Proceedings of the Annual General Donald R. Keith Memorial Conference
West Point, New York, USA
April 28, 2022
A Regional Conference of the Society for Industrial and Systems Engineering

Drone-Based Thermal Imaging Inspection of Solar Energy Equipment

Daniel Fee, William Florio, Jenna-Marie Gaston, Rajesh Persad, Yaseen Alwesabi, and Yong Wang

Department of Systems Science and Industrial Engineering
Binghamton University
Binghamton, NY 13902

Corresponding author's Email: jgaston2@binghamton.edu

Author Note: Daniel Fee, William Florio, Jenna-Marie Gaston, and Rajesh Persad are students at Binghamton University, studying Industrial and Systems Engineering. All team members contributed to the success of this project with support from senior advisors Dr. Yong Wang and Dr. Yaseen Al-Wesabi. This project is funded by the Thomas J. Watson College of Engineering and Applied Science at Binghamton University.

Abstract: The solar industry is expected to grow faster than any other renewable energy sources\ through 2050. Most solar panels consist of seven different layers. Each with the potential to endure normal wear and tear from usage. The industry standard for inspecting solar panels involves manual inspection by grounded maintenance crews using handheld thermal cameras, power meters, and other instrumentation. These processes pose a physical risk to operators depending on their surface location and height from the ground. On industrial large-scale solar farms, inspection is a timely and labor-intensive process. Drone-based inspection is an alternative to this that decreases costs and risk. The main objective of this project is to develop and test a machine learning algorithm, using Python and TensorFlow, that determines whether a solar panel is damaged based on thermal image data acquired using a drone and thermal camera.

Keywords: Drone, Inspection, Solar, Machine Learning, Python

1. Introduction

Drone-based inspection is an emerging technology that falls under the evolution of Industry 4.0. While current solar panel inspections are expensive and laborious processes that take a physical toll on inspection operators, and drone-based inspection, these risks are mitigated, and companies can detect defects within their solar panels more quickly while cutting costs. Maintenance costs are also decreased because defects can potentially be detected before they become serious problems for energy providers. The main objective of this project is to develop and test a machine learning model that determines whether a solar photovoltaic (PV) panel is damaged based on red-green-blue (RGB), and thermal image data acquired using a drone and thermal camera. This software will be integrated into one functioning system of drone, thermal camera, and computer and will be tested for functionality. An overview of the system is as follows: the deep learning model created by the team was trained and tested using existing solar panel thermal data taken from a literature source, as explained below. The team collected thermal images from solar panels, a drone, and a thermal camera purchased for this project to test the accuracy and functionality of the machine learning model.

For applications of inspection in industry, the drone will fly above the desired array of solar panels and be programmed to automatically capture thermal images of each panel. These images can be put into the trained model to evaluate the health condition of each panel. The model will output these results in the form of a binary decision: defect or no defect. From this output, appropriate action can be taken by energy-producing companies and inspection operators to repair the panels via the creation of a maintenance plan or continue the inspection. The future of this project includes using this process for large-scale solar farms that generate electricity not only for businesses, but residential communities. Today, outsourced infrared flyovers are available for inspecting solar panels, but their availability is limited and adds to the cost of the inspection. The system created in this project eliminates the need for this and provides companies with the opportunity to perform thermal image scans of their panels more frequently. Focusing on drone-based solar panel inspection will eliminate costs in the future and minimize potential physical risks along with the time consumption that results from manual inspection.

2. Methodology

The equipment used for this project included a drone, thermal camera system, a solar panel kit for testing, and appropriate computer hardware necessary for successfully storing large amounts of data to be used for the deep learning algorithm. Multiple options for this equipment were prepared by the team for review by the senior capstone faculty advisors. These options were based on research done by the team on current equipment being used in the industry for drone-based inspection, not only for solar equipment but outdoor locations and thermal applications in general.

Based on standards established by the Institute of Electrical and Electronics Engineers (IEEE), the standard thermal camera resolution for these applications is 640x512 (FLIR, 2019). Considering this, the most important piece of equipment contributing to the accuracy of the inspection was the thermal camera used. The thermal camera chosen was the DJI Zenmuse XT2 for its exceptional thermal imaging capabilities and industry reviews. The DJI Matrice 300 RTK drone was also selected as it is commonly paired with this camera. The drone comes with a charging kit to ensure the drone has adequate power to fly for a substantial amount of time (55 minutes). The system weighs approximately 20lbs with the batteries and thermal camera connected to the drone. A ground computer capable of processing images and running the deep learning model developed by the team was required. For this, the Dell Precision 7920 tower workstation was selected along with a 5TB external hard drive to provide additional storage for the image data used in training and testing the deep learning model. This hard drive is also used to store images of test solar panels taken by the team. Lastly, a Renogy solar panel kit was purchased to provide a base for testing the accuracy of the deep learning model. The drone was successfully registered with the Federal Aviation Administration (FAA) and Binghamton University to mitigate the legal and safety concerns regarding flying this UAV on private and public property. The following figure shows a use case diagram for our drone-based inspection system.

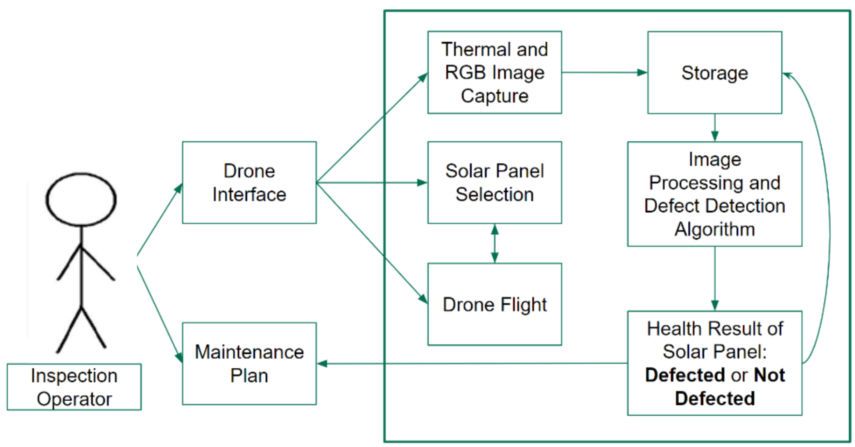

Figure 1. Drone-Based Inspection System Use Case Diagram

One of the top-level objectives for the deep learning model created in this project was image classification using Python and TensorFlow. Deep learning is a subset of machine learning and Artificial Intelligence (AI) and encompasses all techniques of computer learning from data, whereas deep learning includes models and processes that imitate the brain's own network of neurons. Deep learning is based on pattern recognition and requires far less supervision than other machine learning techniques (Chollet, 2018). For this reason, deep learning models require a large amount of data. Using large amounts of data allows the model to use a variety of methods to learn from itself and understand more with each piece of data entered. In this project, the team leverages this for their image recognition and classification capabilities.

The tools used to deploy deep learning models are the Python programming language and TensorFlow. In modern computing, many open-sourced resources have become baselines for deep learning algorithms. TensorFlow is an open-source software library for Python that greatly reduces the complexity of creating neural networks from scratch (freeCodeCamp.org, 2020). Models can quickly be created with few lines of code when assigned an optimizer. Optimizers are algorithms that machine learning models use to learn and establish pattern recognition (freeCodeCamp.org, 2020). Using the correct optimizer could quickly convert the machine learning model into a deep learning model to be used. There are a variety of optimizers to choose from that are appropriate for different instances. For example, the Adam (adaptive moment estimation) optimizer, which will be used in the team's model, uses past gradients as fractions to calculate current gradients. As a result, the optimizer will learn from itself and only improve as more data is fed to it. The optimizer creates a gradient descent algorithm with weights (parameters) that change throughout its iteration to better understand the pattern of the data (Trehan, 2021). Essentially, the

ISBN: 97819384962-2-6

data is weighed more heavily if it results in greater accuracy. The panels are randomly chosen from the imported data to create unbiased sampling.

A dataset published at the International Conference on Learning Representations (ICLR) by Millendorf et al. (2020), was used to train and test deep learning models. The researchers were part of a team employed by Raptor Maps, Inc. The dataset was published to counter the lack of publicly available image data of anomalies in solar panels. According to the researchers, the purpose of the dataset is to “facilitate research to solve problems well suited for machine learning that can have environmental impacts” (Millendorf et al. 2020). The data contains 20,000 24x40-pixel infrared images of solar panels. These images were collected by piloted and unmanned aircraft vehicles using infrared and visible spectrum imaging systems. Image resolution was cited as 3-15 cm/pixel. The 12 classes that separate the images in the data set are listed in Table 1 below along with the number of images that fall into the respective classes.

Table 1. Dataset Image Classes

Class Name	Number of Images
Cell	1,877
Cell-Multi	1,288
Cracking	941
Hot-Spot	251
Hot-Spot-Multi	247
Shadowing	1,056
Diode	1,499
Diode-Multi	175
Vegetation	1,639
Soiling	205
Offline-Module	828
No-Anomaly	10,000

The dataset is balanced, containing 10,000 images of solar panels with no anomalies and 10,000 images of solar panels exhibiting anomalies. The researchers note that Ewanich et al. concluded that 2.2% of all solar panels contain anomalies. However, a dataset having 2.2% images containing anomalies would not be suitable for machine learning. To account for this, the team developed an 80/20 ratio to split the dataset into a training set and a test set, with 80% of the images being used to train the model and the remaining 20% used as test images to verify the accuracy of the deep learning model.

Publications from Le et al. and Alves et al., both published in 2021, utilize this dataset. The model from Le et al. achieved 94% accuracy in terms of predicting anomalies and correctly identified the anomaly class 86% of the time. The model from Alves et al. achieved 92.5% accuracy for detecting anomalies and 78.9% accuracy for identifying anomalies belonging to eight selected classes of the 11 anomaly classes in the dataset.

3. Results and Analysis

Figure 2 shows an image of a graphical user interface (GUI) developed by the team using PyQt. Figure 3 shows the deep learning model's prediction results of a single solar panel. The development of this GUI was done usingQtDesigner, an application that allows users to translate a visual interface into python code. In using this application, the team was able to design the GUI with the layout and aesthetics being prominent factors. After the GUI was created, new code was written by the team to connect the widgets of the GUI to active code and the working machine learning model. The decision to develop the GUI stemmed from the need for the program to have an intuitive approach that allows it to be widely adopted with little training.

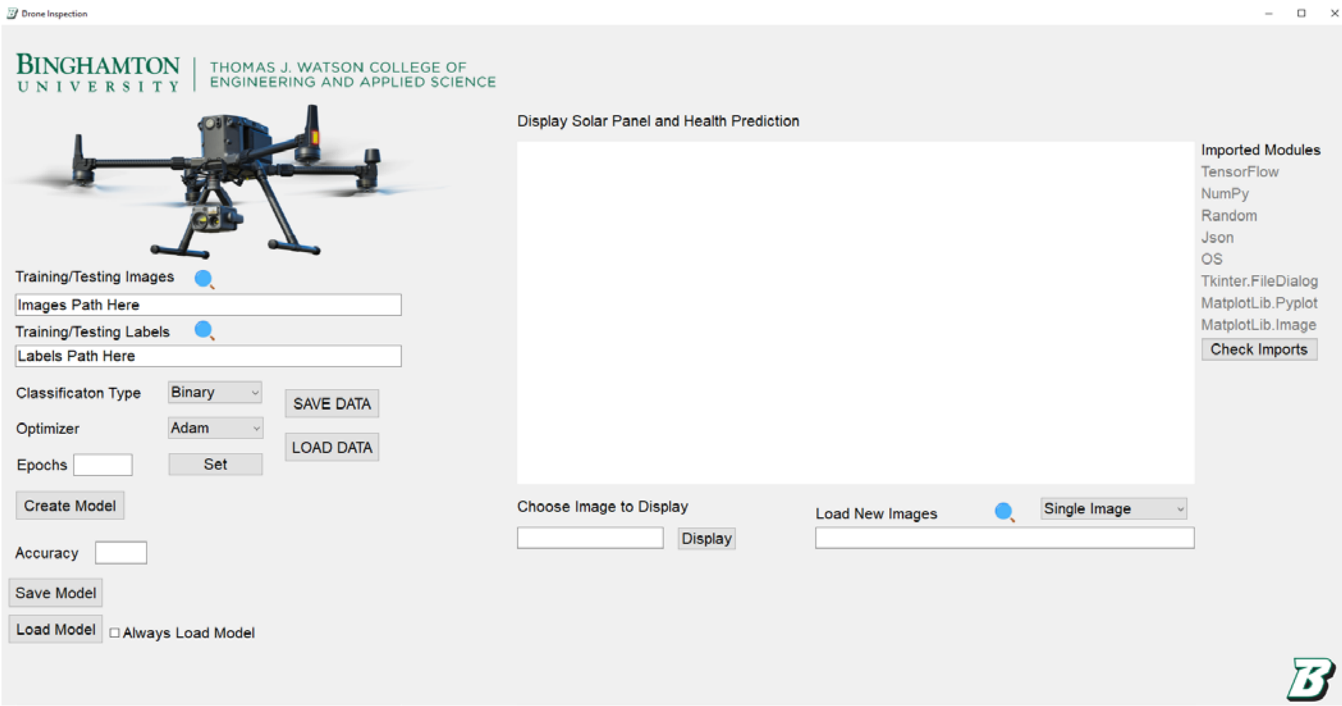

Figure 2. Graphical User Interface

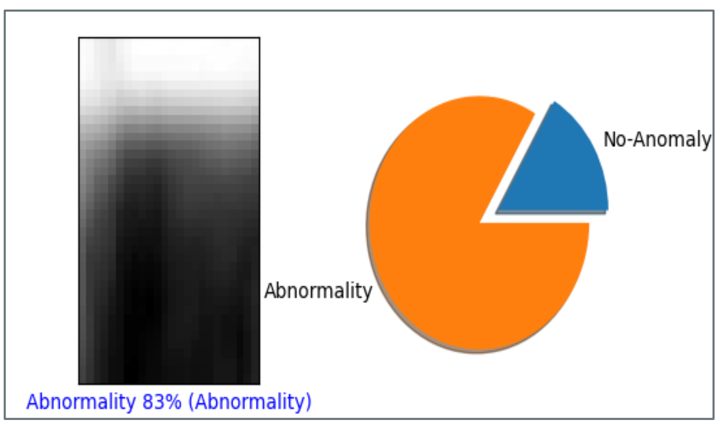

Figure 3. Prediction Results for a Single PV Panel

The code is able to create a working model in a few lines of code. There have been some roadblocks such as the accuracy of the model being lower than expected. The accuracy has been consistently improving by implementing necessary methods such as normalizing the pixel data to a range from 0.0 to 1.0 and by only creating the model to handle as many classifications as necessary. The system uses binary classification so that only two classifications are necessary which increases the accuracy of the data.

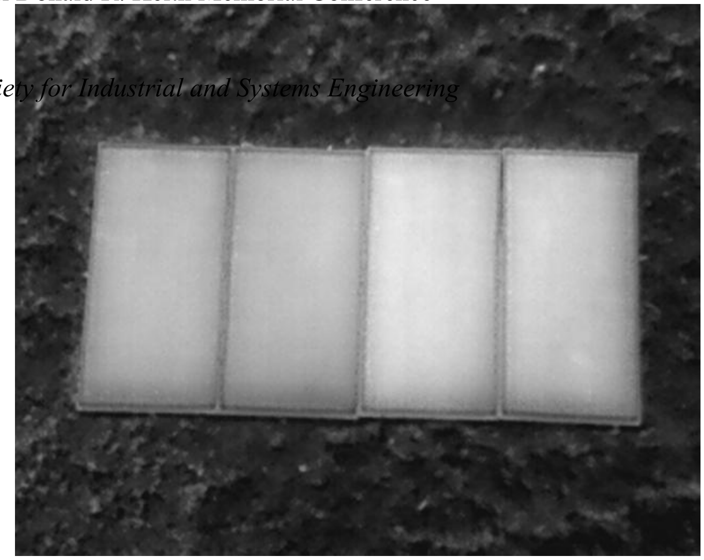

Figure 4. Thermal Image of Unpowered Solar Panels on Grass Taken using the Zenmuse XT2

4. Conclusions

The objective of this project is to implement and test a non-labor-intensive solar panel inspection system that can determine the health status of solar PV cells based on input data from thermal imagery. The system consists of two major components: data processing and prediction software with a data collection apparatus. The former is a Python-based machine learning algorithm, and the latter consists of a drone (DJI Matrice 300 RTK) and a thermal camera (DJI Zenmuse XT2). The software features an intuitive GUI for data uploading, choice of defect classification type, optimizer type selection, epoch number selection, and graphical representation of the algorithm's prediction results for a panel of the user's choice. Utilization of the system will allow independent and commercial energy producers to ensure maximum collection of solar energy with ease. In comparison, the current inspection system is limited by manual drone flight and camera operation for data collection, including the physical transfer of that data to a local computer equipped with the developed software. Future capabilities of the system include drone and camera autonomy and live-streamed RGB and thermal video during flight with real-time indications of panels with defects. With the rise of drone technology and emerging sustainability initiatives, this project is more relevant than ever and has the potential to help facilitate a substantial increase in solar energy utilization.

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