# Anomaly Detection for Solar PV Modules Inspection Using IR Thermography

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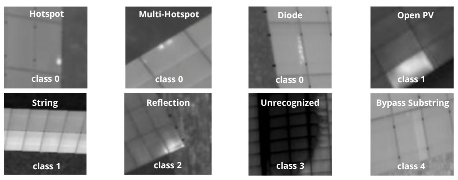
## Problem Statement / Objective

- Time-consuming, expensive, and subjective modern PV anomaly detection would benefit from an anomaly detection algorithm [1-4]
  - Traditionally, checking for anomalies:
    - Requires turning off all PV panels
    - May be dangerous for operators, as PV panels are often at a significant height or steep angles



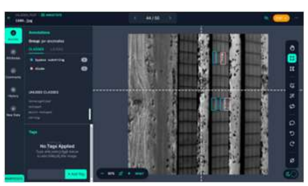

Images from combined datasets of [5], [6]

### Objective

- Develop a lightweight detection and classification method for anomalies using Deep Learning models with input IR images in real-time
- Implement onto an edge device to simplify, automate, and overall reduce the budget of PV panel anomaly detection

## Dataset & Data Preparation

- Datasets are from public, online collections of IR images with an aerial view of PV panels
- Images went through the following preprocessing:
  - Resize to 640x640px
  - Rotate -10 to 10 degrees
  - Flipped vertically or horizontally
- Images containing no PV panels, "background images," are around 10% of the training dataset

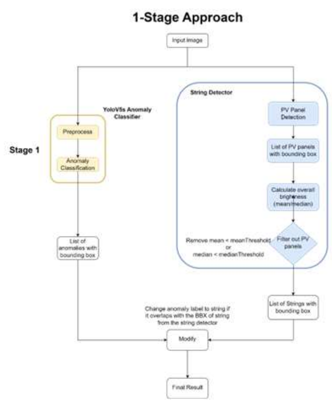


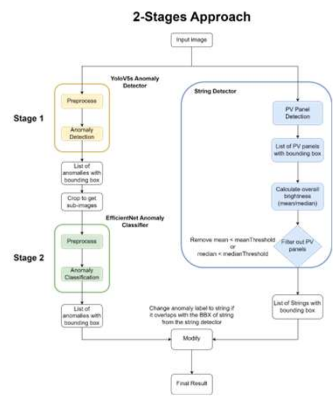
- Dataset storage and creation done within Roboflow

## Requirements

- Software Requirements for running models includes Yolov5s and Efficient Net:
  - Operating System: Ubuntu 18.04
  - Language: Python >= 3.6.9
- Hardware Requirements
  - Jetson Nano: NVIDIA Tegra X1, 3964MiB

## Methods & Algorithms




### Yolov5s

- Open-source object detection model developed by Ultralytics for multi-class classification
- Used in 1-Stage Approach to both detect and classify anomalies
- Used in 2-Stage Approach to detect defect panels
- Fast and efficient when doing detection with real-time inference
- Yolov5s selected for its accuracy with minimal resources, best suited for the Jetson Nano, which has smallest model size

### EfficientNet-B0

- Convolutional Neural Network developed by AutoML MNAS with comparatively better performance for our application
- Used in 2-Stage Approach for Classification of all individual PV panels
- Selected network B0 due to minimal resource use to implement on the Jetson Nano

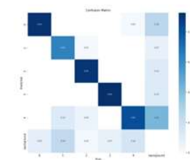
### String Detector

- String anomaly was most difficult for the above classification models to detect accurately
- Team-built CV method classifies abnormally bright panels as String anomalies using statistical analysis
  - Threshold for String anomalies is 1.5 * mean brightness and 1.5 * median brightness
- Was used in both 1-Stage and 2-Stage Approach as the final decision-maker for anomalies to be classified as a String, but was found to have decreased performance of detection algorithm and is therefore not included in final implementation

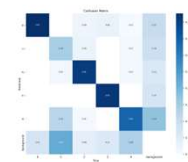
## Results

| mAP | 1-Stage Approach | 2-Stage Approach |
|---|---|---|
| with String Detector | 0.792 | 0.671 |
| w/o String Detector | 0.872 | 0.708 |

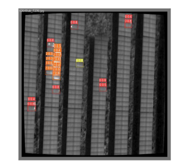
| Speed Test on Jetson Nano | 1-Stage Approach | 2-Stage Approach |
|---|---|---|
| with String Detector | 1.016 sec / image | 0.982 sec / image |
| w/o String Detector | 0.473 sec / image | 0.59 sec /image |



Confusion Matrix for 1-Stage w/o String Detector



Confusion Matrix for 2-Stage w/o String Detector



Example Output

## Conclusion

- Our objective was to develop an anomaly detection algorithm as an alternative to traditional inspection techniques used by solar farm inspectors
  - Two solutions are proposed: 1-stage and 2-stage approaches, both of which offer more efficient and consistent predictions of solar panel anomalies than the conventional techniques
  - These anomaly detection algorithms can significantly improve the efficiency o inspections
    - Inspectors can rely on automated data analysis and machine learning t identify anomalies, enabling them to prioritize their efforts on specific panels that require attention. This streamlines the inspection process, saving valuable time and resources
- In conclusion, our findings indicate that the 1-stage approach without a string detector exhibits the best performance, with high accuracy and real-time capabilities, making it an optimal solution for anomaly detection.

### Future Work

- Implement into a drone equipped with an IR camera
- Real-time detection and classification within drone

## References

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[7] Jetson Nano Developer Kit. NVIDIA Corporation, 2019.

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