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Enhancing defect classification in solar panel with Electroluminescence imaging and advanced machine learning strategies

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Abstract*— Electroluminescence (EL) imaging provides an effective non-destructive approach for identifying internal defects in photovoltaic (PV) cells and solar panels that may not be visible through conventional inspection techniques. However, accurate classification of EL images remains challenging due to complex defect structures, variations in defect severity, low-intensity patterns, and similarities between different defect categories. This paper proposes an advanced deep learning framework for automated solar panel defect classification using EL images. The proposed approach investigates convolutional neural network (CNN) architectures integrated with deep residual and densely connected feature-learning mechanisms. ResNet is employed to extract hierarchical and discriminative visual representations through residual learning, while DenseNet enhances feature reuse and information propagation across convolutional layers. The extracted representations are subsequently processed through fully connected classification layers to categorize photovoltaic cells into different defect conditions. The framework is designed to distinguish defective and non-defective cells and further identify specific defect patterns such as cracks, inactive regions, and other cell-level abnormalities. A comprehensive evaluation is performed using accuracy, precision, recall, F1-score, and confusion-matrix analysis to assess classification effectiveness across multiple defect categories. The proposed framework focuses on improving feature discrimination and classification reliability while maintaining an efficient deep learning architecture suitable for automated photovoltaic inspection. Experimental analysis demonstrates the potential of combining residual and dense feature representations for robust EL-based solar panel defect classification. The proposed methodology can support automated quality assessment, reduce dependence on manual inspection, and improve the reliability of photovoltaic manufacturing and maintenance processes.

Keywords*— Electroluminescence Imaging, Photovoltaic Defect Classification, Convolutional Neural Network, Residual Learning, ResNet, DenseNet, Deep Learning, Solar Panel Inspection, Defect Detection, Feature Extraction, Non-Destructive Testing, Automated Quality Assessment.

I. INTRODUCTION

Solar photovoltaic (PV) energy is vital for clean-energy generation, but cell defects such as micro-cracks and inactive regions reduce efficiency. Electroluminescence imaging effectively detects these hidden defects non-destructively [4], [9].

Conventional defect assessment in PV modules generally relies on manual visual inspection of EL images by trained experts. Although this approach can identify major defects, it is time-consuming, subjective, prone to inter-examiner variation, and impractical for large-scale industrial inspection of thousands of solar cells [11], [14]. Machine-learning and deep-learning techniques have therefore been increasingly applied to automate EL image analysis, enabling faster and more consistent defect classification [5], [6].

Deep convolutional neural networks (CNNs) have shown strong capability in learning discriminative visual features directly from EL images without relying on hand-crafted feature extraction. Architectures incorporating residual learning, such as ResNet, allow deeper networks to be trained effectively by mitigating vanishing-gradient issues, while densely connected architectures such as DenseNet improve feature reuse and gradient flow across layers [1], [2]. These architectures have been successfully applied to related defect-detection and crack-segmentation tasks in EL imaging [7], [8], [10].

Despite these advances, accurate EL-based defect classification remains challenging due to complex and irregular defect structures, variation in defect severity, low-contrast and low-intensity defect regions, visual similarity between different defect categories, and limited or imbalanced labeled datasets [12], [13]. A practical automated inspection system should therefore integrate robust feature extraction, reliable multi-category classification, and comprehensive performance evaluation. This project therefore aims to:

1. Review machine-learning and deep-learning approaches for EL-based solar panel defect classification.
2. Examine CNN architectures, including residual and densely connected networks, for feature extraction from EL images.
3. Analyze existing crack-detection, segmentation, and defect-classification techniques applied to photovoltaic cells.
4. Compare the strengths, limitations, and applicability of existing EL-based inspection methods.
5. Formulate an integrated deep learning framework combining ResNet and DenseNet for defect classification.
6. Evaluate classification performance using accuracy, precision, recall, F1-score, and confusion-matrix analysis.
7. Identify evaluation requirements, research challenges, and future directions for reliable, automated photovoltaic quality inspection.

The remainder of this paper discusses existing defect-detection approaches, the proposed comprehensive framework, evaluation requirements, challenges, future research directions, and concluding observations.

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II. EXISTING METHODS FOR EL-BASED SOLAR PANEL DEFECT CLASSIFICATION

Existing EL-based defect classification approaches can be broadly classified into manual inspection, conventional image-processing methods, conventional machine learning, deep learning, and hybrid/ensemble feature-based systems.

A. Manual Visual Inspection

Manual inspection depends on expert review of EL images to identify cracks, inactive regions, and other abnormalities. It can provide reliable judgment for clearly visible defects, but frequent large-scale inspection becomes impractical for industrial production lines. Subjective interpretation and inconsistent standards among different inspectors can limit reliable and repeatable defect identification [11], [14].

B. Conventional Image-Processing Techniques

Early automated approaches applied classical image-processing techniques, such as independent component analysis and structural decomposition, to detect abnormal regions in EL images. These methods can support basic defect localization but often struggle with irregular crack shapes, background noise, and varying illumination conditions across cells [4], [13].

C. Conventional Machine Learning

Machine-learning approaches use hand-crafted features extracted from EL images, combined with classifiers such as Support Vector Machines, to distinguish defective from non-defective cells. Their advantages include relatively efficient computation and interpretability. However, performance depends heavily on the quality of manually engineered features and often struggles to generalize across diverse defect patterns [4].

D. Deep Learning-Based Detection

Deep-learning models can automatically learn hierarchical visual representations directly from EL images, removing the need for manual feature engineering. Convolutional architectures, including residual and densely connected networks, have been investigated for classifying defect severity and identifying specific defect types [1], [2], [6]. These approaches provide improved discrimination of subtle and complex defect patterns but generally require larger labeled datasets and greater computational resources.

E. Segmentation and Localization-Based Methods

Segmentation-based approaches aim to precisely localize defect regions, such as cracks, at the pixel level rather than only classifying entire cell images. Semantic segmentation and weakly supervised segmentation techniques have been applied to extract detailed crack features and quantify defect severity [7], [10]. Such methods can provide finer-grained defect information but often involve higher annotation cost and model complexity.

F. Field and Environmental Defect Monitoring

Field-based EL studies examine how defects evolve under real operating and environmental conditions over time, such as crack propagation due to mechanical stress or thermal cycling. Machine learning can transform field-collected EL data into estimated degradation and reliability indicators [5], [16]. Although such approaches improve real-world applicability, practical challenges include data collection cost, environmental variation, and long-term monitoring requirements.

TABLE I: COMPARISON OF EXISTING SOLAR PANEL DEFECT CLASSIFICATION METHODS

Method	**Main Technique**	**Strength**	**Major Limitation**
Manual inspection	Human visual review	Direct expert judgment	Time-consuming, subjective
Conventional image processing	ICA, structural decomposition	Basic defect localization	Struggles with irregular/noisy defects
Machine learning	Hand-crafted features + SVM	Efficient, interpretable	Limited generalization
Deep learning	CNN, ResNet, DenseNet	Automatic hierarchical feature learning	Requires large labeled data
Segmentation-based	Semantic/weak segmentation	Fine-grained defect localization	High annotation cost, complexity
Field monitoring	Real-world EL data analysis	Captures real degradation patterns	Costly, environment-dependent
Proposed framework	**ResNet + DenseNet integrated CNN**	**Robust multi-category defect classification**	**Requires comprehensive validation**

The literature therefore indicates a transition from manual, subjective inspection toward automated, deep-learning-based defect classification. However, many existing approaches focus primarily on a single architecture or defect type. A comprehensive framework should integrate robust feature extraction, multi-category classification, and thorough performance evaluation into a unified automated inspection pipeline.

III. PROPOSED DEEP LEARNING FRAMEWORK FOR SOLAR PANEL DEFECT CLASSIFICATION

The proposed system considers EL-based defect classification as an integrated sequence of interconnected processing stages:

EL Images of Solar Cells
↓
Image Acquisition
↓
Image Preprocessing
↓
Feature Extraction (ResNet + DenseNet)
↓
Feature Fusion and Representation Learning
↓
Defect Classification
↓
Defect Type Identification (Cracks, Inactive Regions, etc.)
↓
Performance Evaluation and Reporting

The architecture consists of five major functional layers: image acquisition, preprocessing, feature extraction, classification, and evaluation. The first layer collects EL images of PV cells captured under controlled illumination and imaging conditions. The preprocessing layer removes noise, corrects distortion, normalizes intensity variations, and prepares images for consistent input into the deep learning models.

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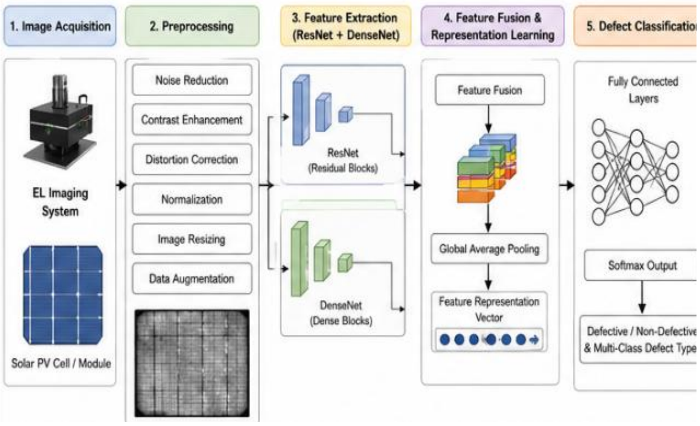

Fig. 1. Overall Architecture of the Proposed Deep Learning-Based Solar Panel Defect Classification System

The feature-extraction layer applies ResNet to learn hierarchical and discriminative visual representations through residual connections, enabling effective training of deeper networks without degradation. In parallel, DenseNet enhances feature reuse and strengthens information propagation across layers, improving sensitivity to subtle and low-intensity defect patterns. The classification layer processes the extracted and fused representations through fully connected layers to categorize cells as defective or non-defective and to identify specific defect types.

Finally, the evaluation layer reports classification outcomes, confidence levels, and performance metrics to support quality-control decisions. The architecture is designed as a decision-support tool for automated inspection, assisting quality-control personnel rather than completely replacing expert verification for critical decisions. This integrated approach enables consistent, scalable, and efficient defect classification across large volumes of EL images.

IV. EL IMAGE DATA AND DEFECT REPRESENTATION

A. EL Image Data Acquisition and Processing

The proposed system collects EL images capturing internal defect patterns of individual PV cells, including cracks, inactive regions, finger interruptions, and other visible abnormalities. Preprocessing handles noise reduction, contrast enhancement, image resizing, and normalization to ensure consistent input quality across the dataset.

The structured EL image representation considers multiple defect-related aspects: crack-related features, inactive-region intensity patterns, edge and boundary characteristics, and overall cell-intensity distribution. These aspects are jointly analyzed to assess the condition of each solar cell.

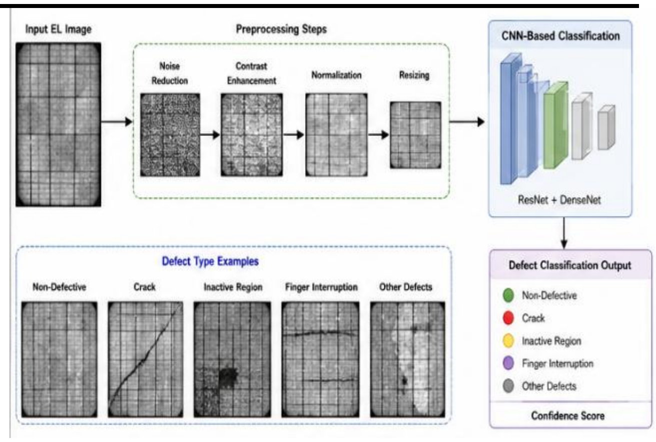

Fig. 2. EL Image Preprocessing and Defect Classification Pipeline

B. Defect Condition Representation

The defect condition of a solar cell is represented using relevant visual and structural indicators extracted from the EL image. The system extracts:

- Crack presence and pattern
- Inactive-region size and location
- Intensity distribution across the cell surface
- Edge and grid-line irregularities
- Finger-interruption indicators
- Overall defect severity level
- Cell boundary and shape consistency

Representing the extracted EL image features using a unified structure enables the proposed system to analyze the relationship between visual defect patterns and cell authenticity condition. The resulting representation is subsequently provided to the ResNet–DenseNet-based deep learning model for defect classification, defect-type identification, and severity assessment, depending on the objective of the proposed system.

V. FEATURE–DEFECT PATTERN MATCHING AND CELL CONDITION SCORING

A central component of the proposed system is feature-to-defect-pattern matching. Unlike simple intensity-threshold analysis, the proposed approach identifies relationships between the extracted visual features of an EL image and known defect patterns learned during training. The system considers indicators such as crack shape, inactive-region intensity, edge irregularity, and overall cell brightness distribution to determine the likelihood and type of defect present in a given cell.

The deep feature representation extracted through ResNet and DenseNet is compared against learned representations of known defective and non-defective cell patterns. A higher similarity to defective patterns indicates a greater likelihood that the cell contains a specific type of defect, while a higher similarity to non-defective patterns indicates a healthy cell.

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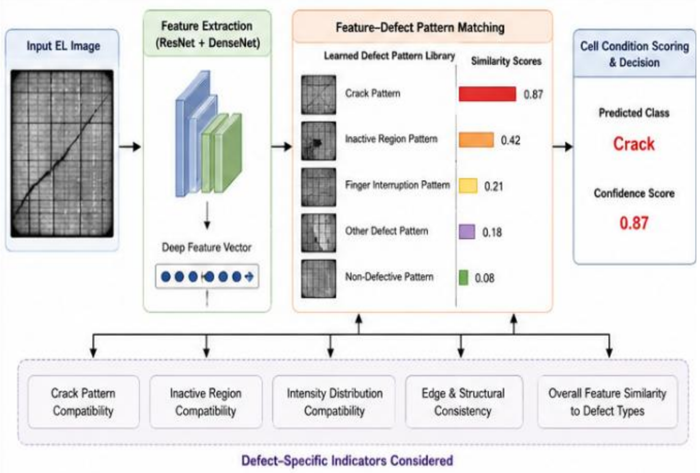

Fig. 3. Feature–Defect Pattern Matching and Cell Condition Scoring

Similarity to a general defect pattern alone, however, should not determine the final classification decision. A cell with an overall pattern similar to non-defective cells may still contain a small but critical defect, such as a fine micro-crack, that can significantly affect long-term performance. Therefore, the proposed system combines learned feature similarity with explicit, defect-specific indicators, including:

- Crack-pattern compatibility
- Inactive-region compatibility
- Intensity and brightness-distribution compatibility
- Edge and structural-consistency compatibility
- Overall learned feature similarity to known defect categories

This combined evaluation allows the defect classification system to assign appropriate importance to different visual indicators depending on the defect type being assessed. For example, crack detection may emphasize edge and structural irregularities, whereas inactive-region detection may emphasize localized intensity drops.

The EL images are subsequently evaluated according to their combined feature assessment to generate a final defect classification status and corresponding quality-control recommendation, enabling timely identification of defective cells during manufacturing or maintenance inspection.

VI. EXPLAINABLE AI AND DECISION-AWARE DEFECT CLASSIFICATION

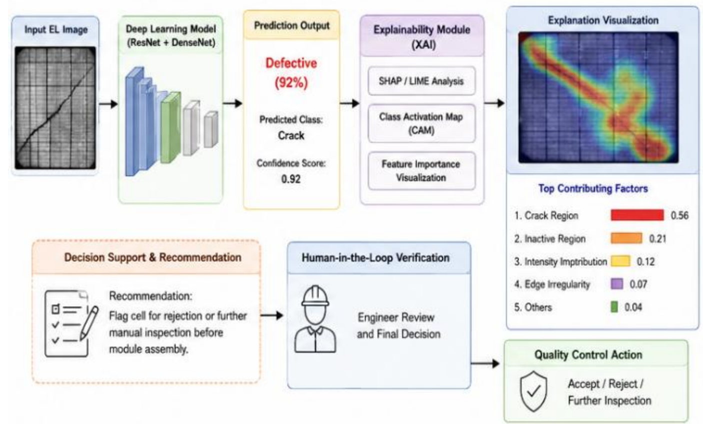

Fig. 4. Explainable AI Framework for Solar Panel Defect Classification and Decision Support

AI-based defect classification systems should provide more than a binary prediction or numerical score. Quality-control engineers and manufacturers need to understand why the system classified a particular cell as defective or non-defective. Explainable AI (XAI) techniques such as SHAP and LIME, along with visualization methods such as class-activation mapping, can provide feature-level and region-level explanations of model predictions.

For each prediction, the proposed system can generate an explanation containing:

1. Crack-region contribution
2. Inactive-region contribution
3. Edge and grid-line irregularity influence
4. Intensity-distribution influence
5. Localized defect-region highlighting
6. Major factors contributing to the final classification
7. Recommended quality-control action

For example:

Solar Cell Condition — 92% Defective

- Crack pattern: clearly visible diagonal crack detected.
- Inactive region: moderate-sized inactive area near cell edge.
- Intensity distribution: uneven brightness across cell surface.
- Edge consistency: minor grid-line irregularity detected.
- Major influencing factor: crack pattern combined with localized inactive region.
- Recommendation: Flag cell for rejection or further manual inspection before module assembly.

Such explanations help engineers understand whether the AI prediction is supported by meaningful visual defect indicators rather than relying only on the final classification score.

A. Explainability and Decision Monitoring

Defect classification models can be influenced by multiple visual and structural parameters within an EL image. Therefore, the system should continuously monitor the contribution of each region and feature to the prediction. Explainability helps identify which visual indicators have the greatest influence on

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classifying a cell as defective, non-defective, or a specific defect type.

The proposed framework therefore integrates explainability as a decision-support component. The system should report both:

Performance = How accurately does the system classify solar cell defects?

Explainability = Can the engineer understand which visual features caused the classification?

This dual objective is important because a highly accurate model that provides no understandable reasoning may be difficult to trust or act upon in practical manufacturing quality-control environments.

VII. ADAPTIVE LEARNING AND HUMAN-IN-THE-LOOP QUALITY CONTROL

Solar cell defect patterns are not entirely static. Manufacturing processes, material batches, and environmental exposure conditions can introduce new or evolving defect characteristics over time. A defect classification model trained using a fixed set of historical defect patterns may therefore become less effective when new defect types or manufacturing variations emerge.

Model Update

Adaptive mechanisms can update learned defect representations, classification thresholds, feature importance, and quality-control recommendations while maintaining model version control.

The system can periodically incorporate newly collected and labeled EL images to improve its understanding of evolving defect patterns. However, adaptive AI should not automatically modify critical quality-control decisions, such as cell rejection criteria, without validation. Model updates should first be evaluated using historical and newly collected labeled datasets before being deployed.

Human-in-the-Loop Workflow

The final defect classification decision-support workflow is:

EL Image Collection → AI Classification → Defect Assessment → Explanation → Engineer Verification → Quality-Control Recommendation → Final Engineer Decision

The quality-control engineer or inspection specialist remains responsible for the final decision, particularly when defect indicators are ambiguous or when additional contextual information, such as manufacturing batch history, is required.

This human-in-the-loop design allows engineers to combine AI-based predictions with practical manufacturing knowledge and physical cell inspection. Engineer feedback can also be captured and used for future system improvement, while preventing the AI system from making completely autonomous rejection decisions without human supervision.

VIII. EVALUATION FRAMEWORK

A comprehensive evaluation framework is adopted to assess the proposed solar panel defect classification system across classification performance, feature-pattern matching, explainability, robustness, and efficiency. Rather than relying on a single performance measure, the evaluation considers multiple complementary dimensions to determine the practical effectiveness of the proposed framework.

A. Classification Performance

The classification module is evaluated using accuracy, precision, recall, and F1-score. Accuracy measures overall classification correctness, while precision indicates the proportion of cells classified as defective that are actually defective. Recall measures the ability to correctly identify genuinely defective cells, and F1-score provides a balanced assessment of precision and recall. These metrics are important because both false rejection of good cells and missed detection of defective cells can affect manufacturing yield and product reliability.

B. Confusion Matrix Analysis

Since multiple defect categories may exist, the system is evaluated using confusion-matrix analysis to examine per-class performance. This analysis determines whether specific defect types, such as cracks versus inactive regions, are being confused with one another, and helps identify categories requiring further model refinement.

C. Feature-Pattern Matching

The feature-based defect-matching component is compared with a conventional threshold-based or hand-crafted-feature baseline. The evaluation examines whether the learned ResNet–DenseNet representations can identify defects despite variations in defect severity, cell orientation, and imaging conditions. This assessment determines the effectiveness of the learned feature representation for defect discrimination.

D. Explainability

The generated defect-classification explanations are evaluated based on faithfulness, consistency, completeness, and human understandability. The explanation should accurately represent the visual regions and features influencing the classification decision and enable engineers to verify the presence of cracks, inactive regions, or other abnormalities.

E. Efficiency and Robustness

Computational evaluation considers image-processing time, classification latency, memory consumption, and scalability to large batches of EL images typical of industrial production lines. Robustness is evaluated through testing on images with varying illumination, contrast, cell orientation, and defect severity levels, ensuring that the proposed system maintains reliable performance under diverse real-world inspection conditions.

TABLE II: EVALUATION DIMENSIONS OF THE PROPOSED DEFECT CLASSIFICATION FRAMEWORK

Dimension	Evaluation Metrics / Criteria	Purpose
Classification	Accuracy, Precision, Recall, F1-Score	Evaluate defect identification performance
Confusion Matrix	Per-class true/false positive & negative rates	Identify inter-class confusion among defect types
Feature-Pattern Matching	Learned-feature similarity vs. threshold baseline	Assess defect discrimination effectiveness
Explainability	Faithfulness, Consistency, Completeness, Human Understandability	Evaluate decision transparency
Efficiency	Processing Time, Classification Latency, Memory	Assess computational efficiency at scale

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Robustness	Illumination, contrast, orientation, severity variation testing	Evaluate generalization capability

IX. RESEARCH CHALLENGES AND FUTURE ROADMAP

Although AI-powered classification can improve solar panel defect detection, several challenges remain in developing a reliable and practical inspection system.

A. Dataset Availability

EL image datasets may contain a limited number of labeled defective samples, class imbalance between defect types, and variations in imaging equipment across manufacturers. Developing sufficiently diverse and representative datasets is therefore important for reliable defect classification.

B. Defect Pattern Complexity

Defects may appear with irregular shapes, low contrast, and overlapping characteristics between categories. The proposed system must therefore handle variations in defect severity, size, and visual similarity to achieve reliable multi-category classification.

C. Classification Reliability

Defect classification should consider multiple visual and structural factors rather than relying on a single feature type. Future improvements should focus on maintaining consistent classification accuracy across different manufacturing batches and imaging conditions.

D. Explainability

AI-generated defect classifications should provide understandable reasons for quality-control decisions. Future systems should improve the transparency of region-level defect localization and feature-importance visualization.

E. Computational Efficiency

Deep architectures such as ResNet and DenseNet can be computationally intensive. Future systems should explore lightweight or optimized architectures suitable for real-time inspection on production lines with high throughput requirements.

F. Manufacturing and Defect Evolution

New manufacturing processes, materials, and cell designs continuously emerge. Future detection systems should therefore support updated defect representations and evolving defect patterns without reducing previously learned classification capabilities.

G. Human–AI Interaction

AI recommendations should assist quality-control engineers rather than completely replace human judgement. Future systems should provide effective engineer feedback mechanisms and decision-support interfaces for reviewing and validating flagged cells.

H. Deployment and Integration

Integrating AI-based defect classification into existing manufacturing and field-inspection workflows requires compatibility with imaging hardware, production-line timing constraints, and existing quality-management systems.

The research roadmap can therefore be organized into three stages:

Short Term: Improve feature extraction, multi-category classification accuracy, explainability, and confusion-matrix-guided model refinement.

Medium Term: Develop lightweight and optimized architectures, improved cross-batch generalization, and diverse, well-labeled datasets.

Long Term: Develop reliable, human-centered automated inspection intelligence that combines robust feature learning, explainable classification, adaptive learning, and human-in-the-loop quality-control support.

X. CONCLUSION

This paper presented a deep learning framework for automated classification of solar panel defects using electroluminescence (EL) imaging. The framework addresses the limitations of conventional manual inspection and hand-crafted feature-based methods by incorporating residual and densely connected convolutional neural network architectures for robust feature extraction and multi-category defect classification.

The proposed approach evaluates EL images using deep hierarchical features extracted through ResNet and DenseNet, combining residual learning and feature reuse to improve classification accuracy for cracks, inactive regions, and other cell-level abnormalities. Feature-pattern matching enables the system to identify contextual relationships between observed visual defects and known defect categories beyond simple intensity-threshold rules.

Explainability is incorporated to improve the transparency and reliability of classification outcomes. Quality-control engineers can examine the major visual regions and factors contributing to a defect classification, supporting informed decision-making during manufacturing and maintenance inspection. The human-in-the-loop design ensures that AI-generated recommendations support engineer decision-making rather than completely replacing human judgement.

Future research should focus on diverse and well-labeled EL image datasets, lightweight and computationally efficient architectures, robust cross-batch and cross-manufacturer evaluation, faithful explainability, and reliable AI-based automated photovoltaic quality-inspection solutions.

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