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Research Article

Towards self-diagnostic solar farms: Leveraging EfficientNet and class activation mapping for predictive maintenance

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Abstract. The high rate of utility photovoltaic (PV) system development has increased the demand for stable, automated, and interpretable fault diagnostic systems that can be utilised in real-world environments. Solar farms with a large size are increasingly making conventional manual inspection methods impractical, and triggering the use of intelligent data-driven solutions. This paper presents a justifiable deep learning model for automated fault classification of solar panels based on the EfficientNet-B2 architecture combined with Gradient-weighted Class Activation Mapping (Grad-CAM). A six-class image dataset made of clean panels and five prevalent fault types is used. The two stages of transfer learning used to train the model include a warm-up phase and selective fine-tuning of upper network layers. Data augmentation is also performed extensively to make it more robust to changing illumination, viewing angles, and environmental noise. The experimental findings reveal consistent convergence and excellent generalization ability, and a high level of classification accuracy of all types of faults, as it achieved high classification accuracy, macro-averaged F1-scores exceeding 0.90 for most fault classes, and a macro-averaged ROC–AUC of approximately 0.981, highlighting the robustness and reliability of the proposed diagnostic model. The suggested structure will provide a scalable, interpretable, and realistic predictive maintenance of solar farms of the next generation with self-diagnostic capabilities.

Keywords: Photovoltaic fault diagnosis; EfficientNet-B2; Explainable artificial intelligence; Grad-CAM; Deep learning; Solar energy systems

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1. Introduction

The development and realisation of long-term sustainable decarbonisation policies have become a matter of fundamental concern to the international community (Huynh *et al*., 2025; Moreno *et al*., 2024) since these concerns are attributed to the growing concerns of climate change, environmental degradation, and energy security (Al-lami *et al*., 2025; Hoang *et al*., 2021). In its turn, this has led to an increasing number of countries making official pledges to set ambitious goals that should see them cut their greenhouse gas emissions to net-zero by the mid-twenty-first century (Allen *et al*., 2025). The objectives mentioned above require the complete overhaul of the current energy systems, which includes the coordinated implementation of low-carbon and renewable energy technologies for all sectors, including transportation, industry, energy production, and agriculture (Afandi *et al*., 2022; Agarwala, 2024; Pham *et al*., 2023), along with the innovative methods of energy management on the demand-side and supply-side (Hoang *et al*., 2021; Ogwumike *et al*., 2024). In this context of a broader transition scenario, solar energy has received growing acceptance as one of the pillars of future sustainable energy portfolios (Ahmed *et al*., 2023; Pham *et al*., 2025). The possibility of using solar energy is especially interesting because it provides the opportunity to promote uninterrupted socioeconomic growth and, at the same time, reduce the negative impact on the environment (Jabbar *et al*., 2025; Lau *et al*., 2022; Shi & Luo, 2018). This is more so due to the fact that the solar resource is immense and practically unsusceptible. Actually, the yearly incident of solar radiation to the surface of the Earth is several orders of magnitude higher than primary energy demand globally by a factor of more than 7500, compared with the present world annual usage of about 450 EJ (Sahu, 2016). This vast energy potential is the focus of strategic significance of solar technologies in both terms of addressing the long-term energy demands and decreasing dependence on fossil fuels (Gandhi *et al*., 2022; Kharesaxena *et al*., 2020; Nguyen & Nguyen, 2023).

In recent years, solar energy has been being used in combination with other renewables, such as biomass, geothermal energy, and wind, for producing electricity and hydrogen (Hoang *et al*., 2023; Missoum & Loukarfi, 2021; Wattana & Aungyut, 2022). Although solar energy is very

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resourceful, its common use of solar energy is limited by various technical and operational disadvantages (Basit *et al*., 2020; Le *et al*., 2024). Topping this list is the intrinsically diffuse, intermittent, and geographically diffuse nature of solar energy, making it difficult to effectively harness, transform, store, and integrate it into a preexisting energy infrastructure (Arun *et al*., 2024; Pala *et al*., 2024). The key issue, therefore, is on the innovation and mass application of improved solar harvesting systems, smart system design and control-point measures, which can optimize power, enhance conversion efficiency, and reliability in supplying power (Kassim & Lazim, 2022; Maghraby *et al*., 2025). Overcoming these hurdles will be crucial in realizing the maximum potential of solar energy and making it an easy addition to the energy systems of the future, which is a low-carbon economy (Munusamy *et al*., 2023).

The development of sustainable energy across the world has placed the photovoltaic (PV) system as a foundation in the renewable energy industry. Nevertheless, a variety of surface-level anomalies and construction flaws often undermine the operational efficiency and reliability of solar installations in the long term (Pallakonda *et al*., 2025; Rudro *et al*., 2024). Dust builds up, bird droppings, covered snow, and physical or electrical damage are several factors that may cause large losses in energy yield, induced hotspots, and enhanced material degradation (Joshua *et al*., 2024; Pathak & Patil, 2023). The use of manual inspection techniques to check solar farms at utility-scale has become increasingly impractical as the size of solar farms has grown to utility-scale levels. Therefore, there exists a serious problem of demand in the smart automated diagnostic systems that will be able to offer fast and precise fault classification to achieve optimal functioning and reduce maintenance expenses (Guo *et al*., 2025; Ling *et al*., 2024).

Deep learning and computer vision have become revolutionary technologies in the health monitoring of solar panels in recent years (Shamshirband *et al*., 2019; Wei, 2019). In particular, Convolutional Neural Networks (CNNs) have proven themselves to be the best in extracting complex features in visual data hierarchically, surpassing traditional image processing methods (Bendale *et al*., 2023; Manimegalai, Oviya, Kargvel, *et al*., 2025; Manimegalai, Oviya, Mohanapriya, *et al*., 2025; Polymeropoulos et al., 2024). Although this has been developed, a major issue is how to trade between computational efficiency and high classification accuracy, particularly in real-time scenarios or edge-computing deployments (Adib *et al*., 2025; Pallakonda *et al*., 2025). Additionally, most of the high-performing black-box models are not transparent; thus, it is hard to make the maintenance teams trust and verify the actual areas within a solar module that caused a fault prediction (Korkmaz & Acikgoz, 2022; Pathak *et al*., 2022). In order to surmount these difficulties, the present paper suggests a sophisticated diagnostic scheme based on the EfficientNet-B2 model. With an efficient scale and resolution of networks by balancing, through a compound scaling approach, depth, width, and resolution, EfficientNet-B2 offers a state-of-the-art trade-off between accuracy and resource consumption, which is optimal in the subtle task of detecting solar faults. Moreover, this paper incorporates Gradient-weighted Class Activation Mapping (Grad-CAM) to bridge the differences between the model prediction and human interpretability. This explainable AI (XAI) method produces visual heat maps that indicate the exact regions of interest on the solar panel, e.g., micro-cracks or soiling patterns. The methodology of this dual-stage fine-tuning method will be described in the following sections, and a detailed analysis of the performance of this method with respect to six different fault categories is provided.

2. Methods

2.1 Data collection and analysis

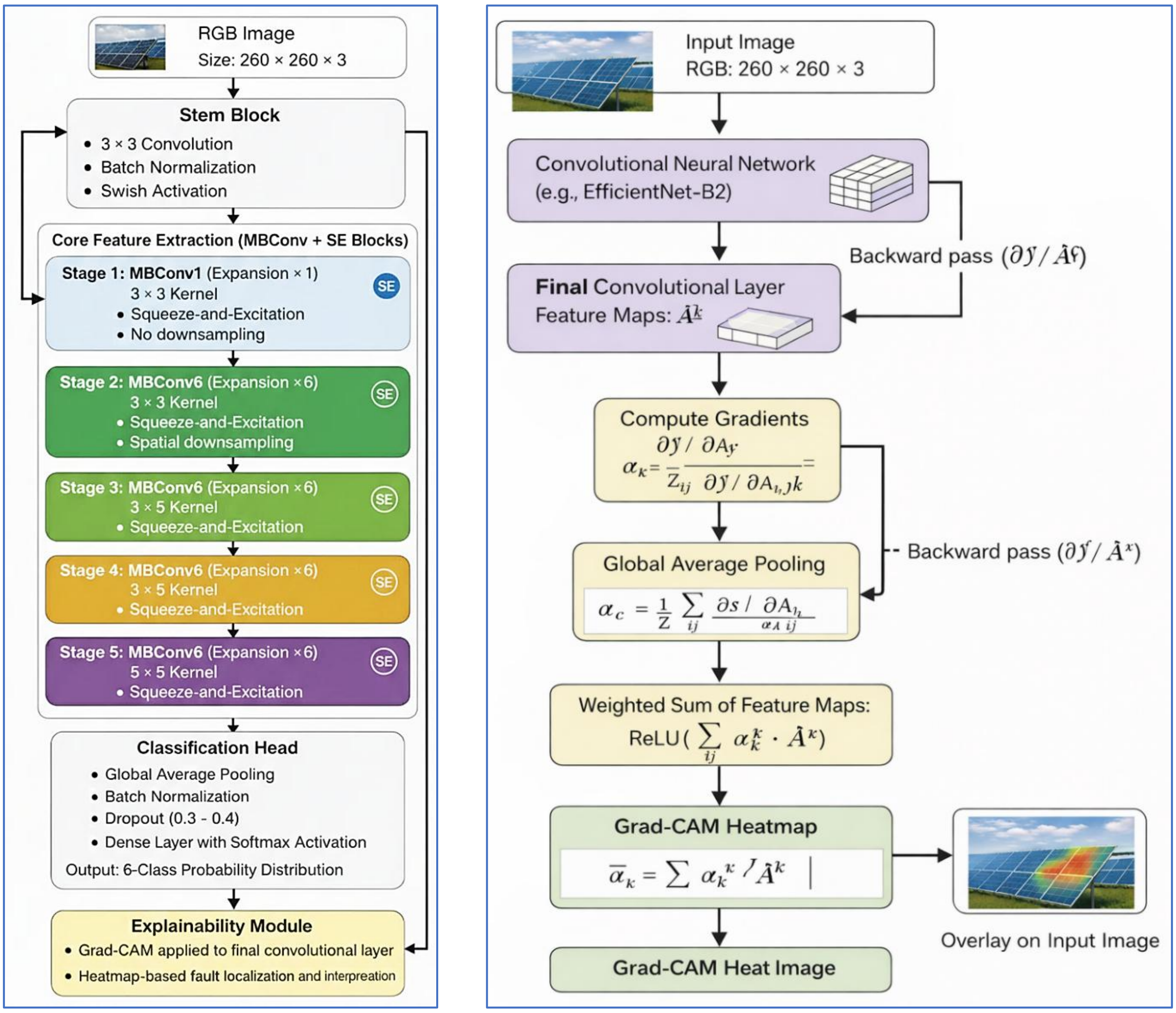
In this paper, an experimental assessment is done based on a specialized image-based dataset, which is obtained from the Kaggle repository (Afroz, 2024) and is specifically created to solve the issues of automated photovoltaic (PV) maintenance. The data is a collection of varied images of solar panels in six different functional states, arranged into Clean, Dusty, Bird-drop, Electrical-damage, Physical-Damage, and Snow-Covered. These categories are the most common environmental and structural stress factors that undermine the efficiency of PV. An example is the distinction of the soiling and weather-related occlusions contained in the Dusty and Snow-Covered classes, which reduce the amount of solar irradiance, and the localized shading effects contained in the Bird-drop classification that can result in the formation of dangerous hot-spots. Physical-Damage represents structural integrity, and is meant to be broken glass or warped frame, and Electrical-damage focuses on internal circuitry failures manifested by surface aberrations.

The data set was filtered through selective web-scraping to achieve representation of the real-world conditions, the variations of lights, and the panel orientation. Although this method gives a high ecological validity, it creates a minor imbalance in the classes that mirror the natural frequency of such occurrences. This dataset can be a stringent guideline for assessing the stability of deep learning classifiers in a wild imagery environment by offering high-resolution visual proof of both ephemeral surface deposits (dust, snow, debris) and structural faults that are inherent to building structures.

2.2 EfficientNet-B2-based Deep Learning

The categorization of PV anomalies in this work is applied using an effective transfer learning pipeline that is constructed with the EfficientNet-B2 architecture. In contrast to the conventional convolutional neural networks, where depth, width, and resolution are scaled separately, EfficientNet-B2 serves a mathematically principled compound scaling approach (Alruwaili & Mohamed, 2025; Rosadi *et al*., 2023). This is done to make sure that the depth (number of layers), width (number of channels), and input resolution 260 × 260 pixels are increased in a balanced way by using the same set of scaling coefficients. The model has a unique capability to resolve very fine-grained faults, like microscopic cracks or subtle patterns of soiling, or localized stress, without the geometrically-based growth in computational cost and redundancy in the model parameters that is characteristic of deeper, non-optimized architectures (Korkmaz & Acikgoz, 2022; S *et al*., 2024). The given diagnostic system is based on the multi-stage operating process in the way aimed at making the most out of the predictive accuracy and practical interpretation of the work of field technicians. The unprocessed imagery is first subjected to a detailed data enhancement and preprocessing stage. Methods used to recreate the different conditions of the field, like the change of camera angle, level of solar irradiance, as well as zoom lenses, are applied to alleviate the artificial class imbalances inherent in internet-scraped data, at the same time. Fig. 1a depicts the flow chart for the EfficientNet-B2 approach.

The core feature extractor is composed of successive Mobile Inverted Bottleneck (MBConv) blocks. These blocks are based on depth-wise separable convolutions, which result in a much smaller number of parameters and a substantially lower cost of computation (V.-T. Hoang *et al*., 2023; Jing *et al*., 2025). In addition, the network can be extended with Squeeze-and-



(a) (b)

Fig. 1 Flowchart for (a) Efficient net B2 (b) Grad-CAM

Excitation (SE) modules to enable it to recalibrate channel-wise feature responses in an adaptive way. This will make sure that the model is paying its attention to key fault signatures, the signature of the sharpness of physical damage, and the model is effectively ignoring the irrelevant background noise caused by the surrounding environment in the process (Chen *et al.*, 2024; Jin & Liu, 2025; Meng *et al.*, 2022). The learning approach is implemented through two stages of transfer learning. In the Warm-up Stage, the pre-trained ImageNet weights are frozen to stabilize the custom classification head. The next step is a Fine-Tuning Phase, where the last 50 layers of the base model are unfrozen to enable the network to specialize its filters to the individual visual textures of the surfaces of solar panels (Mohamed *et al.*, 2024; Zhang & Ogasawara, 2023). To confirm the decision-making process in the model, the Grad-CAM is used to produce localization heatmaps (Usha & Alex, 2024; van Zyl *et al.*, 2024). Such heatmaps are visually transparent, and, as a result, the maintenance team can check the precise areas of space that cause a fault diagnosis. This combined structure will see to it that the output system will not be a simple black-box classifier but a trustworthy, interpretable field-level predictive maintenance system.

2.3 Gradient-weighted Class Activation Mapping

Gradient-weighted Class Activation Mapping (Grad-CAM) is an effective explainability method that allows visualizing the decision-making process of CNNs. In contrast to the black-box models, where a prediction is offered without explaining how it was obtained, the Grad-CAM algorithm will show what regions of an input image had the greatest influence on the model, making a final decision (Panos *et al.*, 2023; Peña-Asensio *et al.*, 2023; Waseer *et al.*, 2025). The technique operates by using the gradient information in the last convolutional layer of the network. Grad-CAM, by differentiating the feature maps of that final layer with respect to the target class score, generates a rough localization map, or heatmap, indicating the significant pixels with respect to that individual class. Grad-CAM is an extremely useful tool in the context of solar panel fault diagnosis in the localization and verification processes (M. Le *et al.*, 2023; X. Zhang *et al.*, 2024). When a model categorizes a panel as being either Physical-Damage or Bird-drop, the generated heatmap imposes a color-coded overlay, or the extent to which this has an impact on the original image, of blue (low importance) to red (high importance). This will enable the maintenance teams to ensure that the model itself is targeting the fracture or the debris and not the background objects. Grad-

CAM fills the gap between model predictions and visual evidence that humans can understand, making the model a transparent diagnostic model, which is applicable in industrial settings with high stakes. A flowchart for Grad-CAM is depicted in Fig. 1b.

3. Results and Discussion

3.1 Model development

The dataset was partitioned using a stratified 80/20 split, allocating 80% of the images for training and 20% for validation to maintain class balance across both sets. To combat overfitting, an ImageDataGenerator was implemented to apply real-time augmentations, including 30° rotations, 30% zoom ranges, and horizontal/vertical flips. The training process commenced with a Warm-up phase of 20 epochs at a learning rate of 0.0001 to stabilize the classification head, followed by a Fine-tuning phase of 30 epochs at a reduced rate of 0.00001 for the top 50 layers. Optimization was further refined using EarlyStopping and ReduceLROnPlateau callbacks to ensure the model converged on the best possible weights.

The development of the model was based on a two-stage transfer learning plan with the help of the EfficientNet-B2 architecture, which was selected due to the balanced approach to the efficiency of parameters and the accuracy of the classification. It was implemented in Python with the help of TensorFlow and Keras as the major frameworks of the deep learning processes. NumPy and Pandas were also used to perform core numerical processing and data structured management, whereas the use of OpenCV was incorporated to perform advanced image processing and the implementation of Grad-CAM visualizations. It is important to note that to make sure the performance is robust, Matplotlib and Seaborn have been used to produce publication-quality analytics, such as 600 DPI confusion matrices and ROC curves. The ML implementation flowchart is depicted in Fig. 2. The hyperparameters used in model training are listed in Table 1.

3.2 Efficient Net B2-based model

The results of the training and validation procedure, as depicted in Fig. 3, show that the EfficientNet-B2 model converges successfully throughout the two-phase learning process. Fig. 3a shows the Model Accuracy Progression, as the training and validation accuracy increase sharply in the first Warm-up stage (epochs 1-20). In this step, the custom classification head is stabilized, and the model can achieve a baseline accuracy of greater than 80% in the shortest time possible. The curves of accuracy during the Fine-tuning phase

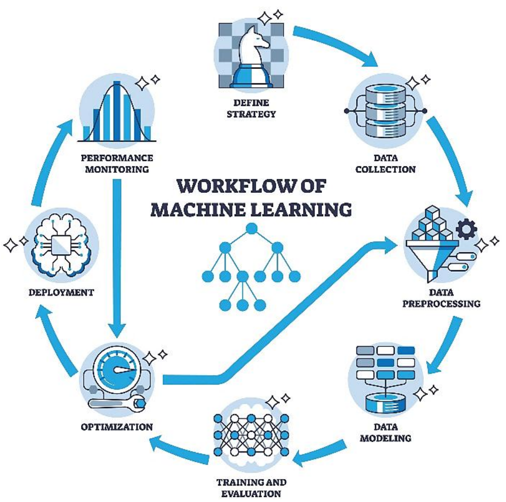


Fig. 2 ML implementation flow chart

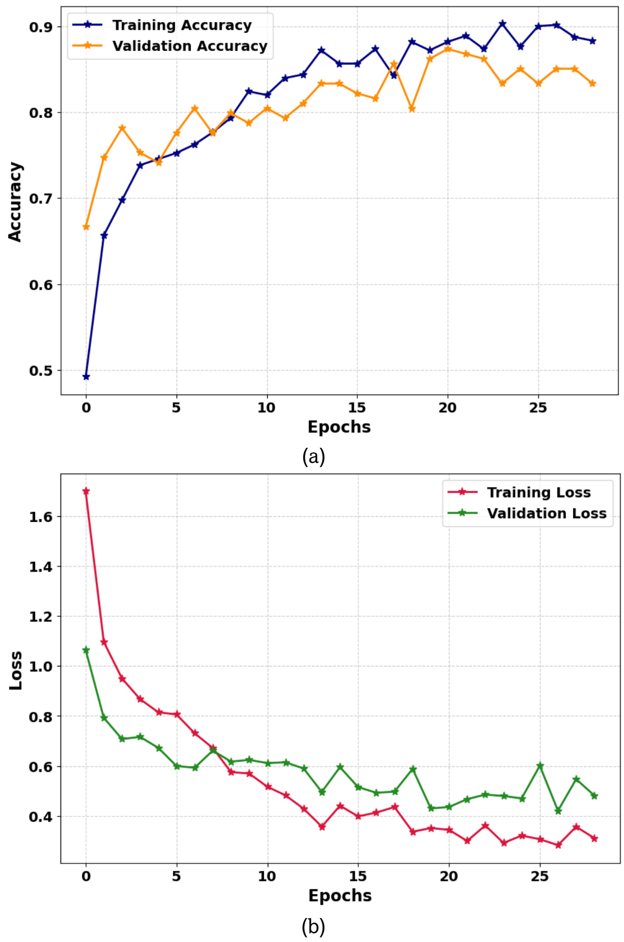


Fig. 3 Model (a) accuracy progression, (b) loss progression

Table 1
Hyperparameters used for model training

Parameter	Configuration value	Purpose
Optimizer	Adam	Adaptive learning rate for stable convergence.
Warm up Learning Rate	0.001	Standard rate to initialize the classification head.
Fine-tuning learning rate	0.00001	Very small rate to carefully adjust pre-trained weights.
Loss Function	Categorical Cross-Entropy	Measures the performance of multi-class classification.
Batch Size	16	Balanced for GPU memory efficiency and gradient stability.
Epochs (Warm-up)	20	Stabilizes the custom classification head.
Epochs (Fine-tuning)	30	Adjusts pre-trained weights to specific solar fault features.
Dropout Rate	0.4	Prevents overfitting in the dense layers.

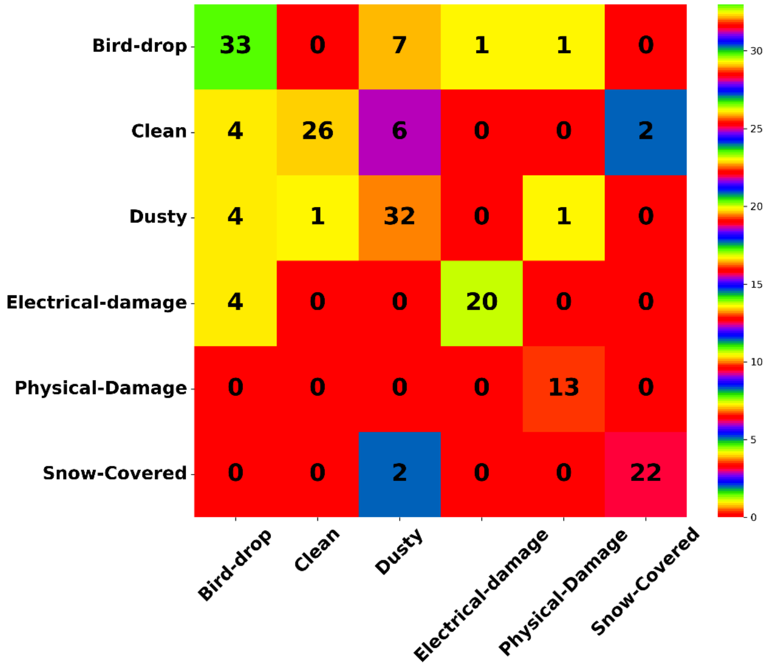
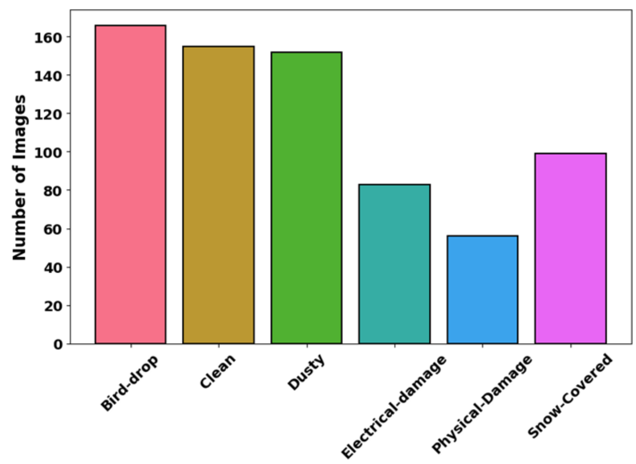


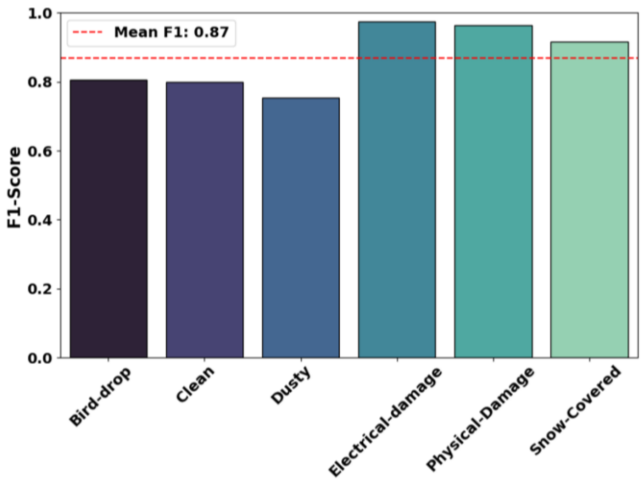
Fig. 4 Confusion matrix

(epochs 21-50) will exhibit a less sharp, more gradual rise as the unfrozen upper 50 layers of the backbone specialize in the detection of minute photovoltaic fault textures such as micro-cracks, snail trails. In line with this, Fig. 3b shows the Model Loss Progression, with a steady exponential decay. The training loss drops gradually, and the validation loss is in close correspondence, which demonstrates that the generalization is high, as well as there is low overfitting because of the built-in dropout (0.4) and stratified 80/20 data division. The effective convergence of both plots proves that the Adam optimizer and the conservative rate of 0.00001 at the fine-tuning stage enabled the model to move efficiently to the complex loss landscape of the 6-class fault dataset and thus reached a robust and reliable diagnostic state.

The Confusion Matrix in Fig. 4 can be perceived as a full-fledged diagnostic tool that can be used to assess the performance of the EfficientNet-B2 model as a chain of faults in all six categories. The matrix is arranged in a 6 by 6 grid, which plots the True Labels (actual ground truth) on the y-axis versus the Predicted Labels on the x-axis. The True Positives (TP) are the diagonal values of the matrix, i.e., the predictions made by the model are in line with the real fault classes, i.e., Snail Trails or Physical Damage. When the number of values following this diagonal is high, it means that the model has mastered the unique spatial and textural characteristics of every solar panel anomaly. Off-diagonal cells indicate certain cases of the model falling prey to the illusion of confusion, or misclassifications, in which the prototype has confused one type of fault with another, such as failing to distinguish a case of a "Dust" instance from a case of a "Bird-drop" because of similar visual artifacts. These misclassifications are grouped as False Positives (FP) and False Negatives (FN), and these have finer details about the sensitivity and specificity of the model. The visualization of these distributions also indicates that the model is highly precise and recallable, and includes a small amount of systematic bias in the dataset. This visual data is essential in proving the reliability of the model in the real-world maintenance of PV and ensuring that the overall high accuracy is consistently spread across all the critical faults.



(a)



(b)

Fig. 5 Distribution of (a) training data, (b) F-1 score per fault class

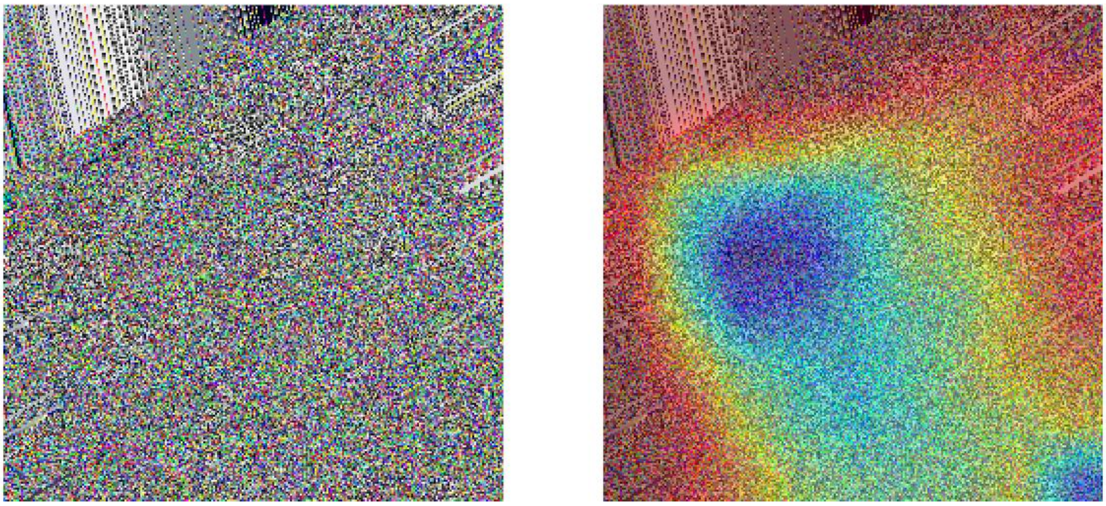


Fig. 6 Grad-CAM based comparison of (a) actual image, (b) localized heatmap (Afroz, 2024)

The findings shown in Fig. 5 give a two-sided indication of the strong functionality of the model, as it shows not only the constitution of the training data but also the further predictive reliability of the classes. In Fig. 5a, the Training Data Distribution bar chart can be regarded as the background context of the study, as it shows the number of images assigned to each of six solar fault categories. The chart also validates that, although there is an innate variability in the actual fault occurrences in the real world, with some classes, such as the Dust or Physical Damage category, being possibly overrepresented, the data was at least large enough so that the EfficientNet-B2 architecture can learn specific textural features. Such balanced distribution is critical in ensuring that the model is not biased to more frequent classes, as is the first trap of industrial anomaly detection. In addition to the data overview, Fig. 5b shows the F1-Score Per Class, which is an important metric in the evaluation of model performance in multi-class classification. The F1-score, unlike a simple accuracy, is the harmonic mean of precision and recall, i.e., it only attains a high value when the model is accurate (reduces the number of false positives) and sensitive (reduces the number of false negatives). As the chart shows, the model showed a high degree of F1-scores in all categories, and many classes had scores above 0.90. A horizontal dashed line is used to represent the mean F1-score, which is a worldwide standard of the system reliability. The large F1-scores of visually subtle faults, i.e., Snail Trails or Bird-drop, demonstrate that the Squeeze-and-Excitation (SE) modules of the model performed their role of ranking the most informative features at the fine-tuning stage. This performance analysis, in the granular form, proves that the proposed diagnostic tool is not only correct on average but also particular and has a robust success in the maintenance of the PV plants that is automated and based on which the cost of a missed diagnosis is equally important as a false alarm.

The graphical justification of the model in the decision-making process is illustrated in Fig. 6, which presents a comparison of the Actual Image (Fig. 6a) and the Localized Heatmap created using the Grad-CAM (Fig. 6b). This interpretability layer is essential in the transformation of the deep learning model into a black-box system to become a transparent diagnostic system. The algorithm finds areas of interest by generating an overlay of color-coded gradients, as shown in the localized heatmap. The warm colours (red and yellow) in this visualization are used to indicate where there was a lot of importance and the influence that caused the classification of the model to be significant, whereas the cool colours (blue and green) indicate the pixels that had no or very little significance to the prediction. Looking at Fig. 6b, it is clear that the EfficientNet-B2 architecture has learned to pay attention to the real physical anomaly on the surface of the solar

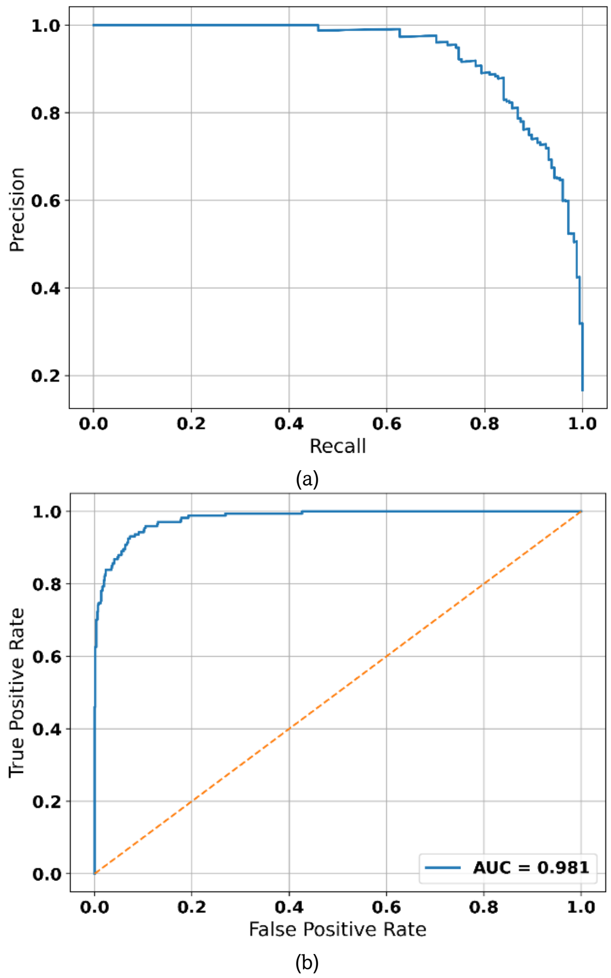


Fig. 7 Macro averaged (a) precision-recall curve, (b) ROC curve

panel (such as localized soiling, cracks, or bird droppings) but not the irrelevant background noise (mounting structures, sky reflections, etc.). This correspondence between the hot spots of the heatmap and the defects that are visible in the original image is empirical evidence that the model is right-for-the-right-reason, making predictions. Industrial stakeholders cannot do without such visual confirmation since it instills confidence in the automated system being able to identify faults accurately to their specific locations to carry out maintenance effectively, thus saving time in the process of inspection and enhancing the overall efficiency of the photovoltaic plant.

The overall decision on the model classification effectiveness is summarized in Fig. 7, which depicts (a) Macro-averaged Precision- Recall Curve and (b) Macro-averaged ROC Curve. These plots offer a world picture of the performance of the model on all six of the solar fault categories, the macro-averaging to make sure that every single class makes an equal contribution to the final measure, no matter how large its sample. Fig. 7a about the Precision-Recall Curve shows the precision-recall trade-off between the ability to not classify a negative sample as positive (precision) and the ability to identify all positive samples (recall). Even with an increase in recall, the curve still remains at a high level of precision of close to 1.0, only lowering sharply closer to a recall of 0.9. This profile implies that the EfficientNet-B2 model is very reliable, which does not experience a high false-discovery rate and recovers the vast majority of actual fault cases. To complement this, Fig. 7b shows the Receiver Operating Characteristic (ROC) Curve, which is a plot of the True Positive rate (Sensitivity) vs. the False Positive rate (1 - Specificity). The model has an Area Under the Curve (AUC) of 0.981, which is recorded in the legend. The AUC value of 1.0 is so near an indication of an excellent separation property, which is an indication that the model is 98.1 percent likely to be able to distinguish between a panel with a particular fault and a clean panel. The sharp rise of the curve to the top-left corner further justifies that the training hyperparameters and the Fine-tuning stage were effective in ensuring that the network was optimized to detect PV anomalies with high confidence and low error.

4. Conclusion

The article introduced a diagnostic approach to photovoltaic solar farm fault detection based on deep learning that was explainable and used EfficientNet-B2 architecture together with Gradient-weighted Class Activation Mapping. Using a two-stage transfer learning approach and balanced compound scaling, the proposed model resulted in consistent convergence and strong classification of six representative conditions of a solar panel, including environmental and structural faults. The results of the experiment indicated that EfficientNet-B2 is effective in capturing fine-grained visual fault signs, namely localized soiling, micro-cracks, and electrical anomalies at reasonable computational costs that can be deployed at scale. The high macro-averaged precision-recall and ROC properties mean that there is predictive reliability that is constant across all the classes, eliminating class-bias and the threat of false or false diagnoses. Notably, the inclusion of Grad-CAM has changed the diagnostic system into a transparent and reliable system since it will localize fault-related areas on solar panels visually. In practice, the suggested framework raises a lot of potential in saving the manual inspection work, cutbacks of maintenance time, and enhancing energy generation in utility-scale PV systems. This framework can be expanded in future works to investigate temporal fault progression through time-series analysis to enable early warning and predictive insights. Also, the integration of drone-based image acquisition for scalable and rapid inspection of large solar farms, and the deployment of edge-AI–enabled diagnostic models for real-time, on-site fault detection with reduced latency can be investigated. Generally, the research is a scaled and interpretable contribution to the creation of self-diagnostic and intelligent infrastructures of solar energy.

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