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Full Length Article

Defect Detection in Solar Cell Images Using Deep Learning

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Abstract
This research study introduces a unique method that makes use of a wide range of deep learning (DL) techniques for automated flaw identification in solar cell images. The research paper investigates how well 24 distinct convolutional neural network (CNN) architectures — ResNet, DenseNet, VGG, Inception, MobileNet, Xception, SqueezeNet, and AlexNet — classify solar cells into defected and non-defective categories. The study performs a thorough assessment of a wide variety of models, concentrating on high-performance architectures and lightweight models suitable for resource-constrained contexts. A balanced and well-curated dataset of 3,102 images of solar cells with a range of common faults was used. MobileNetV2 and Xception demonstrated excellent performance in defect identification, with accuracy rates of 99.95% and 99.29% respectively, with minimal validation losses. This study demonstrates the potential of efficient models such as MobileNetV2 for real-world use in solar energy generation.

Keywords: *computer vision, defect detection, deep learning, image classification, photovoltaics.*

Introduction

Solar energy has become an essential component in the global effort to reduce dependence on fossil fuels and transition to renewable energy alternatives. Solar Photovoltaic (PV) systems are important because they directly convert sunlight into electricity, making use of the plentiful and renewable energy from the sun. The popularity of these systems has increased rapidly due to technological breakthroughs, cost reductions, and growing awareness of the environmental advantages of clean energy generation.

While PV systems offer numerous savings, upkeep and inspection of solar cells remains a major challenge. The generation of defects such as micro-cracks, hot spots, and physical worsening during the lifetime of solar cells is sensitive to a large number of environmental variables. These defects not only reduce the efficiency of solar cells but also increase maintenance costs due to requiring regular maintenance and possible replacements.

There are numerous downsides to conventional ways of spotting flaws in solar cells. Manual inspection is intrinsically subjective and relies on human judgment. This approach also requires an inordinate amount of manual work and time to execute, and becomes significantly less effective when applied to large-scale solar farms. Classical image processing methods, while less subjective, often fail to detect the complex traits of different types of cell faults, resulting in a considerable amount of false positives (FPs) and false negatives (FNs).

Electroluminescence (EL) imaging provides superior spatial resolution and the capability to detect faults that would otherwise be undetectable. Nevertheless, the interpretation of these images necessitates substantial expertise, and the process of manual analysis continues to be expensive and ineffective. Deep learning (DL) is a highly effective method for tackling these difficulties, as it is particularly skilled at identifying intricate patterns from extensive datasets.

The primary objective of this research is to develop and evaluate DL models for the automated detection of defects in solar cell images. The study examines 24 advanced DL algorithms including ResNet (18, 34, 50, 101, 152), DenseNet (121, 161, 169, 201), VGG (11, 13, 16, 19), Inception (V1–V4), MobileNet (V1, V2, V3), Xception, SqueezeNet (1.0, 1.1), and AlexNet. The effectiveness of these models is assessed using accuracy, precision, recall, F1-score, and loss metrics.

Related Work

Significant progress has been made in the field of automated flaw detection in solar cell images using DL in recent years. Several distinct DL techniques have been suggested, each offering different approaches and reaching different levels of success. Table 1 presents an overview of major studies in this area. Studies have employed varied methodologies including EfficientNet-B0, Xception, Vision

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Transformer (ViT), GAN-based augmentation, YOLO variants, and hybrid models. Key findings include: (i) ViT achieved 98.23% binary classification accuracy on thermographic IR images; (ii) KDBiDet obtained AP50 of 82.2% for hot-spot detection; (iii) EfficientNet-B0 with CLAHE and focal loss achieved 97.81% accuracy; (iv) DFB CNN achieved 98.15% for binary and 95.35% for multi-class detection; and (v) ResNet50 with transfer learning achieved 99.4% accuracy on steel surface defects

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Table 1. Summary of Related Work in Solar Cell Defect Detection

Ref.	Year	Method / Contribution	Key Findings / Performance
[23]	2024	MobileNet-based DL for edge devices (SoilingEdge) — FPGA deployment	Ideal balance between cost and inference speed
[24]	2024	Knowledge distillation bi-branch (KDBiDet)	AP50 = 82.2% for hot-spot detection
[25]	2024	Vision Transformer (ViT) with IR thermographic images	98.23% binary classification accuracy
[26]	2024	GAN-based infrared-visible image fusion	93.7% fine-grained fault detection accuracy
[32]	2024	EfficientNet-B0 with CLAHE preprocessing and Grad-CAM	97.81% accuracy, outperforms state-of-the-art
[38]	2022	ResNet152-Xception hybrid with Attention mechanism	96.17% binary, 92.13% multi-class accuracy
[40]	2022	Deep Feature-Based (DFB) CNN	98.15% binary, 95.35% multi-class accuracy
[35]	2023	Transfer Learning with ResNet50	99.4% accuracy on testing set

Methodology

A. Dataset

The dataset consists of 3,102 solar cell images collected from multiple sources, of which 1,570 are categorized as defective and 1,532 as non-defective, demonstrating a significant degree of balance. The images were preprocessed and normalized to a uniform size of 244 × 244 pixels. The dataset was divided into training and validation sets with a ratio of 80:20 (80% training, 20% validation).

Table 2. Dataset Composition

Category	Count
Defective	1,570
Non-Defective	1,532
Total	**3,102**

B. Training Configuration

Table 3 provides the essential training parameters used in the solar cell image classification model. A random seed value of 42 was utilized to ensure reproducibility. Models were trained for 25 epochs using a batch size of 16, with binary cross-entropy as the loss function and the Adam optimizer.

Table 3. Training Hyperparameters

Parameter	Value	Description
img_height / img_width	244	Image size for preprocessing
random_state	42	Random seed for reproducibility
batch_size	16	Samples per gradient update
epochs	25	Maximum training iterations
optimizer	Adam	Optimization algorithm
loss	binary_crossentropy	Loss function for binary classification
patience	3	Early stopping patience threshold
min_delta	0.01	Minimum improvement required
restore_best_weights	True	Restore best model weights on training completion

C. Evaluation Metrics

The following evaluation metrics were used throughout this study:

Precision measures the proportion of correctly predicted positive observations to total predicted positives:

$$Precision = TP / (TP + FP) \quad \dots \quad (1)$$

Recall (Sensitivity) is the ratio of correctly predicted positive observations to all actual positives:

$$Recall = TP / (TP + FN) \quad \dots \quad (2)$$

F1-Score is the harmonic mean of Precision and Recall:

$$F1\text{-}Score = 2 \times (Precision \times Recall) / (Precision + Recall) \quad \dots \quad (3)$$

Accuracy is the proportion of correctly predicted observations to total observations:

$$Accuracy = (TP + TN) / (TP + TN + FP + FN) \quad \dots \quad (4)$$

Binary Cross-Entropy Loss function used for model training:

$$Loss = -(1/N)\ \Sigma\ [y_i \cdot \log(p_i) + (1 - y_i) \cdot \log(1 - p_i)] \quad \dots \quad (5)$$

D. Workflow

The automatic flaw detection process is organized into multiple crucial phases as follows:

Data Preparation: Load data from multiple sources (defective and non-defective solar cell images).

Normalize Images: Scale pixel values to range [0, 1] for training stability.

Split into Training and Validation Sets (80:20 ratio).

Algorithm Selection: Choose DL algorithm (ResNet, DenseNet, VGG, Inception, MobileNet, Xception, SqueezeNet, AlexNet).

Model Development: Build selected model with appropriate layers, activation functions, optimizer, and loss function.

Train Model on training dataset using backpropagation and Adam optimizer.

Evaluate Model using validation set; compute accuracy, loss, precision, recall, F1-score.

Results Visualization: Plot training/validation metrics, generate confusion matrices and classification reports.

E. Model Architectures

The study implements and evaluates 24 CNN architectures across 8 families. Table 4 presents a comparison of key model characteristics.

Table 4. Comparison of CNN Architecture Characteristics

Architecture	Parameters	FLOPs (M)	Complexity	Feature Extraction	Edge Suitability
ResNet-18/34	11.7M–21.8M	44–85	Moderate	Strong	Moderate
ResNet-50/101/152	25.6M–60.2M	98–230	High	Strong	Low
DenseNet-121/161/169/201	8.0M–20.2M	33–88	High	Very Strong	Low
VGG-11/13/16/19	132.9M–143.7M	507–548	High	Moderate	Low
InceptionV1/V2/V3/V4	5.6M–41.2M	21–153	Moderate–High	Strong	Moderate
MobileNetV1/V2/V3	2.5M–4.2M	10–17	Low	Moderate	High
Xception	22.9M	88	High	Very Strong	Moderate
SqueezeNet-1.0/1.1	1.2M	4.6–4.8	Low	Moderate	High
AlexNet	61M	240	High	Moderate	Moderate

Results and Discussion

A. Model Performance Comparison

Table 5 presents the comparative performance of all 24 DL models evaluated in this study. Models are ranked within each architecture family by performance. MobileNetV2 achieves the highest accuracy at 99.95% with a minimal validation loss of 0.0068, demonstrating exceptional generalization to unseen data. Xception achieves 99.29% accuracy and 99.03% validation accuracy. SqueezeNet models performed poorly with accuracy near 47.71%, indicating significant limitations for this task.

Table 5. Comparative Model Performance (Best Models Highlighted)

Model	Train Acc. (%)	Train Loss	Val. Acc. (%)	Val. Loss	Rank
SqueezeNet-1.0/1.1	47.71	0.6940	47.34	0.6941	Poor
VGG-11	88.16	0.4855	84.70	0.5081	—
VGG-13	90.64	0.2637	88.24	0.2930	Best VGG
ResNet-18	92.27	0.2047	89.86	0.2333	—
ResNet-50	92.44	0.2259	90.34	0.2589	Best ResNet
AlexNet	92.80	0.2137	90.82	0.2533	—

Model	Train Acc. (%)	Train Loss	Val. Acc. (%)	Val. Loss	Rank
DenseNet-121	95.12	0.1300	93.56	0.1544	—
DenseNet-169	95.72	0.1197	93.88	0.1458	Best DenseNet
InceptionV3	98.82	0.0329	98.55	0.0416	Best Inception
Xception	99.29	0.0306	99.03	0.0299	—
MobileNetV1	99.42	0.0134	99.19	0.0174	—
MobileNetV2	**99.95**	**0.0075**	**99.84**	**0.0068**	**Best Overall**
MobileNetV3	90.50	0.2459	87.92	0.2766	—

B. Classification Metrics

Table 6 presents classification metrics for the best-performing model from each architecture family. MobileNetV2 achieves a perfect F1-score of 1.00 for both classes. Xception and InceptionV3 both achieve F1-scores of 0.99 for all classes. DenseNet-169 achieves an F1-score of 0.94, while AlexNet achieves 0.91.

Table 6. Per-Class Classification Metrics (Best Models Per Family)

Model	Class	Precision	Recall	F1-Score	Accuracy	Weighted Avg
SqueezeNet-1.1	Non-defective / Defective	0.47 / 0.00	1.00 / 0.00	0.64 / 0.00	—	0.32
VGG-13	Non-defective / Defective	0.80 / 1.00	1.00 / 0.78	0.89 / 0.87	—	0.88
ResNet-152	Non-defective / Defective	0.83 / 1.00	1.00 / 0.81	0.90 / 0.90	—	0.90
AlexNet	Non-defective / Defective	0.84 / 1.00	1.00 / 0.83	0.91 / 0.90	—	0.91
DenseNet-169	Non-defective / Defective	0.91 / 0.96	0.96 / 0.92	0.94 / 0.94	—	0.94
InceptionV3	Non-defective / Defective	0.98 / 0.99	0.99 / 0.98	0.98 / 0.99	—	0.99
Xception	Non-defective / Defective	0.99 / 0.99	0.99 / 0.99	0.99 / 0.99	—	0.99
MobileNetV2	**Non-defective / Defective**	**1.00 / 1.00**	**1.00 / 1.00**	**1.00 / 1.00**	**—**	**1.00**

C. Training Behaviour and Convergence

Across all models, the following training behavior was observed: (i) SqueezeNet-1.1 accuracy hovered around 50%, indicating underfitting; (ii) VGG-13 reached approximately 88% validation accuracy within the first epoch with minimal overfitting; (iii) ResNet-152 showed a steady increase to nearly 90% on both training and validation sets; (iv) AlexNet rapidly increased validation accuracy to approximately 91%; (v) DenseNet-169 converged at approximately 94% for both metrics; (vi) InceptionV3 demonstrated validation accuracy close to 99%; (vii) Xception achieved near-perfect validation accuracy of approximately 99%; and (viii) MobileNetV2 achieved high validation accuracy by the second epoch, demonstrating its ideal balance of depth and processing efficiency.

D. Confusion Matrix Analysis

Confusion matrix results confirmed the quantitative findings. MobileNetV2 achieved near-perfect classification with only 1 non-defective sample misclassified. Xception misclassified only 4 defective and 2 non-defective samples. InceptionV3 misclassified only 5 defective and 4 non-defective samples. DenseNet-169 correctly identified 300 defective and 283 non-defective examples with minimal misclassifications. SqueezeNet-1.1 failed completely to identify any defective samples, classifying all observations as non-defective.

Conclusion

This study comprehensively evaluated 24 DL architectures for automated defect detection in solar cell images. The key conclusions are:

MobileNetV2 is the top-performing model, achieving 99.95% accuracy, 99.84% validation accuracy, and a perfect F1-score of 1.00, making it ideal for real-time industrial deployment.

Xception and MobileNetV1 also demonstrated exceptional performance with near-perfect classification metrics, suitable for complex quality control tasks.

DenseNet-169 and InceptionV3 are strong moderate performers with F1-scores of 0.94 and 0.99 respectively, offering a good balance between accuracy and computational cost.

SqueezeNet models and VGG-16 underperformed significantly, with accuracy near or below 50%, indicating insufficient model complexity for this task.

Lightweight models like MobileNetV2 are recommended for resource-constrained environments (edge deployment), while heavier models like ResNet and InceptionV3 offer superior feature extraction at higher computational cost.

The integration of these DL models into industrial PV inspection workflows can significantly enhance quality control systems, reduce manual inspection costs, and improve the long-term reliability of solar energy generation.

Future Work

Based on the findings of this research, the following directions are identified for future work:

Dataset Expansion: Broaden the dataset to include a wider variety of defect types and environmental conditions for improved model generalization across different PV system installations worldwide.

Transfer Learning and Ensemble Methods: Investigate combining pre-trained models and ensemble architectures to further enhance detection accuracy and reliability.

Edge Computing Deployment: Optimize top-performing models for deployment on edge devices using model pruning and quantization techniques to maintain high accuracy with reduced computational overhead.

Multi-Class Defect Classification: Develop more detailed multi-class defect classification to differentiate between specific defect types (micro-cracks, hotspots, discoloration) to guide targeted maintenance interventions.

Real-Time Integration: Integrate DL models with automated inspection systems and manufacturing pipelines for end-to-end, real-time defect monitoring of large-scale PV farms.

Extended PV System Compatibility: Expand the methodology to cover various categories and generations of solar cells and PV modules to enhance versatility.

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