OXFORD BROOKES UNIVERSITY

Rui Gao

IABiLSTM-NET Deep Learning Model 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

There are various types of defects that can occur in photovoltaic (PV) panels, and manual detection may lead to errors. Additionally, human inspection in the field results in high labor costs. Current deep learning methods for PV panel defect detection mostly rely on a single model, and when the classification task becomes more complex, the performance of a single model may degrade. To address these challenges, this project proposes an ensemble approach to enhance classification accuracy and robustness. The model uses a weighted ensemble technique to combine three deep learning architectures—Inception, BiLSTM, and Attention mechanisms. This approach is further strengthened by integrating the attention mechanism, which improves the model's ability to focus on critical regions in thermal infrared images, leading to more accurate defect detection.

Dataset

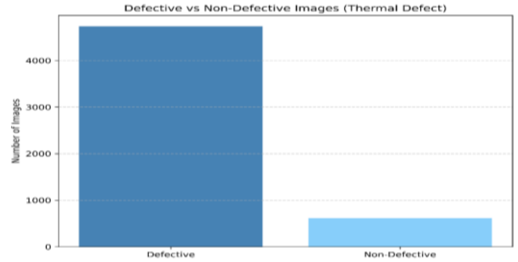

Figure 1. Dataset Distribution

Images: 5,352 thermal images

Defective: 4733

Non-Defective: 619

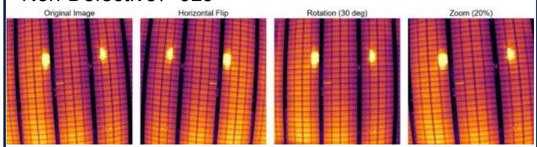

Figure 2. Examples of data augmentation

In dataset preprocessing, the augmentation method include: rescaling, random rotation, width shift, height shift, shear transformation, zooming and horizontal flip.

There are three Separation split ratio used in the project: 80:10:10, 70:20:10, 60:20:20.

The images are resized the pixels to 128 * 128

Proposed models

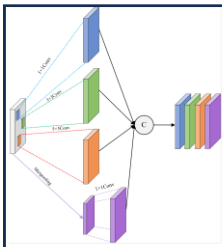

Figure 3. Inception Module

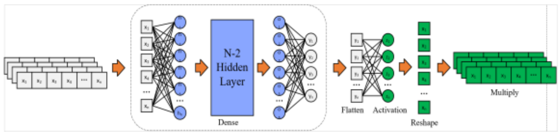

Figure 4. Attention Block

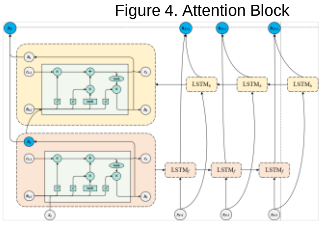

Figure 5. BiLSTM Module

The proposed model is a hybrid deep learning architecture combining Inception modules, Bidirectional LSTM (BiLSTM) and add an Attention mechanism

The proposed model consists of five main steps. First, an RGB image with the shape (128, 128, 3) is input into the model.

The second step involves the Inception module, which extracts relevant features from the image. In the third step, a BiLSTM is applied to model temporal dependencies. The fourth step incorporates the Attention mechanism to prioritize important features. Finally, the fully connected layer and output layer generate the final result, providing the probability of the image belonging to each category.

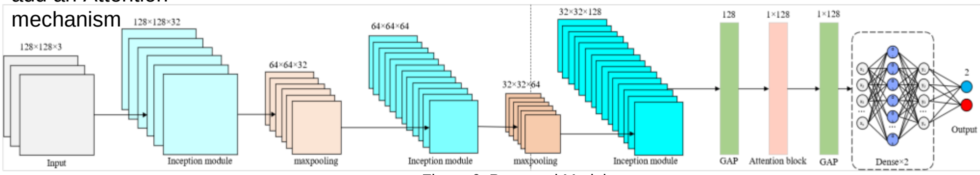

Figure 6. Proposed Model

Model evaluation

Figure 7. Loss curve

Figure 8. Accuracy curve

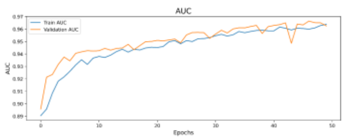

Figure 9. AUC curve

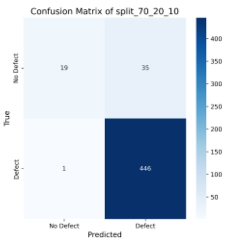

Figure 10. confusion matrix

The figures above show the evaluation obtained from the proposed model with split 70:20:10 ratio and table 1 illustrates split 70:20:10 performs the best, slightly outperforming the other two ratios.

Split Ratio	Accuracy	Loss	Precision	Recall/Sensitivity	AUC	Specificity	F1-Score
80:10:10	0.9142	0.0456	0.9142	0.9142	0.9684	0.3898	0.9540
70:20:10	0.9156	0.0464	0.9156	0.9156	0.9677	0.3518	0.9533
60:20:20	0.8870	0.0559	0.8870	0.8870	0.9544	0.3284	0.9392

Table 1. Overall Comparison of three split radio

Model	Accuracy	Loss	Precision	Recall/Sensitivity	AUC	Specificity	F1-Score
Proposed	0.9156	0.0464	0.9156	0.9156	0.9677	0.3519	0.9533
Inception	0.9043	0.0492	0.9043	0.9043	0.9651	0.2241	0.9550
Inception_Attention	0.9193	0.0460	0.9193	0.9193	0.9697	0.3442	0.9633
CNN	0.9118	0.0556	0.9118	0.9118	0.9565	0.2787	0.9581

Table 2. Overall Comparison of four models

The table 2 above show the comparison among three different split radio and among four model. The comparison shows that proposed model is the most balanced and robust across multiple metrics.

Interpretability and significance analysis of the model

The goal of Explainable AI is to make AI systems more comprehensible and transparent without sacrificing performance. In addition, it allows non-experts to understand the model's behavior, increase user trust in AI system decisions, facilitate the diagnosis of biases or issues in the model, and ensure compliance with regulatory requirements.

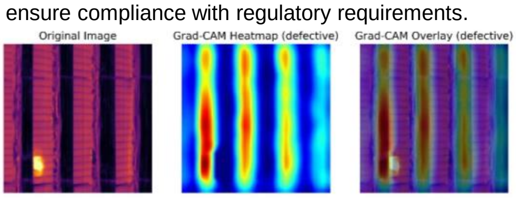

Figure 11. The Grad-Cam example

It then uses the output of one of the convolutional layers of the model along with the predicted gradients to generate a weighted feature map, resulting in a heatmap which helping to understand the model's decision-making process. This allows us to observe the areas that the model focuses on when classifying a specific image, thereby enhancing the model's credibility

WEB APPLICATION DEVELOPMENT

Figure12. Web homepage to the model

Figure13. Detection page to the model

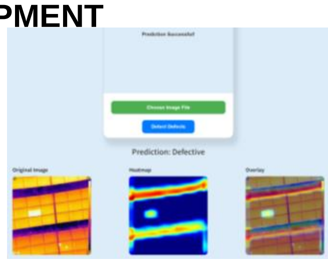

Figure14. Detection result page

Figure15. Dataset information page

The user interface (UI) is designed to showcase the proposed model. On the homepage, users can explore the website's topic and access various functions via links. The 'Detect Defects' section directs users to the detection page. Scrolling down reveals the dataset section, which provides an introduction to the dataset along with a 'Dataset Website' button that navigates to the dataset's source.

Future work

- Expand dataset with diverse defects.
- Explore lightweight models for edge devices.
- Integrate temperature and metadata.
- Use advanced attention mechanisms.
- Investigate self-supervised learning
- Develop an end-to-end monitoring system.