Multi-task convolutional neural networks for damage prediction on solar panels

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ABSTRACT

Maintaining solar panels in the solar energy industry is crucial for ensuring consistent energy production. Experts often rely on electroluminescence (EL) imaging to identify defects in solar panels; however, this conventional approach is manual, time-consuming, and struggles to keep pace with the growing scale and complexity of modern solar installations. In this work, we propose a multitask deep convolutional neural network (multi-task CNN) that not only classifies solar panels as Monocrystalline or Polycrystalline but also predicts the probability of defects and damage on the panel surface. The performance of the model is evaluated on a dataset of 2624 EL solar cell images [2], where each image is annotated by type and defect probability. The motivation behind this work is to investigate the capability of multitask deep learning to enhance classification and defect prediction results, while also highlighting potential limitations of AI in handling complex, real-world scenarios. By automating these tasks, the proposed method addresses critical challenges in solar farm maintenance, including scalability, cost reduction, and the need for consistent and accurate inspections.

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1. INTRODUCTION

The enormous need for renewable energy on a global basis has led to the rapid success of solar power, particularly with photovoltaic (PV) systems becoming well-known technology in sustainable advancements. With the expansion of solar energy infrastructure, one crucial factor in deploying such technology on a large scale is how effectively we can currently maintain existing and new generation investments that ensure continued optimal performance. Despite this, conducting large-scale solar farm maintenance is very challenging as traditional inspection methodologies are manual and time-consuming.

Electroluminescence (EL) imaging has become an important tool in identifying and characterizing defects and damage on solar panels, enabling the assessment of microcracks, cell fractures, and other issues that can cause a decrease in module performance. Although EL imaging is a powerful method in general, it has traditionally been performed manually and requires expert analysis to interpret the results properly. This process is not only labor-intensive but also struggles to keep pace with the ever-increasing scale and complexity of modern solar installations.

These challenges call for automated solutions that can streamline inspections, increase scalability, and lower operational costs—all without compromising accuracy. In this paper, we pro- pose a multitask deep CNN [6] to automate the analysis of EL images. The final important point is that our model does not only evaluate the two types of Monocrystalline and Polycrystalline solar cells but also estimates the likelihood of defects and damage in each cell, providing a comprehensive assessment of the panel.

Our method provides a scalable, cost-effective way to inspect and maintain PV systems. In this paper, we present our methodology first, followed by the results of experimental evaluations, along with a brief discussion on their potential impact on the solar

2. ELPV-DATASET

The ELPV dataset consists of 2,624 8-bit grayscale images, each sized 300x300 pixels, depicting functional and defective solar cells with varying degrees of degradation. These images are extracted from 44 different solar modules and include defects classified as either intrinsic or extrinsic, both of which are known to reduce the power efficiency of solar panels.

To ensure consistency, all images are normalized with respect to size and perspective, and any distortion

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introduced by the camera lens during the capture of the EL images was corrected before solar cell extraction. This preprocessing step ensures that the dataset is suitable for computational analysis without introducing additional variability.

However, the dataset is inherently imbalanced, with 1,508 images labeled as undamaged, 295 labeled with a 33% probability of damage, 106 labeled with a 66% probability of damage, and 715 labeled as damaged. This imbalance poses a challenge for model training, as it can bias the predictions toward the majority class.

To address the dataset's small size and imbalance, data augmentation techniques can be employed, such as rotating the images by 90° or 180° and flipping them horizontally. These techniques effectively increase the dataset size and diversity, helping to mitigate the challenges posed by the imbalance.

3. PROPOSED MODEL

3.1 Convolutional Neural Network

The proposed model is a multitask convolutional neural network (CNN) designed to simultaneously perform two tasks: binary classification of solar cell types (Monocrystalline and Polycrystalline) and damage probability estimation. The network comprises three shared convolutional layers, after which it branches into two task-specific paths (Figure 1).

The binary classification branch consists of two dense layers followed by an output layer, while the damage probability branch includes an additional convolutional layer before branching into a similar architecture of two dense layers and an output layer (Figure 2). The shared architecture ensures that feature extraction is leveraged across both tasks, enhancing the model's efficiency.

The Rectified Linear Unit (ReLU) activation function is used for all intermediate layers, ensuring non-linearity and efficient training. The output layers utilize task-specific activation functions: Sigmoid for binary classification and Softmax for multi-class damage prediction, catering to the nature of each task.

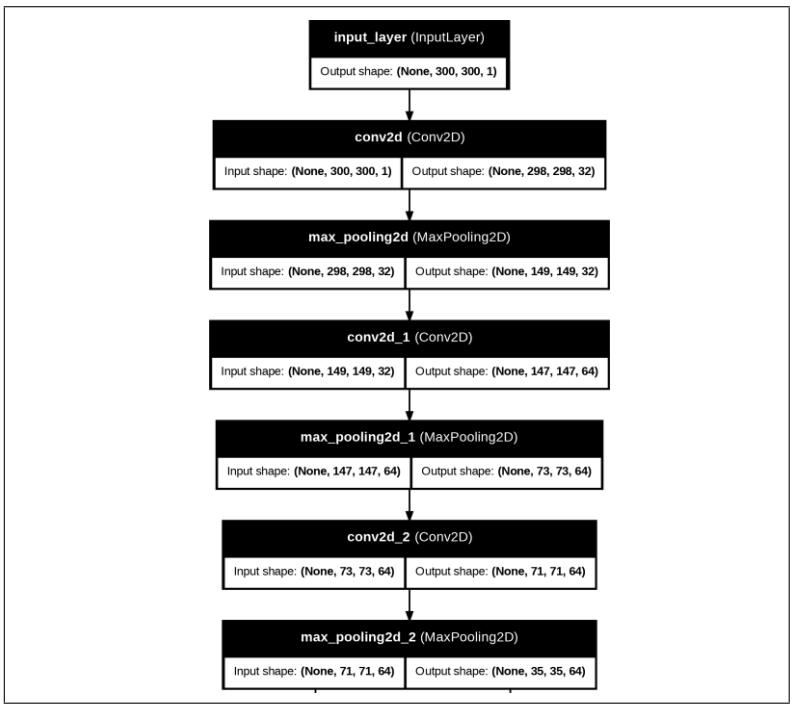


FIGURE 1 – Multitask Convolutional Neural Network: Shared Layers

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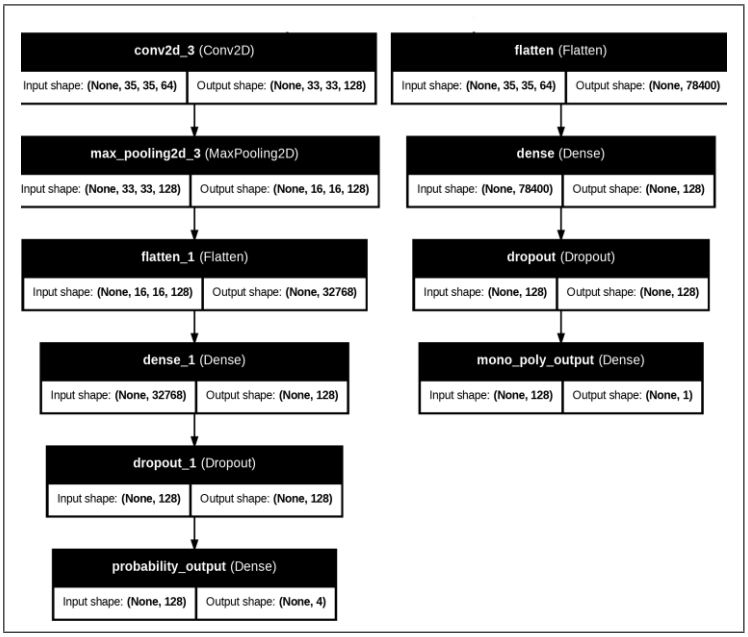


FIGURE 2 – Multitask Convolutional Neural Network: Separate Branches

3.2 Data Augmentation

Data augmentation is critical for small and imbalanced datasets, as it expands the training set and improves model robustness by simulating variations. In this work, simple yet effective
augmentation techniques were employed, capitalizing on the invariance of crack and damage features to transformations such as rotation and mirroring.

Specifically, the dataset was augmented by rotating the images by 90°, 180°, and 270°, as well as flipping them horizontally. These augmentations preserve the integrity of the defects while effectively increasing the dataset size and diversity. An example of augmented images is shown in Figure 3.

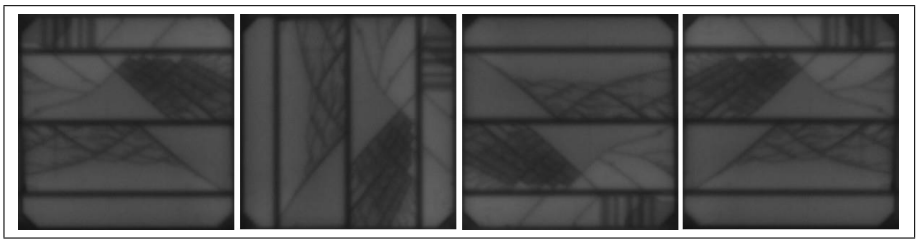


FIGURE 3 – Sample Solar Cell after Applying Data Augmentation Techniques

4. RESULTS

4.1 Numerical Experiment

The model was trained on the ELPV dataset using the Adam optimizer with a learning rate of 0.001 and a batch size of 32. Training was conducted over 40 epochs, and the model's performance was evaluated on a test set comprising 20% of the original dataset. This split ensured a reliable assessment of the model's generalization capability.

Task	Without Data Augmentation	With Data Augmentation
Binary Classification	99.6 %	99.4 %
Damage Probability	69.5 %	80.2 %

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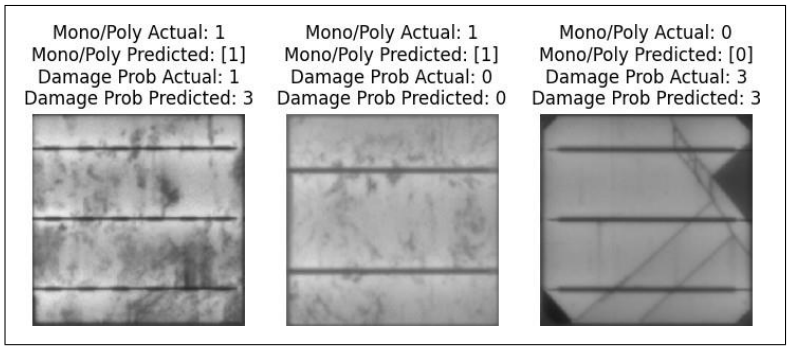


FIGURE 4 – Example of model prediction

4.2. Discussion

The damage probability prediction task, while improved to 80.2% accuracy with basic data augmentation, still leaves room for further enhancement. However, it is worth noting that even without augmentation, our multitask deep learning model demonstrated superior performance compared to the results reported in previous studies [1], which achieved 61% accuracy prior to extensive augmentation techniques. This observation suggests that multitask deep learning may provide a distinct advantage by enabling the shared layers to learn robust and generalizable features from multiple tasks simultaneously, improving performance across both classification and probability prediction.

The confusion matrix for the damage prediction task (Figure 5) reveals challenges in distinguishing intermediate damage probabilities (e.g., 33% and 66%). This underscores the need for additional strategies, such as dataset balancing or advanced augmentation methods, to refine the model's handling of subtle distinctions in damage severity.

Previous work [1] applied resource-intensive augmentation techniques, such as Gaussian blur and contrast enhancement, which significantly boosted their accuracy to 95%. While incorporating similar methods into our framework could further enhance our results, the superior baseline performance of our multitask model indicates that the architecture itself contributes to better feature extraction and task integration. This highlights the potential of multitask deep learning as a promising avenue for advancing solar panel defect detection with limited resources.

The greatest advantage of using AI is its speed. While human experts typically take 1 to 3 seconds per image for full recognition [7], our model processed approximately 288 images per second with comparable accuracy. However, the main drawback is the requirement for clean, large, and balanced datasets, as well as substantial resources for tackling more complex tasks.

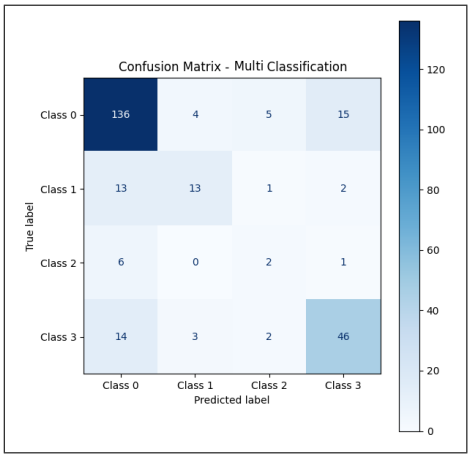


FIGURE 5 – Confusion Matrix for Damage Prediction Using Basic Data Augmentation

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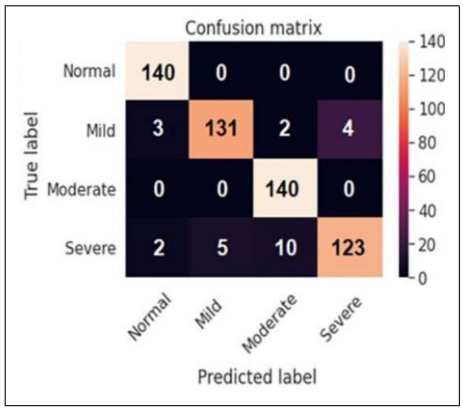


FIGURE 6 – Confusion Matrix after Dataset Balancing (Adapted from Al-Waisy et al. [1])

5. CONCLUSIONS

This study introduced a multitask deep convolutional neural network for automated solar panel inspection using electroluminescence (EL) images. By jointly addressing binary classification (Monocrystalline vs. Polycrystalline) and damage probability prediction, the model offers a comprehensive solution for photovoltaic (PV) system maintenance. Our results demonstrate a notable advantage of the multitask architecture: the model achieved a strong baseline performance in both tasks, with 99.6% accuracy in binary classification and 69.5% accuracy in damage probability prediction without data augmentation. This significantly outperforms previous studies under similar conditions, suggesting that multitask deep learning may inherently provide an edge by leveraging shared feature representations across tasks.

While basic data augmentation improved damage probability accuracy to 80.2%, additional gains could likely be achieved by integrating advanced augmentation techniques such as Gaussian blur and image contrast adjustments. Future work will explore these strategies alongside deeper architectures and improved hardware support to further refine the model's predictive capabilities.

The proposed method represents a scalable, cost-effective solution for automating solar farm maintenance, reducing reliance on manual inspection while ensuring consistent and accurate assessments. The multitask deep learning approach's strong baseline performance underscores its potential to transform solar panel defect detection and maintenance workflows, particularly in resource-constrained environments.

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