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Fault Detection in Solar PV Panels Using Artificial Intelligence and Embedded Systems

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A B S T R A C T

Solar energy is a sustainable and renewable resource that plays a vital role in mitigating climate change by reducing greenhouse gas emissions. However, its efficiency can be compromised by different operational faults such as dust accumulation, surface cracks, or electrical failures. Detecting these issues early is necessary to maintain optimum performance and avoid costly system failures. In this study, we propose an AI-based approach for automated fault detection in solar panels, built on a lightweight deep learning model adapted from the MobileNetV2 architecture. The model is trained and validated on a publicly available dataset with data balancing and augmentation to improve classification accuracy across different fault categories. To assess practical feasibility, we deployed the system on an embedded Jetson Nano platform. Extensive results and comparisons demonstrate the superior performance of the proposed method, achieving an accuracy of 93.14% and an F1-score of 93.12%, while maintaining a low model size (2.8M parameters) and an inference speed of 44.4 ms per image on the Jetson Nano, which is fast enough to meet real-time inspection requirements in embedded devices. Overall, the findings indicate that our solution provides an effective framework for on-site solar panel monitoring and maintenance without the need for cloud resources.

1. Introduction

Government policy and rising public demand to reduce dependence on fossil fuels and speed up the adoption of renewable and carbon-free resources are driving a main transformation in the global energy space. This shift requires well-structured energy strategies that balance resource saving, environmental protection, and economic growth particularly in emerging countries [1, 2]. Without such measures, achieving sustainable development will remain difficult. Solar and wind are projected to make the highest contributions to global renewable growth, according to the International Energy

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Agency (IEA) [3]. Nonetheless, solar and wind reliability depend on the effectiveness of the maintenance of frameworks that ensure reliable energy generation. Solar energy, which is the production of electricity from sunlight based on the panels of photovoltaic (PV), offers important benefits with economic stats and remains highly accessible because of its worldwide availability and the growing request for electricity power. A main challenge lies in the common neglect of power plant monitoring and maintenance [4]. Monitoring is critical to the systems properties (guarantee the performance, safety, and cost-effectiveness). While fossil fuel plants need to review boilers and turbines, operators must continually monitor performance. The installations of solar power face challenges like dusting, shading, cracks, and other damage on the surface, which can meaningfully reduce the efficiency of energy if left unrestricted. In addition, in order to decrease output energy, deserting these issues leads to shorter asset lifespans and higher costs. Preventive and condition-based maintenance are preferred, as they lessen downtime and maximize the yield of energy [5].

Field inspections are often costly, need a long time, and are dependent on the subjective judgment and limited technicians expertise [6]. As an alternative way, automated methods of inspection have been established by using Artificial Intelligence (AI) methods, which have fundamentally transformed the situation in terms of how are monitored and maintained the power plants. In the sector of solar, AI techniques combined with computer vision and image processing are applied to detect various environmental and technical issues in the panels [7]. Deep learning networks, particularly Convolutional Neural Networks (CNNs), are a popular choice to analyze images of PV modules for enabling accurate and automated fault detection. Different architectures of CNN have been created (e.g., GoogleNet, AlexNet, DenseNet, etc.) to address key aspects such as accuracy and computational cost [8]. These deep networks learn the classification tasks through training on a specific dataset given with respect to the application domain. In case of limited labeled data, transfer learning can be used to take advantage of pre-trained models on large-scale datasets and adapt them to the solar fault detection task. This manner reduces the need for a broad annotated dataset in addition to speeding up the training process and increasing generalization [9].

In recent years, embedded systems and CNN-based inspections through drones have dramatically enhanced efficiency as well as real-time fault diagnosis. Embedded systems provide local processing and low-power consumption without the need for cloud resources [10]. This offers earlier decision-making, lower latency, and reduced costs for data transmission, which are important for solar with large-scale the farms of solar. On the other hand, drones can provide a flexible and a coverage of wide-area by taking photos with high-resolution in places that are difficult or dangerous to reach for inspectors [11]. These technologies, composed with AI-based ones, constitute a robust platform for scalable, cost-effective, and reliable monitoring for solar panels.

Research is presence led for solar fault detection by using techniques with different imaging, including thermal, electromagnetic, and RGB imaging. Images in thermal are recorded by Infrared Cameras (IR) to recognize hotspots and abnormal heating shapes in PV modules. Electromagnetic imaging, like Electroluminescence (EL) and Photoluminescence (PL), takes fine-grained cell-level defects as micro-cracks and slothful areas, and flow conditions under a controlled environment. In contrast, RGB (visible spectrum) imaging employs regular color cameras for detecting the issues of surface-level like cracks, dust, and shading. The advantage of RGB imaging lies in its low cost, easy accessibility, and suitability for outdoor scenarios and large-scale applications, while other modalities are costly or need unusual equipment [12, 13].

Dissimilar previous studies in PV fault detection that typically emphasize high-complexity CNN models or rely on expensive imaging methods, our work focuses on RGB imaging in order to present a lightweight and computationally efficient deep learning method specifically tailored for real-time fault detection on embedded devices. The mixing of MobileNetV2 with optimized data augmentation, balanced dataset training, and placement on the Jetson Nano demonstrates a practical framework for on-site solar panel monitoring without depending on cloud resources. The key contributions of this work are summarized in the following points:

1- Developing an efficient solar fault detection approach utilizing a lightweight deep learning model tailored for PV panel inspection.
2- Real-time deployment of the proposed model on the Jetson Nano to ensure suitability for embedded and resource-constrained environments.

3- Comprehensive analysis of different deep learning architectures to identify the best trade-off between accuracy and computational cost for practical deployment.

2. Related Work

The field of solar fault detection has been widely investigated using the application of image processing and deep learning methods. A review of the existing literature shows that these approaches can be divided into three main categories based on their imaging modality, including thermal imaging, electromagnetic imaging, and RGB (i.e., visible spectrum) imaging technology [12]. Focusing on thermal imaging, H. Ling et al. [14] introduced a new method named deep edge-based fault detection for solar panel fault detection using deep learning and infrared (IR) images, assuming that the image is captured by a drone. The authors used a CNN architecture for a two-stage process: first for edge detection and then for object detection to identify faults. The suggested method classifies solar panels into two classes: either "normal" or "faulty". They used a dataset of 2060 images and achieved a high F1 score. Furthermore, the model is tested on an RTX 2080 Ti GPU on PC and achieved a frame rate of 28 fps. S. Boubaker et al. [15] investigated both machine learning and deep learning techniques for fault detection and diagnosis of PV modules using infrared thermography images. The authors formed two sub-datasets, one for binary classification (normal and faulty) and the second for multi-class classification contains four types of fault (bypass diode failure, soiling, short-circuit, and shading). Experimental results offered that models of deep learning outperform machine learning methods in both binary and multi-class classification with an accuracy of 98.71%. Likewise, other works [16-18] applied several CNNs and texture-based features from thermal images for detecting the cracks and hotspots, ensuring that deep learning methods provide higher performance under different situations. K. Awedat et al. [19] offered an enhanced deep learning technique for fault detection in photovoltaic (PV) panels by using thermal images. The authors enhance the U-Net architecture by including Residual Blocks, Atrous Spatial Pyramid Pooling (ASPP), and Attention Mechanisms to strengthen feature extraction, contextual understanding, and accurate fault localization. This method attained over 29% higher F1-score and 62% better Intersection over Union (IoU) than the standard U-Net, while reducing the losing of segmentation by 71%. These enhancements meaningfully outperform other benchmarks like U-Net with ASPP and DeepLabV3+, which proves strong robustness to environmental noise and thermal variability.

Based on electromagnetic imaging, Z. Meng et al. [20] presented a defect object detection method using electroluminescence images based on a DL approach. They introduced the YOLO-PV algorithm to detect defects in PV modules by modifying the original version of YOLOv4 for object detection. The method was validated on the EL image dataset and achieved 94.5% average precision and 35 fps as inference speed on RTX 2080 Ti. Similarly, the authors in [21] introduced a comparative study of an improved YOLOv5 and YOLOv8 for PV defect identification on EL images. The study is evaluated on the ELDDS1400C5 dataset and obtained mAP@0.5 of 76.3% using the improved YOLOv5 and improved to 77.7% using YOLOv8. Another study [22] focused on CNN feature fusion using the ResNet152 and Xception networks to detect faults in EL imaging. Additionally, the fusion model combined with an attention mechanism achieves 96.17% accuracy for binary classification and 92.13% for multi-class defect detection on public EL datasets. H. Tella et al. [23] investigated a defect detection method in solar photovoltaic (PV) cells using drone-captured electroluminescence (EL) images through an ensemble-based deep learning framework. Eight advanced architectures namely AlexNet, SENet, GoogleNet, Xception, ViT, DarkNet53, ResNet18, and SqueezeNet, were refined on the ELPV dataset (2,624 samples). The ensemble methods (voting and bagging) achieved accuracies of 68.36% and 68.31%, respectively, outperforming the previous hybrid model (61.15%). Notably, ResNet18 reached 73.02% accuracy in binary classification.

Utilizing the RGB imaging, O. Kilci et al. [24] proposed a fault detection method by integrating deep learning with machine learning approaches. The pre-trained Inceptionv3 was used as a feature extraction network, while the three types of machine learning classifiers were used for image classification including logistic regression, ANN, and SVM. The highest accuracy obtained was 83.9% using the Faulty Solar Panel Dataset. By using a similar dataset in earlier work [24], the authors in [25] presented a federated transfer learning framework by using a pre-trained VGG-16 model to categorize six solar panel types of faults. The model realized 74% testing correctness with federated learning and 75% with centralized learning. Likewise, the study in [26] presented an explainable AI model for detecting anomalies in solar photovoltaic panels by using an improvement for CNN based on the VGG16 architecture. The model was integrated with a PyQt5-based user-interface to deliver an environment with user-friendly type in order to support decision-making. The model achieved 91.46% accuracy on the Faulty Solar Panel Dataset. Concentrating on snow coverage, the work [27] talked about the impact of snow accumulation on PV panels by developing a deep learning detection model. The model includes a CNN for feature extraction and a U-Net for determining the areas which covered by snow. Additional study [28] addressed the influence of the accumulation of dust on solar panels based on a grouping of deep learning and machine learning. The DenseNet169 was used for feature extraction, while the SVM was used for the classification process. In [29], E. Quiles-Cucarella et al. introduced fault diagnosis in photovoltaic (PV) systems using multiple machine learning models on a large-scale dataset from a laboratory PV system involving seven fault types (inverter failures, partial shading, sensor faults, etc.). Models were evaluated under Maximum Power Point Tracking (MPPT) and Limited Power Point Tracking (LPPT) conditions. Results indicate that the ensemble bagged tree classifier achieved the highest overall accuracy (92.2%), while neural networks performed better under MPPT.

Recent works have also investigated the use of embedded devices for providing real-time and energy-efficient deployment to various systems of solar monitoring. D. Pujara et al. [30] explored real-time monitoring and control of PV panels by using an intelligent monitoring and control device. The system employed embedded machine learning to classify four conditions, including soiling, partial shading, extreme soiling, and standard test conditions. An Arduino-based transmitter and receiver with a data transceiver for communication were used as the edge device. In [31], a panel fault in photovoltaic systems using thermal images is proposed. A drone equipped with a thermal camera was deployed to capture images of rooftop solar panels, which were recorded on an onboard SD card during flight. These recorded images were later uploaded to the Jetson TX2 embedded AI device, where a YOLOv3-based convolutional neural network was trained and used for fault detection involving three types: cell fault, module fault, and panel fault. The main outcomes of the methods described above are summarized in Table 1. **Research gap**: Despite significant progress in solar panel fault detection, some challenges remain. Many earlier introduced methods depend on expensive thermal or electromagnetic imaging techniques, which limit their scalability. RGB imaging methods are more affordable but often produce moderate accuracy and lack optimization for embedded systems. Also, most previous works paid attention to accuracy rather than computation cost and energy efficiency, which is critically needed for real-time inspection. To fill this gap, we propose a lightweight CNN model for RGB-based fault detection and demonstrate its suitability for embedded deployment on the Jetson Nano.

3. Materials and Methods

The suggested method for solar PV panel fault detection is presented in this section, involving dataset presentation, dataset pre-processing, the proposed model architecture, and model deployment on Jetson Nano, as presented in Figure 1. Notably, the implementation code and trained models used in this study are publicly available at https://github.com/renewable-research/solar-energy.

3.1. Dataset Presentation

In the deep learning field, the quality of the dataset is an essential factor that affects the model performance, including diversity, image resolution, standardization, and access availability for fair comparison with existing methods. To address these issues, the titled dataset ‘Faulty Solar Panel’ is utilized in this work, which is publicly available on the Kaggle platform [32] in 2023.

Table 1. Summary of prior research on solar panel fault detection

Authors	Year	Imaging Technique	Method and Algorithm	Dataset	Classes	Hardware Implementation	Inference Speed
Meng, et al. [20]	2021	Electromagnetic	CNN, YOLO, SVM	User-collected	Normal, defect	RTX 2080 Ti GPU	35 fps
Wang et al. [22]	2022	Electromagnetic	Various CNNs	Two public datasets	Normal, Defective	RTX 2080 GPU	N/A
Boubaker et al. [15]	2023	Thermal	VGG16, K-NN, SVM	User-collected	Normal, Faulty, bypass diode failure, shading, short-circuit, and soiling	N/A	N/A
Alatwi et al. [28]	2024	RGB	DenseNet169, SVM	Solar Panel Dust Detection	Clean, Dusty	N/A	N/A
Ling et al. [14]	2024	Thermal	Edge detection, object detection, CNN	BSDS500	Normal, Faulty	RTX 2080 Ti GPU	28 fps
Araji et al. [27]	2024	RGB	CNN, U-Net	User-collected	clean, snow-covered	Google Colab and Kaggle	N/A
Pujara et al. [30]	2024	RGB	ML algorithms	User-collected	No fault, Partial shading, Soiling, Extreme soiling	Arduino	N/A
Kayci et al. [31]	2024	Thermal	YOLOv3	User-collected	Panel fault, Cell fault, Module fault	Jetson TX2	N/A
Awedat et al. [19]	2025	Thermal	Attention mechanism, U-Net	User-collected	single anomaly, multiple anomalies, contiguous anomalies	N/A	2.8s
Tella et al. [23]	2025	Electromagnetic	CNNs, Vision Transformer	ELPV dataset	non-defective, defective	Multiple GPUs	N/A
Kilci et al. [24]	2025	RGB	Inceptionv3, SVM, logistic regression	Faulty Solar Panel	Bird-drop, Clean, Dusty, Electrical damage, Physical damage, and Snow-covered	N/A	N/A
Kazemi et al. [25]	2025	RGB	VGG-16	Faulty Solar Panel	Bird-drop, Clean, Dusty, Electrical damage, Physical damage, and Snow-covered	N/A	N/A
Quiles-Cucarella et al. [29]	2025	RGB	Machine learning	User-collected	Inverter failures, partial shading, and sensor faults	N/A	N/A

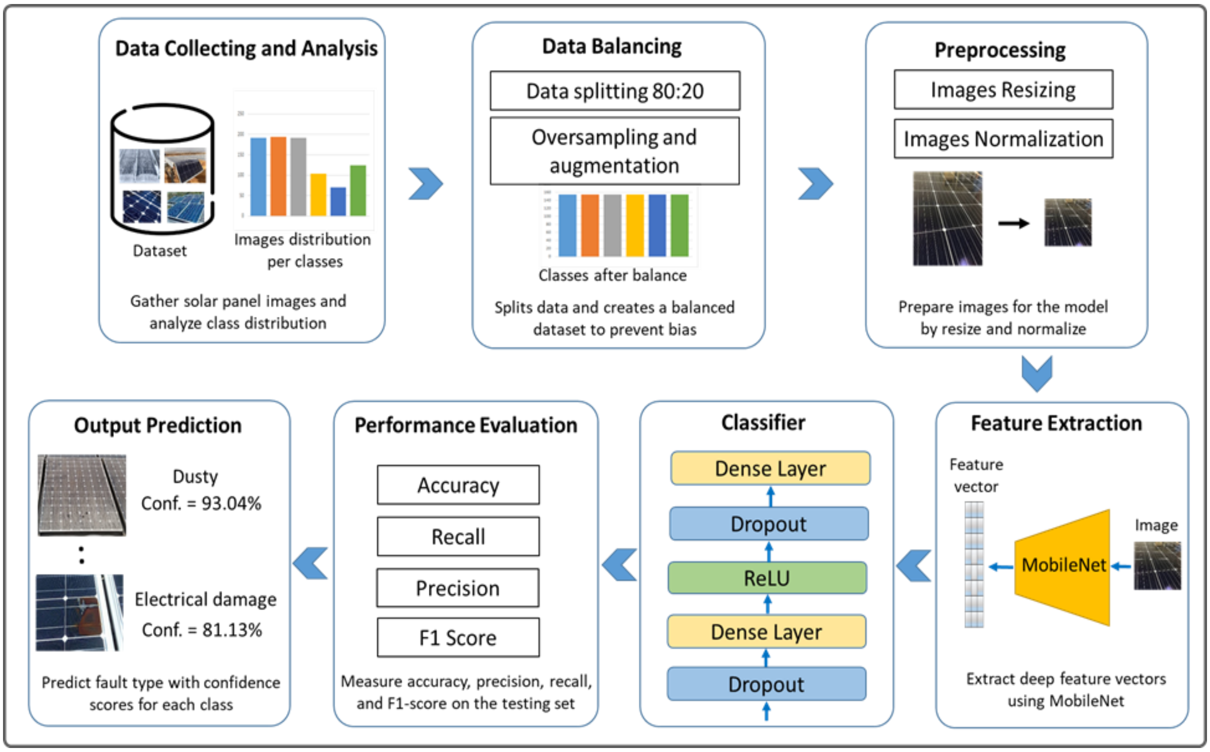

Figure 1. Overview of the proposed framework with end-to-end solar PV fault detection

This dataset consists of a total of 885 images distributed into six distinct categories covering different surface conditions of solar panels. The classes of the dataset include bird-drop, clean, dusty, electrical damage, physical damage, and snow-covered panels (see Table 2). Additionally, sample examples from the dataset are presented in Figure 2. These categories demonstrate the key environmental and mechanical problems with solar panels that directly impact performance. For example, dust and snow can minimize or prevent the absorption of sunlight, leading to a considerable decrease in energy yield. Bird droppings, which are acidic, can also damage the panel and make the surface darker. And also, the electrical parts of a solar panel might get damaged due to voltage fluctuations or lightning, while physical damage from wind or external factors can cause cracking or breaking of the panel surface. This variety and realism of the dataset guarantee that the trained model is exposed to diverse scenarios and realistic conditions and thus increases generalization.

Table 2. A brief description of each class in the Faulty Solar Panel dataset

Class	Description
Bird-drop	Bird droppings are present on the solar panels
Clean	The solar panel is clean and free from dirt, dust, or any other damage
Dusty	A layer of dust covers the solar panel
Electrical damage	Solar panels with defects in electrical parts or connections
Physical damage	Solar panels showing signs of cracking or breakage
Snow-covered	Solar panels blanketed in snow

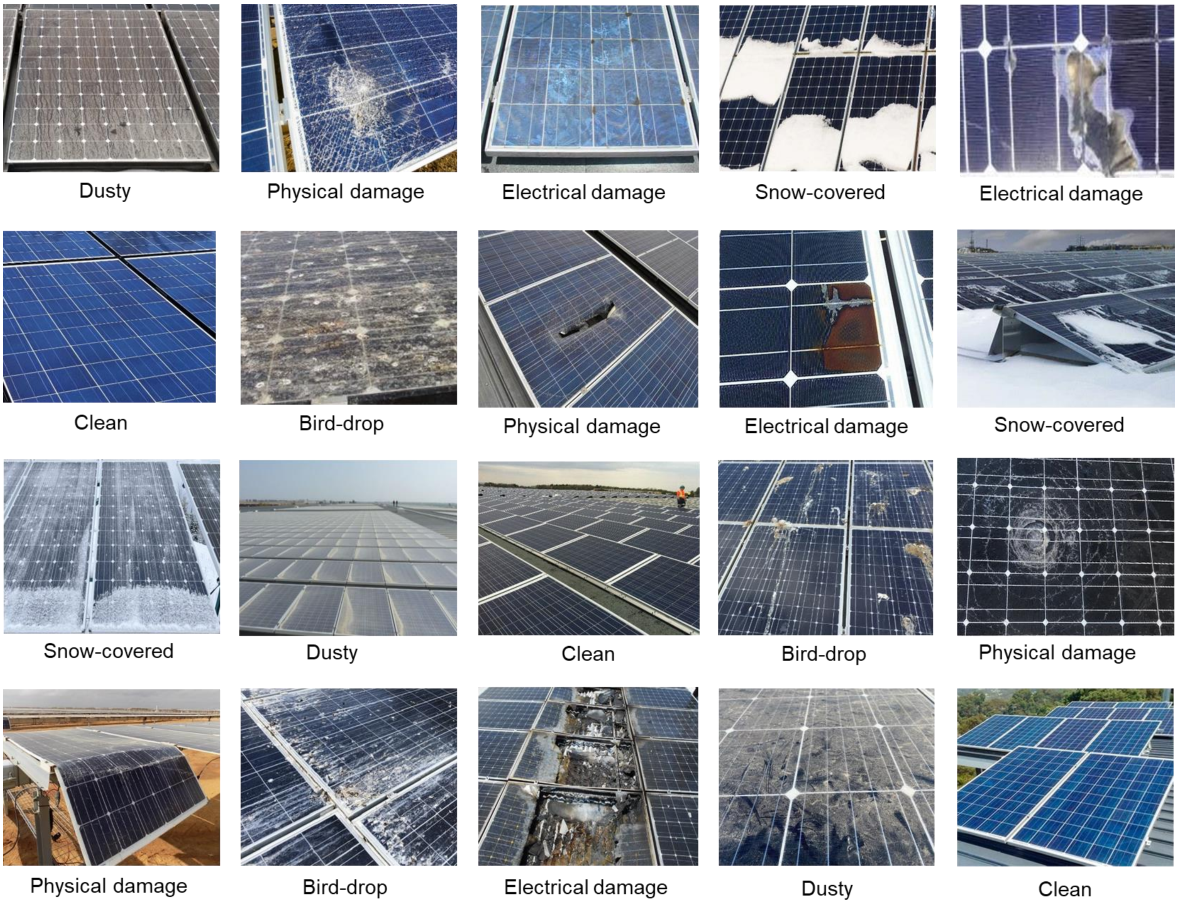

Figure 2. Representative samples of the Faulty Solar Panel dataset

3.2. Data Balancing and Preprocessing

The original "Faulty Solar Panel" dataset is imbalanced. Some categories in this dataset contain significantly fewer samples than others (see Table 3). For example, the images in the physical damage and electrical damage classes are noticeably fewer than the images in the clean or bird-drop classes. This issue is called an imbalance in the dataset. The deep learning model may become biased toward the majority classes due to this imbalance. Hence, the model becomes less capable of accurately classifying minority categories. To solve this problem, we actually use oversampling and data augmentation methods. First, the dataset is split into training and testing data: 80% for training the model and 20% for testing. Then, the training set is balanced and then expanded using image augmentation techniques including horizontal flipping, rotation, brightness adjustment, blurring, and random cropping. Figure 3 presents some examples of image augmentation used in this work. As a result, the dataset is expanded more than 5 times, from 885 original images to 4795 images. This step ensures that each category is fairly represented in the training phase. In addition to balancing, pre-processing of the images is performed to standardize the input before feeding it for training the model. All images are resized into some fixed dimension (e.g., 224×224×3) suitable for the input shape of the DL model. Thereafter, the intensity values of the images are adjusted and scaled to the same range from 0 to 1. This step is known as normalization. It makes the learning process easier for the model by removing unnecessary differences caused by lighting, resolution, or scaling.

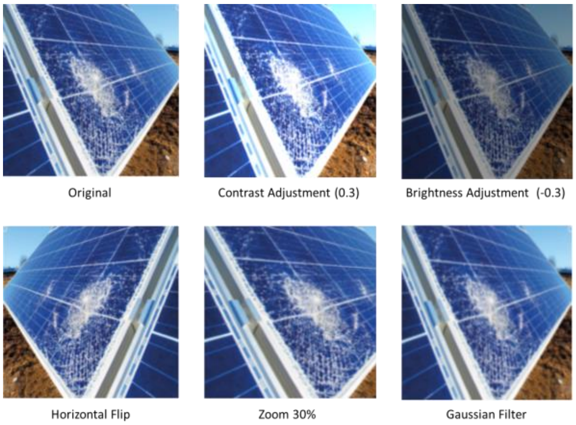

Figure 3. Examples of image augmentation applied to training data

Table 3. Image distribution per class

Class	Number of Images
Bird-drop	192
Clean	194
Dusty	191
Electrical damage	104
Physical damage	70
Snow-covered	124
Total (original)	885
Total (after augmentation)	4795

3.3. Proposed Model Architecture

The method proposed for fault detection and classification in PV solar panels depends on the deep learning approach. The proposed model, seen in Figure 4, consists of a lightweight feature extraction network followed by fully connected layers that will be used for data classification. The goal behind this design is to produce an efficient model that can operate smoothly on resource-limited devices such as the Jetson Nano with minimum computational cost and at the same time retain high accuracy in fault identification. The MobileNetV2 architecture represents the core part of our model and acts as a backbone network for image feature extraction through the use of transfer learning techniques. This network is adapted for the fault classification in solar panels based on the utilized dataset by replacing the final classification layer, originally set for 1000 classes, with global average pooling to flatten the features, followed by the proposed classification network. The reason for choosing MobileNetV2 is its lightweight design and fast inference speed, which makes it appropriate for real-time applications and embedded systems. This network extracts key visual elements from the input images, like patterns, textures, and shapes. The flatten operation is applied to convert the extracted features into a vector that summarizes the important information from the fed images.

Following feature extraction, the model involves a number of dense layers that carry out the classification task. A dropout layer is used between dense layers to stop the model from memorizing the training data and causing the overfitting problem. Dropout is considered a generalization technique. It forces the DL model to learn more general patterns rather than depending on specific details by arbitrarily ignoring some neurons during the training process. In order to help the model capture more complicated relationships between the input features and the output categories, nonlinearity is also introduced using the ReLU activation function.

3.4. Model Deployment on Jetson Nano

After training the model on the collected dataset using a personal computer, we actually need to deploy it on an embedded platform to definitely check how it performs in real-time conditions with limited resources. For this purpose, the NVIDIA Jetson Nano is chosen as an embedded platform due to its low cost, low power consumption, compact portable design, and compatibility with edge AI applications. In this implementation, the trained fault detection model is exported and executed on the Jetson Nano board for running inference on unseen solar panel images belonging to the testing set. In this stage, the preprocessing steps described earlier are applied to the input images before passing them to the model. The Jetson Nano then performs forward propagation through the MobileNetV2 backbone and classification layers for providing fault detection results in real time. The predictions are displayed on the terminal or saved for further analysis.

In a real-life application, the suggested model can be combined into an intelligent inspection framework for PV solar farms. Figure 5 illustrates a practical example of employing the proposed method for a drone-based solar panel inspection. In this scenario, a drone with a camera and a Global Positioning System (GPS) receiver can automatically fly above the solar farm and take shots together with the geographic location coordinates of each panel. It then sends those images to the Jetson Nano which runs the introduced model to monitor or detect possible faults like dust accumulation, physical damage, electrical damage, and others in real-time. An alternative scenario, the Jetson Nano can be installed directly on the drone for enabling onboard processing without requiring image transmission, and also saving bandwidth and latency. The detection results with GPS data can be sent to a fault reporting or alert system for providing maintenance teams with the faulty panels and their precise locations. As a result, this combination of drones, GPS, and embedded systems can essentially reduce manual inspection costs and increase the efficiency of the solar power plants. However, in this study, the drone and GPS components shown in Figure 5 are presented as a part of the conceptual framework for real-world applications, not included in the current experimental setup.

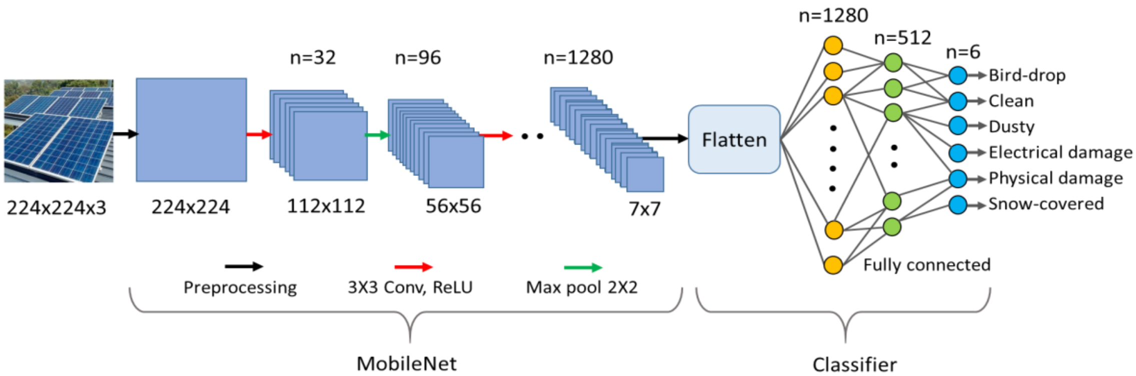

Figure 4. Architecture of the proposed classification model

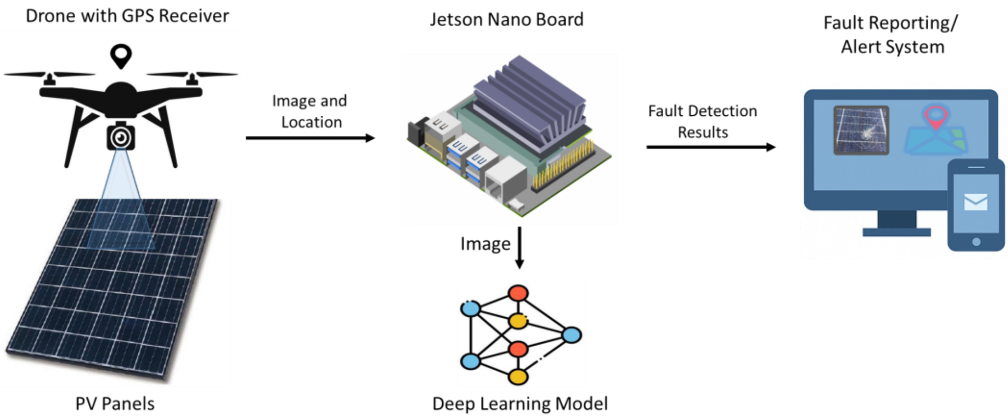

Figure 5. Illustrative example of deploying the proposed model in real-life applications

4. Experimental Results

This section presents a comprehensive analysis and evaluation of the proposed method, including implementation setup, training procedures, and performance comparison with related methods. Both qualitative examples and quantitative metrics are provided for validating the effectiveness of our approach.

4.1. Implementation Details

The initial execution of all experiments for our work is performed using a laptop computer that has the following specifications: an NVIDIA RTX 3060 GPU, an Intel Core i7 11th-gen CPU, and 16 GB of RAM. After training the model and saving the model weights from the epoch with the highest testing accuracy, the model is deployed on the Jetson Nano device that is equipped with a 128-core Maxwell GPU, 4 GB RAM, and a Quad-core ARM Cortex-A57 CPU. This device works with 5 DC volts. Both the used laptop and the Jetson Nano are set up with the Linux operating system, CUDA Toolkit, Python, and PyTorch framework to enable GPU acceleration. Figure 6 illustrates the implementation of the proposed model in the Jetson Nano.

Figure 6. Embedded implementation of the proposed method using Jetson Nano

4.2. Training and Fine-tuning

The proposed model is trained utilizing the transfer learning technique based on the pre-trained weights of the MobileNetV2 architecture on the ImageNet dataset. Instead of keeping the MobileNetV2 part frozen like in many approaches, the entire model is trained at once by leaving the MobileNetV2 backbone unfrozen and fine-tuned together with the appended classifier. This end-to-end training strategy enabled the gradients to be propagated through the entire network. As a result, the model can adapt its feature extraction ability to the solar panel dataset and improve the final classification accuracy. The model is trained for 30 epochs, and the progress is assessed by tracking training and testing accuracy after each epoch, as shown in Figure 7. Additionally, Table 4 summarizes the hyperparameters used for model training after tuning.

Table 4. Hyperparameter configuration used in the proposed method

Hyperparameter	Configuration
Batch size	32
Training epochs	30
Learning rate	0.0005
Dropout ratio	0.5
Size of hidden layers in the classifier	512, 6
Activation function	ReLU
Loss function	Cross Entropy
Optimizer	SGD

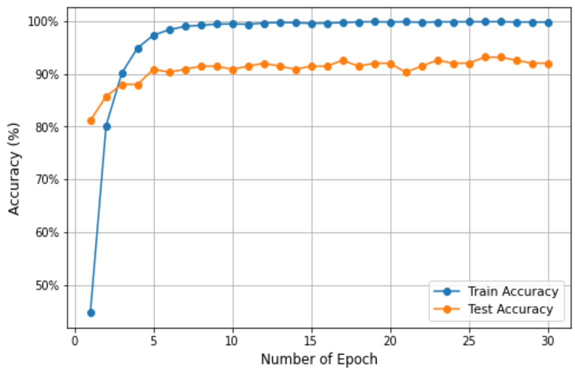

Figure 7. Training and testing the accuracy of the proposed model

4.3. Performance Analysis and Comparisons

To select the best model in terms of accuracy and inference speed for deployment on the Jetson Nano, various well-known CNN architectures are tested and evaluated, including GoogleNet, VGG19, ResNet18, SqueezeNet, AlexNet, ShuffleNet, XceptionNet, EfficientNet-B1, DenseNet121, and MobileNetV2. Table 5 reports the comparison of these models with respect to classification accuracy using different evaluation metrics, involving accuracy, recall, precision, and F1 score. In addition, Table 6 presents the comparison with respect to computational cost, involving the number of parameters, training time, and inference speed.

Table 5. Accuracy analysis of the proposed method with different CNN architectures

Model	Accuracy	Precision	Recall	F1-score
GoogleNet	93.71	94.09	93.37	93.70
VGG19	91.43	93.84	91.80	92.55
AlexNet	88.00	89.17	89.50	89.09
ResNet18	92.00	93.71	92.85	93.25
DenseNet121	90.29	90.37	89.63	89.96
EffeceintNet-B1	89.71	89.61	89.61	90.11
ShuffleNet	69.14	73.71	69.14	69.15
SqueezeNet	89.71	91.40	90.02	90.45
Xception	88.57	91.26	88.76	89.78
Frozen_MobileNetV2	90.29	91.44	91.97	91.60
MobileNetV2	93.14	93.37	92.94	93.12

Table 6. Computational cost analysis of the proposed method with different CNN architectures

Model	Accuracy	Precision	Recall	F1-score
GoogleNet	93.71	94.09	93.37	93.70
VGG19	91.43	93.84	91.80	92.55
AlexNet	88.00	89.17	89.50	89.09
ResNet18	92.00	93.71	92.85	93.25
DenseNet121	90.29	90.37	89.63	89.96
EffeceintNet-B1	89.71	89.61	89.61	90.11
ShuffleNet	69.14	73.71	69.14	69.15
SqueezeNet	89.71	91.40	90.02	90.45
Xception	88.57	91.26	88.76	89.78
Frozen_MobileNetV2	90.29	91.44	91.97	91.60
MobileNetV2	93.14	93.37	92.94	93.12

According to Table 5, GoogleNet achieved the highest accuracy (93.71%) among all tested networks, followed closely by the proposed end-to-end trained MobileNetV2 (93.14%). The performance gap is minor (<0.6%). This indicates that both models are effective at extracting features related to solar panel fault detection. Particularly, the MobileNetV2 attains this result with far fewer parameters and less implication time associated to GoogleNet, see the Table 6. When comparing the end-to-end trained network against its version of frozen backbone, a pure development is observed, and the accuracy growths from 90.29% to 93.14%, and the F1-score increases from 91.6% to 93.12%. This development guarantees the importance of letting the backbone adapt its feature extraction capabilities to the solar panel dataset, instead of depending solely on pre-trained ImageNet representations. It is worth observing that this improvement in accuracy does not need any additional cost of computation at the stage of inference (check Table 6). When comparing a big and hard-working model like the DenseNet121 with lightweight models like MobileNetV2, the small model performs better. From our point of view, this is due to the nature of the solar panel image, which offers a simple texture, limited color differences, and a shape with static properties. So, these characteristics do not require a complex architecture like in DenseNet121, and this complexity can reduce performance.

Based on Table 6, the computational results show the trade-off between accuracy and efficiency (i.e., computational cost). While models such as VGG19 and Xception achieved competitive accuracy, they required large numbers of parameters (20M and 21.8M, respectively) and performed slow inference speeds on the Jetson Nano (294.6 ms and 201.8 ms, respectively). These delays make them impractical for real-time deployment on limited-resource devices. On the other hand, the MobileNetV2 achieved one of the best trade-offs using only 2.8M parameters and keeping an inference speed of 44.4 ms on Jetson Nano, and still achieving >93% accuracy. By comparison, GoogleNet (65.3 ms) is slower and heavier (6.1M parameters), whereas SqueezeNet is extremely lightweight (0.9M parameters, 24.6 ms inference time) but reduces accuracy (89.71%). Therefore, MobileNetV2 offers an optimal balance between accuracy and efficiency, which makes it the most suitable model for deployment on the Jetson Nano.

The per-class performance of the proposed model is also considered to identify strengths and limitations as presented in Table 7. Furthermore, to assess the effectiveness of the proposed model against existing approaches, various related works [24-26, 33-36] that used the same dataset in our work (e.g., the Faulty Solar Panel dataset) are selected for comparison. The comparative results are presented in Table 8.

Table 7. Accuracy analysis across each class of the proposed model

Class	Precision	Recall	F1-score
Bird-drop	90	92	91
Clean	97	97	97
Dusty	89	87	88
Electrical damage	95	95	95
Physical damage	92	86	|89
Snow-covered	96	100	98

The comprehensive class-wise evaluation in Table 7 demonstrates that the suggested model consistently performs well across various fault categories in terms of per-class performance. The model achieved almost perfect detection in classes like clean (precision, recall, and F1-score: 97%) and snow-covered (precision 96%, recall 100%, F1-score 98%). Similarly, electrical damage is identified quite well with balanced precision and recall for both at 95%. More difficult cases are dusty (precision 89%, recall 87%, F1-score 88%) and physical damage (precision 92%, recall 86%, F1-score 89%). We observe that the visual similarities between dust accumulation and other surface irregularities may occasionally confuse the model. Nevertheless, the overall per-class results prove the robustness of the proposed method in handling both common and rare classes.

Table 8 shows that the proposed method outperforms all previous baseline models with an accuracy of 93.1% and an F1-score of 93.1%. This is about a 2% upgrading from the previous method in work ([26], which obtained an accuracy 91.4%. Other works, like [33, 34, 36], obtained accuracies below 88%, once more emphasizing the efficiency of the proposed fine-tuned MobileNetV2 method. Particularly, the methods in works [24] and [25] are significantly lower accuracies 75% and 83.9%, respectively. The consistent advantage across accuracy, precision, recall, and F1 demonstrates that the proposed model not only generalizes better but also ensures reliable deployment in real-world solar panel inspection situations. Overall, the results presented in this section demonstrate that the proposed approach offers a relatively good balance between accuracy and efficiency, which makes it highly feasible for embedded devices like the Jetson Nano.

Table 8. Performance comparison with existing works

Method	Year	Accuracy	Precision	Recall	F1-score
Akinca et al. [33]	2024	87.5	87.9	88.7	88.1
Nunes et al. [34]	2024	87.6	-	-	88.0
Ghahremani et al. [35]	2024	-	89.7	87.7	90.0
Ledmaoui et al. [26]	2024	91.4	-	-	91.6
Kazemi et al. [25]	2025	75.0	-	-	-
Kilci et al. [24]	2025	83.9	84.0	83.9	83.9
Gasparyan et al. [36]	2025	87.4	-	-	85.8
Proposed	2025	93.1	93.3	92.9	93.1

5. Limitations and Future Work

Despite the effective presentation of the proposed method, some challenges remained. First, the current study depends on only the RGB imaging technique, which may limit the detection process of micro-cracks or internal cell defects that could better identified by thermal or electroluminescence imaging. Second, the model was evaluated on a publicly available dataset, and real-world deployment in large-scale solar farms may encounter variations in lighting, weather, and panel orientation that could affect accuracy. Third, although the Jetson Nano succeeded in providing real-time inference for single images, processing a large number of images continuously or integrating with multiple drones may require further optimization or more powerful embedded platforms. Additionally, certain categories, such as dusty and physical damage, indicated relatively lower recall values due to visual similarities with other classes. Future research will focus on incorporating advanced data augmentation, attention mechanisms, in addition to multimodal inputs (e.g., thermal or electromagnetic signal) to further improve classification robustness. Furthermore, extending the framework to drone-based or IoT-based inspection systems can allow fully autonomous solar farm monitoring at large scales.

6. Conclusion

This study presented an artificial intelligence-based method to detect faults in solar PV panels utilizing a lightweight deep learning model and embedded platform deployment. For training and testing the proposed model, we used a publicly available dataset that consists of six different conditions of solar panels. Data balancing with augmentation strategies is applied to handle class imbalance and improve generalization. Our network is an adapted version of the MobileNetV2 architecture and trained in an end-to-end fashion to fully utilize transfer learning and achieve optimal feature extraction for solar panel images. Extensive experiments are conducted to compare the proposed model with state-of-the-art CNN architectures, including GoogleNet, VGG19, ResNet18, DenseNet121, EfficientNet-B1, and others. The experiments showed that the fine-tuned MobileNetV2 achieved an excellent balance between accuracy and efficiency, with a classification accuracy of 93.1%, a recall of 92.94%, a precision of 93.37%, and an F1-score of 93.1%. It outperforms many well-known CNNs and surpasses recent related works on the same dataset. Importantly, when deployed on the resource-constrained Jetson Nano, the model maintained real-time performance with an average inference speed of 44.4 ms per image and a model size of 2.8M parameters. The obtained results confirm the suitability of the proposed method for embedded applications in solar panel inspection and reveal its practical value for smart and cost-effective monitoring of PV solar farms. By enabling real-time fault detection without reliance on cloud networks, the system supports scalable, on-site, and energy-efficient inspection. Such a solution has the potential to reduce maintenance costs, minimize downtime, and ultimately enhance the efficiency and reliability of solar energy production.

Nomenclature

AI	Artificial Intelligence
ANN	Artificial Neural Network
ASPP	Atrous Spatial Pyramid Pooling
BSDS	Berkeley Segmentation Dataset and Benchmark
CNN	Convolutional Neural Network
CPU	Central Processing Unit
CUDA	Compute Unified Device Architecture
DL	Deep Learning
EL	Electroluminescence
ELPV	Electroluminescence Photovoltaic
fps	Frame per Second
GB	Gigabyte
GPS	Global Positioning System
GPU	Graphics Processing Unit
IEA	International Energy Agency
IoT	Internet of Things
IoU	Intersection over Union
IR	Infrared Cameras
K-NN	K-Nearest Neighbours
LPPT	Limited Power Point Tracking
MPPT	Maximum Power Point Tracking
ms	Millisecond
PC	Personal Computer
PL	Photoluminescence
PV	photovoltaic
RAM	Random Access Memory
ReLU	Rectified Linear Unit
RGB	Red Green Blue
RTX	Ray Tracing Texel eXtreme
s	Second
SD	Secure Digital
SGD	Stochastic Gradient Descent
SVM	Support Vector Machine
Ti	Titanium
ViT	Vision Transformer
YOLO	You Only Look Once

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