., Abanda, H., Nche, C. (2020). A critical appraisal of PV-systems performance. *Buildings, 10*(11), 192. https://doi.org/10.3390/buildings10110192
4. Ali, W., Farooq, H., Rehman, A. U., Awais, Q., Jamil, M., Noman, A. (2018). Design considerations of stand-alone solar photovoltaic systems. In *Proceedings of the International Conference on Computing, Electronic and Electrical Engineering* (ICE Cube) 1–6. IEEE. https://doi.org/10.1109/ICECUBE.2018.8610970
5. Khan, S. U., Wazeer, I., Almutairi, Z., Alanazi, M. (2021). Techno-economic analysis of solar photovoltaic powered electrical energy storage (EES) system. *Alexandria Engineering Journal, 61*, 6739–6753. https://doi.org/10.1016/j.aej.2021.12.025
6. Blum, S., Buckland, M., Sack, T. L., Fivenson, D. (2021). Greening the office: Saving resources, saving money, and educating our patients. *International Journal of Women's Dermatology, 7*, 112–116. https://doi.org/10.1016/j.ijwd.2020.04.013
7. Gołebiowska, A., Jakubczak, W., Prokopowicz, D., Jakubczak, R. (2021). The post-pandemic development of the green circular economy and the declarations made during the UN Climate Change Conference (COP26) as security determinants. *European Research Studies Journal, 24*, 251–275. https://doi.org/10.35808/ersj/2517
8. Energy Informative. (2019). How much do solar panels cost. https://energyinformative.org/solarpanelscost/
9. Yu, Y., Wang, K., Zhang, T., Wang, Y., Peng, C., Gao, S. (2022). A population diversity-controlled differential evolution for parameter estimation of solar photovoltaic models. *Sustainable Energy Technologies and Assessments, 51*, 101938. https://doi.org/10.1016/j.seta.2021.101938
10. Zhang, C., Zhang, Y., Su, J., Gu, T., Yang, M. (2020). Modeling and prediction of PV module performance under different operating conditions based on power-law I–V model. *IEEE Journal of Photovoltaics, 10*(6), 1816–1827. https://doi.org/10.1109/JPHOTOV.2020.3016607
11. National Renewable Energy Laboratory. (2021). Research cell efficiency records. https://www.nrel.gov/pv/assets/images/efficiency-chart.png
12. Thebault, M., Gaillard, L. (2021). Optimization of the integration of photovoltaic systems on buildings for self-consumption—Case study in France. *City and Environment Interactions, 10*, 100057. https://doi.org/10.1016/j.cacint.2021.100057
13. Nezamisavojbolaghi, M., Davodian, E., Bouich, A., Tlemçani, M. (2023). Characterization and sensitivity analysis of a photovoltaic panel. *Advances in Energy Conversion Materials, 4*, 164–173. https://doi.org/10.1016/j.aecm.2023.164173
14. Long, W., Jiao, J., Liang, X., Xu, M., Tang, M., Cai, S. (2022). Parameters estimation of photovoltaic models using a novel hybrid seagull optimization algorithm. *Energy, 249*, 123760. https://doi.org/10.1016/j.energy.2022.123760
15. Kazem, H. A., Chaichan, M. T., Saif, S. A., Dawood, A. A., Salim, S. A., Rashid, A. A., Alwaeli, A. A. (2015). Experimental investigation of dust type effect on photovoltaic systems in north region, Oman. *International Journal of Scientific and Engineering*

Research, 6(4), 293–298.

16. AmerDahham, I., MohdZainuri, M. A., Abdullah, A. A., Fauzan, M. F. (2023). Modeling the effect of dust and wind speed on solar panel performance in Iraq. *Energies, 16*(12), 6397. https://doi.org/10.3390/en16126397
17. Deepak, Malvi, C. S. (2023). Experimental investigation of different types of dust effect on the grid-connected rooftop solar power plant. *Energy Sources, Part A: Recovery, Utilization and Environmental Effects, 45*(1), 12343–12364. https://doi.org/10.1080/15567036.2023.2267496
18. Shariah, A., Al-Ibrahim, E. A. (2023). Impact of dust and shade on solar panel efficiency and development of a simple method for measuring the impact of dust. *Journal of Sustainable Development of Energy, Water and Environment Systems, 11*, 1–14. https://doi.org/10.13044/j.sdewes.d11.0448
19. Ghosh, S., Yadav, V. K., Mukherjee, V. (2019). Impact of environmental factors on photovoltaic performance and their mitigation strategies—A holistic review. *Renewable Energy Focus, 28*, 153–172. https://doi.org/10.1016/j.ref.2018.12.005
20. Salim, S., Narayanan, D. (2020). The dust attenuation law in galaxies. *Annual Review of Astronomy and Astrophysics, 58*, 529–575. https://doi.org/10.1146/annurev-astro-032620-021818
21. Ma, X., Hayward, C. C., Casey, C. M., Hopkins, P. F., Quataert, E., Liang, L., Faucher-Giguère, C. A., Feldmann, R., Kereš, D. (2019). Dust attenuation, dust emission, and dust temperature in galaxies at z ≈ 5: A view from the FIRE-2 simulations. *Monthly Notices of the Royal Astronomical Society, 487*(2), 1844–1864. https://doi.org/10.1093/mnras/stz1324
22. Abuqaauud, K. A., Ferrah, A. (2020). A novel technique for detecting and monitoring dust and soil on solar photovoltaic panel. In *2020 Advances in Science and Engineering Technology International Conferences (ASET)* 1–6. IEEE. https://doi.org/10.1109/ASET48392.2020.9118363
23. Aji, B. H., Prasetya, S., Hidayati, N. (2023). Smart detection of solar panel cleanliness using artificial intelligence for the remote area maintenance. In *AIP Conference Proceedings*. AIP Publishing.
24. Alfaris, F. E. (2023). A sensorless intelligent system to detect dust on PV panels for optimized cleaning units. *Energies, 16*(3), 1287. https://doi.org/10.3390/en16031287
25. Ayyagari, K. S., Munian, Y., Inupakutika, D., Reddy, B. K., Gonzalez, R., Alamaniotis, M. (2022). Simultaneous detection and classification of dust and soil on solar photovoltaic arrays connected to a large-scale industry: A case study. In *2022 18th International Conference on the European Energy Market (EEM)* 1–6. IEEE. https://doi.org/10.1109/EEM54602.2022.9921025
26. Bassil, J., Noura, H., Salman, O., Chahine, K., Guizani, M. (2024). Deep learning image classification models for solar panels dust detection. In *2024 International Wireless Communications and Mobile Computing (IWCMC)* 1516–1521. IEEE. https://doi.org/10.1109/IWCMC61514.2024.10592387
27. Bose, I., Sengupta, S., Ghosh, S., Saha, H., Sengupta, S. (2024). Development of smart dust detector for optimal generation of SPV power plant by cleaning initiation. *Solar Energy, 276*, 112643. https://doi.org/10.1016/j.solener.2024.112643
28. Cruz-Rojas, T., Franco, J. A., Hernandez-Escobedo, Q., Ruiz-Robles, D., Juarez-Lopez, J. M. (2023). A novel comparison of image semantic segmentation techniques for detecting dust in photovoltaic panels using machine learning and deep learning. *Renewable Energy, 217*, 119126. https://doi.org/10.1016/j.renene.2023.119126
29. Elyanboiy, N., Eloutassi, O., Khala, M., Elabbassi, I., Elhajrat, N., Elhassouani, Y., Messaoudi, C. (2024). Advanced intelligent fault detection for solar panels: Incorporation of dust coverage ratio calculation. In *2024 4th International Conference on Innovative Research in Applied Science, Engineering and Technology (IRASET)* 1–6. IEEE. https://doi.org/10.1109/IRASET.2024.1234567
30. Gracia, R. L., Caroline, B. E. (2024). Enhancement of photovoltaic dust detection using deep learning technique. In *2024 International Conference on Advances in Modern Age Technologies for Health and Engineering Science (AMATHE)* 1–6. IEEE. https://doi.org/10.1109/AMATHE.2024.2345678
31. Hassan, G., Yilbas, B. S., Al-Sharafi, A., Al-Sulaiman, F., Abubakar, A. A. (2024). Dust mitigation strategies concerning solar energy applications: A comprehensive review. *Solar Energy, 277*, 112728. https://doi.org/10.1016/j.solener.2024.112728
32. He, H., Zhou, C., Yu, P., Lu, X. (2024). 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)* 707–712. IEEE. https://doi.org/10.1109/IAEAC59436.2024.10503927
33. Karima, N. N., Rimon, K., Molla, M. S., Hasan, M., Bhuyan, M. H. (2023). Advanced image processing-based solar panel dust detection system. In *2023 26th International Conference on Computer and Information Technology (ICCIT)* 1–6. IEEE. https://doi.org/10.1109/ICCIT60459.2023.10441647
34. Maity, R., Shamaun Alam, M., Pati, A. (2020). An approach for detection of dust on solar panels using CNN from RGB dust image to predict power loss. In *Cognitive Computing in Human Cognition: Perspectives and Applications* 41–48. https://doi.org/10.1007/978-3-030-48118-6_4

35. Mamdouh, M., Zaghloul, Y. A. (2024). Fusion between image processing and machine learning for dust detection on solar panels. In *2024 Fifteenth International Conference on Ubiquitous and Future Networks (ICUFN)* 169–174. IEEE. https://doi.org/10.1109/ICUFN61752.2024.10625232
36. Mohammed, H. A., Baha'a, A. M., Al-Mejibli, I. S. (2018). Smart system for dust detecting and removing from solar cells. In *Journal of Physics: Conference Series, 1032*, 012055. IOP Publishing.
37. Olorunfemi, B. O., Nwulu, N. I., Ogbolumani, O. A. (2023). Solar panel surface dirt detection and removal based on Arduino color recognition. *MethodsX, 10*, 101967. https://doi.org/10.1016/j.mex.2023.101967
38. Pillai, S. R., Yadav, A., Saquib, D., Nasser, N. (2023). Forecasting the effect of dust and irradiance in PV panel using image processing and ANN. In *International Conference On Systems Engineering* 22–29. Springer Nature Switzerland. https://doi.org/10.1007/978-3-031-40579-2_3
39. Saquib, D., Nasser, M. N., Ramaswamy, S. (2020). Image processing based dust detection and prediction of power using ANN in PV systems. In *2020 Third International Conference on Smart Systems and Inventive Technology (ICSSIT)* 1286–1292. IEEE. https://doi.org/10.1109/ICSSIT48917.2020.9214216
40. Shah, M., Joshi, M., Patel, P., Mevada, N., Baria, R., Chauhan, M. (2023). 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)* 448–456. IEEE. https://doi.org/10.1109/ICUIS60567.2023.00080
41. Shao, Y., Zhang, C., Xing, L., Sun, H., Zhao, Q., Zhang, L. (2024). A new dust detection method for photovoltaic panel surface based on Pytorch and its economic benefit analysis. *Energy and AI, 16*, 100349. https://doi.org/10.1016/j.egyai.2024.100349
42. Keerthana, S., Hariharasudhan, S. (2024). Image processing-based dust detection for solar panels. In *2024 International Conference on Smart Systems for Electrical, Electronics, Communication and Computer Engineering (ICSSEECC)* 511–515. IEEE. https://doi.org/10.1109/ICSSEECC61126.2024.10649473
43. Yadav, A., Pillai, S. R., Singh, N., Philip, S. A., Mohanan, V. (2021). Preliminary investigation of dust deposition on solar cells. *Materials Today: Proceedings, 46*, 6812–6815. https://doi.org/10.1016/j.matpr.2021.04.361