SEBHA UNIVERSITY CONFERENCE PROCEEDINGS, VOL.5 NO. 4 2026
DOI: 10.51984/1K2XPY51

وقائع مؤتمرات جامعة سبها
Sebha University Conference Proceedings
Confrence Proceeeding homepage: http://www.sebhau.edu.ly/journal/CAS

Leveraging ResNet50 Architecture for Solar Panel Defect Classification

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Keywords:
Classification
Defects
Photovoltaic
ResNet50
Solar

ABSTRACT

The rapid growth of photovoltaic (PV) energy systems has increased the need for efficient, automated methods to monitor solar panel conditions and identify operational defects. Various aspects, including dust accumulation, bird droppings, snow coverage, and structural failures, can negatively affect power generation efficiency and reduce the operational lifespan of PV modules. As a result, intelligent image-based diagnostic systems have gained considerable attention as an alternative to conventional manual inspection approaches. This study presented a deep learning frame-work for the classification of solar panel conditions using the ResNet50 architecture. The proposed approach categorized solar panel images into three major groups: Normal Condition (NC), Surface Coverage Conditions (SCC), and Structural Damage (SD). The dataset images were subjected to several preprocessing operations prior to training, including image resizing and augmentation techniques to improve data variability and enhance model generalization capability. To address the imbalance among dataset categories, class-weighting techniques were incorporated during the training stage to ensure balanced learning across all classes. The model was trained and evaluated by means of commonly adopted performance indicators. Experimental findings demonstrated satisfactory classification capability, achieving an accuracy of 88.42%, precision of 88.58%, recall of 88.23%, and F1 _ score of 88.32%. These results reinforce the effectiveness of the proposed framework in distinguishing between normal and defective PV panel conditions, ensuring a practical and reliable approach for smart PV monitoring, fault diagnosis, and predictive maintenance systems.

استخدام نموذج ResNet50 لتصنيف عيوب الألواح الشمسية

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قسم الفيزياء، كلية التربية، جامعة وادي الشاطئ ، وادي الشاطئ ، ليبيا

الكلمات المفتاحية:
تصنيف
التعلم العميق
الخلايا الكهروضوئية
الطاقة الشمسية
العيوب

الملخص

أدى النمو السريع لأنظمة الطاقة الكهروضوئية إلى زيادة الحاجة لأساليب فعالة وآلية لمراقبة حالة الألواح الشمسية وتحديد العيوب التشغيلية، ويمكن أن تؤثر عوامل متعددة مثل تراكم الغبار، فضلات الطيور، تراكم الثلوج، والأعطال الهيكلية سلبا على كفاءة إنتاج الطاقة وتقلل من العمر التشغيلي للوحدات الكهروضوئية. ونتيجة لذلك، حظيت أنظمة التشخيص الذكية المعتمدة على الصور باهتمام كبير كبديل لأساليب الفحص اليدوية التقليدية. قدمت هذه الدراسة إطارا قائما على التعلم العميق لتصنيف حالات الألواح الشمسية باستخدام نموذج ResNet50. يقوم النهج المقترح بتصنيف صور الألواح الشمسية إلى ثلاث مجموعات رئيسية: الحالة الطبيعية، وحالات التغطية السطحية والأضرار الهيكلية. خضعت صور البيانات لعدة عمليات معالجة مسبقة قبل تدريب النموذج، بما في ذلك تغيير حجم الصور وتقنيات زيادة الصور لتحسين تنوع البيانات وتعزيز قدرة النموذج على التعميم. ولمعالجة عدم التوازن بين فئات الصور، تم استخدام تقنيات أوزان الفئات خلال مرحلة التدريب لضمان تعلم متوازن عبر جميع الفئات. تم تدريب النموذج وتقييمه باستخدام مؤشرات الأداء الشائعة. أظهرت النتائج التجريبية قدرة تصنيف جيدة، حيث حقق النموذج دقة بلغت 88.42%، ودقة إيجابية

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Article History : Received 30 May 2026 - Received in revised form 30 September 2026 - Accepted 11 November 2026

(Precision) بلغت 88.58%، واسترجاع (Recall) بلغ 88.23%، ودرجة F1 بلغت 88.32%. تؤكد هذه النتائج فعالية الإطار المقترح في التمييز بين حالات الألواح الشمسية السليمة والمعيبة، مما يوفر نهجا عمليا وموثوقا لأنظمة المراقبة الذكية للألواح الكهروضوئية وتشخيص الأعطال وأنظمة الصيانة التنبؤية.

Introduction

The growing global demand for energy has accelerated the exhaustion of fossil fuel resources, which remain the main source for electricity generation. The extraction and use of these fuels contribute to major environmental complications such as greenhouse gas emissions, air pollution, and depletion of natural resources. In comparison, solar energy offers a clean and sustainable alternative capable of reducing the environmental effects associated with conventional energy production and consumption [1]. Solar photovoltaic (PV) cells convert sunlight directly into electrical energy through the PV effect. They operate using semiconductor materials, usually silicon, which release energized electrons when exposed to sunlight, generating an electric voltage. Since a single PV cell produces only a small amount of power, multiple cells are combined into solar panels, and several panels can be connected together to form larger arrays capable of generating significant amounts of electricity [2]. Solar PV technology is regarded as one of the cleanest methods of electricity generation, providing an effective approach for reducing climate change impacts and strengthening energy security. Through reducing emissions and providing reliable energy, solar PV contributes significantly to global sustainability efforts [3]. Solar panels can experience several types of damage during manufacturing or long-term outdoor use. These defects reduce efficiency, decrease power generation, and shorten panel lifespan. Solar panel faults are generally grouped into mechanical defects (physical damage, delamination, manufacturing flaws), thermal defects (hotspots, overheating, uneven heat distribution), electrical defects (short circuits, insulation failures, bypass diode faults, overvoltage), and environmental defects (UV degradation, moisture, dust, wind, and mechanical stress) [4]. Solar panels are exposed to environmental contaminants such as dust, bird droppings, and industrial residues, which can block sunlight and reduce energy production. Some cleaning methods may also accelerate surface deterioration by using chemicals that attract more dust. Panel performance is influenced by several factors, including surface coating, tilt angle, orientation, and surface roughness [5]. Studies in arid and semi-arid regions reported that dust buildup can decrease produced power by 20%–50% during long dry periods without cleaning, while dust storms may cause daily losses of 5%–8% per event. Snow coverage can decrease daily energy production by 90%–100%, with seasonal losses amounting to 10%–30% in cold regions. Even partial shading of only 10% of the panel area may lower power output by 50%–80% due to bypass diode activation and hot-spot effects [6]. PV faults require maintenance strategies ranging from routine cleaning for surface contamination to diagnostic repair and module replacement for electrical and physical damage [7].

Damage detection in solar panels can be performed using either traditional inspection techniques or advanced AI methods. AI-based approaches, are more effective in large-scale systems because they automate the detection process and reduce the need for human intervention. Recent studies show a significant increase in the use of AI for fault detection due to its higher accuracy and efficiency compared with conventional methods [4]. The adoption of AI in renewable energy systems has improved energy generation, distribution, and consumption processes. AI techniques enhance efficiency, flexibility, and scalability, making them important for supporting sustainable energy goals. In particular, deep learning methods have proven effective in tasks such as energy demand prediction, fault detection, and energy optimization [8]. Deep learning has become an effective approach for identifying and diagnosing defects in PV modules, overcoming the limitations of traditional methods that may struggle with large-scale systems. PV panels can develop faults at different stages, including manufacturing, transport, installation, and operation, which negatively affect their efficiency and lifespan. This is important for ensuring PV system efficiency and safety, as defects can reduce energy output and may even pose fire hazards. However, despite their strong performance, deep learning-based methods still face challenges such as the requirement for large annotated datasets and limited generalization across different module types and surrounding conditions [9].

Previous studies, including [10–14] have explored solar panel defect detection and classification. Despite the progress achieved, further work is required to improve the accuracy, stability, and practical use of automated inspection systems. Expanding the evaluation of deep learning models and datasets is important for identifying more effective detection and classification methods. AI techniques provide faster and more reliable inspection than conventional manual approaches. Since surface defects and other damages can reduce panel efficiency and energy production, continuous monitoring is necessary for early fault identification. Manual inspection is often slow and less suitable for large PV systems, increasing the need for automated and efficient defect monitoring solutions.

This study focuses on the classification of solar panel defects using AI techniques, particularly deep learning models. The proposed approach aims to automatically identify and categorize different types of defects, enabling appropriate maintenance actions such as cleaning, repair, or panel replacement. This approach will provide faster detection, reduced human intervention, higher accuracy, and improved scalability, making them more suitable for modern PV monitoring systems.

Method

The methodology adopted in this study focuses on the classification of solar panel defects into three principal categories using the ResNet50 architecture. The proposed framework involves a sequence of processing stages, beginning with dataset preparation and image preprocessing, followed by model training, and concluding with defect categorization and performance evaluation. The developed approach aims to enhance the reliability and efficiency of automated PV fault recognition under different operating conditions. To provide a clearer overview of the implemented procedure, the overall workflow of the proposed classification system is illustrated in **Fig. 1**.

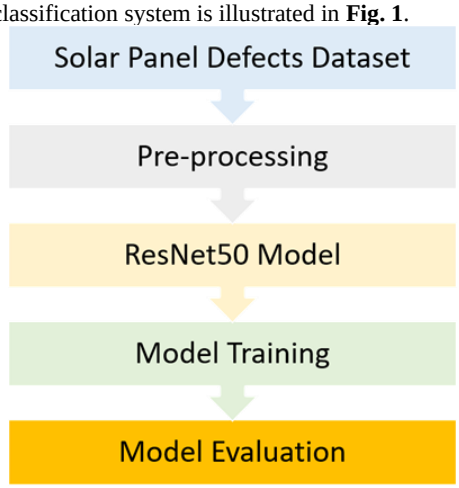


Fig. 1: Method summary

1. Dataset and preprocessing

The images utilized in this study were obtained from Kaggle [15] and consist of six categories representing different operating conditions and defect types in PV panels: clean, dusty, bird-drop, snow-covered, physical damage, and electrical damage. Examples of the collected samples are presented in **Fig. 2**.



Fig. 2: Samples from dataset

Prior to model training, all images were standardized to a resolution of 224×224 pixels to ensure consistency during feature extraction and network training. In order to increase dataset variability and reduce the risk of overfitting, a set of augmentation operations was incorporated into the preprocessing stage. These operations involved image rotation, horizontal reflection, and contrast modification, allowing the model to learn under different visual and illumination conditions. For the purpose of simplifying the classification task and improving interpretability, the six original categories were reorganized into three broader groups. The first group, Normal Condition (NC), contains only the clean panel images. The second group, Surface Coverage Conditions (SCC), combines defects caused by external surface obstructions, including dusty panels, bird-drop contamination, and snow-covered surfaces. The third group, Structural Damage (SD), includes panels affected by physical damage and electrical damage. The prepared dataset was partitioned into training, validation, and testing subsets using a ratio of 70%, 20%, and 10%, respectively. Table 1 summarizes the number of images in each category before and after augmentation, while Table 2 presents the distribution of the regrouped classes.

Table 1: Dataset composition.

Class	Before augment	After augment
Clean	193	965
Dusty	190	380
Bird drop	191	382
Snow covered	123	246
Electrical damage	103	515
Physical damage	69	345
Sum	869	2833

Table 2: Distribution of the regrouped classes.

Regrouped Class	Contained classes	No. of images
NC	Clean	965
SCC	Dusty, Bird-drop, and Snow-covered	1008
SD	Electrical and Physical damage	860
Sum		2833

2. Model training and evaluation

In this study, ResNet-50 was used to classify PV panel images according to their operating conditions: NC, SCC, and SD. The network was initialized with weights pretrained on ImageNet and subsequently adapted to the PV image dataset. The original classification layer was replaced with a three-class output layer corresponding to NC, SCC, and SD. The network was trained over 50 epochs using a batch size of 32 and a learning rate of 0.0001. Model optimization was carried out using the Adam optimization algorithm. To minimize the influence of class imbalance within the dataset, weighted class values were incorporated during the training phase, enabling the network to assign greater importance to underrepresented categories. The effectiveness of the developed classification framework was assessed using widely adopted performance indicators.

Results and discussions

The training and validation performance of the ResNet50 model over 50 epochs is presented in **Fig. 3**, where the top plot displays the accuracy for both the training and validation sets, and the bottom plot shows the corresponding loss values. These graphs provide a comprehensive overview of the model's learning progress and its capability to generalize to unseen data.

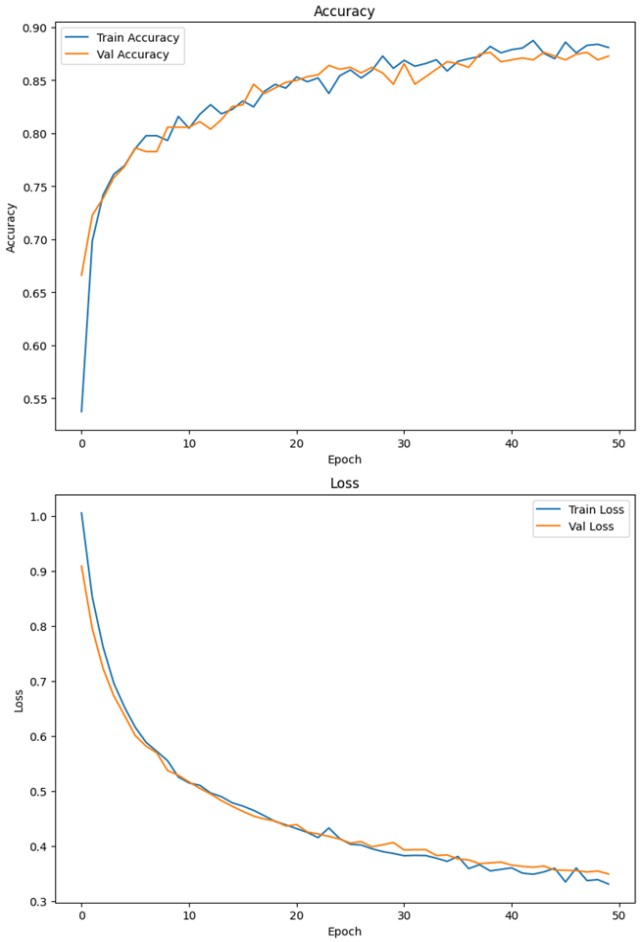


Fig. 3: Training development curves

Fig. 3 demonstrates that the model achieved stable and effective learning performance. Both training and validation accuracy increased steadily and converged around 87–88% by epoch 50, with no significant gap between the curves, indicating good generalization capability. Similarly, the training and validation loss curves showed a smooth decline from high initial values to approximately 0.33, without any increase in validation loss, confirming the absence of overfitting. Overall, the close alignment between the curves suggests that the selected architecture and training parameters were well optimized, and the model reached a strong performance level suitable for final evaluation and deployment.

The classification performance of the model across different solar panel condition classes using evaluation metrics is presented in Table 3.

Table 3: Evaluation results.

Class/Metric	Precision	Recall	F1-score
NC	0.9011	0.8454	0.8723
SCC	0.8649	0.9412	0.9014
SD	0.8916	0.8605	0.8757
Average	0.8858	0.8823	0.8832
Accuracy	0.8842		

As shown in Table 3, the results indicate that the model achieves strong and balanced performance across all categories. For the Normal Condition (NC) class, the model obtains a precision of 0.9011, a recall

of 0.8454, and an F1-score of 0.8723, indicating reliable but slightly lower sensitivity compared to other classes. The Surface Coverage Condition (SCC) class demonstrates the best recall value of 0.9412 and a strong F1-score of 0.9014, reflecting the model's high capability in correctly identifying most affected samples in this category. For Structural Damage (SD), the model maintains consistent performance with a precision of 0.8916, recall of 0.8605, and F1-score of 0.8757, showing balanced detection ability. Overall, the average precision, recall, and F1-score are 0.8858, 0.8823, and 0.8832 respectively, with an overall accuracy of 0.8842, confirming the robustness and stability of the model across all classes.

Fig. 4 presents the classification performance of a multi-class predictive model evaluating three distinct classes: NC, SCC, and SD. It serves a significant investigative tool for identifying the model's strengths and weaknesses in class-wise prediction performance.

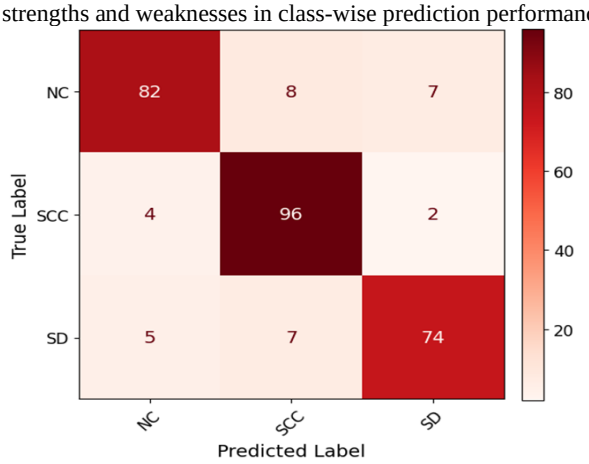


Fig. 4: Confusion matrix

From **Fig. 4**, a strong concentration of values along the main diagonal indicates that most samples are correctly classified, reflecting overall effective learning and reliable discrimination between the classes. The highest correct predictions are observed for SCC with 96 correctly classified instances, followed by NC with 82 correct predictions and SD with 74 correct predictions, showing consistent performance across all categories.

A more detailed examination reveals that the main classification errors occur between visually similar classes. NC samples are mainly confused with SCC (8 instances) and SD (7 instances), while SD is also occasionally misclassified as SCC (7 instances) or NC (5 instances). SCC shows relatively strong robustness, though a small number of samples are misclassified as NC (4) and SD (2). These patterns suggest that most errors are mild inter-class confusions rather than severe misclassifications. As illustrated in **Fig. 4**, the model demonstrates strong overall reliability, with particularly high performance in identifying SCC and maintaining a low rate of critical misclassifications.

The ROC curve, which illustrates the classification performance of the model across the three classes (NC, SCC, and SD), is presented in **Fig. 5**.

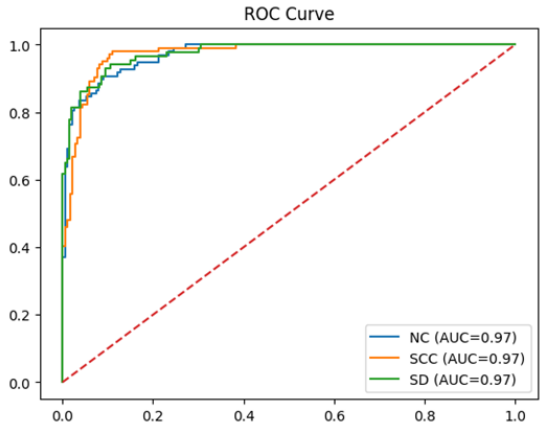


Fig. 5: ROC curve

As shown in **Fig. 5**, each class achieves an AUC of approximately 0.97, which reflects a very high capability of the model to distinguish between positive and negative samples. Overall, the curves show a consistent and stable performance across all classes, with minimal variation between NC, SCC, and SD. The steep rise in true positive rate at low false positive rates suggests that the model maintains high sensitivity while keeping misclassification low. This confirms that the trained model is highly reliable for multi-class PV defect classification and performs well in separating normal and faulty conditions.

Conclusion

This work introduced a deep learning framework for identifying and classifying PV panel conditions using the ResNet50 architecture. The experimental results demonstrated that the model is capable of accurately differentiating between normal panel conditions and various types of solar panel defects. The findings highlight the effectiveness of this technique in automated PV inspection and fault detection tasks. In addition, the developed framework can contribute to intelligent monitoring and maintenance procedures in high-capacity solar power systems by minimizing reliance on traditional manual inspection methods. Future studies may concentrate on enhancing classification performance through the use of larger and more heterogeneous datasets collected from multiple environmental conditions, including dry, semi-dry, desert, and other climatic regions. Further investigations may also explore the adoption of additional architectures to improve feature extraction and classification capability. Moreover, future developments could involve implementing the framework within real-time smart monitoring systems for continuous PV supervision and predictive maintenance applications.

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