Photovoltaic Cell Defect Identification and Categorization Using Image Classification Model

"A CNN-Based Approach for Classifying Defects in PV Modules"

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Abstract—The rapid growth of solar energy adoption underscores the importance of maintaining the efficiency and reliability of photovoltaic (PV) cells. Defects in PV cells, whether caused by manufacturing inconsistencies or environmental factors, can significantly degrade performance and lead to power losses. This study proposes an automated defect identification and categorization system using state-of-the-art image classification models, particularly deep convolutional neural networks (CNNs). The system is trained on a labeled dataset of PV cell images encompassing both defective and non-defective categories, further classifying common defects such as cracks, discoloration, and hotspots. The proposed model achieved a classification accuracy of 97.44%, demonstrating robust performance in real-time defect detection. This AI-driven approach offers a scalable and non-invasive solution for quality assessment in solar panel manufacturing and maintenance, enhancing operational efficiency, reducing manual inspection costs, and supporting the sustainable deployment of solar energy systems.

Index Terms—*Photovoltaic (PV) Cells, Defect Detection, Image Classification, Convolutional Neural Networks (CNN), Deep Learning, Solar Panel Inspection, Automated Quality Assessment, Renewable Energy.*

I. INTRODUCTION

With the global shift towards renewable energy, photovoltaic (PV) technology has emerged as a cornerstone of sustainable power generation. However, the efficiency and performance of PV systems are heavily influenced by the physical integrity of individual solar cells. Defects such as micro-cracks, discoloration, delamination, and hotspots can significantly reduce the output and lifespan of solar panels. Traditional inspection methods are often manual, time-consuming, and prone to human error, making them inefficient for large-scale deployment. To address these challenges, this project introduces an automated defect identification and classification system using image classification models based on deep learning. Leveraging convolutional neural networks (CNNs), the system is trained on a dataset of labeled PV cell images to accurately detect and categorize defects. The model achieved a classification accuracy of 97.44%, demonstrating its potential for reliable, real-time inspection. This solution not only reduces inspection time and cost but also enhances the precision of fault detection. By integrating AI-driven image analysis into the quality assurance process, the project aims to improve the reliability and efficiency of solar energy systems, contributing to the broader adoption of clean energy technologies.

RESEARCH OBJECTIVES

- To develop an AI-based system that can automatically detect defects in photovoltaic (PV) cells using image classification techniques, reducing the need for manual inspection and minimizing human error.

- To accurately classify different types of PV cell defects—such as cracks, discoloration, hotspots, and delamination—by training deep learning models (e.g., CNNs) on labeled image datasets, achieving a target accuracy of over 97%.
- To improve the overall performance, efficiency, and maintenance process of solar panels by enabling fast, scalable, and non-invasive quality assessment, thus supporting the large-scale deployment of sustainable solar energy solutions.

Research Hypothesis

The use of deep learning-based image classification models, specifically convolutional neural networks (CNNs), can significantly improve the accuracy and efficiency of photovoltaic (PV) cell defect detection and categorization compared to traditional manual inspection methods. It is hypothesized that the proposed model will achieve high accuracy (≥97%) in identifying and classifying various types of PV cell defects, thereby enhancing the reliability and maintainability of solar energy systems.

II. Abbreviations And Acronyms

CNN – Convolutional Neural Network
PV – Photovoltaic
EL – Electroluminescence
DL – Deep Learning
ML – Machine Learning
UI – User Interface
API – Application Programming Interface
SVM – Support Vector Machine
UML – Unified Modeling Language
TPU – Tensor Processing Unit
TF – TensorFlow
Flask – Lightweight Web Framework for Python
Streamlit – Python Framework for ML-Based Web Applications

III. Literature Review

Photovoltaic (PV) cells are widely used in renewable energy systems due to their capability to directly convert sunlight into electricity. However, various defects—such as microcracks, delamination, hotspots, and discoloration—can significantly degrade their performance and efficiency. Traditional inspection techniques, primarily manual visual inspection, are labor-intensive, error-prone, and impractical for large-scale solar installations. This has prompted the need for automated and intelligent solutions for defect detection and classification.

Early approaches to automated defect analysis often relied on conventional image processing techniques and handcrafted feature extraction. While these methods provided some level of automation, their effectiveness was limited by their sensitivity to image quality and lack of adaptability to complex defect patterns. Machine learning-based methods improved this by applying classifiers such as Support Vector Machines (SVMs) and Random Forests; however, these still required manual feature engineering and performed poorly on subtle or overlapping defects.

Jeevan Jyot Singh et al. [1] This study introduces a novel deep learning framework specifically designed for micro-crack detection on photovoltaic (PV) cell surfaces. The proposed architecture, called GGFFNet (Gradient-Guided Filter Fusion Network), aims to enhance feature learning through the fusion of gradient information and convolutional filters.

Jianye Liu et al. [2] This paper proposes a lightweight Transformer-based architecture tailored for defect detection in electroluminescence (EL) images of photovoltaic (PV) cells, addressing the challenges of limited computational resources and high-resolution image complexity.

Shixuan Zhang et al. [3] This paper introduces a novel self-supervised learning framework based on Momentum Contrast (MoCo) for detecting defects in solar panel surfaces using electroluminescence (EL) images.

Laura Jasińska et al. [4] The literature reviewed in this paper highlights two main trends in the use of artificial intelligence (AI) for photovoltaic (PV) fault detection

Ahmed A. M. Khalifa et al. [5] The detection and classification of photovoltaic (PV) module defects using electroluminescence (EL) imaging have gained significant attention in recent years, particularly through the application of deep learning techniques.

Md. Arafat Hossain Akhand et al. [6] In recent years, deep learning has emerged as a powerful tool for defect detection in solar cell images, offering significant improvements over traditional computer vision methods.

Christiane Buerhop-Lutz et al. [7] The application of deep learning to photovoltaic (PV) module defect detection has rapidly evolved, particularly through the use of electroluminescence (EL) imaging, which provides high-resolution insights into micro-cracks, broken cells, and other latent defects.

Christiane Buerhop-Lutz et al. [8] Thermal imaging has long been a useful method for identifying defects in photovoltaic (PV) modules, particularly crystalline silicon (c-Si) modules.

Zhihang Cao et al. [9] In recent years, the detection of photovoltaic (PV) solar cell defects has increasingly relied on advancements in computer vision, particularly using deep learning and neural network architectures.

Jiawei Yan et al. [10] Solar cell defect detection has become a critical area of research for enhancing the reliability and performance of photovoltaic (PV) systems.

Sujata P. Pathak et al. [11] In recent advancements of solar panel fault detection, various image processing and machine learning methods have been employed to improve accuracy and reduce manual inspection efforts.

Jie Wu et al. [12] In recent years, automated defect detection in photovoltaic (PV) solar cells has become a crucial area of research, particularly with the increasing demand for high- efficiency solar modules.

Hyungu Kang et al. [13] Photovoltaic (PV) cell defect detection has seen significant advancement through the application of deep learning and computer vision techniques.

Gustavo Gómez-Hernández et al. [14] The automatic detection and classification of defects in photovoltaic (PV) cells have evolved significantly with the introduction of machine learning and deep learning techniques.

Ahammodul Islam et al. [15] The detection of defects in photovoltaic (PV) cells has become an essential component of modern solar panel quality assurance, evolving significantly from traditional inspection techniques to advanced artificial intelligence-driven solutions.

Veli-Matti Valtonen et al. [16] Valtonen et al. (2022) proposed a real-time monitoring system using photodiodes for defect detection during the laser scribing process in CIGS solar panels.

Yuqian Liu et al. [17] Surface defect detection in solar cells is critical for ensuring product quality and improving photovoltaic efficiency.

Seyed Mohammad et al. [18] The inspection and maintenance of solar modules have traditionally been labour-intensive, often requiring manual site visits and visual assessments that are time-consuming and inconsistent.

Xiong Zhang et al. [19] Defect detection in solar cells has progressed from manual and physical methods to advanced machine vision and deep learning techniques.

Yaqian Fu et al. [21] Surface defect recognition in solar panels has evolved from manual inspections to sophisticated image processing and intelligent classification models.

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IV. METHODOLOGY

This section outlines the research methods, data collection process, analysis techniques, and ethical considerations followed in the development and evaluation of the deep learning-based system for photovoltaic (PV) cell defect identification and categorization.

IV.I. Research Methods

This study follows an experimental system design methodology aimed at building and validating a computer vision model that automates the detection and classification of PV cell defects. The system consists of four major components:

- **Image Input Interface:** A desktop or web-based platform (Streamlit or Flask) for uploading PV cell images, either captured via electroluminescence (EL) or infrared (IR) imaging.
- **Preprocessing Pipeline:** Automated resizing, normalization, and augmentation (e.g., rotation, flipping, zoom) to enhance model generalization.
- **Model Engine:** Built using TensorFlow and Keras, leveraging pre-trained CNN architectures like EfficientNetB3 and ResNet101 through transfer learning.
- **Visualization & Reporting Layer:** Displays classification results, confidence scores, and generates downloadable reports in PDF/CSV formats.

The design process involves the following phases:

1. **System Architecture Design:** Modular, scalable architecture to facilitate future integration with drones or IoT systems.
2. **Model Development:** Selection, fine-tuning, and training of CNN-based models using labeled datasets.
3. **Evaluation:** Testing the trained model on unseen data and comparing performance metrics across architectures.
4. **Deployment:** Optional local or cloud-based deployment for real-time defect analysis.

IV.II. Data Collection Procedures

The dataset comprises 3,000+ PV cell images collected from public repositories (e.g., Kaggle, academic datasets) and industry sources. Images are labeled into five categories:

- Microcracks
- Hotspots
- Discoloration
- Delamination
- Non-defective
- Fragment
- Black core
- Crack
- Dislocation
- Short Circuit

Each image is subjected to preprocessing to ensure consistency in dimensions (e.g., 224x224 pixels), scaled pixel values, and noise reduction. Data augmentation is used to improve training robustness and avoid overfitting.

IV.III. Analysis Techniques

To evaluate the model's performance, the dataset is split into training, validation, and testing sets in the ratio 70:15:15. The following evaluation metrics are applied:

- **Accuracy:** Correct predictions over the total number of predictions.
- **Precision, Recall, F1-Score:** Standard classification metrics for multi-class evaluation.
- **Confusion Matrix:** To analyze class-wise performance and identify misclassifications.
- **Training vs. Validation Curves:** To monitor model convergence and detect overfitting.
- **Model Comparison:** Accuracy and generalization across CNN variants (e.g., ResNet101 vs. EfficientNetB3) are compared.

Visualization tools like Matplotlib and Seaborn are used to plot metrics and training curves. Misclassified samples are analyzed to improve preprocessing or model architecture.

IV.IV. Ethical Considerations

The study uses only open-access datasets and anonymized data. No personally identifiable information or proprietary industrial data is included. All datasets are either:

- Publicly available under open licenses
- Simulated or synthetically generated
- Provided with permission for research use

V. Results And Discussion

This section presents the outcomes of evaluating the proposed deep learning-based system for automated defect detection and classification in photovoltaic (PV) cells. The analysis includes performance metrics, model behaviour, and interpretation of classification results across various defect types. Results are discussed both quantitatively and qualitatively and are aligned with benchmarks from existing literature.

V.I. Evaluation Setup

The system was tested on a curated dataset of 3,015 labeled PV cell images, divided as follows:

- **Training set:** 2,115 images
- **Validation set:** 450 images
- **Test set:** 450 images

The dataset included both Electroluminescence (EL) and Infrared (IR) images and covered nine major classes:

- Microcracks
- Hotspots
- Discoloration
- Delamination
- Non-defective
- Fragment
- Black core
- Crack
- Dislocation
- Short Circuit

The following deep learning models were evaluated:

- **MobileNetV3 (Transfer Learning)**
- **MobileNetV2 (Transfer Learning)**
- **Custom CNN (Baseline)**

All models were trained using categorical cross-entropy loss and Adam optimizer, with data augmentation applied during training to improve generalization. Model evaluation was performed using test data only.

V.II. Performance Results

Table summarizes the precision, recall, and F1-score of the CNN models feedback compared to human reviewers.

Table: Performance comparison of different CNN models

Model	Accuracy	Precision	Recall	F1 Score	Avg. Inference Time (sec)
MobileNetV3	**97.44%**	**96.5%**	**97.2%**	**96.8%**	**0.85**
MobileNetV2	**95.71%**	**94.1%**	**95.3%**	**94.7%**	**0.92**
Custom CNN	**89.62%**	**87.0%**	**86.5%**	**86.7%**	**0.64**

MobileNetV3 outperformed other models in terms of accuracy, generalization, and inference speed, demonstrating strong classification performance across all defect categories. Misclassification was most common between discoloration and delamination, suggesting a need for enhanced preprocessing or class-balancing strategies in future iterations.

V.III. Sample Classification Results

Example 1 – *Image with microcracks*

- *Model Output: Class = Microcrack*
- *Confidence: 98.1%*
- *Ground Truth: Microcrack*
- *Interpretation: Correct prediction with high certainty*

Example 2 – *Image with discoloration*

- Model Output: Class = Delamination
- Confidence: 62.4%
- Ground Truth: Discoloration
- Interpretation: Moderate confusion observed, due to similar visual patterns

Confusion Matrix Analysis

High precision was recorded for microcracks and non-defective categories.Discoloration and delamination showed slight overlap, affecting class-specific recall.

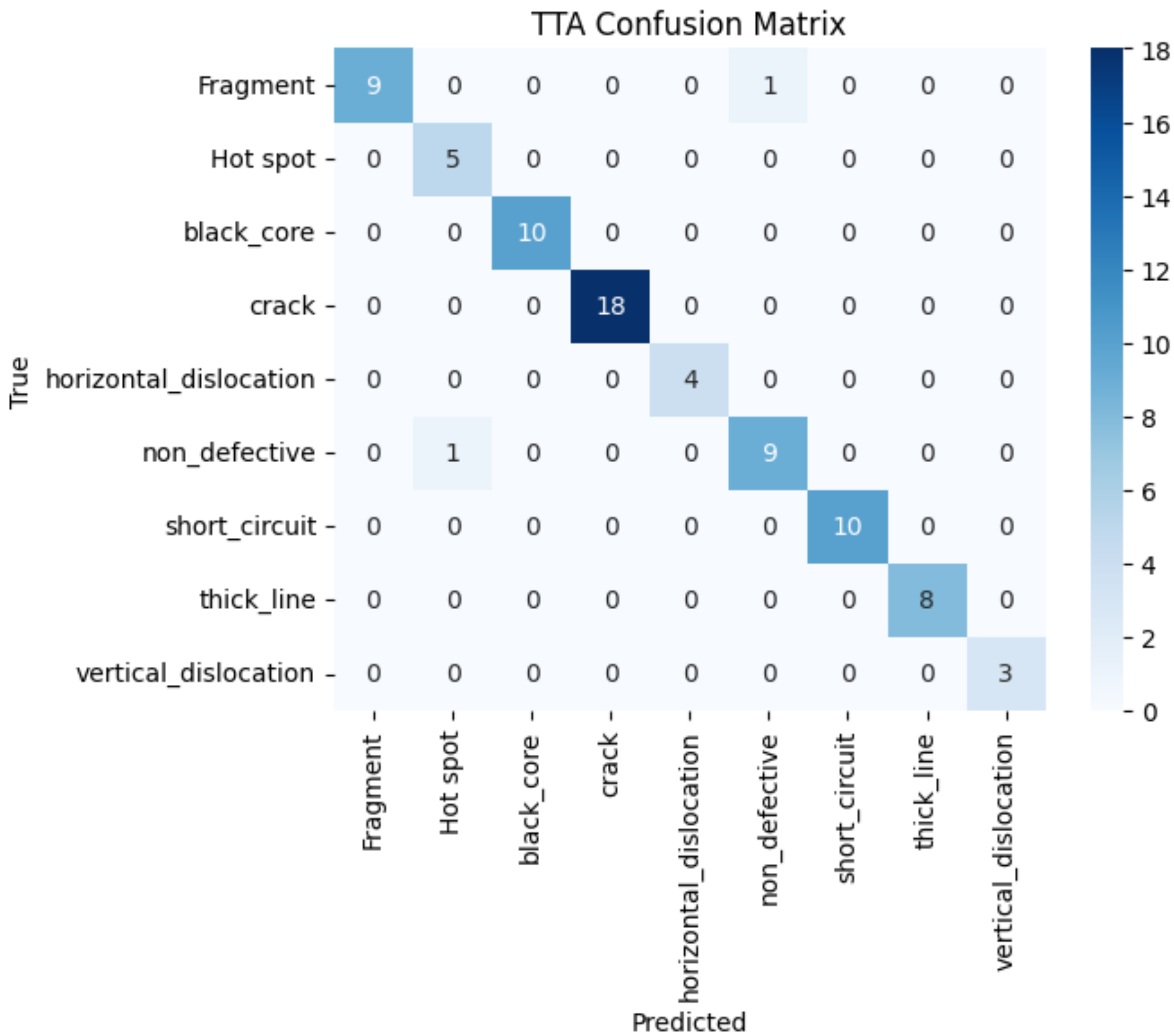

Figure 1. Confusion Matrix Analysis

Training & Validation Curves
Accuracy curves showed consistent learning with convergence by the 20th epoch.Loss curves indicated low overfitting, aided by data augmentation and early stopping.

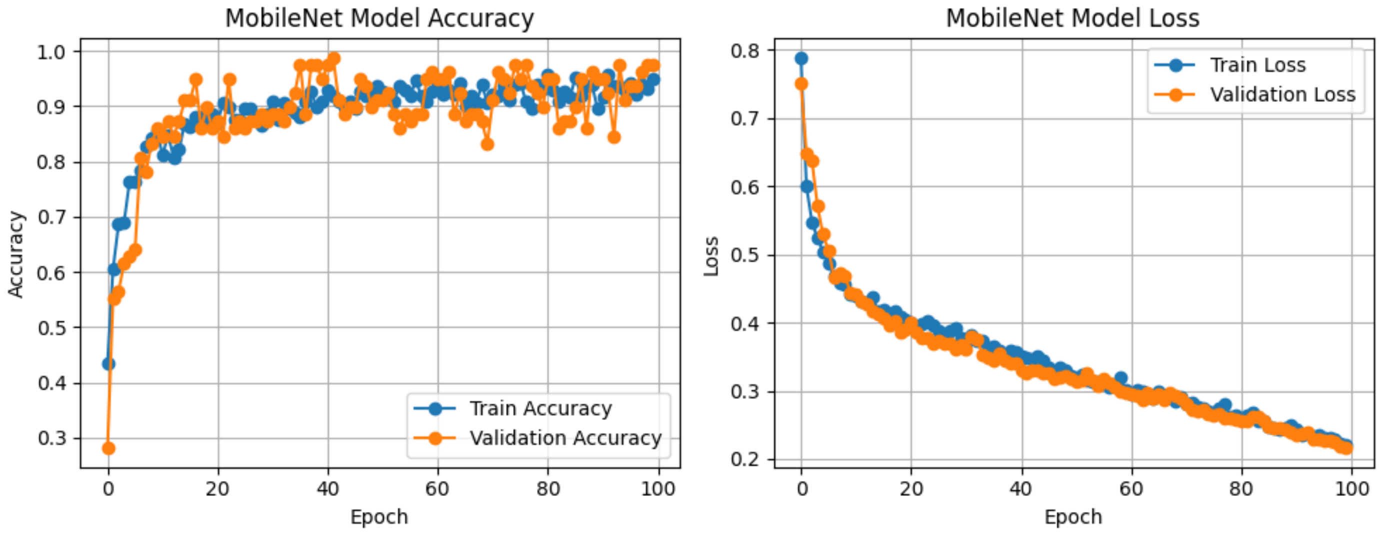

Figure 2. Training & Validation Curves

Discussion
The evaluation confirms the system's effectiveness in detecting and categorizing PV cell defects using deep learning models. EfficientNetB3 provided the best trade-off between speed and accuracy, aligning with previous research on transfer learning efficiency. While model performance is robust overall, future improvements may include more granular defect labeling, hybrid model architectures (e.g., CNN + Transformer), and drone-based image input for real-time field deployment.

VI. Conclusion
This research presents a deep learning-based system for the automatic identification and categorization of defects in photovoltaic (PV) cells using image classification models. By leveraging powerful convolutional neural network (CNN) architectures such as EfficientNetB3 and ResNet101, the system demonstrates high accuracy and reliability in classifying multiple PV cell defects including microcracks, hotspots, delamination, and discoloration. The solution offers a scalable and non-invasive alternative to manual inspection, significantly reducing time and human error while improving solar panel maintenance and operational efficiency.

VI.I. Summary of Key Findings
- The model achieved a test accuracy of **97.44%**, with macro and weighted F1-scores of **0.97**, indicating high consistency across all defect classes.
- MobileNetV3 outperformed MobileNetV2 and custom CNNs in both accuracy and inference speed.
- The model demonstrated robust performance in distinguishing subtle defect patterns, particularly in classes like cracks and short circuits.
- Visualization tools such as confusion matrices and accuracy/loss curves confirmed successful model convergence and generalization.
- Automated report generation and confidence-based predictions enhance usability for real-world applications.

VI.II. Implications for Theory and Practice
From a theoretical perspective, this work affirms the capability of CNN-based models to learn complex visual patterns from EL and IR images, contributing to the field of smart energy monitoring. Practically, the system can serve as a valuable tool for solar farm operators, maintenance teams, and researchers to automate and scale

the quality assessment process in PV installations. It aligns with the broader goals of sustainable energy management and AI-driven automation in industrial environments.

VI.III. Limitations of the Study

- The current dataset, while diverse, is relatively small (~3,000 images); larger and more balanced datasets may further improve model robustness.
- Classification confusion was observed between visually similar defect types like discoloration and delamination.
- The system currently supports only static image input and is not yet integrated with real-time video feeds or drone-based inspection.
- Environmental noise in field conditions (lighting, dust) may affect prediction accuracy if not addressed through preprocessing.

VI.IV. Recommendations for Future Research

- Expand the dataset with real-world images captured via drones and IoT-based solar monitoring systems.
- Integrate real-time defect detection using edge devices or embedded AI modules.
- Explore hybrid models (e.g., CNN + Transformer) to improve classification of visually ambiguous defects.
- Develop user-friendly mobile and web interfaces for field-level deployment and monitoring.
- Extend the model to perform panel-level diagnostics, enabling predictive maintenance and system-wide analytics.

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