AI-Based Solar Panel Anomaly Detection Using Images

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Table of Contents

Table of Contents 2
Chapter 1 Introduction 3
Chapter 2 Problem statement 3
Chapter 3 Related works 3
3.1 Deep learning based automatic defect identification of photovoltaic module using electroluminescence images 3
Our Approach 4
Chapter 4 Datasets 4
4.1 Infrared solar module 4
4.2 A Benchmark for Visual Identification of Defective Solar Cells in Electroluminescence Imagery 5
4.3 Solar cell EL image defect detection dataset 5
Chapter 5 Methodology 6
5.1 Data Collection 6
5.2 Preprocessing 6
5.3 Model Architecture 6
5.4 Training 7
5.5 Anomaly Detection 7
Chapter 6 Results 7
Chapter 7 Conclusion 12
References 14

Chapter 1 Introduction

The rapid global adoption of solar energy as a sustainable power source has propelled the need for efficient and reliable solar panel systems. As solar farms expand and rooftop installations become more commonplace, ensuring the optimal performance of individual solar panels is paramount. The detection and timely mitigation of anomalies, such as defects, soiling, or damage, are crucial to maximizing energy production and prolonging the lifespan of solar installations.

Traditional methods of solar panel monitoring often rely on periodic inspections or sensor-based systems. However, these approaches may fall short in providing real-time, granular insights into the health of individual panels. This research seeks to bridge this gap by harnessing the power of Artificial Intelligence (AI) for the automated identification and classification of anomalies in solar panels using image analysis.

In Japan and EU countries, there are lots of solar power plants that cover more than a few football fields. That’s why its very hard to identify the exact solar cell that causes any anomaly. Recently, many drone companies are taking drone pictures to identify anomalies. However, this is also time-consuming and expensive. That’s why the necessity of using AI to detect solar panel anomalies can reduce the maintenance cost of the green energy industry and ensure a sustainable, low-carbon emission model for the world.

Chapter 2 Problem statement

To reduce the maintenance cost of big solar power plants, thermal images taken by drones are being used to check panel anomalies. However, most of the checking process is still manual. So, we’ll try to automate the process through AI models and predict the exact anomaly location in a power plant using those thermal drone images.

Chapter 3 Related works

3.1 Deep learning based automatic defect identification of photovoltaic module using electroluminescence images

This paper addresses the challenge of maintaining large-scale photovoltaic (PV) power plants by proposing a deep learning-based defect detection system for PV modules using electroluminescence (EL) images. Two primary technical challenges are tackled: (1) the generation of a substantial number of high-quality EL images, overcoming the limitations of the available EL image samples, and (2) the development of an efficient model for automatic defect classification using the generated EL images.

The authors employ a hybrid approach for EL image generation, combining traditional image processing techniques with the characteristics of Generative Adversarial Networks (GANs). This method allows for the creation of a large number of EL image samples with high resolution, even when only a limited number of samples are available. Subsequently, a Convolutional Neural Network (CNN)-based model is introduced for the automatic classification of defects in EL images. The CNN extracts deep features from EL images, significantly enhancing the accuracy and efficiency of PV module inspection and health management compared to alternative solutions.

The proposed solution is extensively evaluated through experiments, utilizing established machine learning models (VGG16, ResNet50, Inception V3, and MobileNet) as benchmarks for comparison. The numerical results affirm that the deep learning-based solution presented in the paper can effectively and accurately detect defects automatically using electroluminescence images. This suggests its potential for improving the maintenance and management of large-scale PV power plants. (Tang et al., 2020)

Our Approach

Most of the research used different CNN models, and there are many approaches to detect individual anomaly type. However, in that case we need colored image which increased the training cost significantly. Also, we need to take care of the False Positive, False Negative & detection failure for each anomaly type.

However, since our main goal is to reduce the labor cost, we only want to know if there is an anomaly or not. In that case, we just need to take care of one False Positive, False Negative & detection failure. And when our system confirms there is an anomaly, labors can directly go there. As a result the searching radius for the target place will significantly reduced.

Also, for this its enough to train our model with a grayscale data which takes very short time & computing power to be trained. And that’s how we can reduce the training cost as well.

Based on the above two gaps, we decided to go for a binary classification using Auto-Encoder.

Chapter 4 Datasets

4.1 Infrared solar module

InfraredSolarModules is a dataset that contains infrared images of different anomalies found in solar farms. The dataset consists of 20,000 infrared images that are 24x40 pixels each. The file module_metadata.json contains the image directory and anomaly class of each image. This collection contains genuine, one-of-a-kind solar module abnormalities. The Raptor Maps team compiled data obtained by piloted aircraft and unmanned aerial systems equipped with midwave or longwave infrared (3–13.5 m) and visible spectrum imaging devices. The image resolution ranges between 3.0 and 15.0 cm/pixel. Anomalies were trimmed to the particular module and classified. To improve accuracy, corresponding visible spectrum images were used during classification. (Millendorf et al., 2022)

Link: https://www.kaggle.com/datasets/marcosgabriel/infrared-solar-modules

4.2 A Benchmark for Visual Identification of Defective Solar Cells in Electroluminescence Imagery

This dataset provides solar cell images extracted from high-resolution electroluminescence images of photovoltaic modules. The dataset includes 2,624 samples of 300x300 pixel 8-bit grayscale photos of working and degraded solar cells with variable degrees of degradation collected from 44 distinct solar modules. The faults in the annotated photos are either inherent or extrinsic in nature, and they have been shown to affect the power efficiency of solar modules. All pictures have been adjusted in terms of size and perspective. Furthermore, prior to solar cell extraction, any distortion caused by the camera lens used to record the EL images was removed. Every image is tagged with a defect probability (a floating point number between 0 and 1) and the kind of solar module (monocrystalline or polycrystalline) from which the solar cell image was retrieved. (Verlinden et al., 2018)

Link: https://github.com/zae-bayern/elpv-dataset

4.3 Solar cell EL image defect detection dataset

Photovoltaic Electroluminescence Anomaly Detection (PVEL-AD) contains 36,543 near-infrared images with diverse internal faults and varied backgrounds. This dataset includes 1 class of anomaly-free photos and 12 types of anomalous images, including crack (line and star), finger interruption, black core, thick line, scratch, fragment, corner, printing_error, horizontal_dislocation, vertical_dislocation, and short_circuit faults. In addition, 40358 ground truth bounding boxes are provided for 12 different categories of faults. This is a long-tail object detection task that is both difficult and important for smart manufacturing. (binyi, 2022)

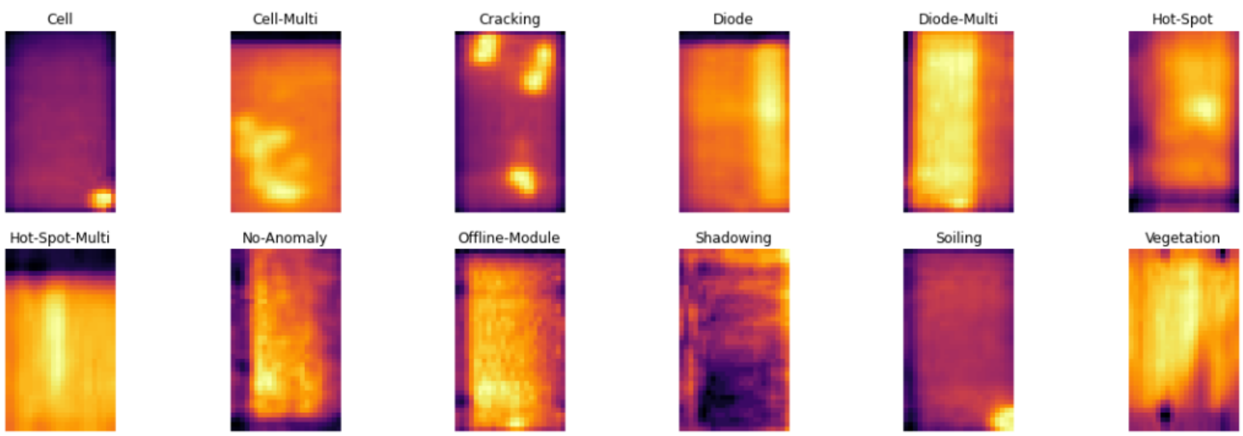
Link: https://kaggle.com/competitions/pvelad or https://github.com/binyisu/PVEL-AD

Chapter 5 Methodology

5.1 Data Collection

Collect a diverse dataset of images representing normal and anomalous conditions in solar panels. Anomalies may include cracks, soiling, delamination, and other types of damage. Ensure a balanced representation of positive and negative cases to avoid bias in the model.

Figure 5.1 Sample images classes (Millendorf et al., 2022)



5.2 Preprocessing

Prepare the dataset by normalizing pixel values, resizing images, and augmenting the data to enhance model generalization. Divide the dataset into training, validation, and test sets.

5.3 Model Architecture

In the real world, anomalies are hard to find. Usually, normal class samples are much more compared to anomaly classes. In this project, we will use an autoencoder, which is a type of artificial neural network used for unsupervised learning, particularly in tasks related to data compression, dimensionality reduction, and feature learning. While autoencoders are not inherently designed for classification, they can be adapted for such tasks by leveraging the learned representations in their hidden layers. The encoder part should compress the input images into a lower-dimensional latent space, while the decoder should reconstruct the input from this latent representation. This architecture allows the model to learn a compact representation of normal solar panel images.

5.4 Training

Train the autoencoder using the normal images from the dataset. The model should learn to reconstruct normal images accurately. Use a validation set to monitor training progress and prevent overfitting.

5.5 Anomaly Detection

After training, apply the autoencoder to reconstruct both normal and anomalous images. Anomalies are detected when the reconstruction error (the difference between the input and the reconstructed image) exceeds a predefined threshold.

Chapter 6 Results

Here is the summary of the result:

1. **Data Exploration:** This section includes an exploration of the datasets used, highlighting the characteristics and features of the solar module images.
2. **Model Training:** The model, a convolutional autoencoder, is trained on the solar module images. The training process involves using TensorFlow and Keras, focusing on anomaly detection in solar modules.

Relevant Code Snippet:

```
# train the convolutional autoencoder
H = autoencoder.fit(
    X_train, X_train,
    validation_data=(X_val, X_val),
    epochs=EPOCHS,
    batch_size=BS)
```

3. **Visualization of Predictions:** The results include visualization of original and reconstructed images, differentiating between 'No-Anomaly' and 'Anomaly'.

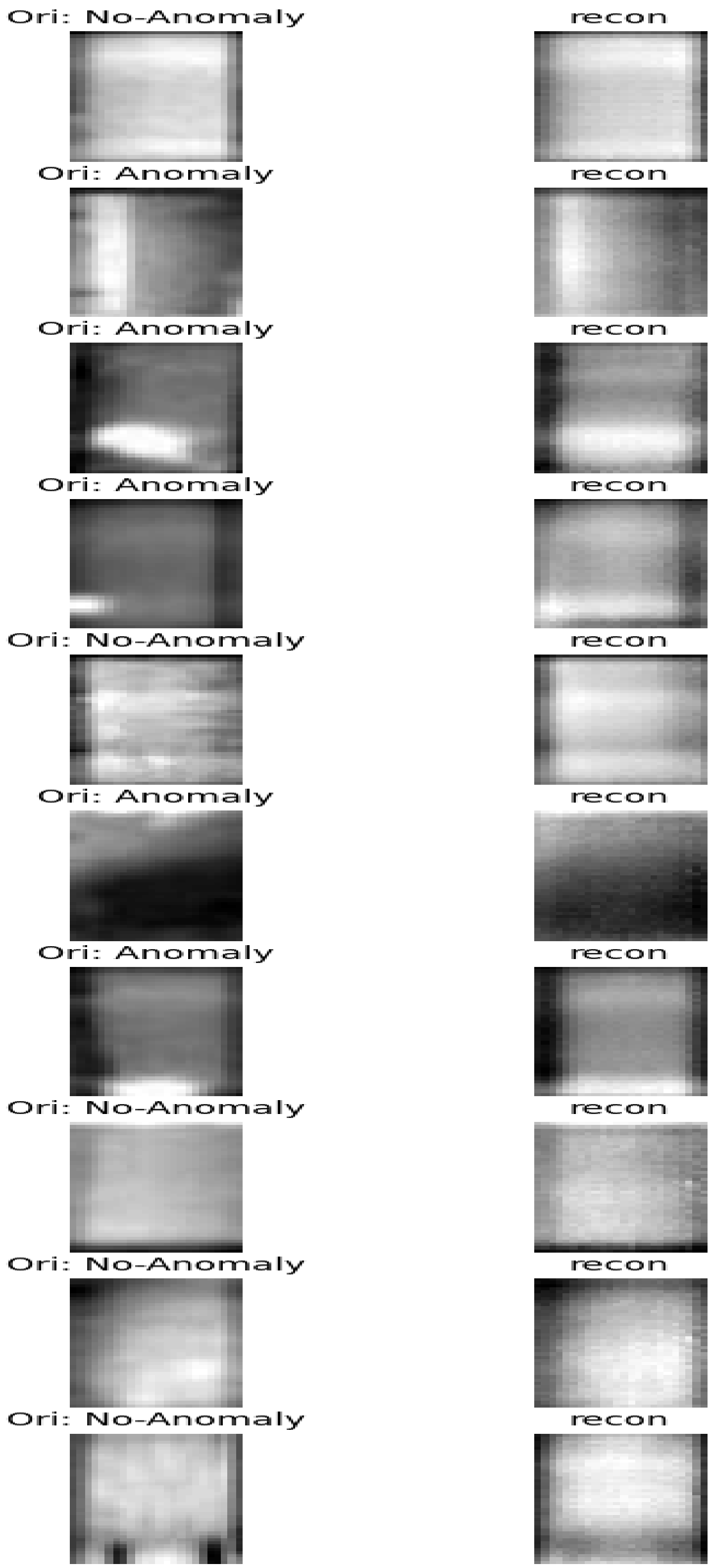
Relevant Code Snippet:

```
def visualize_predictions(decoded, X_test, y_test, samples=2):
    idx = 1
    # loop over our number of output samples
```

```
for i in range(0, samples):
    # grab the original image and reconstructed image
    original = X_test[i]
    recon = decoded[i]
    if y_test[i] == 0:
        title = 'No-Anomaly'
    else:
        title = 'Anomaly'
    plt.subplot(samples,2, idx)
    plt.imshow(original, cmap='gray')
    plt.title('Ori: ' + title)
    plt.axis('off')
    idx += 1
    plt.subplot(samples,2, idx)
    plt.imshow(recon, cmap='gray')
    plt.title('recon')
    plt.axis('off')
    idx += 1
```

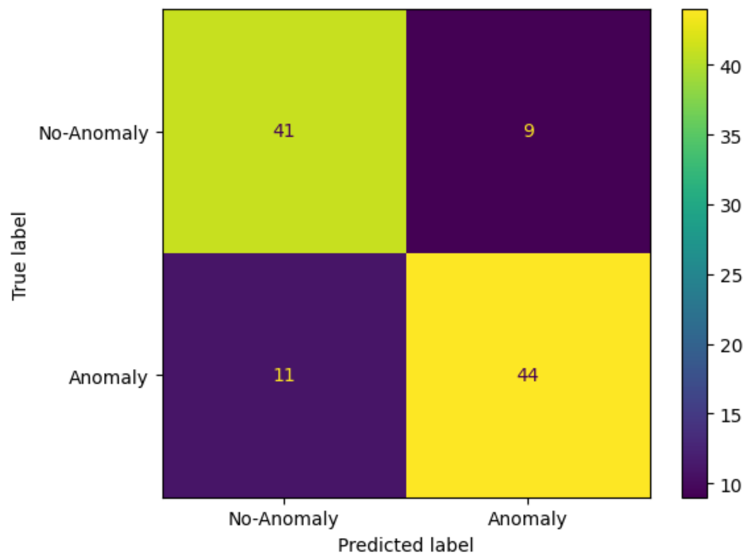
Output:

Fig 6.1 Actual image and reconstructed image


Ori: No-Anomaly
recon
Ori: Anomaly
recon
Ori: Anomaly
recon
Ori: Anomaly
recon
Ori: No-Anomaly
recon
Ori: Anomaly
recon
Ori: Anomaly
recon
Ori: No-Anomaly
recon
Ori: No-Anomaly
recon
Ori: No-Anomaly
recon

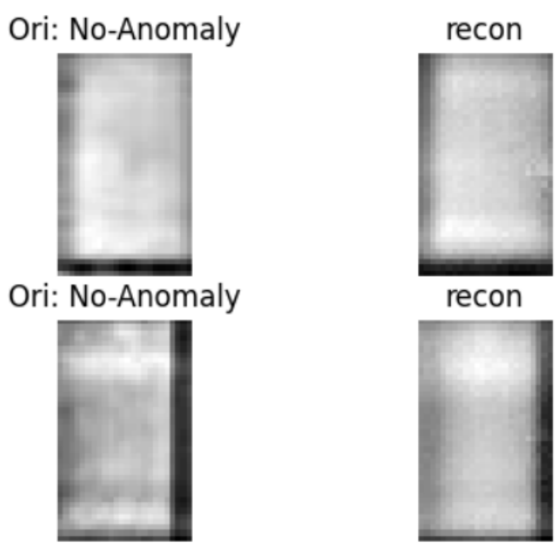
Here is the confusion Matrix Display of our output.

Fig 6.2 Confusion matrix



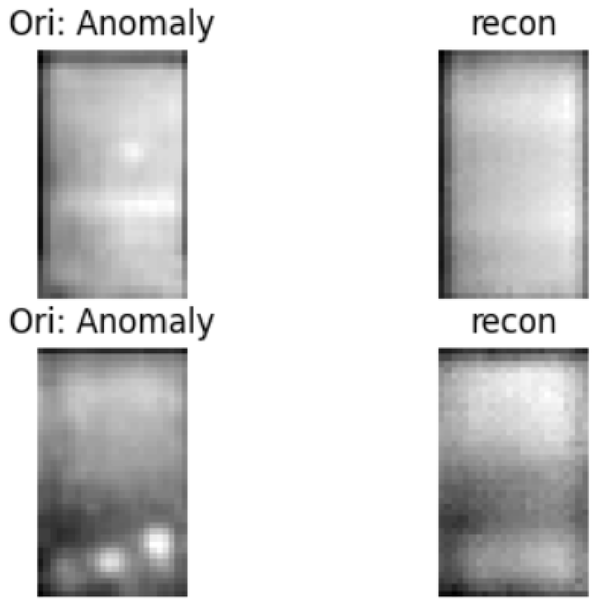
It can be seen in the Figure 6.3 that the false positive case, which means the model predicts an anomaly class but the actual image is a no-anomaly class, occurs when the image contains a black strip. This causes the calculated MSE to be higher than our threshold because for reconstructed image, the border between the black and white areas, if not reconstructed properly, will result in a high MSE.

Fig 6.3 Example of false positive

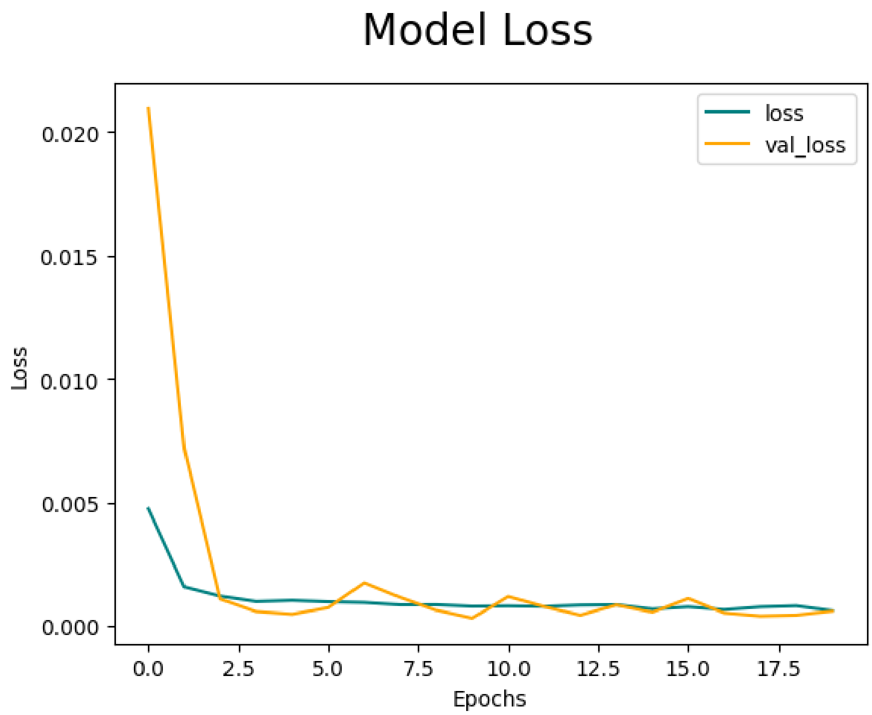


The false negative case, which means the model predicts a no-anomaly class but the actual image is an anomaly class, occurs when the faulty area in the image is not that distinctive and has more similarity to the no-anomaly image.

Fig 6.4 Example of false negative



Also, here is the model loss. The loss curves converge very fast.



Chapter 7 Conclusion

This project represents a significant advancement in solar energy technology, introducing an AI-driven approach for efficient anomaly detection in solar panels. Utilizing a convolutional autoencoder model to analyze thermal images, we achieved notable precision (0.79 for no-anomaly, 0.83 for anomaly) and recall (0.82 for no-anomaly, 0.80 for anomaly) rates, culminating in an overall accuracy of 0.81. These results not only demonstrate the model's effectiveness in identifying defects but also indicate a considerable enhancement over traditional inspection methods.

The insights and methodology established in this project have important implications for the future of renewable energy maintenance. By integrating AI with drone technology for real-time monitoring, there's potential to further streamline solar panel maintenance processes.

In conclusion, our project underscores the transformative potential of AI in the renewable energy sector, setting the stage for more efficient, sustainable, and technologically advanced solar energy management systems.

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