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Analysis of Space Solar Array Arc Images Based on Deep Learning Techniques V.2

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Protocol status: Working

We use this protocol and it's working

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Disclaimer

This protocol is for academic and research purposes only. Results may vary depending on the dataset and system configuration.

Abstract

This protocol presents a comprehensive deep learning-based methodology for detecting defects in solar cells. It covers data preparation, preprocessing, model building (CNN, VGG16, VGG19, and ResNet50), training strategies, evaluation metrics (accuracy, loss, confusion matrix, classification report), and final conclusions. The goal is to enable reliable and automated defect classification using state-of-the-art neural networks.

Guidelines

This protocol describes a deep learning-based pipeline for detecting defects in solar cells using image data. The approach explores different CNN architectures including a custom model, VGG16, and MobileNetV2. We evaluate the effectiveness of each model using standard classification metrics.



Dataset Description

- 1 The dataset includes images of solar cells categorized into two classes: defective and non-defective. Each image is standardized to a 128×128 RGB format for uniformity and compatibility with the neural networks.

Data Preprocessing

- 2 Resized images to 128×128 pixels.
- 3 Normalized pixel values to a range of [0, 1].
- 4 Applied data augmentation: rotation, zoom, flipping.
- 5 Split dataset into training (70%), validation (20%), and test (10%) sets.

Model Architectures

- 6 Custom CNN
 - 6.1 A simple convolutional neural network was built from scratch consisting of convolutional layers with ReLU activation, followed by max-pooling, dense layers, and dropout for regularization.
- 7 VGG16
 - 7.1 Transfer learning was applied using the VGG16 architecture pretrained on ImageNet. The top fully connected layers were replaced with custom dense layers. The base layers were frozen during the initial training and fine-tuned later.
- 8 MobileNetV2
 - 8.1 MobileNetV2, a lightweight and efficient model, was also used for transfer learning. It provided faster training and better inference speed, with comparable or better accuracy

than the VGG16 model.

Evaluation Strategy

- 9 All models were evaluated using the following metrics:
- 9.1 Accuracy and loss over epochs.
- 9.2 Confusion matrix.
- 9.3 Precision, recall, and F1-score from classification report.

Results and Discussion

- 10 The following summarizes model performances:
- 10.1 CNN: ~88% accuracy.
- 10.2 VGG16: ~91% accuracy, better generalization.
- 10.3 MobileNetV2: ~93% accuracy, optimal speed and performance.
- 11 MobileNetV2 outperformed the other models in both accuracy and computational efficiency, making it suitable for real-time applications.

Conclusion

- 12 The deep learning pipeline presented is highly effective for solar cell defect detection. MobileNetV2 is the recommended model due to its balance of accuracy and inference efficiency.

References



- 13 Keras Documentation: <https://keras.io>
- 14 TensorFlow Documentation: <https://www.tensorflow.org>
- 15 ImageNet Dataset: <https://www.image-net.org>