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Implementation of Deep Learning Based on Convolutional Neural Network for Detecting Images of Solar Panel Damage in Smart Grid Systems

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Abstract

This study aims to implement Deep Learning based on Convolutional Neural Network (CNN) in detecting solar panel damage using thermal images as part of a Smart Grid system. The main problem addressed is the difficulty of early automatic identification of solar panel cell damage using conventional methods. Through the CNN approach, this study developed a classification model to distinguish between damaged (Defective) and undamaged (Non-Defective) solar panel conditions. The research stages included thermal image dataset collection, pre-processing, model training, and performance evaluation. The results showed that the CNN model was able to achieve an accuracy of over 87% with stable performance on the validation data. Visualization using the Grad-CAM method helps interpret the damaged areas that are the focus of the model's decision.

***Keywords**: CNN; Deep Learning; Grad-CAM; Solar Panels; Smart Grid.*

1. Introduction

Advances in Deep Learning technology, particularly CNN, have opened up enormous opportunities in image-based error detection without manual feature engineering. This research focuses on automating solar panel inspection to support adaptive and predictive smart grid systems. The problem statement in this research is how to apply the CNN algorithm for automatic detection and measure its accuracy and performance in supporting predictive maintenance.

2. Research Methodology

This research is quantitative experimental in nature with a computational experimental approach. The research objects are thermal and RGB images of solar panels categorized as defective and non-defective.
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2.1. Research Stages

The research process began with data acquisition, pre-processing (0-1 pixel normalization, 128x128 resizing), model training with 15 epochs, and evaluation using a confusion matrix. The hardware used included a PC with 8 GB of RAM and Google Colab as the development environment.

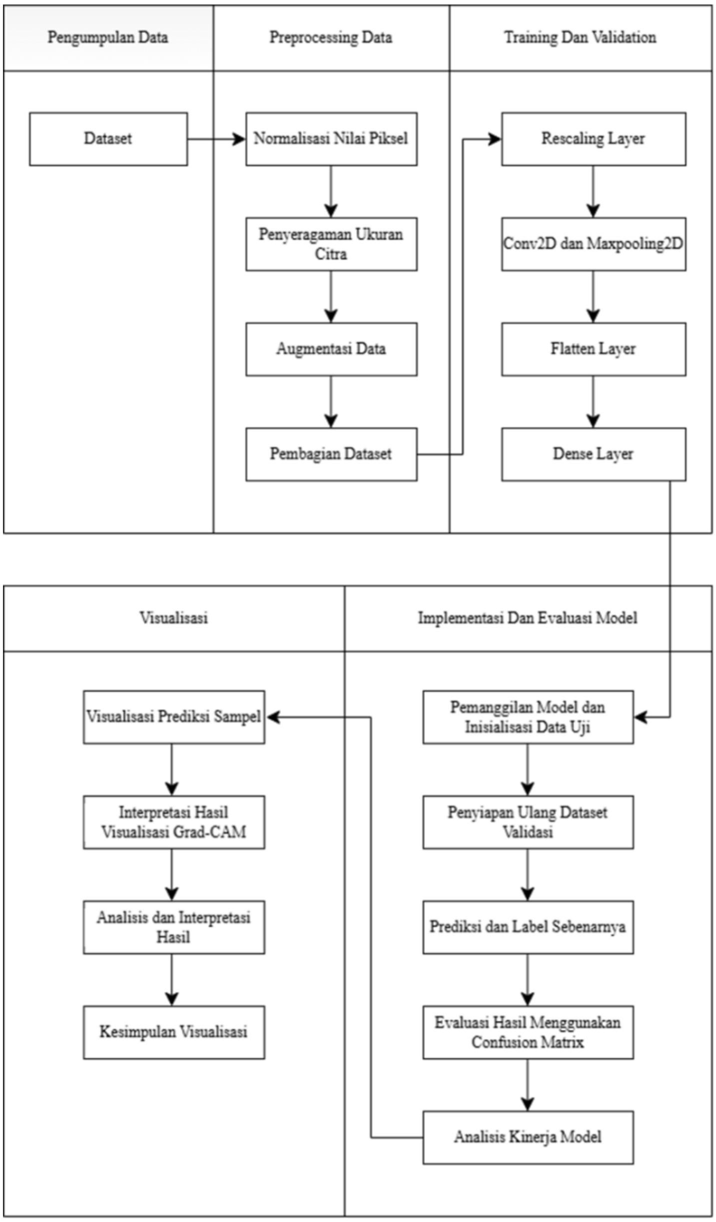

Fig.1: Research Design

3. Results And Discussion

3.1. Data Collection Results

The dataset has been successfully integrated via Google Drive, covering two main folders: 'Defective' (hotspots/cracks) and 'Non-Defective' (normal conditions).

3.2. Data Preprocessing Results

The dataset is divided into 80% training data and 20% validation data. Images are standardized to a resolution of 128x128 pixels with a batch size of 32.

3.3. Training and Validation Results

Training was conducted for 15 epochs. The results showed a consistent improvement in accuracy on the training and validation data.

```
--- Memulai Pelatihan Model ---
Epoch 1/15
22/22 ━━━━━━━━━━━━━━━━━━━━ 416s 5s/step - accuracy: 0.7159 - loss: 0.6265 - val_accuracy: 0.8324 - val_loss: 0.4122
Epoch 2/15
22/22 ━━━━━━━━━━━━━━━━━━━━ 25s 1s/step - accuracy: 0.8339 - loss: 0.4079 - val_accuracy: 0.8439 - val_loss: 0.3579
Epoch 3/15
22/22 ━━━━━━━━━━━━━━━━━━━━ 23s 1s/step - accuracy: 0.7920 - loss: 0.4180 - val_accuracy: 0.8555 - val_loss: 0.3496
Epoch 4/15
22/22 ━━━━━━━━━━━━━━━━━━━━ 24s 1s/step - accuracy: 0.8203 - loss: 0.3862 - val_accuracy: 0.8613 - val_loss: 0.4025
Epoch 5/15
22/22 ━━━━━━━━━━━━━━━━━━━━ 41s 1s/step - accuracy: 0.8435 - loss: 0.3831 - val_accuracy: 0.8266 - val_loss: 0.4403
Epoch 6/15
22/22 ━━━━━━━━━━━━━━━━━━━━ 25s 1s/step - accuracy: 0.8662 - loss: 0.3249 - val_accuracy: 0.8497 - val_loss: 0.3567
Epoch 7/15
22/22 ━━━━━━━━━━━━━━━━━━━━ 23s 1s/step - accuracy: 0.8864 - loss: 0.2520 - val_accuracy: 0.8150 - val_loss: 0.3897
Epoch 8/15
22/22 ━━━━━━━━━━━━━━━━━━━━ 27s 1s/step - accuracy: 0.8970 - loss: 0.2401 - val_accuracy: 0.8497 - val_loss: 0.4339
Epoch 9/15
22/22 ━━━━━━━━━━━━━━━━━━━━ 44s 1s/step - accuracy: 0.8952 - loss: 0.2349 - val_accuracy: 0.8382 - val_loss: 0.4372
Epoch 10/15
22/22 ━━━━━━━━━━━━━━━━━━━━ 36s 1s/step - accuracy: 0.9472 - loss: 0.1480 - val_accuracy: 0.8671 - val_loss: 0.4184
Epoch 11/15
22/22 ━━━━━━━━━━━━━━━━━━━━ 24s 1s/step - accuracy: 0.9671 - loss: 0.1144 - val_accuracy: 0.8555 - val_loss: 0.5194
Epoch 12/15
22/22 ━━━━━━━━━━━━━━━━━━━━ 43s 1s/step - accuracy: 0.9573 - loss: 0.0844 - val_accuracy: 0.8324 - val_loss: 0.6279
Epoch 13/15
22/22 ━━━━━━━━━━━━━━━━━━━━ 23s 1s/step - accuracy: 0.9763 - loss: 0.0662 - val_accuracy: 0.8382 - val_loss: 0.5687
Epoch 14/15
22/22 ━━━━━━━━━━━━━━━━━━━━ 24s 1s/step - accuracy: 0.9896 - loss: 0.0363 - val_accuracy: 0.8555 - val_loss: 0.6420
Epoch 15/15
22/22 ━━━━━━━━━━━━━━━━━━━━ 24s 1s/step - accuracy: 0.9998 - loss: 0.0099 - val_accuracy: 0.8439 - val_loss: 0.7641
```

Fig. 2: Output of Model Training Results

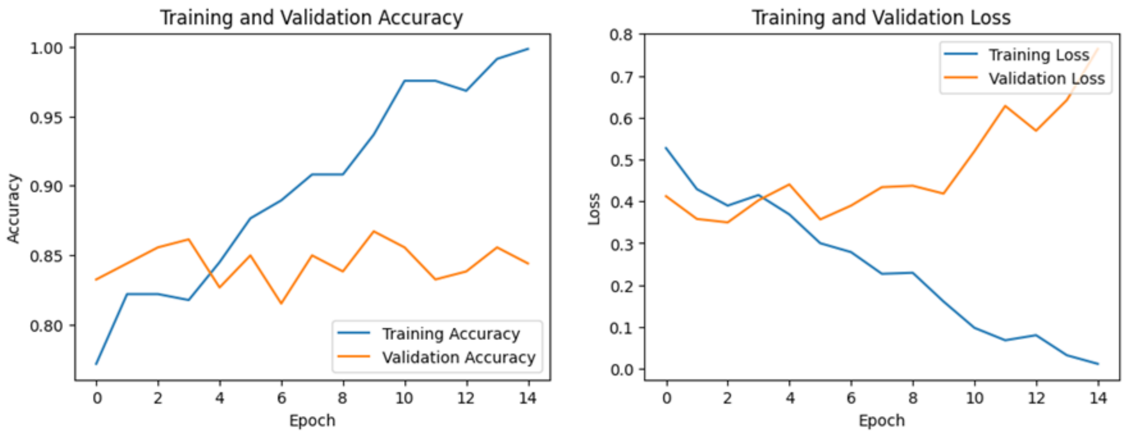

Fig. 3: Accuracy and Loss Graph

3.4. Implementation and Evaluation Results

3.4.1. Model Invocation and Test Data Initialization

The trained model is called upon to make predictions on the prepared validation dataset.

3.4.2. Re-preparation of the Validation Dataset

The test data was reprocessed without augmentation to ensure objective evaluation results.

3.5. Visualization of Detection Results

Visualization was performed to verify whether the model focused on the correct damage area using random image samples.

Fig. 4: Model Prediction Results

3.6. Discussion

The model achieved a validation accuracy of 87.28%. The use of Grad-CAM provides high interpretability, allowing operators to understand the basis of AI decisions in detecting hotspots on panels.

4. Conclusion

This research successfully developed a reliable CNN model for solar panel damage classification. High accuracy and Grad-CAM visualization prove the effectiveness of this system in supporting maintenance automation in Smart Grids.

5. Recommendations

For further development, it is recommended to test a wider variety of datasets and integrate the model into a real-time IoT-based monitoring system.

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