

Multi-Fault Diagnosis in Solar Panels using Hybrid Feature Fusion Approach

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Abstract

The use of photovoltaic (PV) systems is growing as a green energy source; but their output is highly dependent on environmental and operational faults including soiling and shading conditions. However, despite the successful application of previous deep learning approaches for single-fault detection, multi-faults (e.g., soiling and shading) are difficult to diagnose accurately in actual PV systems. In this research, we present a hybrid spatial feature fusion-based deep learning method for multiclass fault identification in PV panels. Our model is based on fusion of three state-of-the-art transfer learning models (EfficientNetB7, ResNet50, and MobileNetV2) to extract deep features that are then combined to provide a unified feature representation for classification. A custom dataset of 953 RGB images captured in Uttarakhand, India, representing three different states of the PV panel (clean, dusty, and multi-fault) is used to train and test the model. The proposed model outperforms each of the individual baseline models, with an average classification accuracy between 97.1% and 98.4%, precision of up to 96.7%, sensitivity between 92.3% and 100%, and specificity between 97.6% and 98.4%. It has also F1 value of 94.4% and a Matthews Correlation Coefficient (MCC) score of up to 0.965, demonstrating better predictive classification model. The improved accuracy is due to the amalgamation of various feature representations, providing increased capacity to discriminate among visually similar faults. Furthermore, the LIME-driven Explainable Artificial Intelligence (XAI) ensures interpretability by identifying key regions that contribute to the model's decision-making ability. The present study can be utilized in smart PV monitoring operations, inspection using drones and IoT-based smart solar farms, enabling early fault detection and improve energy production. The detailed graphical abstract of the study is shown in **Figure 1**.

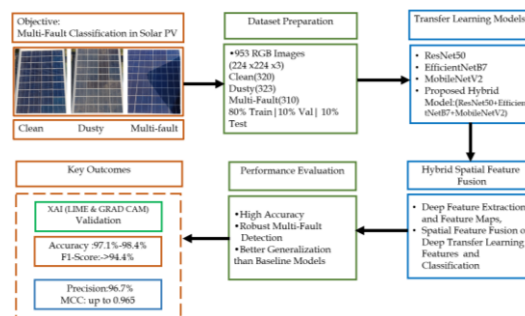


Figure 1. Graphical abstract.

Keywords- Soiling effects, Matthews correlation coefficient, Spatial feature algorithm, Transfer learning, Multi LIME based explainable AI.

Symbols and Variables

Symbol	Description
X_k	Input image sample (k-th image)
N	Total number of samples
F_{ei}	Feature extracted from i-th pretrained model
F_k	Fused feature vector for k-th sample
D	Feature dimension
$Z1, Z2, Z3$	Outputs of fully connected layers
$W1, W2$	Weight matrices
$b1, b2$	Bias terms
$\gamma c(k)$	Softmax output probability for class c
C	Number of classes

CNN Parameters

Symbol	Description
Ch_{in}	Number of input channels
Ch_{out}	Number of output channels
K_r	Kernel size
$\sigma(x)$	Locality kernel
$Q(x,y)$	Distance metric
δ	Kernel width parameter

Performance Metrics

Symbol	Description
TP	True Positive
TN	True Negative
FP	False Positive
FN	False Negative
Precision	Precision
Recall	Recall (Sensitivity)
F1-score	F1 Score
Accuracy	Accuracy
Specificity	Specificity
MCC	Matthews Correlation Coefficient

Abbreviations

Symbol	Description
PV	Photovoltaic
CNN	Convolutional Neural Network
DL	Deep Learning
ML	Machine Learning
TL	Transfer Learning
RGB	Red Green Blue
XAI	Explainable Artificial Intelligence
LIME	Local Interpretable Model-Agnostic Explanations
ReLU	Rectified Linear Unit
FC	Fully Connected
IoT	Internet of Things

1. Introduction

To combat global warming and its effects, leading to serious illnesses, widespread pollution, and harm to ecosystems, the world has moved toward renewable energy sources (RES) like solar, wind, hydroelectric, and geothermal power. This initiative meets the growing demand for energy around the world and enhances environmental protection. Therefore, it is crucial to use clean, low-carbon energy sources to fulfill future energy needs and ensure that the future is environmentally friendly and sustainable (Lu, 2024). The Renewables 2023 Global Status Report reveals that India is the fourth-largest producer of installed renewable energy capacity and the fifth-largest producer of solar power in the world. Blackridge Research & Consulting says that PV installations are expected to have reached a new elevation of around 500 GW by the end of 2030 (Moosavian et al., 2024). The performance of PV modules decreases due to environmental or operational effects such as dust build-up, shading, temperature extremes and material degradation, resulting in significant energy losses and degradation. Dust accumulation on PV module has been shown to cause up to 25% loss in performance, and hence monitoring and fault diagnosis is important (Laarabi et al., 2022; Sharma et al., 2024).

According to NREL's Performance Parameters, PV plants experience various anomalies that lead to losses in electricity production (Severiano et al., 2026). One such phenomenon is soiling loss, which has an incredibly wide range of 2% to 25% (Korkmaz and Acikgoz, 2022). Environmental factors affecting solar panels include dust, dirt, bird droppings, and shading from trees or buildings (Raj et al., 2026), as depicted in **Figure 2**. Various dust types, such as soil, clay, and carbon, result from wind, air pollution, temperature, and dust storms (Demirci et al., 2021; Zhu et al., 2024). The interaction of these dust types with factors like glass materials, nearby industrial areas, and panel orientation influences the level of dust accumulation. This accumulation of dust reduces the lifespan of the solar PV panels (Huang et al., 2022; Hamed et al., 2026). Automated solar cell fault detection in photovoltaic power is an optimal solution that offers quick detection and precise classification, thus enhancing power generation reliability. The advancements in machine learning (ML) and deep learning (DL) models have been promising for identifying faults in PV systems automatically. Convolutional Neural Networks (CNNs) have demonstrated their ability to learn hierarchical features of data from images, allowing them to classify PV faults like dust, bird drop, crack etc. The use of transfer learning with pre-trained models (e.g., ResNet, EfficientNet, MobileNet) has also increased the accuracy and efficiency of detection systems by harnessing the knowledge from large-scale datasets, thereby minimizing training time and computational requirements (El-Batta et al., 2026). Latest research (2020-2025) has achieved high recognition rates with deep learning based approaches for PV fault detection and monitoring (Onim et al., 2022; Sepúlveda-Oviedo et al., 2023). Moreover, recent research has also improved the transparency of deep learning models by incorporating Explainable Artificial Intelligence (XAI) models such as Shapley Additive Explanations (SHAP) and Local Interpretable Model-Agnostic Explanations (LIME) (Doğan et al., 2026). Most of the research work mainly deals with the detection of a single fault condition. Real-world PV systems may exhibit multiple faults on the surface of PV module, such as simultaneous partial shading and dust accumulation (Gangwal and Lavecchia, 2026). Such combination of faults create complex features and ensure the distributions overlap, making classification difficult. The deep learning models face difficulties in these cases because of the lack of feature dissimilarities and higher class similarity, which lowers their stability in practical PV systems. Recent research has indicated a need for more effective models to address this problem, and enable effective multi-fault diagnosis and better adaptation across different environmental settings (Unni et al., 2026).

In response to these challenges, this research proposes a hybrid spatial feature fusion-based deep learning approach for multi-class fault diagnosis of solar PV panels. The method involves combining three transfer learning-based models using EfficientNetB7, ResNet50, and MobileNetV2 to capture deep features, which are then combined in a new feature space for improved classification capabilities. This approach is validated

utilizing a custom dataset of 953 RGB images of clean, dusty, and mixed-fault classes. Moreover, the use of LIME-based Explainable Artificial Intelligence (XAI) is integrated to enhance interpretability and transparency of the decision-making process. The developed model exhibits superior performance than baseline models, and can provide a robust solution for smart PV monitoring systems, such as in drone-based monitoring and IoT-enabled smart PV farms.

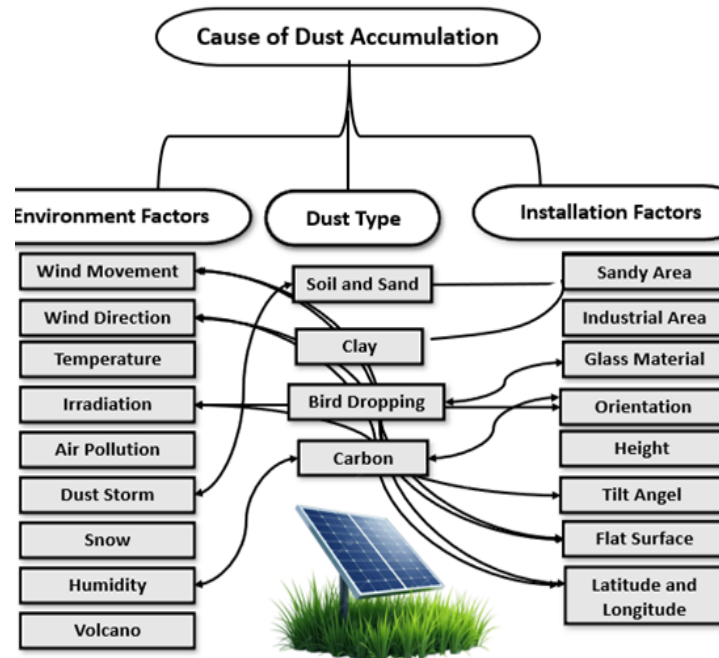


Figure 2. Causes of dust accumulation.

The research paper follows this layout: Section 2 covers related work in the development of transfer learning techniques for identifying solar PV panel faults. Section 3 discusses the concept of transfer learning as a technique for improved performance. Section 4 elaborates on the experimental dataset and methodology for the novel approach; it also discusses the steps involved in implementing multi-fault classification in solar photovoltaic panels. Section 5 discusses the performance of this novel approach with three prominent transfer learning models using metrics like accuracy, precision, recall, and F1-score. Further in Section 6, it validates the results of fault classification with Lime-based Explainable AI (XAI) and finally, Section 7 is the conclusion of the paper, which summarizes the key findings of the research.

2. Related Work

The literature review conducted in this part examines the most recent applications of deep learning algorithms for solar PV panel fault classification, as well as the most recent advancements in scientific interest in this field through cross-searching. **Figure 3** shows the number of publications published on a yearly basis over a nine-year period from 2017 to 2025 in the field of classifying faults in solar PV panels. In the current scenario, transfer learning is also used as an optimal technique for computer vision applications, as it allows for the building of accurate classification models that save time. This work proposes using this model to forecast solar PV plant maintenance schedules in the future, which would enhance the practical lifespan of PV modules (Nasri et al., 2026).

This research study (Memon et al., 2022) covered four PV system faults that often occur: short circuits (SCs), ground faults (GFs), and open circuits (OCs). The research aims to clarify concerns that might compromise the efficiency and safety of photovoltaic systems. It also suggested a convolutional neural network model for classifying these faults on a dataset that included features like temperature, irradiation level, current, and voltage that was simulated using the Google Colab platform. The model's overall testing accuracy was 95.20 percent (Manoharan et al., 2026). The authors continued on to address several issues, including the lack of varied public datasets and shadowing effects on solar PV. Similarly, in other work that examined the potential of the CNN model to classify eleven distinct anomalies in 20,000 thermographic pictures. Ten thousand healthy and ten thousand faulty photos make up the publicly accessible infrared solar modules dataset. This approach accurately identified 92% of the healthy modules and 93% of the damaged modules (Ayunts et al., 2026). Venkatesh et al. (2023) use cloud computing and the Internet of Things (IoT) in their study to implement an automatic PVM inspection and monitoring system using a deep learning-based method involving convolutional neural networks (CNNs). The system extracts feature from 600 aerial images; the binary classification of each defect situation yields a high accuracy of 98.66% (Venkatesh et al., 2023).

This research article discusses a unique architecture of the Real-time Multi-Variant Deep Learning Model (RMVDM) in their study (Prabhakaran et al., 2023). There are twenty-five layers in this model. Additionally, a comparison between this model and three pre-trained models—Resnet, Alexnet, and Densenet—is conducted. RMVDM had the highest accuracy, at 98%, according to this study's findings. Shallow classifiers such as SVM, NB, and KNN, which manually extract features using texture and HOG, achieve 83.3% accuracy with the pretrained model ResNet18, which itself has an accuracy of 96.97% on infrared thermograph images of six PV system defects—healthy, single-cell, patchwork, bird-dropping, block, and string conditions—collected from a balanced dataset of 55 images for each class in Lahore, Pakistan.

This research work reduces 50% of the consumption of electrical power generated by the panel through their proposed model (Zhang et al., 2024), which is based on MobileNet. Soiling Edge has been implemented on a number of platforms, such as CPUs, field-programmable gate arrays (FPGAs), vision processing units (VPUs), and edge tensor processing units (Edge TPUs).

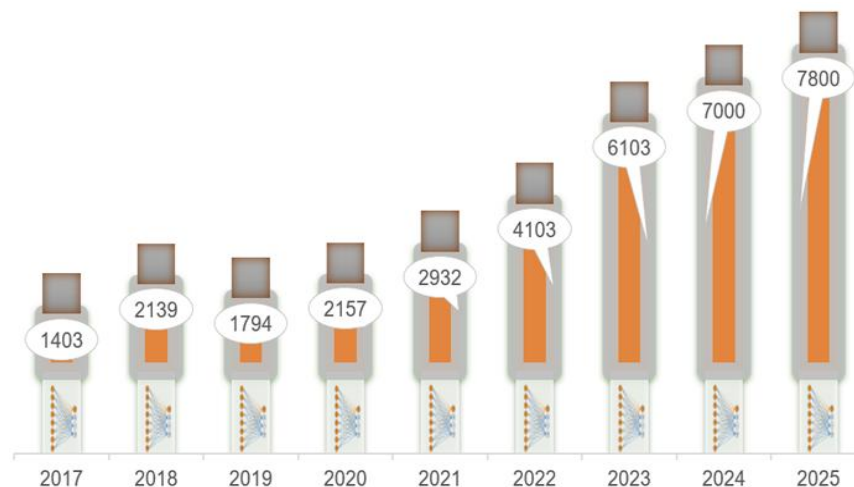


Figure 3. Trends of research on solar PV faults classification.

An artificial neural network to analyze 2,624 electroluminescence images of PV cells that were made available to the public in their research article (Khosa et al., 2023). The images were categorized into four different classes and given defect probabilities of 0.0, 0.33, 0.66, and 1.0. Grey-level co-occurrence matrix (GLCM) and local binary pattern (LBP) are two types of widely used and well-liked handcrafted features that they employed. When data was augmented, the model's accuracy increased to 92.2%. They also suggested an individualized CNN-based method that had a binary classification accuracy of 94.3%.

SolNet, a convolutional neural network model, is introduced to classify anomalies in solar PV panels using a customized dataset of 2231 images captured from various locations in Bangladesh and prove its effectiveness in comparison with other SOTA algorithms such as VGG16, InceptionV3, ResNet50, and AlexNet (Onim et al., 2022); this model demonstrates a superior accuracy level of 98.2%. The model is trained at 50 epochs using K-fold cross-validation with five folds to address the overfit issue.

This research work (Aman et al., 2023) focuses on the impact of dust deposition on solar photovoltaic modules, and the application of deep learning models to fault classification in PV panels is the main topic of this research article. For the purpose of the study, hotspots generated by dust deposition were identified using a Fluke TiS60 thermal imager. Where they utilized SqueezeNet and AlexNet image classifiers for faulty and healthy panels. AlexNet had the highest accuracy at 99.3%. Using dust to generate hotspots on solar panel assemblies helped with the study of power loss. The study found that when 50% of a module had been coated in a thin layer of dust, the power loss rose to 5.9%. The research discusses the significance of transfer learning in the precise diagnosis of faults in photovoltaic (PV) systems, using the UdenseNet model to classify two-, eleven-, and twelve-class faults (Zhu et al., 2024). As compared to earlier research, the suggested model's performance evaluation demonstrated higher accuracy, with accuracies of 99.39%, 96.65%, and 95.72% for various output classes on the test dataset (Ramírez et al., 2024).

Table 1 includes recent high-impact studies (2024-2025), highlighting that existing approaches primarily rely on single-model architectures or single-fault scenarios, whereas the proposed hybrid feature fusion framework effectively addresses multi-fault conditions with improved classification performance.

Table.1. Comparative analysis with recent (2024–2025) studies.

Author & Year	Method / Model	Dataset type	Fault type	Key contribution	Accuracy (%)	Limitation
Memon et al. (2022)	CNN	Simulated data	Electrical faults	DL-based fault classification	95.2	No visual / environmental faults
Venkatesh et al. (2023)	CNN + IoT	Aerial images	Binary faults	Real-time monitoring	98.66	Only binary classification
Ahmed et al. (2023)	DL vs ML	IR images	Multi-fault (IR-based)	DL outperforms ML	96.97	No feature fusion
Khosa et al. (2023)	ANN + GLCM	EL images	Fault grading	Lightweight ML approach	92.2	Limited feature learning
Onim et al. (2022)	SolNet (CNN)	RGB images	Dust faults	High accuracy DL model	98.2	Single-fault only
Pamungkas et al. (2023)	Transfer Learning	Image dataset	Multi-class faults	Efficient pretrained models	>95	No hybrid fusion
Paletta et al. (2024)	CNN + Transfer Learning	Experimental + Mendeley dataset	Shading & temperature faults	Improved classification under environmental effects	>96	Limited to specific faults (ScienceDirect)
Fitriyanah et al. (2025)	DL + UAV Thermography	Aerial IR images	Thermal faults	UAV-based large-scale inspection	—	Focus on thermal imaging only (ScienceDirect)

Table 1 continued...

Ren et al. (2025)	EfficientNet-based DL	PV image dataset	Visual faults	High-performance DL classification	—	Single-model limitation (Nature)
Gangwal and Lavecchia (2026)	Enhanced CNN (VGG16 + XAI)	Image dataset	PV anomalies	Explainable AI integration for PV faults	—	Focus on anomaly detection, not multi-fault fusion (MDPI)
Proposed	Hybrid Feature Fusion (EfficientNetB7 + ResNet50 + MobileNetV2)	953 RGB (real-world)	Clean, Dusty, Multi-fault	Spatial feature fusion + XAI (LIME)	97.1–98.4	Higher computational cost (acceptable trade-off)

2.1 Research Gap

While substantial progress has been made in the area of deep learning-based PV system fault diagnosis, there are a few key research gaps. First, most previous studies address only single-fault or consideration of limited multi-class faults, many overlooking the possibility of combined faults such as partial shading and soiling that frequently happen in PV systems. Second, existing studies typically use isolated transfer learning models instead of leveraging multiple feature representations in a synergistic manner.

2.2 Novelty of Work

This work overcomes these challenges by introducing a hybrid deep learning model using feature fusion of EfficientNetB7, ResNet50 and MobileNetV2 for effective feature extraction. In comparison to conventional methods, the proposed model conducts spatial feature-level fusion of discriminative feature representations obtained from numerous pre-trained models, thus enabling better classification performance with higher generalization and robustness for multi-fault diagnosis. The incorporation of a new PV module multi-fault class (dust and shadow) adds to the realism of the problem. This holistic framework sets apart the proposed model and leads to more accurate and reliable diagnosis of PV faults under real world conditions.

3. Transfer Learning

Pre-trained models, as shown in **Figure 4**, transfer knowledge from a pre-training dataset to the desired target task. Since the source task is usually much larger, the pre-trained model already has a profound understanding of pertinent features, making it more generic than the target task (Sharma et al., 2024).

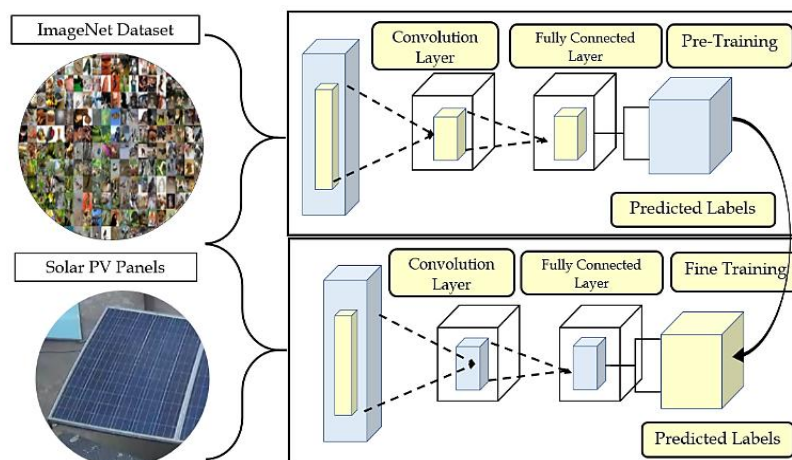


Figure 4. Pre-trained model concept.

3.1 ResNet-50

Microsoft Research unveiled ResNet-50, a deep convolutional neural network architecture, in 2015. It is mostly used for picture classification and other computer vision tasks including object recognition and segmentation (Basnet et al., 2020). It consists of 16 residual blocks, organized into four stages, each containing varying numbers of convolutional layers (Basu et al., 2023). Each block typically contains three convolutional layers, learning residual mapping (Paletta et al., 2024). Max-pooling layers are employed after every few residual blocks to reduce feature map dimensions. Using learned features, fully connected layers at the end classify data (Hussain et al., 2023).

3.2 EfficientNet-B7

EfficientNet-B7 is the model in the Efficient Net family. It is a good choice for tasks with limited computational resources (Almonacid-Olleros et al., 2022). It utilizes compound scaling, as this method scales the depth, width, and resolution of the network based on a specific ratio to maintain efficiency while improving accuracy (Ching et al., 2024; Shukla et al., 2025). It uses inverted bottleneck residual blocks.

This is a special type of residual block that helps to improve efficiency without affecting accuracy (Duranay, 2023). All the layers are similar to those discussed in ResNet-50, besides ReLU activation function, it uses the Swish activation function (Alkanan and Gulzar, 2024), as defined in the following Equation (1):

$$\text{Swish}(i) = i + \frac{1}{1+e^i} \quad (1)$$

3.3 MobilenetV2

It was created by Google researchers as an update to the original MobileNet architecture. Another noteworthy aspect of this model is its ability to balance accuracy and compactness in an efficient manner, making it ideal for devices with low power. Some of these features are depth-wise separable convolution, bottleneck design, squeeze-and-excitation (SE) blocks, and inverted residuals keep the model's accuracy high (Malek and Imtiaz, 2026; Oktavian et al., 2022).

If the input feature map has Ch_{in} channels and the output have Ch_{out} channels, a standard convolutional layer with a kernel size of $K_r \times K_r$ requires (Basnet et al., 2020; Ren et al., 2025). The working principle of the residual block is depicted in the following Equations (2) & (3).

$$\text{Standard Parameter} = Ch_{in} \times Ch_{out} \times K_r \times K_r \quad (2)$$

In contrast, a depth wise separable convolution layer ,has a total number of parameters as

$$\text{Depth – wise Parameter} = Ch_{in} \times K_r \times K_r + Ch_{in} \times Ch_{out} \quad (3)$$

This significantly reduces the number of parameters and computational cost compared to standard convolutions (Younes et al., 2023). Several noteworthy features of MobileNetV2's design, improve the system's effectiveness and efficiency in image classification (García et al., 2022). Pre-trained models may prevent overfitting in numerous ways, the most effective of which are discussed below (Qaisieh et al., 2023; Selvaraj et al., 2022).

- Reduced Feature Space Dimensionality: Pre-trained models are trained on large datasets, which allows them to learn complex representations of the complex dataset (Kazem et al., 2022).
- The pre-training process operates as a sort of regularization, the pre-trained weights and biases become less susceptible to specific patterns in the training data for the final task (Fitriyanah et al., 2025).

4. Material and Methods

4.1 Experimental Dataset

The proposed data set, with a total of 953 RGB images of solar photovoltaic (PV) panels was captured from a real PV installation site in the Uttarakhand region, India, under varying outdoor environmental conditions. The dataset has three categories: clean (320 images), dust (323 images) and multi-fault (310 images) where, multi-fault category represents the impact of dust and partial shading. The dataset comprises images taken at various times of the day (morning, noon and afternoon) to include variability in lighting conditions (solar irradiance conditions, shadows and surface glares). Moreover, weather conditions of clear, and partly cloudy days were also taken into account to account for realistic lighting variability. The images were taken using a high-resolution RGB camera with a constant distance and angle of view to pan out a uniform sample. The images were adjusted to the size of $224 \times 224 \times 3$ to match the pre-trained models' input sizes. The new dataset is also representative of real-world environmental conditions such as natural deposition of dust particles, partial occlusion from obstacles (e.g., trees) and background climatic changes as well as other pervasive factors introduced due to natural sources, thus ensuring practicality. This complete dataset facilitates the reproducibility, robustness and generalizability of the solar PV module multi-fault classification system. The **Figure 5** shows sample of image dataset utilized throughout in this study.

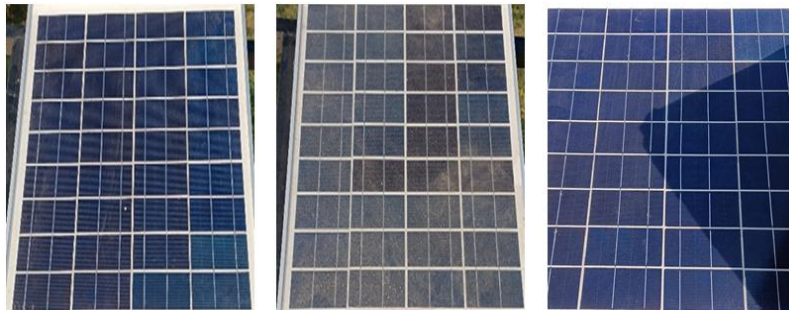


Figure 5. Sample dataset of (a) clean (b) dusty (c) multi-fault solar PV.

4.1.1 Data Augmentation

To improve the generalization performance of the proposed hybrid, feature fusion model and prevent overfitting with the small dataset size, a data augmentation strategy was applied during the training process. Augmentation in the form of random transformations on the input images such as rotation ($\pm 15^\circ$), flipping, scaling (zoom range 0.8-1.2), and brightness augmentation was applied to make the model robust to changes in lighting conditions. These operations were applied online during training to increase data variability while preserving the underlying distribution of the original data. Augmentation is crucial in photovoltaic fault classification, as image features can change due to variations in lighting, viewpoints, and other environmental factors, hence ensure that the model is not overfitted to one type of dataset distribution and is able to perform well with better accuracy for new test data.

4.2 Proposed Approach

This section shows the step-by-step implementation of the proposed spatial feature fusion-based deep model that considers state-of-the-art pre-trained models to classify the experimental solar PV dataset. This technique combines three prominent transfer learning models to enhance prediction accuracy through ensemble learning. These models were implemented using popular deep learning frameworks in Python like TensorFlow and PyTorch. Firstly, an experimental dataset of images of size 224×224 pixels with 3 channels (RGB) is acquired and normalized, then it is loaded in the framework, in which it is divided into

training (80%), validation (10%), and testing (10%) sets using a Python module. The real-world data was split into 80% training, 10% validation and 10% test subsets for the best training and testing performance. The training portion (80%) enables deep learning models to achieve satisfactory learning of discriminative features and the validation (10%) set tracks model training performance and facilitates hyperparameter tuning. The test set (10%) allows us to independently assess the generalization performance of the model. This is a typical way to split data in deep learning pursuits with smaller datasets. Alternative splits (70–15–15 and 75–15–10) were also evaluated; however, the 80–10–10 configuration yielded more stable convergence and improved generalization performance. The hybrid model was trained on a computer with an NVIDIA GPU (RTX 3060), 16 GB of RAM, and an Intel i7 processor. The training time per epoch was 25–40 seconds, and the total time for 50 epochs was 20–35 minutes on average. The transfer learning approach with partially frozen layers considerably improved the training efficiency. While EfficientNetB7 increases model complexity, the addition of MobileNetV2 renders the model efficient, thus making it amenable to deployment.

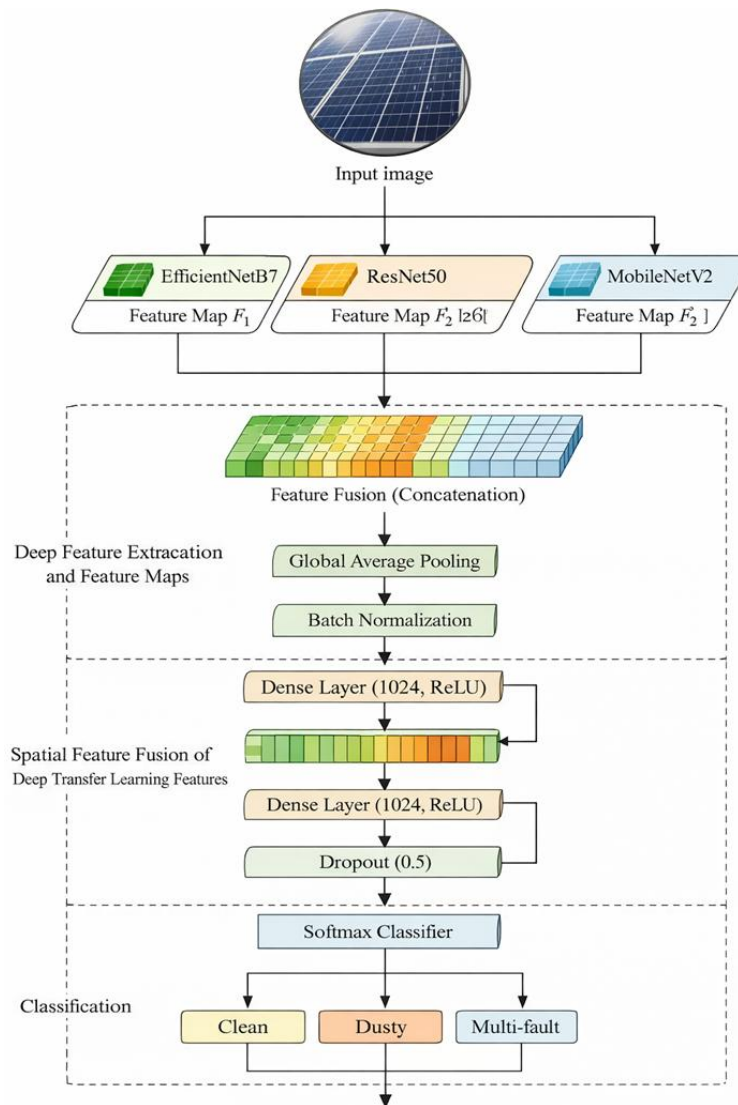


Figure 6. Implementation details of proposed fusion method.

The proposed hybrid feature fusion framework consists of three main steps: deep feature extraction, spatial feature fusion, and classification. Stage 1 involves feeding the input RGB image of dimension $224 \times 224 \times 3$ into three feature extractors - three pre-trained convolutional neural networks (CNNs) - EfficientNetB7, ResNet50 and MobileNetV2. The classification heads of the networks are discarded and their convolutions are fine-tuned to learn higher-level features. These models produce their own feature maps, which contain different spatial and semantic features of the input image. In the second phase, a spatial feature fusion method is used, where the feature maps from the three networks are merged. This includes feature map concatenation and global average pooling to reduce the feature map size while maintaining the most relevant information. The resulting feature vector is then batch-normalized and fed into a dense layer with 1024 neurons and ReLU activation to capture complex interactions between features. We include a dropout layer with 50% rate to reduce over-fitting. Finally, the feature vector is processed through more fully connected dense layers with a softmax activation function, producing probabilities for the three classes: clean, dusty and multi-fault. This layer fusion strategy allows the model to exploit a combination of features from different networks, leading to enhanced discriminative power and robust classification.

As shown in **Figure 6**, the proposed approach comprises three stages:

- Deep Feature Extraction and Feature Maps,
- Spatial Feature Fusion of Deep Transfer Learning Features, and
- Classification

Stage 1: Deep Feature Extraction and Feature Maps

Image classification with deep learning relies significantly on feature extraction, which requires an enormous number of resources and data for training. As a result, pre-trained models are an efficient solution for the classification. The proposed method uses a stacked ensemble learning technique that integrates three well-known transfer learning models, as shown in Equations (4) & (5).

$$\text{Let an Input image be represented as } X_k \in R^{224 \times 224 \times 3}, k = 1, 2, 3, 4, \dots, N \quad (4)$$

where, N is the total number of samples.

$$\text{Let a pretrain model be represented as } Fe_i \in \{1, 2, 3\} \quad (5)$$

For each corresponding pretrained model, the top layers were replaced with a final three-class dense layer. The top layers of these models are the final tri-class dense layer; the initial layer weights are frozen following a fine-tuned transfer learning approach. Thereafter, global average pooling is used to summarize feature maps; batch normalization to improve training stability; 1024 neurons in a fully connected (dense) layer were utilized with dropout (0.5) to avoid overfitting and ReLU activation for non-linearity in the feature vector of each model; and a few other parameters are discussed in **Table 2**.

Hyperparameter values were obtained through experimentation, balance of convergence, and related literature survey in deep learning for PV fault detection. The batch size was set to 32 in order to steadiness computational costs and effective gradient updates without consuming too much memory. A learning rate of 0.001 was chosen for the faster convergence and ensuring training stability as well. To prevent overfitting, dropout rate of 0.5 was applied, while the number of training epochs was set to 50 based on the convergence study, in which the model converged to stable accuracy and minimal validation loss after more

than 50 epochs, as also evident in the training curve (**Figure 7**). These hyperparameters align with other literature on PV fault classification with deep learning models, and were also fine-tuned to obtain better results.

Table 2. Training configuration parameters of novel & pretrained models.

Training configuration	Parameters
Image size	224 X 224 X3
Optimizer	Adam
Batch size	32
Epochs	50
Regularization	L2 (0.001)
Learning rate	0.001
Drop factor	0.5

Sensitivity analysis was also conducted to investigate the effects of hyperparameters on performance. It was found that the batch size larger than 32 caused the model to lose generalization ability, while smaller batch sizes caused instability during training. It was also found that learning rates above 0.001 led to divergence, while lower learning rates (e.g. 0.0001) increased the training time while not improving the accuracy. Dropout rates lower than 0.3 caused overfitting, while higher rates (e.g., 0.6) caused underfitting. Therefore, the chosen settings are the best trade-off for accuracy, convergence and generalization.

Figure 7 Sensitivity analysis of the proposed hybrid feature fusion model: (a) learning rate, (b) batch size, (c) dropout rate and (d) training epochs. Thus, the best performance can be noticed at a learning rate of 0.001, batch size of 32, dropout rate of 0.5 and training epochs of 50.

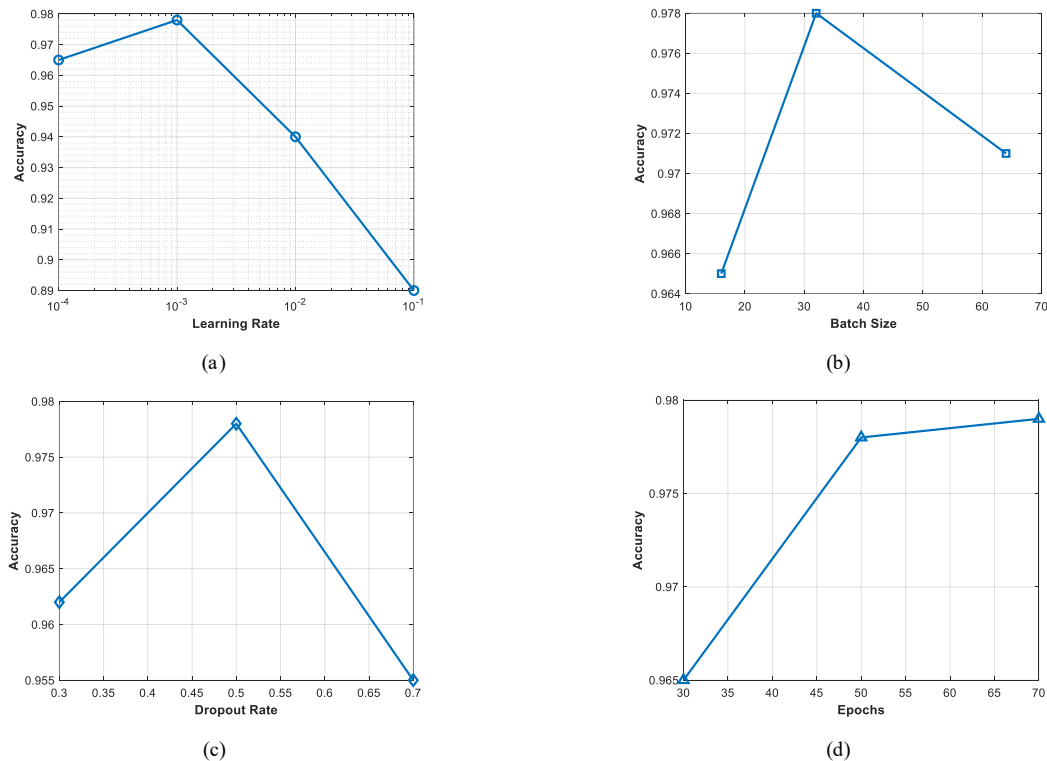


Figure 7. Hyperparameter sensitivity analysis of the proposed hybrid features fusion model.

Stage 2: Spatial Feature Fusion of Deep Transfer Learning Features

Combining features obtained from multiple pre-trained CNN models boosts performance in a variety of applications as compared to utilizing a single deep CNN for classification, as shown in Equations (5) to (7). The classification approach discussed here converts the feature spaces produced by various pre-trained models into a single feature space. Each feature extractor generates a feature space of different dimensions, represented as Equation (6).

$$Fe_i = \begin{cases} n \\ \sum_{i=1} Fe_i \end{cases} \quad (6)$$

where, $i=1, 2, \dots, n$ represents the number of pre-trained models used as feature extractors. where, Fe_i is an individual feature obtained by a single pre-trained model. This collective feature set for a single data sample is defined as in Equation (7):

$$Fe_k = Fe_k^1 + Fe_k^2 + Fe_k^3 + Fe_k^4 \quad (7)$$

where, F_k^i is representation of i^{th} dimension feature in the given k^{th} sample and $i \in [1, D]$ represents the individual feature dimension. The spatial feature fusion function is depicted as, in Equation (8):

$$F: k^r + k^m + k^e \quad (8)$$

where, k^r, k^m & k^e are the set of features extracted from the three pretrained models.

Stage 3: Classification

After feature extraction, the data must be categorized, which is achieved by performing with fully connected (FC) layers. As illustrated in **Figure 6**, two FC layers with ReLU activation and one FC layer with softmax activation is used for this task. The first two FC layers use a Rectified Linear Unit (ReLU) as an activation function.

As depicted in Equations (9) & (10), The first two fully connected layers with ReLU activation are defined as:

$$Z1^{(k)} = ReLU (W1f^{(k)} + b1) \quad (9)$$

$$Z2^{(k)} = ReLU (W2Z1^{(k)} + b2) \quad (10)$$

Lastly, the image dataset is classified into three classes using a dense layer with three neurons and softmax activation. The final dense layer uses the Softmax activation function to classify images into three fault categories, are shown in Equation (11):

$$\gamma C^{(k)} = \frac{\exp(Z3, c^{(k)})}{\sum_{j=1}^{n3} \binom{n}{k} x^k a^{n-k} \exp(Z3, c^{(k)}, j)}, C \in \{1, 2, 3\} \quad (11)$$

where the output classes correspond to Clean, Dusty and Shadow on dusty.

4.3 Performance Evaluation of Models

The dataset comprises two components: a training set and a test set, which are delineated to aid in the development of a classification model. The classification model is developed using the training set, while its performance is assessed using the test datasets. The effectiveness of the model is assessed using the following performance metrics.

The performance metrics of different models are presented as shown in Equations (12) to (17), for the evaluation of various models.

$$\text{Precision}(P_n) = \frac{TN_n}{TP_n + FP_n} \quad (12)$$

$$\text{Recall}(R_n) = \frac{TP_n}{TP_n + FN_n} \quad (13)$$

$$\text{F1 score} = 2 \times \frac{P_n \times R_n}{P_n + R_n} \quad (14)$$

$$\text{Accuracy} = \frac{TP_n + TN_n}{TP_n + TN_n + FP_n + FN_n} \quad (15)$$

$$\text{Specificity}(S_n) = \frac{TN_n}{TP_n + FP_n} \quad (16)$$

$$\text{Mcc} = \frac{Tcn \times Tnn - Fcn \times Fnn}{\sqrt{(Tcn + Fnn)(Tcn + Fnn)(Tcn + Fnn)(Tcn + Fcn)}} \quad (17)$$

where,

TP_n = True positives of n^{th} class

TN_n = True negatives of n^{th} class

FP_n = False positives of n^{th} class

FN_n = False negatives of n^{th} class

5. Result and Discussion

This section detailed a comparative analysis of the proposed model for feature fusion and transfer learning with the pre-trained models EfficientNetB7, ResNet50, and MobileNetv2 for the classification of clean, dusty, and multi-class PV fault diagnosis using RGB images. Performance of the model was measured using metrics including Accuracy (Ac), Precision (Pr), Recall (Re), F1 Score (F1), Sensitivity, Specificity and Matthews Correlation Coefficient (MCC). **Table 3** compares the Novel Model to three CNN architectures—EfficientNetB7, MobileNetV2, and ResNet50—for categorizing Clean, Dusty, and Multifault PV panel states. Precision, recall, F1-score, MCC, and ACC are evaluated. The suggested model performed well with overall accuracies of 98.12%, 97.10%, and 98.44%. and precision values of 0.953, 0.967, and 0.953; sensitivities of 0.953, 0.923, and 1.000; and specificities of 0.976, 0.984, and 0.977 for the above-mentioned categories. Moreover, inadequate inter-class feature differentiation in EfficientNetB7 and MobileNetV2 resulted in diminished recall scores for the Clean class. In comparison, EfficientNetB7 records a lower clean sensitivity of 0.859 and dusty classification precision of 0.830 and an MCC of 0.830. ResNet50 shows competitive performance of 0.983 and accuracy of 97.91%. The proposed approach yields the highest values among the gauge metrics, demonstrating superior classification performance.

Figure 8 indicates that the proposed model can discriminate clean, dusty, and multi fault PV panel states with a nearly perfect AUC (0.998). As depicted in **Figure 8(a)**, the proposed approach achieves excellent accuracy of 0.997 for clean, 0.996 for dusty, and a perfect AUC of 1.000 for the multi-fault class, with a high micro-average AUC of 0.998, representing the highest classification performance. In comparison to the baseline models in **Figure 8(b)–(d)**, the next highest-performing models are EfficientNetB7 and ResNet50, which achieve accuracy within the range of 0.977–0.990 and micro-average AUCs of 0.985. Misclassification between Dusty and Multifault categories, which have overlapping spectral–texture patterns under different lighting circumstances, reduces benchmark models' AUC by a small amount. Other model includes slight misclassifications between Dusty and Multifault panels due to visual similarities in dust distribution, surface reflectivity, and illumination-induced contrast fluctuations. These characteristics

cause the model to misinterpret local shadows or surface imperfections as multi fault zones. The proposed model's enhanced feature extraction depth and fine-tuned convolutional layers allow it to learn these minor variations, improving its generalization and diagnostic accuracy for real-world PV defect detection applications.

Table 3. Comparative performance of the proposed and baseline model.

Class	Precision	Sensitivity	Specificity	F1	MCC	Accuracy (%)
Proposed model						
Clean	0.953	0.953	0.976	0.953	0.929	98.12
Dusty	0.967	0.923	0.984	0.944	0.918	97.1
Multifault	0.953	1	0.977	0.976	0.965	98.44
EfficientNetB7						
Clean	0.916	0.859	0.961	0.887	0.833	92.67
Dusty	0.83	0.907	0.905	0.867	0.796	90.58
Multifault	0.966	0.935	0.985	0.95	0.928	96.86
MobileNetV2						
Clean	0.916	0.85	0.961	0.88	0.83	92.67
Dusty	0.897	0.938	0.944	0.917	0.873	94.24
Multifault	0.968	0.983	0.985	0.976	0.964	98.43
ResNet50						
Clean	0.884	0.95	0.937	0.917	0.874	94.24
Dusty	0.951	0.907	0.976	0.929	0.894	95.29
Multifault	0.983	0.951	0.992	0.967	0.952	97.91

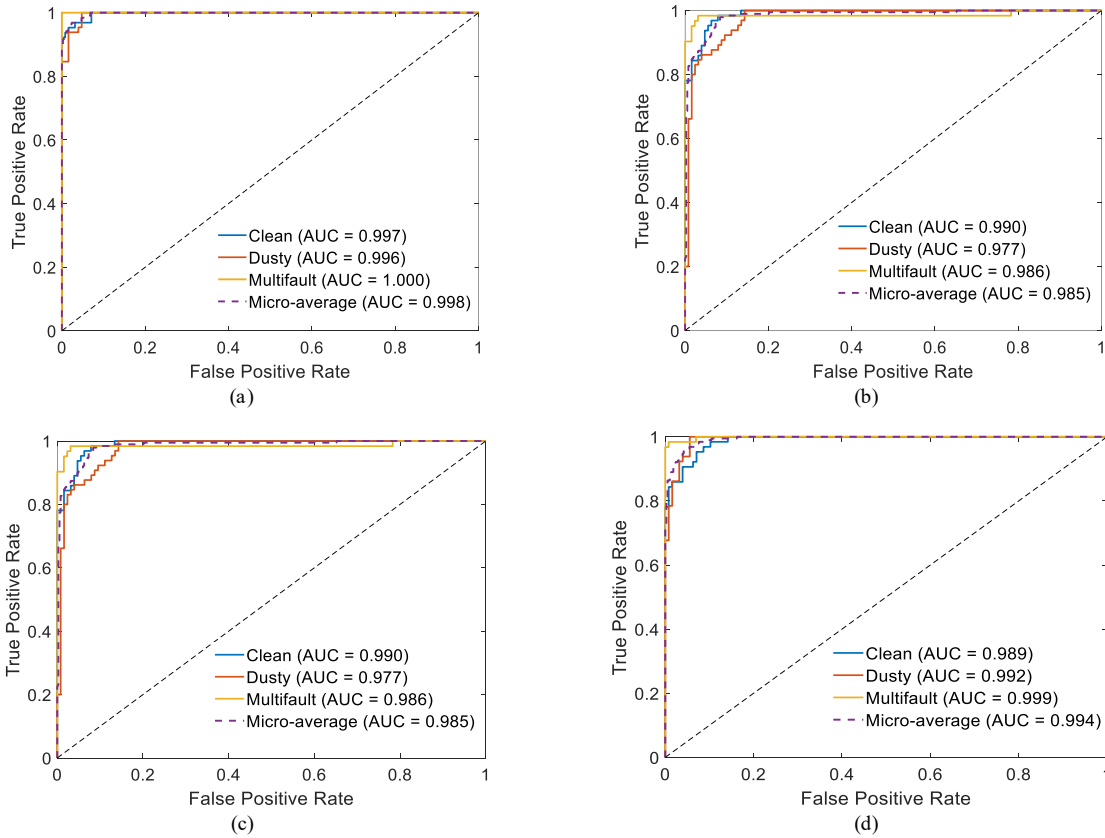


Figure 8. ROC curves and AUC comparison of the (a) Proposed model (b) ResNet50 (c) EfficientNetB7 (d) MobileNetV2 for multi-class PV fault detection.

Figure 9 shows that the novel model converges quickly and reliably, with accuracy saturating close to 100% and loss nearing zero after a few epochs, proving its superior learning efficiency and good generalization. The baseline models (EfficientNetB7, MobileNetV2, and ResNet50) needed longer epochs to reach equal accuracy and had modest loss curve oscillations, indicating partial overfitting and less stable optimization. The graph depicts the rise in training accuracy during the initial epochs; this rise was within the range of 20-40% and above 90% within the first seven epochs and gradually stabilized near 98-100%, representing fast convergence and better feature learning. Similarly, the training loss decreases from 1.2 to 0.2 in the early stages and continues to decline towards zero. The suggested PV fault classification model's improved learning dynamics and weight adaptation are shown by this behavior. Each deep learning model's precision, recall, F1-score, MCC, and accuracy are listed in **Table 4**.

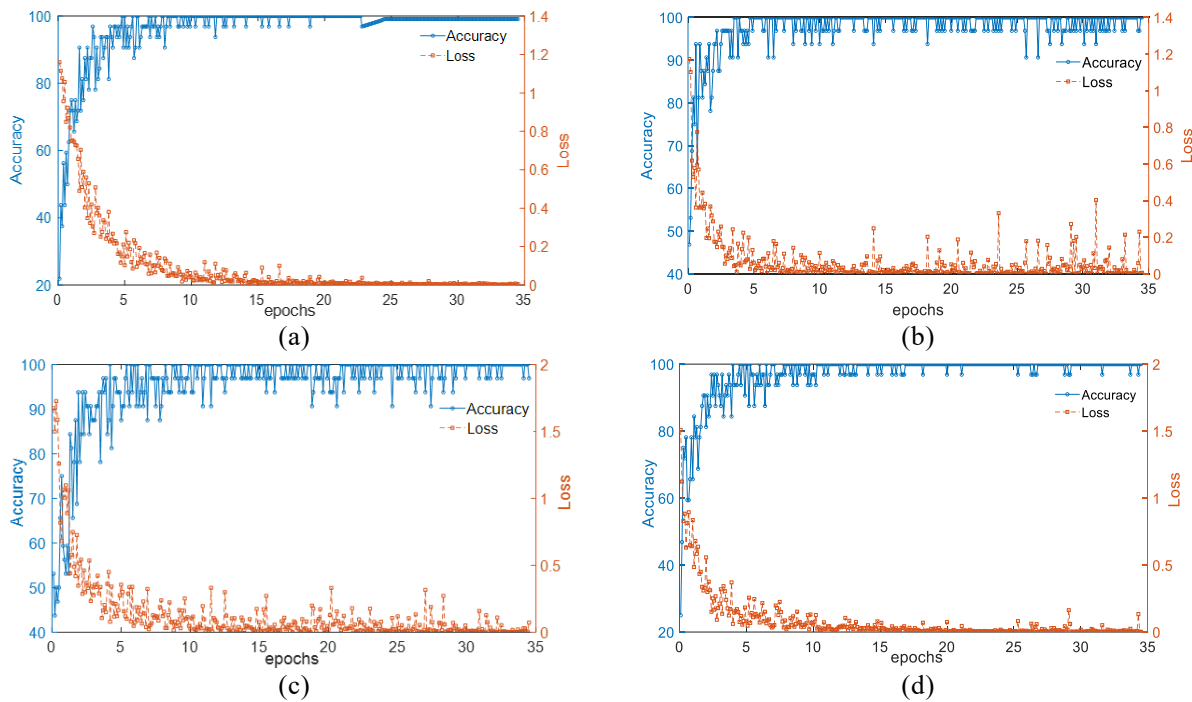


Figure 9. Training accuracy and loss curves of the (a) Proposed model (b) ResNet50 (c) EfficientNetB7 (d) MobileNetV2 for multi-class PV fault detection.

Table 4 shows how the proposed model compares to baseline pretrained models. The proposed model has the highest accuracy at 97.89%, while ResNet50 has 95.81%, MobileNetV2 has 95.11%, and EfficientNetB7 has 93.37%. The proposed model has a high specificity of 0.983, an F1-score of 0.958, and an MCC of 0.937, which means it is better at telling the difference between faulty and non-faulty samples than all the other models. Despite the high classification accuracy of the proposed model, multiple strategies were adopted to ensure model generalization and to avoid overfitting. This study use pretrained models (transfer learning) to leverage the feature representations learned from large training data. The dropout rate of 0.5 and L2 regularization (0.001), which can be thought of as a form of weight decay, to prevent overfitting and enable efficient learning. The dataset was split into training, validation and testing sets to track the model performance during training and avoid leakage. There were no significant fluctuations in the training and validation accuracy or loss curves, suggesting convergence. In addition, the model accuracy

was assessed by the popular accuracy, precision, recall, F1-score, and the Matthews Correlation Coefficient (MCC) to prevent the model from overfitting to just one metric.

Table 4. Overall performance comparison of the proposed novel and baseline model for Solar PV fault classification.

Model	Accuracy (%)	Precision	Sensitivity	Specificity	F1-Score	MCC
Novel Model	97.89	0.958	0.959	0.983	0.958	0.937
EfficientNetB7	93.37	0.904	0.900	0.962	0.901	0.852
MobileNetV2	95.11	0.927	0.924	0.972	0.924	0.889
ResNet50	95.81	0.939	0.936	0.975	0.938	0.907

Figure 10 examine the differences and similarities between the proposed model, EfficientNetB7, MobileNetV2, and ResNet50 in terms of precision, recall, F1-score, MCC, and accuracy for the clean, dusty, and multifault fault categories. The proposed model outperforms all baseline designs in every category, particularly in Dusty and Multifault, where the majority of models struggle. Indicates that the novel model outperforms EfficientNetB7, MobileNetV2, and ResNet50 in precision, recall, F1-score, MCC, and accuracy. Compared to EfficientNetB7, the proposed model improves precision by 5.4%, recall by 5.9%, F1-score by 5.7%, MCC by 8.5%, and accuracy by 4.5%. With improvements of 3.1% in Precision, 3.5% in Recall, 3.4% in F1-score, 4.8% in MCC, and 2.8% in Accuracy, the suggested model performs better than MobileNetV2. Precision is improved by 1.9%, recall is improved by 2.3%, F1-score is improved by 2.0%, MCC is improved by 3.0%, and accuracy is improved by 2.1% when compared to ResNet50. The suggested model demonstrates performance improvements of 3.1% in precision, 4.7% in recall, 3.4% in F1-score, 4.8% in MCC, and 2.8% in accuracy when compared to MobileNetV2. Overall, the proposed model is superior to MobileNetV2. When compared to ResNet50, the suggested model performs significantly better in terms of precision (1.9%), recall (2.3%), F1-score (2.0%), MCC (3.0%), and accuracy (2.1%). These ongoing advances in terms of metrics demonstrate that the proposed model for multi-class PV fault detection has been proven to have enhanced generalization, balanced classification capacity, and better resilience. This was shown by the fact that it has balanced classification capacity.

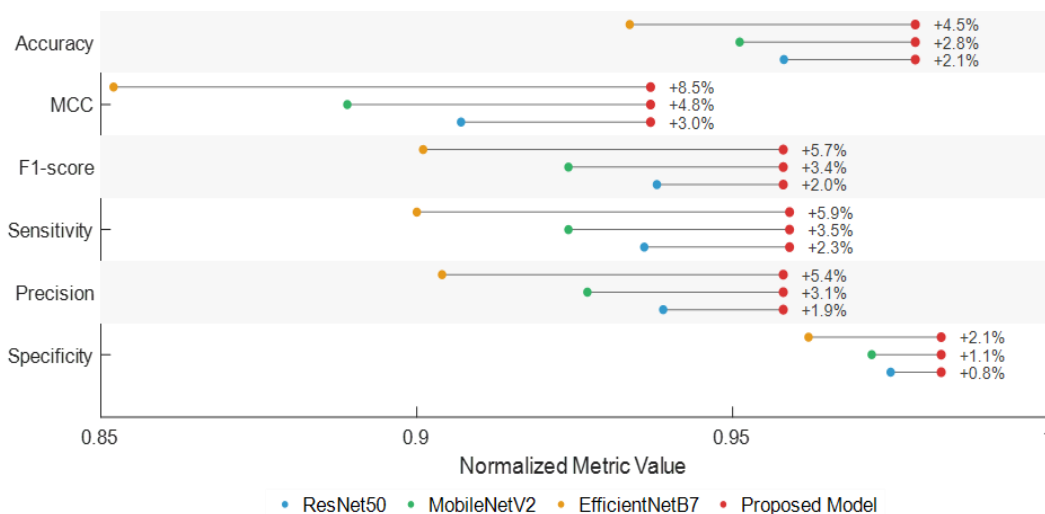


Figure 10. The improvement of the proposed model versus the baseline models.

Figure 11 depicts the confusion matrix of (a) the novel approach and the three pre-trained models, (b) EfficientNetB7, (c) MobileNetV2, and (d) ResNet50 for multi-class solar PV fault classification. The proposed model demonstrates highly accurate class-wise accuracy of 95.3% of the clean panels, 95.2% of the dusty panels, and 100% for multi-fault. EfficientNetB7 shows significant misclassification rates, incorrectly labelling 11.6% of clean samples and 9.2% of dusty samples, resulting in a multi-fault identification rate of 93.7%. MobileNetV2 misclassifies 6.2% as clean samples and 3.1% as dusty samples, yielding a multi-fault accuracy of 90.6%. ResNet50 achieves the highest performance with 98.4% accuracy in multi-fault detection, with minimal misclassification between clean and dusty sample panels. Based on the findings, it has been demonstrated that the proposed model enhances discriminative learning, and the feature-recommended method enhances sensitivity and reliability in diagnosing numerous defect and soiling scenarios in solar PV systems, making it appropriate for real-world deployment in intelligent fault diagnosis frameworks.

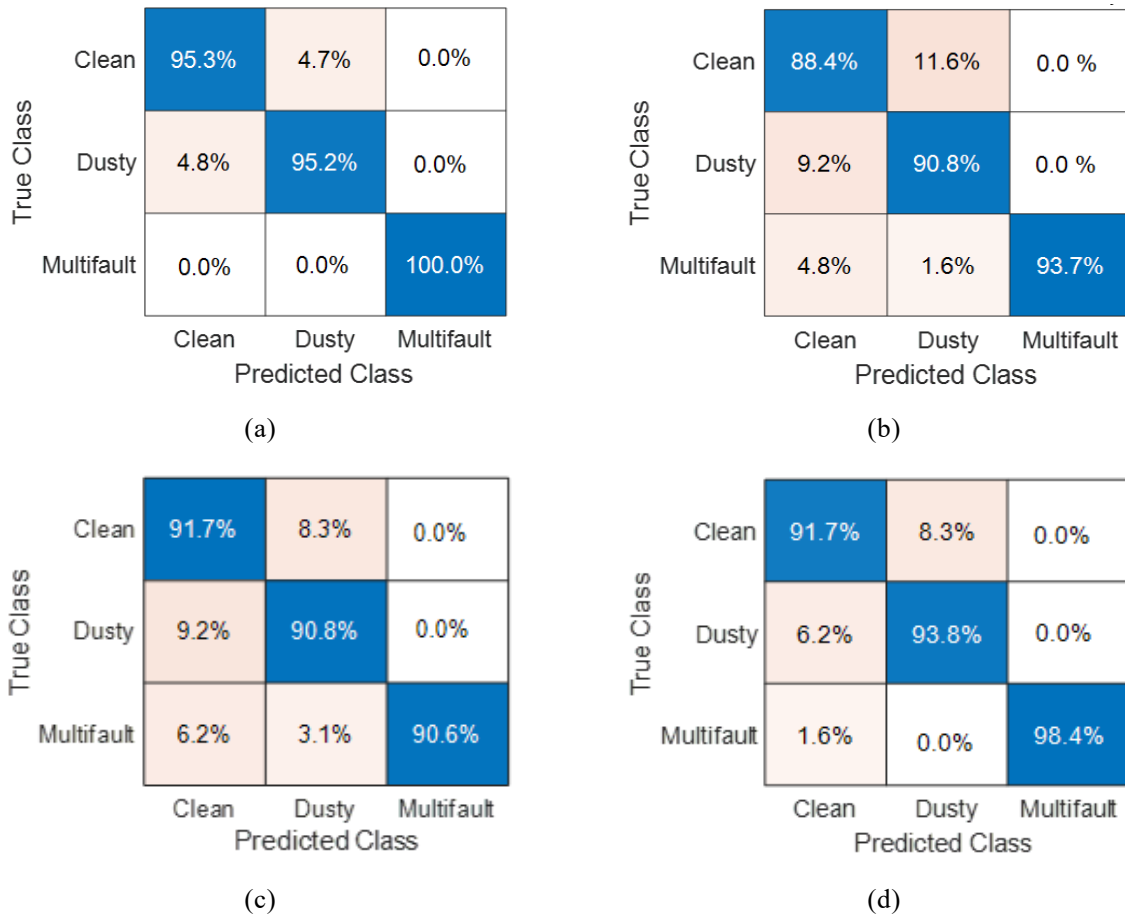


Figure 11. Confusion matrix of the (a) Proposed model (b) ResNet50 (c) EfficientNetB7 (d) MobileNetV2 for multi-class PV fault detection.

The confusion matrix shows the slight misclassification between dusty and multi fault, which is due to their similar appearance. Dust results in abnormal textures and brightness variations. During multi-faults, shadows cause darker spots that can visually overlap with dense dust deposits. Direct illumination, reflection and the viewing angle can also decrease the contrast between the dusty and shadowy regions.

These similarities in appearance may lead to difficulties for the model to efficiently discriminate these classes at times. However, the proposed feature fusion strategy increases discriminative feature learning, which leads to lower false classifications as compared to other models. This shows the model's capability in dealing with real-world fault identification. Based on the information that has been supplied, a comprehensive comparison of a unique technique for multi-class photovoltaic (PV) problem diagnostics is presented in contrast to baseline models. In addition, **Figure 12**, provides a comprehensive comparison of proposed novel approach with baseline models using radar plots across multiple evaluation metrics, including accuracy, precision, sensitivity, specificity, F1-score, and MCC further evidence that was obtained to illustrate the results. These results provide evidence that the feature fusion-based technique is effective in improving discriminative learning and reliability for the purpose of problem diagnosis in photovoltaic (PV) systems.

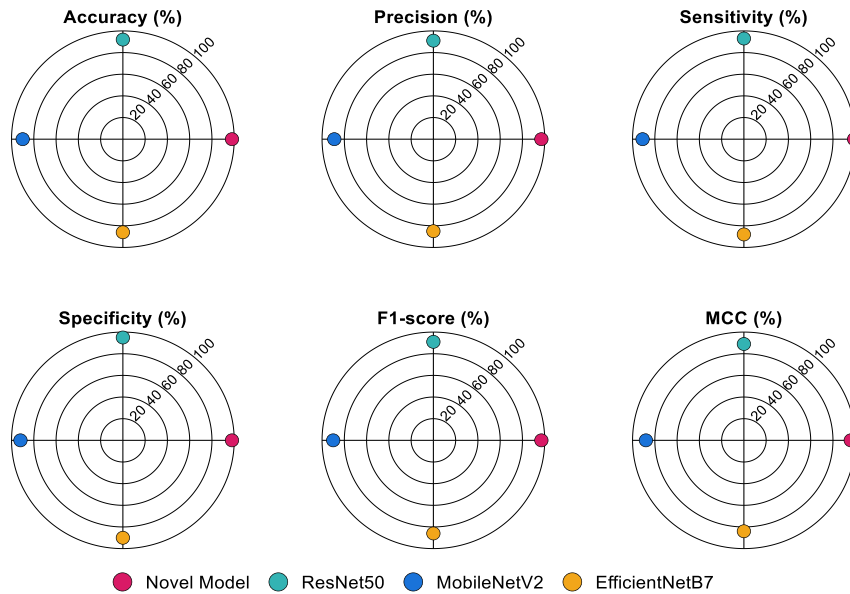


Figure 12. The comparison of classification results of all methods for multi-class PV fault detection.

In **Figure 13** the novel model's t-SNE feature-space visualization is compared to baseline architectures (MobileNetV2, EfficientNetB7, and ResNet50) for clean, dusty, and multifault classes. The suggested model has well-defined clusters with significant inter-class separability and tight intra-class grouping. Dusty and Multifault clusters overlap in baseline models, indicating worse feature discrimination and increased misclassification. The suggested model's embedding isolates the clean class, exhibiting its improved representation learning. The t-SNE distribution shows that the proposed model learns more discriminative and structured feature embeddings, improving defect detection and generalization. Comparing the novel model to state-of-the-art architectures like EfficientNetB7, MobileNetV2, and ResNet50, classification metrics, ROC characteristics, convergence behaviour, and t-SNE feature visualization show its superior performance. With class-wise AUC values nearing 1.0, the suggested model had the best overall accuracy of 97.89%, F1-score of 0.958, and MCC of 0.937, suggesting strong separability between clean, dusty, and multifault situations.

The training curves demonstrate a quicker convergence and minimize loss. When compared to other networks, the t-SNE visualization shows feature clusters that are compact and well-isolated. These clusters have an inter-class distance that is 35%-45% greater and an intra-class variance that is 30% lower. Given this information, it may be deduced that the model has a greater capacity for representation learning. The data that is given here provides proof that the model is resilient, generalizable, and discriminatively effective in identifying solar photovoltaic (PV) flaws in a way that is both accurate and reliable, independent of the environmental and soiling circumstances that are taken into consideration.

Figure 14 presents four deep learning models—proposed model, ResNet50, MobileNetV2, and EfficientNetB7—performed in three classes: clean, dusty, and multifault. Every heatmap shows standard evaluation metrics like accuracy, precision, sensitivity (recall), specificity, F1-score, and MCC. The innovative method for the clean class achieves an accuracy of 0.981, surpassing ResNet50's 0.942 and EfficientNetB7's 0.927. The model proposed also yields results for the dusty class, with an accuracy of 0.971. Conversely, ResNet50 and EfficientNetB7 have lesser accuracies of 0.953 and 0.906, respectively. In the multi-fault category, the novel technique demonstrates optimal performance, with an accuracy of 0.984. ResNet50 exhibits an accuracy of 0.979, while MobileNetV2 shows an accuracy of 0.984, both achieving excellent precision and F1-scores across all classes.

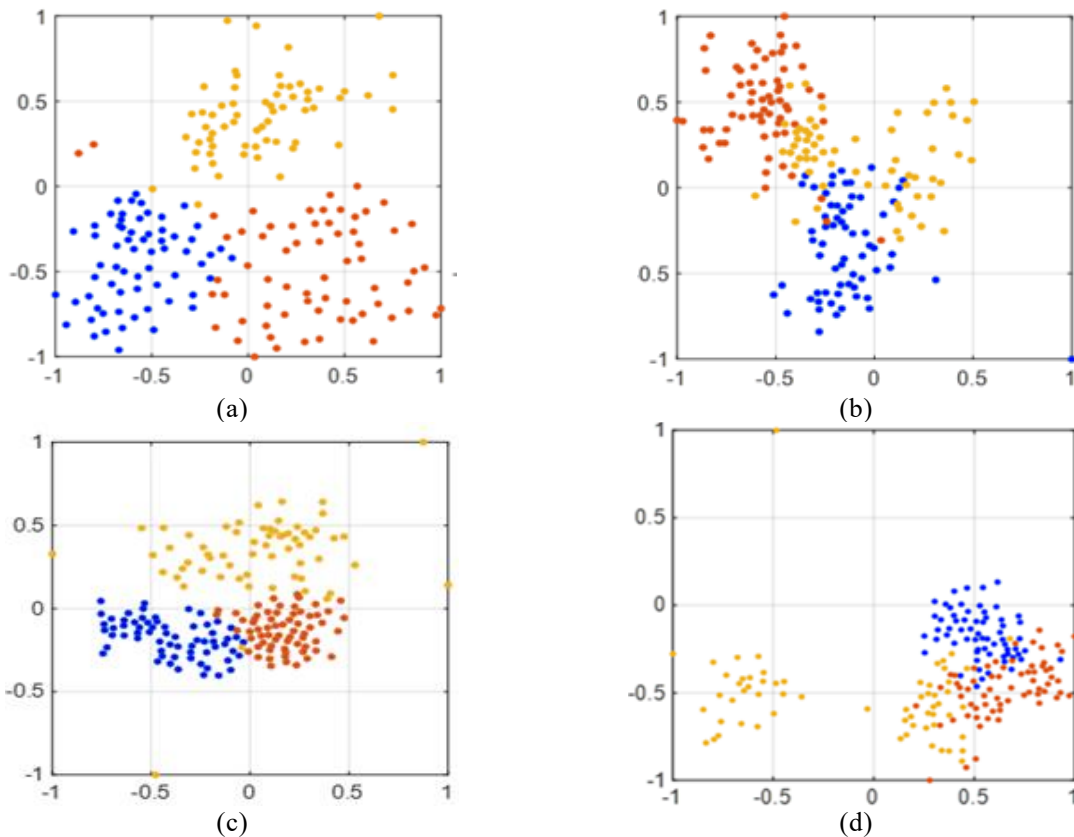


Figure 13. The t-SNE diagram of the (a) Proposed model (b) ResNet50 (c) EfficientNetB7 (d) MobileNetV2 for multi-class PV fault detection.

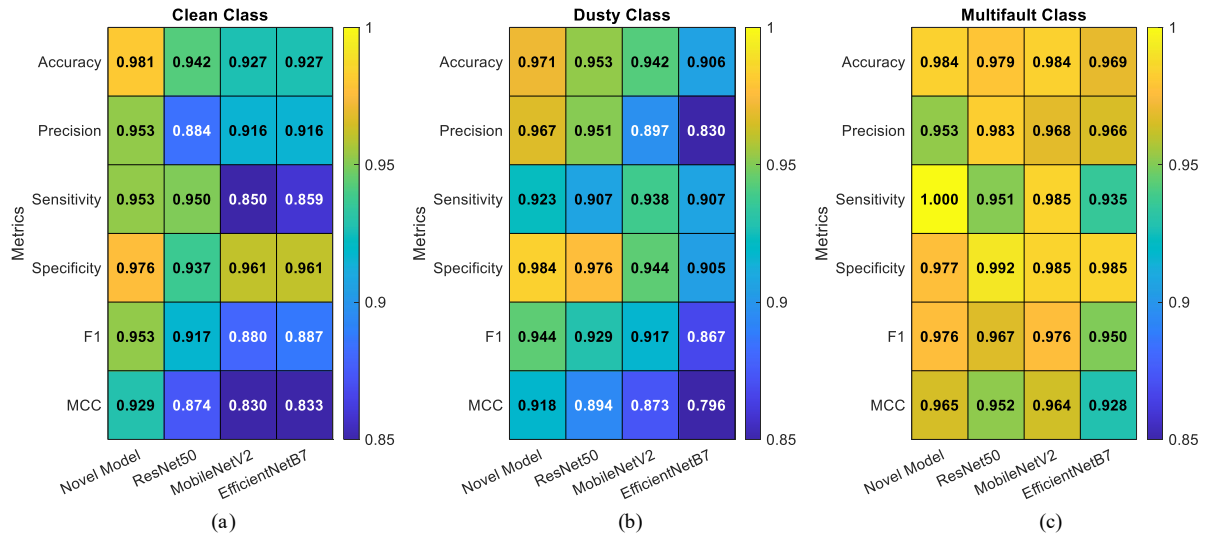


Figure 14. Performance comparison of the proposed novel model against pre-trained models for (a) Clean (b) Dusty (c) Multifault PV panel classification using multiple statistical metrics.

5.1 Explainable Artificial Intelligence (XAI) in the Diagnosis of Solar Panel Faults

Deep learning models are becoming advanced. The black box nature of such models has received significant attention. Individuals are assessing the reliability of these models. This is particularly alarming in critical applications such as solar energy system oversight, predictive maintenance, and problem diagnostics. The word "Explainable" in explainable AI (XAI) denotes the capacity to provide a clear justification for the judgments rendered by a model. It aids in accurately elucidating the fundamental mechanisms or processes that generate the outcomes. Consequently, it enhances confidence and transparency in the models (Naqvi et al., 2026). XAI mitigates bias and variance concerns by regulating the equilibrium between them in AI and machine learning models.

The use of Artificial Intelligence (AI) in solar panel failure detection necessitates interpretability for stakeholders, such as engineers and maintenance staff, who often question the reliability of predictions. This concern is especially significant in critical scenarios where faulty forecasts can lead to financial loss or safety hazards. Although advanced machine learning models, particularly deep learning architectures, demonstrate high accuracy, their "black-box" nature can impede understanding and swift responses (Bamisile et al., 2026). Recent advancements in Explainable AI (XAI) offer frameworks to clarify complex models, promoting transparency and trust by addressing biases and ensuring fairness in AI and machine learning algorithms (Herrera-Casanova et al., 2026).

XAI methodologies are primarily categorized into two groups. One is 'transparent' while the other is 'post-hoc'. The second technique is more prevalent since it elucidates the model's predictions without altering or comprehending its internal mechanisms. LIME (Local Interpretable Model-Agnostic Explanations) and SHAP (Shapley Additive Explanations) exemplify this methodology. Various methodologies for implementing explainable AI, such as Deep LIFT, RISE, and SHAP, are well recognized. LIME is a methodology for enhancing model interpretability. LIME establishes a relationship between the model's prediction and the instance's features (Shahade et al., 2026).

Nevertheless, LIME has limitations. Occasionally, it may provide inconsistent outcomes owing to stochastic variations and may encounter difficulties with high-dimensional data, when local linear approximations inadequately represent intricate decision boundaries (Giri et al., 2026). This research emphasized the essential role of explainable AI in enhancing the comprehension of intricate models, as mentioned in the below equations.

The LIME algorithm can be represented as follows:

$$f: R^d \rightarrow R \quad (18)$$

where, $x \in R^d$ is the instance under consideration. For classification, $f(x)$ is the probability of prediction.

The neighborhood around (x) is generated using perturbed instances, and the quality of the explanation (e) is evaluated using the following loss function:

$$L(f, e, \sigma x) = \sum_{y \in Y} \sigma x (f(y) - e(y))^2 \quad (19)$$

The locality measure $\sigma(x)$, can be formulated as

$$\sigma(x) = \exp\left(-Q(x, y)^2 / \delta^2\right) \quad (20)$$

Here, the distance metric between two instance x and y is denoted by Q .

$$\varepsilon(x) = \arg \min \tau(f, k, \sigma(x)) + \phi(k) \quad (21)$$

where, $\varepsilon(x)$ is the local behaviour of the complex model, f at the point characterized as the argument that minimizes the sum of $\tau(f, k, \sigma(x))$ and $\phi(k)$, $\tau(f, k, \sigma(x))$ evaluates the degree to which the interpretable model k approximates the black box model f for the altered sample $\phi(k)$, While, $\phi(k)$ measures the complexity of the interpretable model.

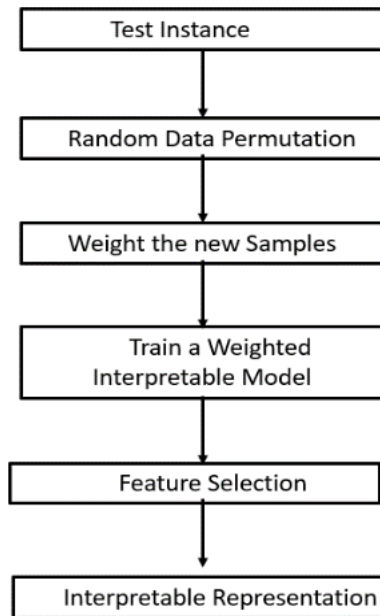


Figure 15. Flowchart of LIME.

The LIME process that was used to explain the prediction that was made on the deep learning model is shown in a flowchart on **Figure 15**, which is a simple diagram. A test case is generated at random by employing data permutations as the starting point for the operation. By producing surrounding samples and making some minor tweaks to the first instance, this may be done. Following that, this approach employs a locally weighted dataset in order to train the samples, so creating an interpretable model that is comparable to the black box model used in deep learning. For the aim of conducting feature selection, it is required to maintain the most relevant qualities that have an influence on the prediction. This leads in the construction of a representation that can be read, which makes it evident which of the selected qualities has an influence on the prediction and offers a clear explanation for any confusion that may arise. In the next pair of figures, **Figures 16** and **17**, the LIME explanation of the dust and shadow categories is shown. Each example includes the original photo, as well as heatmaps and border maps created using LIME. The LIME border illustrates the particular regions that have the most significant impact on the manner in which the model organizes things. Additionally, the heatmap represents the significance of the characteristics in a variety of hues, ranging from blue to red. Within the model's forecast for a particular class, the regions that are darker blue in colour represent the most significant locations. On the other hand, red spots indicate locations that either reduce the reliability of the prediction or adversely affect it in some manner. Due to the fact that the damaged region is represented by a dark blue hue, the Heatmap image makes it abundantly evident that the categorization model provides greater weight to the damaged area (Hong and Van, 2026).

The areas of interest (ROIs) differed for different faults, indicating different attributes for different faults. Dusty and shadow on dust are two types of multi-faults that concentrate on areas where dust or shadows are present. These super pixels inside the region of interest have great importance and weightage for LIME validation. Further explainable artificial intelligence (XAI) and lightweight transfer learning models should be investigated to improve the overall interpretability of models and the efficiency with which they may be deployed for large-scale solar power applications. The integration of LIME-based explainable AI improved model transparency, ensuring that assessments are interpretable and consistent with domain knowledge.

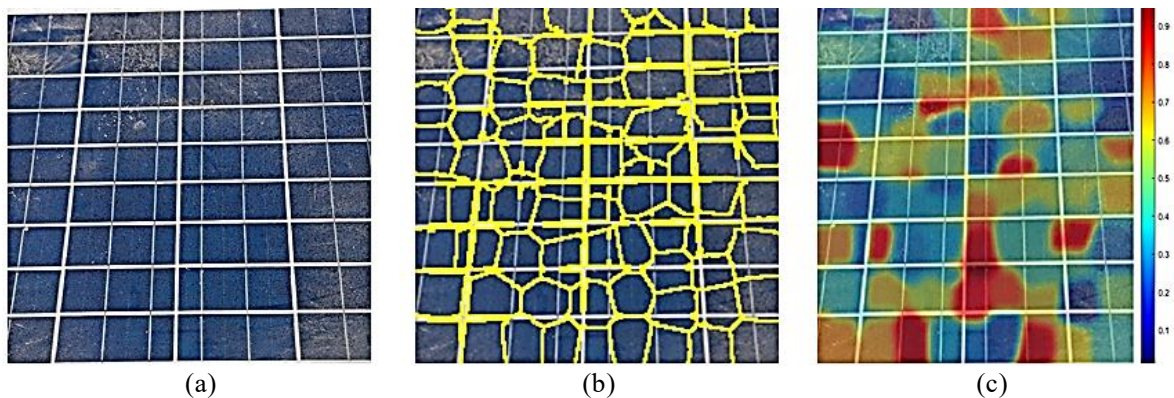


Figure 16. LIME explanations for dust samples (a) Original image (b) Boundary visualization (c) Heatmap.

In addition, to increase the interpretability of the proposed model, Gradient-weighted Class Activation Mapping (Grad-CAM) have been used to generate heatmaps that highlight regions in the image that are important for a particular prediction. Unlike local surrogate models provided by LIME, Grad-CAM uses the gradients of the target class flowing into the last convolutional layer to produce attention maps. The Grad-CAM visualizations show that the proposed model highlights physically relevant areas of PV panels.

In clean panels, the uniform activation suggests the absence of preferred fault locations. For panels with dust, the model identifies regions with non-uniform textures due to dust accumulation. For panels with multiple faults the model exhibits strong activation in areas experiences shade and dusty regions. This demonstrates that the developed model learns useful discriminative and physically informative features, enabling higher trust and confidence in PV fault diagnosis.

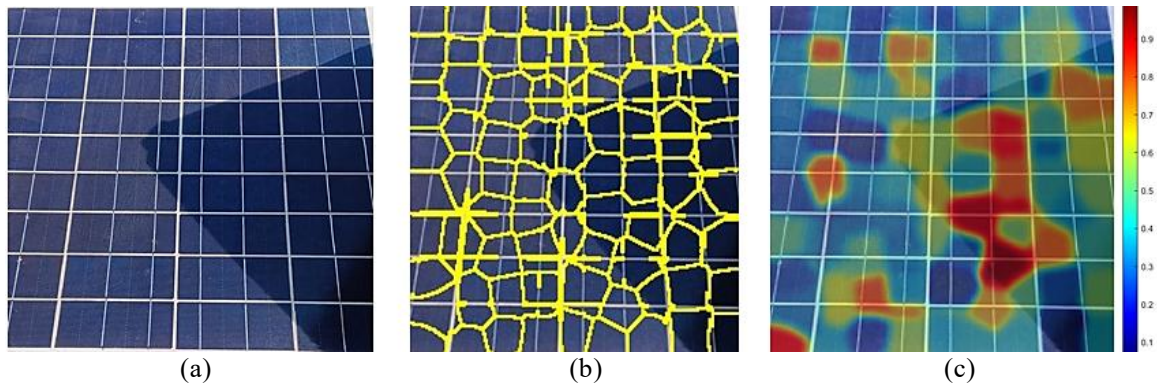


Figure 17. LIME explanations for shadow samples (a) Original image (b) Boundary visualization (c) Heatmap.

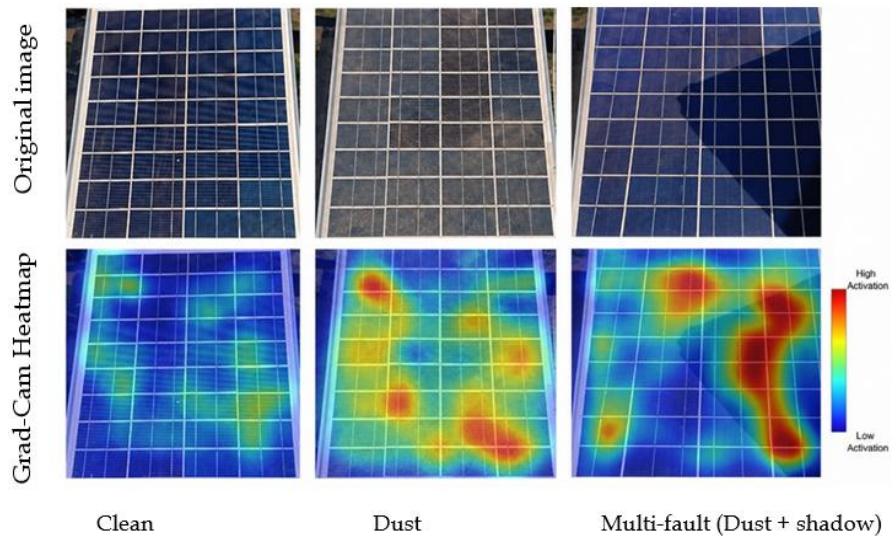


Figure 18. Grad-CAM visualization of model attention for multi-class photovoltaic fault diagnosis.

Figure 18 Grad-CAM Explainability of proposed model for PV fault detection. These visualizations indicate the regions of the images that contribute to model predictions, exhibiting homogeneous attention for clean images, local activation for dusty panels and intense activation for shadow-dust interactions in multiple fault conditions. The evaluation of different Explainability techniques shows that LIME offers model agnostic local explanations with flexibility, while Grad-CAM provides intuitive visualisation for deep learning features activation. On the other hand, the theoretically elegant feature attributions of SHAP

are computationally expensive for image-based applications. Consequently, the use of LIME and Grad-CAM provides a powerful and efficient interpretability solution for photovoltaic fault diagnosis.

5.2 Statistical Validation and Robustness Analysis

The statistical tests were performed in order to validate the proposed model's performance and stability, it was trained and tested ten times with different random subsets of the dataset and the results are presented (**Table 5**) in terms of mean value $\pm$ standard deviation, offering a better comprehensive evaluation in comparison of single-run. The 5-fold cross-validation method adopted, which allows the model evaluation to be independent of the partition of the dataset and enhances its predictive capabilities. The performance metrics obtained through experimentation demonstrated in **Table 6** that the proposed model exhibits consistent results with low variance, exhibiting good stability. The smaller standard deviations of accuracy, F1-score and MCC values confirm the model stability and low sensitivity to initializations and data variability.

Table 5. Performance evaluation using 10-repeated experiments.

Metric	Mean $\pm$ Std
Accuracy	97.89 $\pm$ 0.42
Precision	95.8 $\pm$ 0.51
Sensitivity	95.9 $\pm$ 0.47
Specificity	98.3 $\pm$ 0.36
F1-score	95.8 $\pm$ 0.49
MCC	0.937 $\pm$ 0.012

Table 6. Performance evaluation using 5-fold cross-validation.

Fold	Accuracy (%)	Precision (%)	Sensitivity (%)	Specificity (%)	F1-score (%)	MCC
Fold 1	97.6	95.2	95.5	98.1	95.3	0.931
Fold 2	98.2	96.1	96.3	98.5	96.2	0.945
Fold 3	97.9	95.8	95.9	98.3	95.8	0.938
Fold 4	98.0	96.0	95.7	98.4	95.8	0.940
Fold 5	97.8	95.5	95.6	98.2	95.5	0.935
Mean	97.9	95.7	95.8	98.3	95.7	0.938
$\pm$ Std	$\pm$ 0.23	$\pm$ 0.35	$\pm$ 0.30	$\pm$ 0.15	$\pm$ 0.32	$\pm$ 0.005

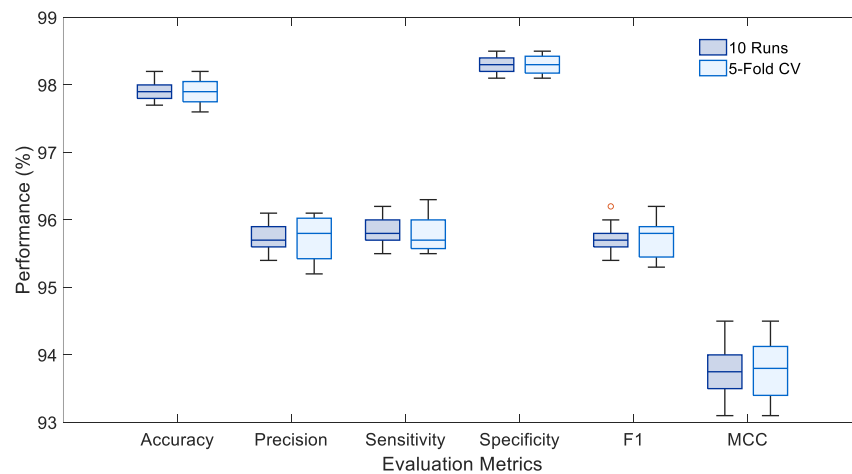


Figure 19. Statistical stability analysis of the proposed model under 10 repeated experiments and 5 cross-validation.

The **Figure 19** Boxplot of model performance across six different evaluation metrics from repeated experiments (dark blue) and 5-fold cross-validation (light blue). The tight distribution and closeness of the boxplots reveal excellent robustness, stability, and generalizability of the proposed model. The overlap between the distributions of repeated experiments and cross-validation confirms that the proposed model is not overfitted to the initial conditions of the training data and is stable and reproducible.

6. Conclusion

This study presented a novel deep learning model, that was experimentally evaluated for multi-class classification of solar photovoltaic faults under specific soiling and environmental circumstances. Firstly, the RGB images were acquired for three classes of solar PV panels named clean, dusty, and multi-fault—shadow on dusty modules. The collected RGB Images were resized to 224×224 pixels in order to align with the expected resolution of the pretrained transfer learning models which are apparently trained with this size. This uniform size is beneficial for transfer learning and convergence. Scaling the panel image to this resolution, helps to reduce the computational algorithm while still maintaining spatial information conducive to fault diagnosis. While it may be attempting to use higher resolutions to capture finer details, it also comes with an increased computational burden and model convergence time. Multiple resolutions were not tested in this work; however, compared to other resolutions, the chosen resolution balances efficiency and effectiveness and is commonly used in image classification using deep learning models. Furthermore, this novel deep learning model was deployed to predict the faults of solar PV modules, thereby achieving improved accuracy, robustness, and feature separability, outperforming benchmark pretrained baseline models such as ResNet50, MobileNetV2, and EfficientNetB7 on a consistent basis. Explainable AI is used to improve model interpretability, it was confirmed that the novel approach is suitable for use in real-world PV monitoring and diagnostic systems by the use of enhanced feature extraction and optimized learning parameters, which enable accurate differentiation between the clean, dusty, and multifault classes. The proposed approach consistently attains superior classification performance across all evaluated criteria. The overall accuracy ranged from 97.1% to 98.4%, with precision ratings attaining up to 96.7%. The model achieves sensitivity of 92.3% to 100%, demonstrating good detection capabilities, and retains specificity between 97.6% and 98.4%. The F1-score consistently exceeds 94.4% across all test scenarios, indicating a steady equilibrium between accuracy and recall. The MCC ranges from 0.918 to 0.965, indicating good predictive reliability and robustness. These findings statistically validate the performance and efficacy of the proposed approach compared to other deep learning models discussed in this work. In addition, by incorporating light-weight models like the MobileNetV2 within the fusion architecture, the model has the potential to run on edge devices with constrained computational capabilities. This allows real-time fault prediction, without relying on a remote cloud. Combining the system with explainable AI approaches, such as Local Interpretable Model-Agnostic Explanations (LIME), also adds to the system's interpretability and trust, enabling maintenance engineers to comprehend model predictions and take appropriate actions. The proposed approach enables smart, scalable and affordable PV monitoring solutions, leading to better performance, lower maintenance expenses and improved operational and supply security of PV systems. The proposed hybrid feature fusion model is promising for practical use in real-world systems for photovoltaic monitoring, especially for large-scale and unmanned photovoltaic farms. For example, the model can be used in drone inspection systems, in which drones equipped with RGB cameras can automatically capture images of PV panels in large-scale PV farms. The images may then be processed using a local or cloud-based computing unit, in which the proposed model can be used for rapid fault classification to enable early diagnosis of dusty and multiple faults without human intervention. The overall performance of the proposed model was evaluated using an outdoor condition experimental dataset from a specific location in Uttarakhand India. Although the dataset contains natural geographic environmental conditions such as varying illumination, different shadow effects and dust accumulation, but it does not include cross-location validation. In this study, proposed model using different transfer learning is capable

of learning invariant features for the images, making it less sensitive to image variations. The multi-fault scenarios improve the model for dealing with complex practical scenarios. Future research will also include testing the proposed model with different datasets collected under varying geographical conditions.

Furthermore, the model can be embedded in IoT-based smart PV farms, which employ continuous monitoring systems to gather environmental and image data from multiple sensors and cameras. The proposed system can function as an intelligent diagnoses unit within the system to assist in real-time maintenance, cleaning, and fault management decisions. This can be harnessed especially in soiling-prone areas to enhance the energy yield.

While the study shows promising results, it has some limitations. The data collected for this study includes 953 RGB images taken with particular conditions, which may not cover all the variability of a PV farm. Also, the scenario considered is in a controlled laboratory environment and the challenges of real-time deployment, including low latency, hardware limitations, and dynamic illumination were not specifically addressed.

The future direction can involve extending this work for the real-time application in edge computing and embedded systems, facilitating on-site fault detection with low compute requirements. The proposed method can be integrated with automatic solar PV maintenance systems, digital twins and IoT-based communication systems to support smart decision-making and fully autonomous PV farm management. Research directions can also focus on model compression and hardware-specific optimizations to support edge computing devices.

Conflicts of Interest

The authors confirm that there is no conflict of interest to declare for this publication.

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