Comprehensive multiclass debris detection for solar panel maintenance using ANN models

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ABSTRACT

Solar photovoltaic (PV) technology has emerged as a leading renewable energy solution globally. However, maintaining optimal performance remains a challenge due to the accumulation of debris, including dust, bird droppings, and other contaminants on the panels. These deposits significantly reduce the efficiency of solar panels, necessitating regular monitoring and cleaning. Automated inspection systems provide a cost-effective alternative to traditional methods by minimizing labor-intensive efforts. This study proposes a machine learning-based framework for detecting and classifying several types of debris on solar panels. The methodology utilizes gray-level co-occurrence matrix (GLCM) texture features and key statistical features extracted from RGB, HSV, and LAB color spaces. A dataset comprising 19 distinct classes, such as "Without Dust," "Bird Droppings," "Black Soil," and "Sand," was employed to train and evaluate the models. Among the tested classification techniques, artificial neural networks (ANN) achieved a notable accuracy of 93.94%, demonstrating their effectiveness in identifying and categorizing debris. This work underscores the potential of machine learning-based feature extraction and classification techniques to automate solar panel inspection and facilitate targeted cleaning interventions, thereby enhancing overall system efficiency.

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1. INTRODUCTION

Solar energy is a widely adopted renewable energy source, with photovoltaic (PV) systems playing a crucial role in sustainable power generation. However, maintaining optimal PV efficiency is a significant challenge due to the accumulation of debris such as dust, bird droppings, and environmental contaminants. These obstructions can reduce energy output by up to 25%, making automated detection and cleaning a critical research area. Manual cleaning is a widely adopted method but is labour-intensive, costly, and impractical for large-scale PV installations. Automated cleaning systems, such as robotic cleaners and water-based washing mechanisms, offer improvements but still have limitations, including high operational costs and water wastage. Additionally, sensor-based monitoring systems require frequent calibration and may not always provide accurate classification of debris types.

The negative effects of both shading and dust accumulation on solar PV module performance have been extensively studied. For instance, shading on a single cell can reduce power output by up to one-third of the original value, while dust accumulation over a three-month period has been shown to decrease output power by approximately 13% [1]. Researchers have also simulated dust accumulation using ~15 µm Arizona test dust to evaluate cleaning methods, revealing an exponential decline in power output as dust coverage increased [2]. This highlights the significant impact of dust accumulation on solar panel efficiency, as illustrated in Figure 1. The decline in power output as dust coverage increases is attributed to the progressive blocking of incident light. In this experiment, a fluorescent lamp was employed as the light source to simulate sunlight.

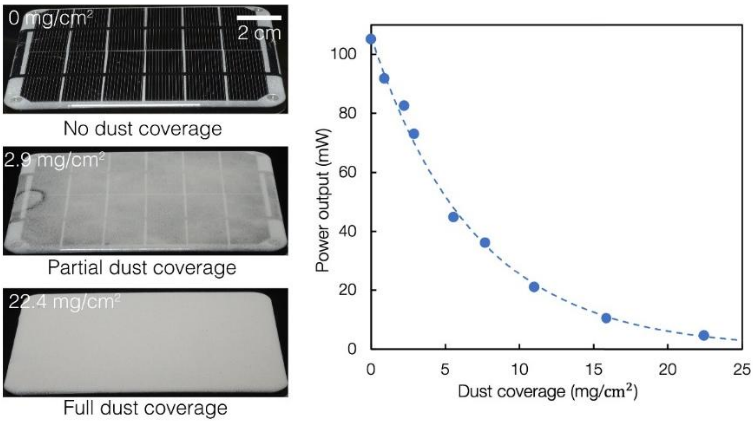


Figure 1. Effect of dust accumulation on solar panel power output [2]

Experimental analysis further indicates that solar panel performance decreases by 15% and 25% for dust densities of 6.388 mg/m² and 10.254 mg/m², respectively [3]. These findings have motivated substantial research into the effects of dust deposition on PV panel performance and the development of effective cleaning techniques. The authors in [4]-[8] explored the critical impact of dust accumulation on the performance and efficiency of PV modules. They emphasize the exponential decline in energy output caused by soiling and environmental factors, particularly in arid regions. Innovative mitigation strategies, such as advanced cleaning techniques, coatings, and techno-economic analyses, are highlighted to optimize solar panel maintenance. These studies underscore the need for interdisciplinary approaches to improve PV system reliability and performance under varying operational conditions.

A bibliometric review [9] identified 207 research papers published between 2015 and 2023 focusing on PV system performance, dust cleaning, and dust deposition. Most current studies, however, address the binary classification of PV dust problems—determining whether dust is present or absent. This approach overlooks the diverse nature of deposits on PV panels, such as feathers, bird droppings, and leaves, which necessitate more granular classification for effective cleaning strategies. Ayyagari *et al.* [10] proposed the classification technique of contaminants on PV arrays for 19 class problems, as shown in Figure 2, in large scale industries that achieved 96.54% detection accuracy using CNN-LSTM technique. This underlines the importance of monitoring systems for reducing energy losses.

Shenouda *et al.* [11] provides a detailed review of the impact of dust accumulation on PV panels in the Middle East, North Africa, and Far East regions, highlighting the severity of the issue. It evaluates advanced manual and self-cleaning techniques while emphasizing the need for innovative, cost-effective, waterless cleaning solutions with minimal human intervention. Such methods are crucial for improving PV panel performance in hot, arid, and dusty environments. Sharma *et al.* [12] introduces a novel dataset and a custom CNN framework achieving 93.63% accuracy in detecting dust buildup on PV panels. The approach sets a benchmark for future research, enabling multiclass categorization and potential performance enhancement through hyperparameter optimization. Abuqaaud and Ferrah [13] proposed a new framework for detecting contamination by utilizing image processing and sensor-based methodologies with 82% recognition rate. Mashhadani *et al.* [14] suggested deep learning models for hotspot fault identification and classification based on thermal image processing, achieving a 95% accuracy rate. Abukhait [15] achieved an accuracy of 92% for a two-class problem by using image features such local binary pattern (LBP), GLCM features, and machine learning model for dust identification. Abuzaid *et al.* [16] presents a review of 278 papers to study the seasonal impact of dust on PV performance. Altogether, these studies emphasize the necessity of interdisciplinarity and the utilization of advancements in image processing, deep learning and smart technologies to deal with the persistent challenge of debris on solar PV systems.

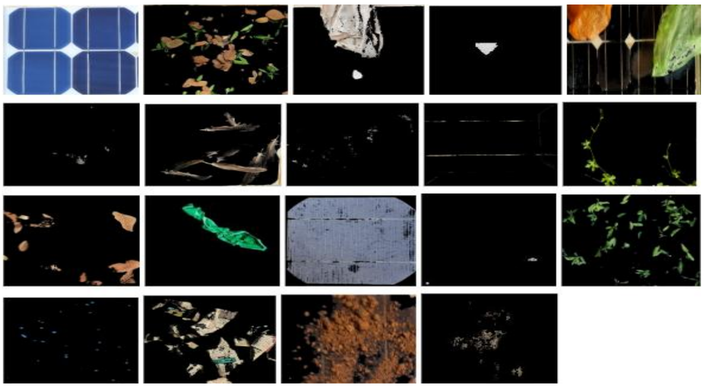


Figure 2. Pre-processed images of 19 classes in dataset [10]

Rahma *et al.* [17] investigates the impact of dust on PV panel performance, using a Fluke TiS60 Thermal Imager to detect hotspots and classify images with SqueezeNet and AlexNet transfer learning methods, achieving 99.3% accuracy with AlexNet. The analysis shows power loss ranging from 4.7% to 10.17% depending on dust coverage and thickness. This work highlights precise and cost-effective methods for PV module inspection and maintenance. Ramalingam *et al.* [18] proposes an IoT based automatic cleaning system for dust removal on solar panel. Table 1 compares these studies that concentrate on dust detection and machine learning algorithms.

Onim *et al.* [19] study introduces SolNet, a CNN architecture designed to detect dust accumulation on solar panels, achieving an accuracy of 98.2%. The research emphasizes the importance of image-based detection methods for effective solar panel maintenance. Karch *et al.* [20] presents a real-time soiling recognition system for PV panels using a deep neural network implemented on an embedded GPU platform, achieving over 90% accuracy in detecting dirt and dust. Ledmaoui *et al.* [21] propose an AI model utilizing a convolutional neural network for detecting anomalies in solar PV panels, including dust and bird droppings, with an accuracy of 91.46%. Jaybhaye *et al.* [22] employs deep neural networks to detect solar panel defects using aerial and electroluminescence images, achieving accuracies up to 93.75% with DenseNet121. Li *et al.* [23] introduces an improved YOLOv5-based model for detecting defects on PV panels, enhancing detection performance for small targets through architectural modifications.

Traditional methods rely on manual cleaning or sensor-based systems, which are labor-intensive, costly, and require frequent calibration. Machine learning and deep learning techniques have recently emerged as promising alternatives for automated debris classification. To overcome these challenges, this study aims to develop an artificial neural network (ANN)-based framework for automatic debris detection and classification on solar panels. By leveraging image processing techniques and machine learning algorithms, the proposed system enables precise identification of different debris categories, thereby facilitating targeted cleaning interventions. This research seeks to enhance the efficiency of solar panel maintenance while reducing operational costs and resource consumption.

This paper proposes a novel ANN-based framework that classifies 19 different debris types with high accuracy. The contributions of this work are:
- Development of a multiclass ANN-based classification model for PV debris detection.
- Integration of texture-based and spatial feature extraction methods for improved classification performance.
- Extensive evaluation and comparison with traditional machine learning models.

Table 1. Comparison of past research based on dust detection and ML models used

Ref	Author	Purpose	Model Used	Accuracy	No. of classes	Year
[10]	Ayyagari *et al.*	Detection and classification of dust and soil on PV arrays	CNN-LSTM	96.54%	19	2022
[12]	Sharma *et al.*	Soil detection framework for solar panels	CNN	93.63%	2	2024
[15]	Abukhait	Dust detection on solar panels using computer vision	LBP and GLCM features used for SVM model	94.3%	2	2024
[17]	Rahma *et al.*	Fault classification and dust impact on PV modules	AlexNet and SqueezeNet	99.3%	2	2023

The proposed method is demonstrated through experimental validation, including performance benchmarking against SVM, KNN, and CNN models. By addressing limitations in prior studies, this research contributes to the advancement of intelligent solar panel maintenance systems. The rest of this document is organized as follows: Section 2 reviews related work, section 3 outlines the proposed methodology, section 4 presents the results and discussion, and section 5 concludes with key findings and future directions.

2. METHOD

The classification of distinct types of debris that are formed on solar PV arrays can be achieved by the following steps shown in Figure 3. The proposed methodology encompasses a three-stage process for image classification: the first step is image acquisition and pre-processing to ensure data standardization and quality. The second stage consists of feature extraction, where key representations and patterns of images are identified. Finally, the third stage involves the training of a machine learning model, which leverages the extracted features to classify images. These steps ensure a structured pipeline for accurate debris classification.

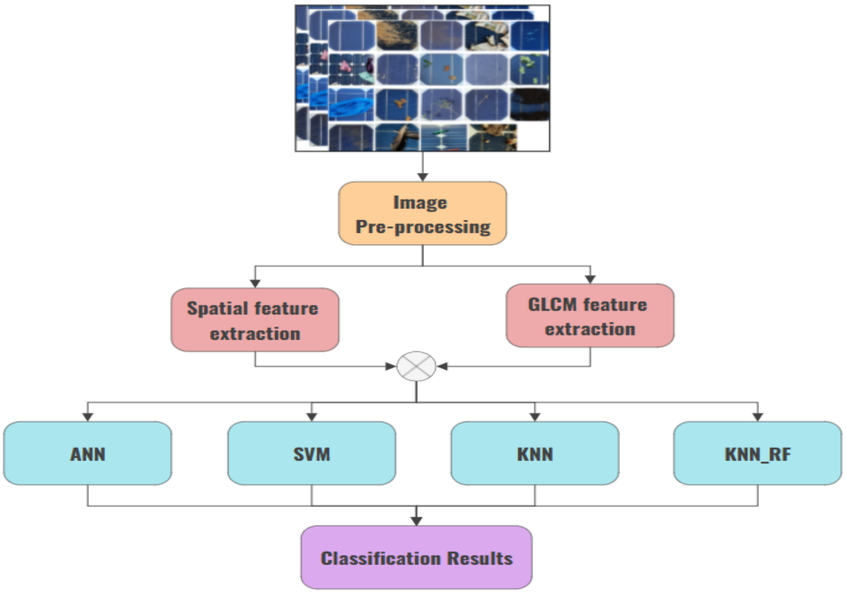


Figure 3. System model for classification of various debris on solar PV arrays

2.1. Image acquisition and preprocessing

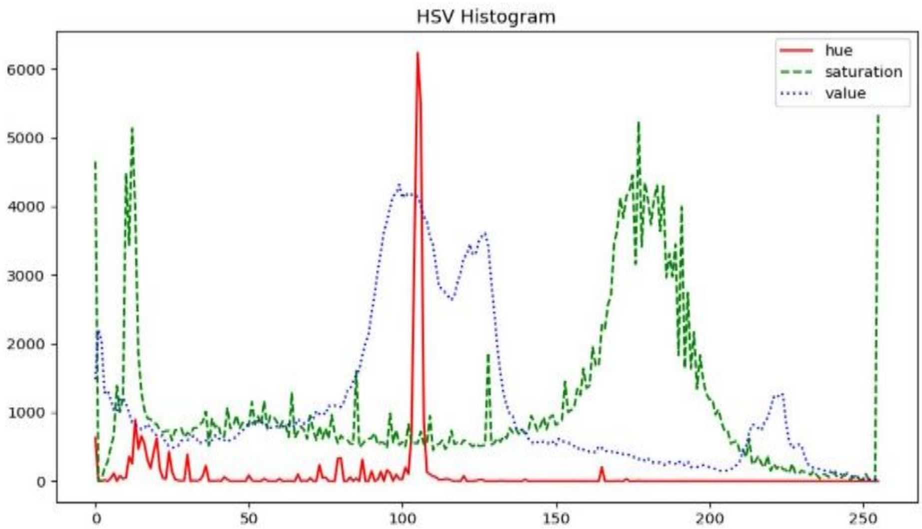
The dataset provides deposits with the following classes: “Without dust”, “Bird droppings”, “Coal dust”, “Dry leaves” and 15 more unique classes shown in Table 2. The dataset used contains a total of 1222 images which are divided into 19 classes. To ensure consistency, all images were resized to a fixed resolution of 256x256 pixels and underwent cropping to remove irrelevant background information. This standardization is essential for efficient feature extraction and classification.

Pre-processing was an essential step to enhance textural information and improve the reliability of the collected data, as the proposed classification method uses texture features. This step involved converting the input images from the standard RGB to HSV color format. HSV is chosen due to its robustness to changes in lighting conditions, making it suitable for real-world applications. Histogram-based thresholding was applied to segment debris from the panel background, ensuring that the extracted features correspond accurately to contaminants. Figure 4 illustrates the overall image preprocessing steps used in the study. It provides a detailed overview of how raw images are processed, including colour space conversion and thresholding, to enhance feature extraction. Figure 4(a) shows a sample image with Figure 4(b) specifically highlights the histogram-based thresholding approach, which plays a crucial role in isolating debris from the panel background. HSV lower and upper thresholds of (100, 50, 50) & (130, 255, 255) respectively are used in this paper. This results in the separated contaminants from the solar panel regions as shown in earlier Figure 2.

Table 2. Image classes in the dataset

S.No	Classes	No. of images
1.	Without dust	48
2.	Bird droppings	53
3.	Birdwings	81
4.	Black soil	43
5.	Coal dust	52
6.	Cobwebs	44
7.	Creepers or weeds	91
8.	Dry-green mix	59
9.	Dry Leaves	136
10.	Electrician cloth	56
11.	Electrician tape	42
12.	Fine dust in winter	87
13.	Fly ash dust-	58
14.	Flying shopper bags	71
15.	Green leaves	107
16.	Paint spills	19
17.	Paper dust	76
18.	Red soil	51
19.	Sand	48

(a)



(b)

Figure 4. Sample database (a) image and (b) HSV Histogram plots

2.2. Feature extraction

After pre-processing of images, a set of discriminative characteristics are obtained from them by integration of spatial features and GLCM based texture features. Feature extraction enhances classification accuracy and ensures the robustness of the model by leveraging statistical and texture-based attributes. A combination of spatial features and texture features was used to enhance classification performance. Spatial features were extracted from three different color spaces (RGB, HSV, and LAB), while texture features were derived using the gray level co-occurrence matrix (GLCM). This multi-feature approach improves the model’s ability to distinguish between different debris types. Spatial features are the statistical descriptions derived from three different colour spaces RGB, HSV and LAB. The statistics that are computed are mean, standard deviation, 25th Percentile, 75th Percentile for each channel of RGB, HSV and LAB. One popular technique for extracting texture features from images is the GLCM [24], [25]. It is a statistical technique that describes how the intensities of the pixels in an image relate to one another spatially. A statistical distribution of pixel intensity pairs is provided by the co-occurrence matrix, which sheds light on the image's texture. One orientation angle of 0° and a constant distance d=3 is used to compute the GLCM. The GLCM is used to calculate the following five properties: contrast, dissimilarity, homogeneity, energy, and correlation. The feature vector of length 41 is the result of combining the spatial and GLCM feature sets.

2.3. Classification model

The machine learning models used in this paper are KNN, SVM, and KNN with random forest and ANN. The parameters used for each of the models are mentioned in Table 3. The ANN model consists of an input layer with 41 features, followed by two hidden layers with 512 and 256 neurons, respectively. ReLU activation was used in the hidden layers, while a Softmax activation function was applied in the output layer to enable multi-class classification. The Adam optimizer was employed to enhance model convergence. These models were trained using an 80-20 split for training and testing, ensuring a reliable performance evaluation.

Table 3. Details of parameters used in the models

Model	Parameters	Model	Parameters
KNN	No. of Nearest neighbours : 5		No. of estimators : 100
	Weights : Uniform	KNN_RF	Maximum depth : None
	Metric : Euclidean		Random state : 42: N_jobs : -1
SVM			Input layer : 41 nodes
	Kernel : RBF		Hidden layer 1 : 512 nodes, ReLU activation
	Kernel coefficient γ : scale	ANN	Hidden layer 2 : 256 nodes, ReLU activation
	Regularization parameter C: 10		Output layer : 19 nodes, Softmax activation
			Optimizer : Adam

3. RESULTS AND DISCUSSION

The experimental analysis was conducted to evaluate the performance of various machine learning models in classifying different types of debris on solar panels. The dataset was split into an 80-20 ratio for training and testing, ensuring a reliable evaluation.

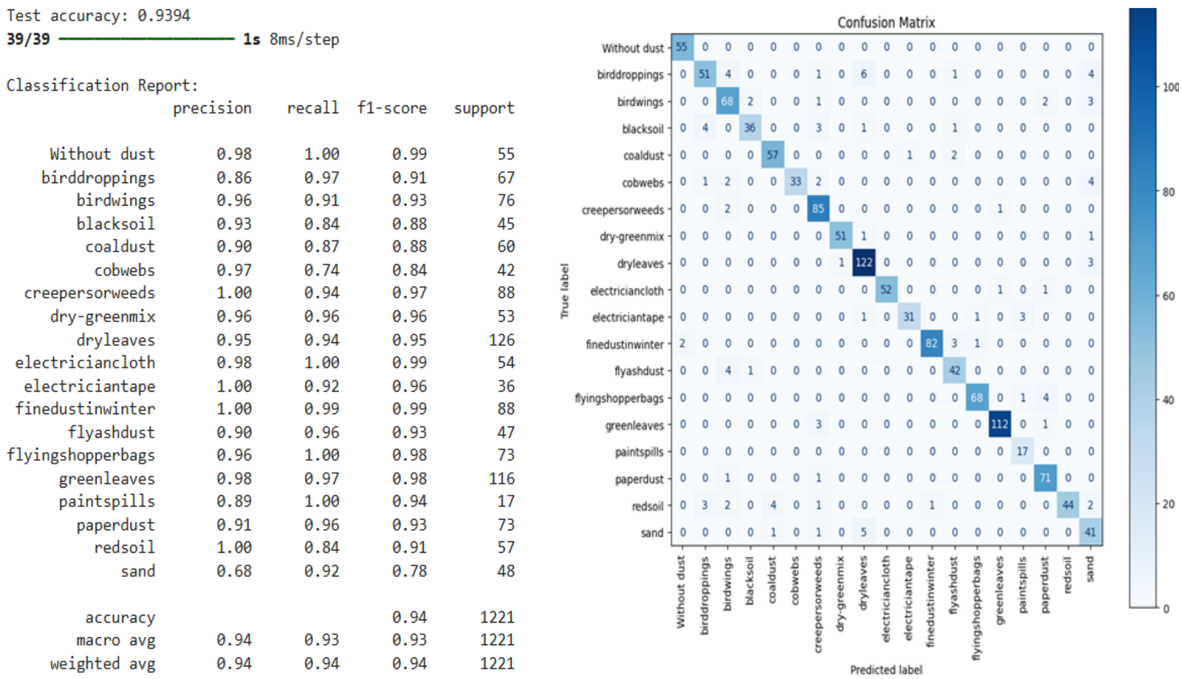
3.1. Key findings

The findings are presented using key performance metrics, including accuracy, precision, recall, and F1-score, which are summarized in Table 4. Figure 5 illustrates the classification performance of different debris categories using the ANN model. Figure 5(a) presents the class-wise accuracy performance, while Figure 5(b) displays the confusion matrix for further analysis. The class-wise accuracy distribution highlights the strengths and limitations of the proposed approach, showcasing variations in model predictions across different debris types. This analysis provides insights into misclassification trends and areas requiring further optimization, ensuring a more effective deployment of the automated debris detection framework. The ANN model demonstrated the highest classification accuracy (93.94%), outperforming traditional machine learning models such as support vector machines (SVM) and K-nearest neighbors (KNN). The class-wise accuracy distribution highlights the strengths and limitations of the proposed approach, showcasing variations in model predictions across different debris types.

The extracted features are also ranked to determine which feature dominates more. Figure 6 illustrates the ranking of all 41 features through the minimum redundancy maximum relevance (mRMR) algorithm. It highlights the top ranked features extracted using mRMR showcasing those that contribute the most significant value to classification accuracy.

Table 4. Performance comparison of machine learning models

ML model	Accuracy (%)	Precision	Recall	F1-score
ANN	**93.94%**	**0.94**	**0.94**	**0.94**
SVM	84.08%	0.85	0.84	0.84
KNN_RF	89.80%	0.91	0.90	0.90
KNN	76.33%	0.79	0.76	0.76



Test accuracy: 0.9394
39/39 ━━━━━━━━━━━━━━━━━━━━ 1s 8ms/step

Classification Report:

	precision	recall	f1-score	support
Without dust	0.98	1.00	0.99	55
birddroppings	0.86	0.97	0.91	67
birdwings	0.96	0.91	0.93	76
blacksoil	0.93	0.84	0.88	45
coaldust	0.90	0.87	0.88	60
cobwebs	0.97	0.74	0.84	42
creepersorweeds	1.00	0.94	0.97	88
dry-greenmix	0.96	0.96	0.96	53
dryleaves	0.95	0.94	0.95	126
electriciancloth	0.98	1.00	0.99	54
electriciantape	1.00	0.92	0.96	36
finedustinwinter	1.00	0.99	0.99	88
flyashdust	0.90	0.96	0.93	47
flyingshopperbags	0.96	1.00	0.98	73
greenleaves	0.98	0.97	0.98	116
paintspills	0.89	1.00	0.94	17
paperdust	0.91	0.96	0.93	73
redsoil	1.00	0.84	0.91	57
sand	0.68	0.92	0.78	48
accuracy			0.94	1221
macro avg	0.94	0.93	0.93	1221
weighted avg	0.94	0.94	0.94	1221

(a) (b)

Figure 5. ANN Model predictions (a) classwise performance and (b) confusion matrix

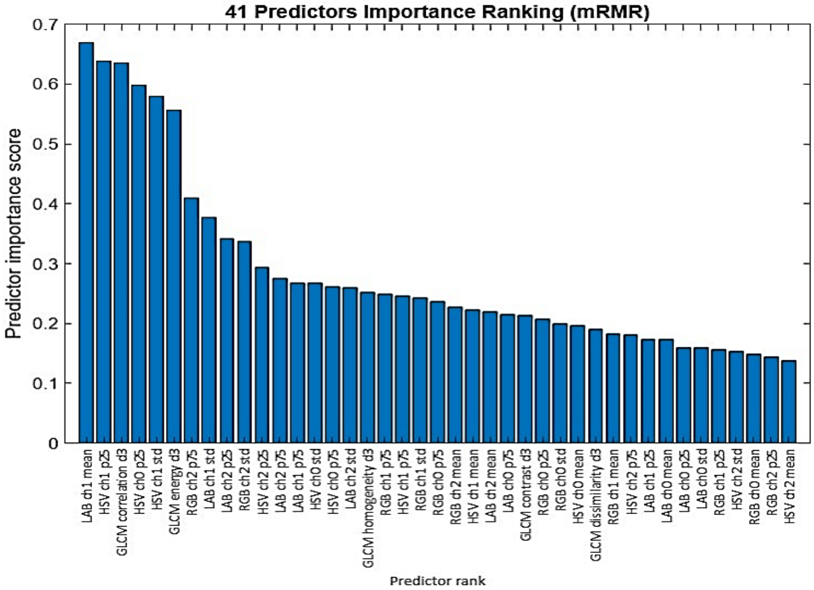


Figure 6. Ranking of 41 features based on feature score

3.2. Interpretation of results and comparison with other studies

The high accuracy of the ANN model suggests that a deep learning approach is well-suited for debris classification in solar panels. However, certain debris categories, such as “Sand” and “Bird Droppings,” showed lower classification accuracy due to their similarity in texture and colour with other classes. These findings are consistent with previous studies, which also reported challenges in distinguishing visually similar contaminants on PV modules. In comparison, studies such as [26]-[28] explored conventional machine learning models (e.g., SVM and decision trees) and achieved lower accuracy levels (80-93%). Our results reinforce that integrating texture-based feature extraction and deep learning techniques significantly enhances classification performance.

3.3. Study limitations and future scope

Despite the promising results, some limitations exist in the study:

– Dataset size and diversity – The dataset contains 1222 images, but incorporating more diverse environmental conditions (e.g., wet panels, varying light intensity) could improve generalization.
– Misclassification in Similar Classes – Certain debris categories require advanced feature extraction or additional preprocessing techniques to improve classification accuracy.
– Real-time implementation – While the current ANN model performs well in experimental settings, its deployment in a real-time solar panel monitoring system needs further validation.

Future work will focus on:

– Expanding the dataset with augmented and real-world images from multiple PV installations.
– Testing real-time inference using edge computing hardware for on-site implementation.
– Integrating spectral imaging techniques to differentiate debris types more effectively.

4. CONCLUSION

This study explored the potential of machine learning techniques for automated debris detection and classification on solar panels. The experimental results demonstrated that the ANN model achieved the highest classification accuracy of 93.94%, significantly outperforming conventional machine learning models such as SVM and KNN. The findings highlight that integrating texture-based feature extraction with deep learning techniques can significantly improve classification performance. This study provides a scalable and efficient framework that can facilitate real-time monitoring and maintenance of PV systems, reducing energy losses due to debris accumulation. Despite the promising results, certain challenges remain. Future studies will integrate real-world images captured under varied environmental conditions such as fog, rain, and extreme sunlight to enhance model robustness. Additionally, the classification of similar-looking debris types (e.g., sand and red soil) remains a challenge that could be addressed through spectral imaging techniques or improved feature extraction methods. The proposed ANN model has the potential to be deployed in smart solar farms, integrating with IoT-based monitoring systems to enable automated debris detection and cleaning. By implementing edge computing-based real-time monitoring systems, PV installations can automatically detect contamination levels and trigger cleaning mechanisms, improving energy efficiency and reducing operational costs. Future research can focus on enhancing dataset diversity by collecting images from multiple geographical locations and PV installations and investigating advanced deep learning models such as transformer-based architectures for improved debris classification. By addressing these challenges and expanding the scope of the research, this study can contribute to the development of autonomous, AI-driven solar panel maintenance systems, ultimately supporting sustainable energy production and grid reliability.

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AUTHOR CONTRIBUTIONS STATEMENT

Name of Author	C	M	So	Va	Fo	I	R	D	O	E	Vi	Su	P
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Gayatri A		✓	✓	✓		✓			✓		✓		
Ragini K.		✓			✓		✓	✓	✓				
Ramesh Reddy K				✓	✓		✓			✓		✓	
Koti Reddy B	✓			✓				✓		✓		✓	

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 available from the corresponding author, KRB, upon reasonable request.

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