

BiLSTM-Based Inception Multi-Head Attention Network for Predicting Solar Cell Degradation Using Thermal Imaging

Oxford Brookes University in collaboration with Chengdu University of Technology
Supervised by Dr Happy Nkanta Monday

Abstract

This study proposes a deep learning model to detect solar cell degradation using UAV thermal images. The hybrid architecture integrates Inception modules, Bidirectional LSTM, and Multi-Head Attention mechanisms for analysis. Preprocessed thermal data classified panels into "defected" or "non-defected" degradation states. The model achieved 89.65% accuracy, 93.67% precision, and 0.9613 AUC, demonstrating robust degradation identification. High-performance metrics validate its capability to distinguish degraded panels effectively. This approach enables automated large-scale solar farm inspections, offering a cost-effective solution for predictive maintenance. By combining advanced neural networks with aerial thermal imaging, the method enhances PV system monitoring efficiency and supports sustainable solar energy management

Dataset & Preprocessing

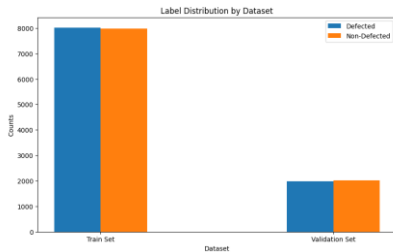


Figure 1 Number of images within defected and Non-defected

The training set, validation set are divided in the ratio of 8:2.

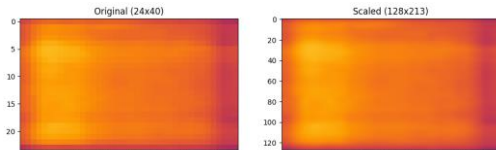


Figure 2 Images Resize

he image resolution of 24*40 pixels is not suitable for the proposed model minimize input. Therefore, this project resizes all images to the same 128 * 213 as the dataset.

Web Application Development

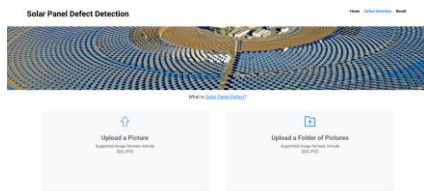


Figure 9 Upload Page

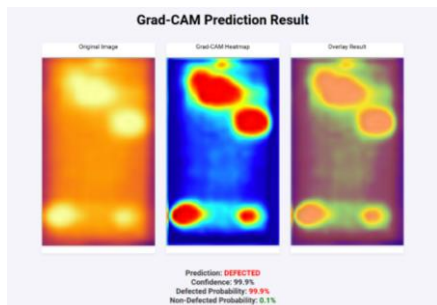


Figure10 Detection Result with Heatmap

Model Architecture



Figure 3 Inception model structure

This mode, introduced by Google researchers in 2016, is a deep learning architecture renowned for its advanced techniques, including inception modules that efficiently learn local and global features using filters of varying sizes. It excels in image recognition and offers scalability

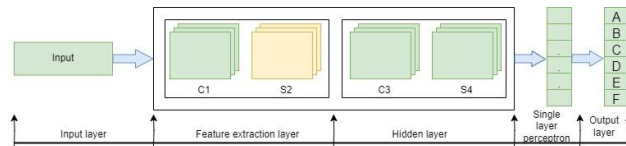


Figure 4 Structure of Convolutional Neural Networks (CNN).

Techniques such as batch normalisation and average pooling are employed for each of the three independent models to speed up training and improve the generalisation ability of the models. In addition, the SE attention mechanism is introduced to enhance the model's attention to the important features in the fruit images to further improve the model performance. The SE module is mainly used to enhance the channel attention by reducing the spatial dimensions to 1x1 through global average pooling and generating weights

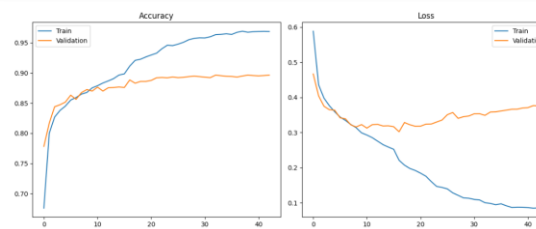


Figure 5 Accuracy and Loss

Result

The figure above shows the feedback obtained from the weighted integration of the three models using transfer learning, which was used to classify the fruit dataset for this experiment.

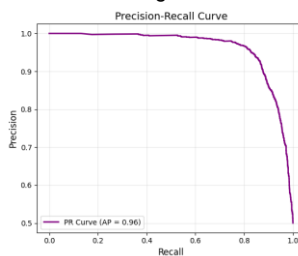


Figure 6 Recall

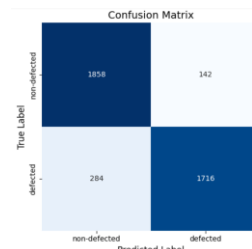


Figure 7 Confusion Matrix

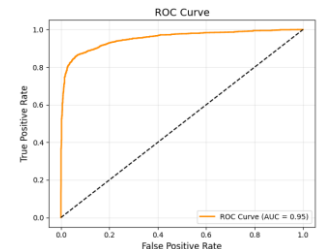


Figure 8 ROC Curve

The deployment runs in a web page, providing a web user interface, JavaScript, TensorFlow, Flask runtime environment, and defect detection still runs in the project terminal

For Figure 9, the two buttons are for uploading pending pictures to the system.

For Figure 10, this page is a results with heatmap page.

For Figure 11, this page is used to show the results of the uploaded images.

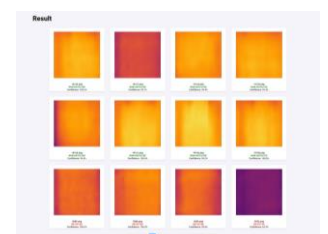


Figure11 Detection Result

Conclusion & Future Work

- Custom model with Inception + BiLSTM + Attention
- 89.65% accuracy, strong interpretability, web GUI deployed

Future work: Multi-class classification (hotspot, crack, etc.) Lightweight deployment on UAVs Explainable AI with attention maps