Technical document (Milestone 2)

Machine Learning & Open Source en Fase Q1

Version 1.0

Introduction

This report aims to define the problem of detecting and classifying various faults in photovoltaic panels using thermographic images in different power supply plants. By creating an image detection software that automatically records the recognition of various types of failures. For this purpose, the methodology used to address this problem is defined along with the various stages in the future development of this process, its limitations and the metrics that are used to guarantee the quality of the solution.

The Problem

The problem posed is based on the detection of several faults present in a functioning photovoltaic panel by means of the automatic recognition of patterns in the thermographic image provided by the aerial inspection carried out by a drone.

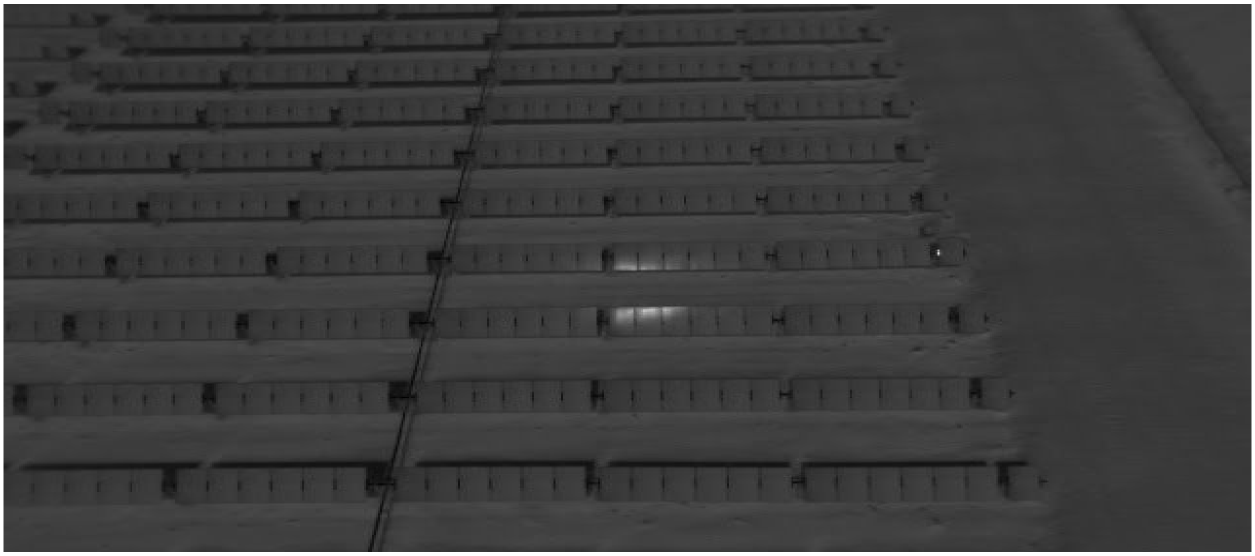
Among the various failures to detect we find the following:

1. An affected panel or connection
2. 2 to 4 affected panels
3. Of 5 or more affected panels
4. Bypass Diode
5. Panel disconnected
6. Connection box
7. Dirty
8. Wrong angle tracker

After the detection of the various faults, these must be analyzed thermally to verify the degree of severity found. To finally integrate this failure into the report provided to each study area, with the geospatial location of each of the failures and their respective characteristic.

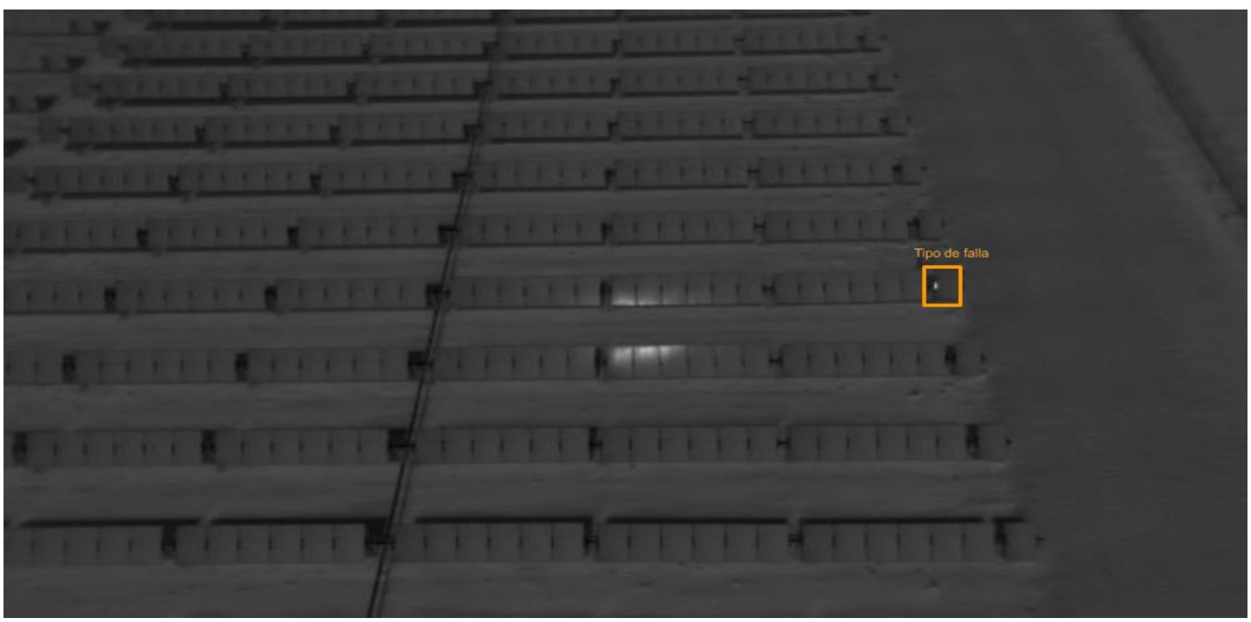
An example of such a problem is the one below, where the input image provided by the inspection to a section of the plant is observed.

Figure 1 : Example of thermographic image



It is desired to automatically detect panels that present some anomaly in their temperature measurements, and therefore some type of failure. In the previous image a desired result would be the following:

Figure 2: Example of thermal image with panel with fault

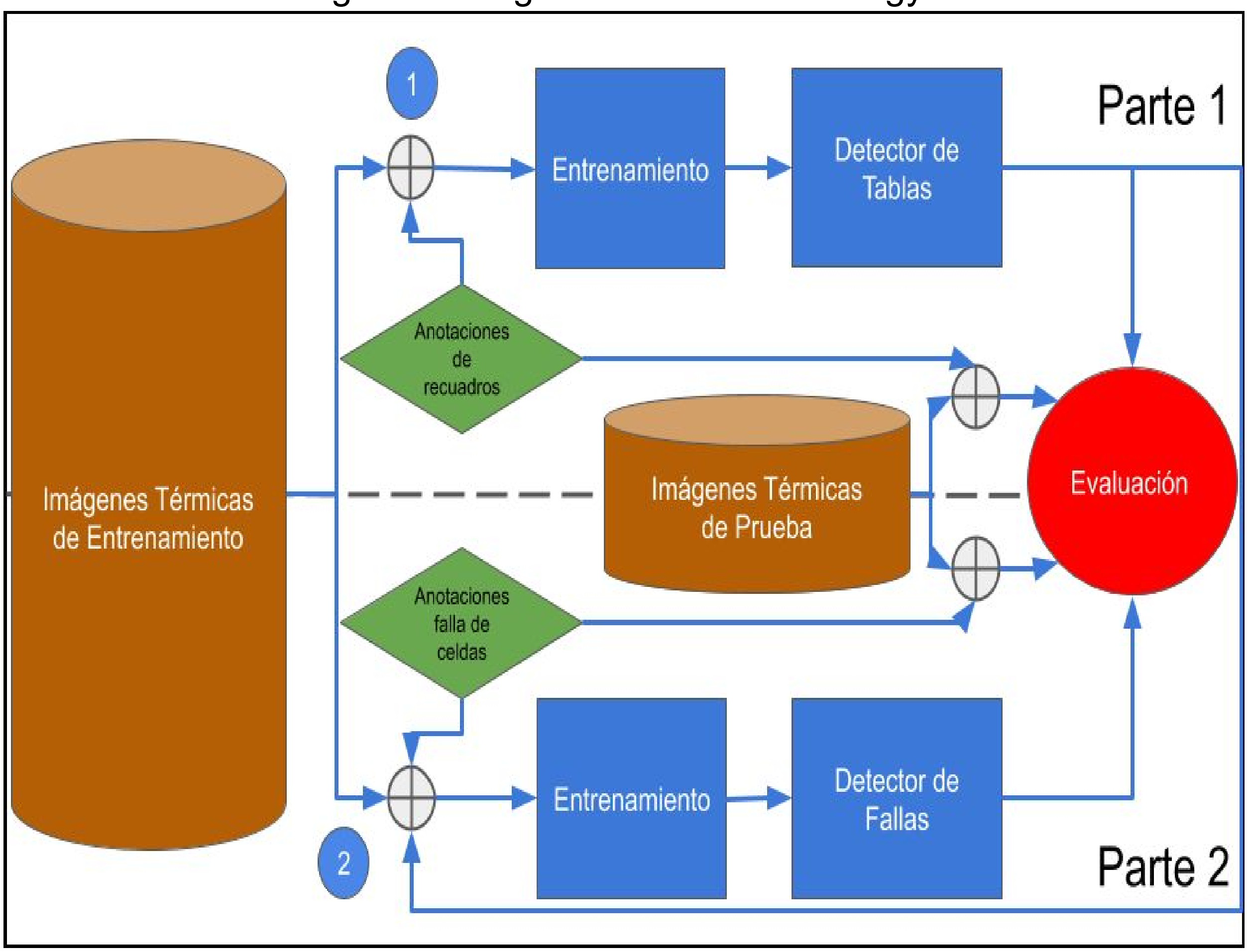


Methodology

The proposed methodology is composed of two stages: detection of photovoltaic Strings (set of panels) and detection of each panel within the Strings together with their corresponding fault. It is clear that the second part depends entirely on the correct execution of the first. However, a third option is evaluated, which is based on the detection of faults directly in the full image.

The next diagram summarizes the stages of the proposed solution:

Figure 3: Diagram of the methodology.



Training and Test Set

For the training of the detection models to be trained, two sets of Training-Test are defined:

- Set A: consists of the use of the first image of each mission performed for the training of the detector together with the second image of each mission used for the validation (test) of the trained detector. These images to be used have associated the previously annotated boxes with their respective class (‘panel’).
- Set B: consists of the use of half of all the images of each mission performed for the training of the detector, while the second half of images of each mission is used for the validation (test) of the trained detector. These images to be used have associated the previously annotated boxes with their respective class (‘panel’).

The database annotations are in XML format, as presented in related investigations such as VOC. This structure can be generated through the graphic interface proposed in LabelImg, which facilitates the annotation of new images for training.

Figure 4: Graphic interface LabelImg

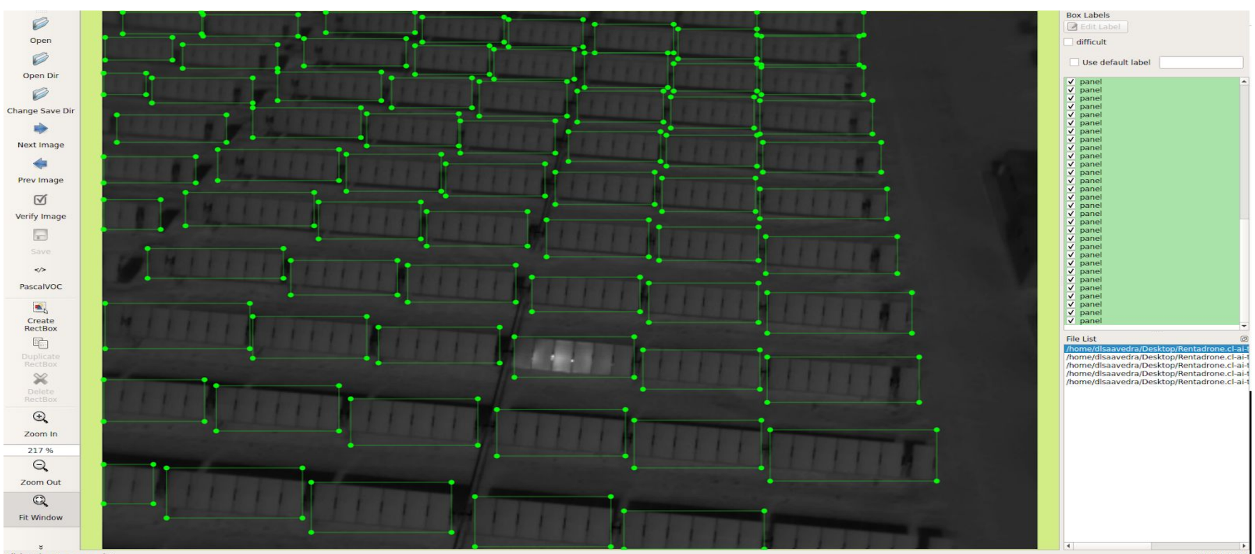


Figure 5: XML Annotation Format


```xml
<annotation verified="yes">
	<folder>images</folder>
	<filename>DJI_0001.jpg</filename>
	<path>/home/dlsaavedra/Desktop/Rentadrone.cl-ai-test/Panel_Detector/Train&amp;Test/images/DJI_0001.jpg</path>
	<source>
		<database>Unknown</database>
	</source>
	<size>
		<width>640</width>
		<height>451</height>
		<depth>1</depth>
	</size>
	<segmented>0</segmented>
	<object>
		<name>panel</name>
		<pose>Unspecified</pose>
		<truncated>0</truncated>
		<difficult>0</difficult>
		<bndbox>
			<xmin>55</xmin>
			<ymin>28</ymin>
			<xmax>120</xmax>
			<ymax>48</ymax>
		</bndbox>
	</object>
</annotation>
```


One hypothesis to clarify is whether the use of Set B will allow for better training, therefore better detection results than Set A. If this hypothesis is false, it is enough to train the detector with only one image, which favors the time spent on the labeling of images.

For training of the flaw detector, the fault entries provided in the database, which is assigned the processed image to the box along with the naturalness of failure is used.

Detection models

Part 1: String Detector

The SSD (Single Shot Detector) is used to carry out the detection. With two variants SSD300 and SSD7, the first consists of the original model proposed by the author while the second consists of a simplification of the previous one, with the intention of being a model with less complexity, therefore of easier implementation and training. For these models, the open source project exposed in SDD-Github is used. The training of this model is carried out in the previously assigned sets.

Metrics

The "Mean Average Precision" (mAP) metric is used in the evaluation of the detection models, which is commonly used for the analysis of detector results. This metric has a range between 0 and 1, 0 being zero detection and 1 a perfect detection of the elements.

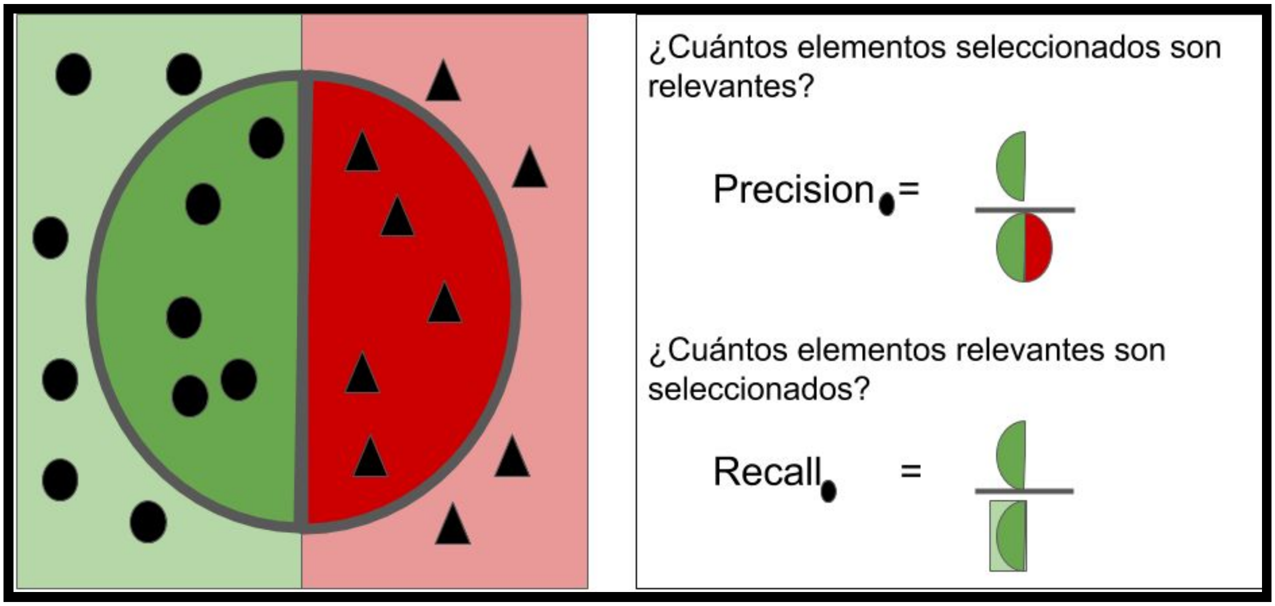
Part 2: Panel Failure Detector

For the problem of fault detection there are two possible solutions: the first is the use of a detector directly in the thermal image, which provides the location and type of fault of the affected panel or String. The second way is the use of the panel detector, trained in part 1, to reduce the complexity of the problem only to the detection inside the Strings of the panels, in order to eliminate the noise produced in the space between panels.

Metrics

In the evaluation of the fault classifier, the Precision & Recall measures are used, which provide information on how many elements are correctly classified and how many elements of the total are classified. By having different images that share certain panels, the classifier has different instances to be able to select the panels with faults. This allows for greater consideration for the Precision value.

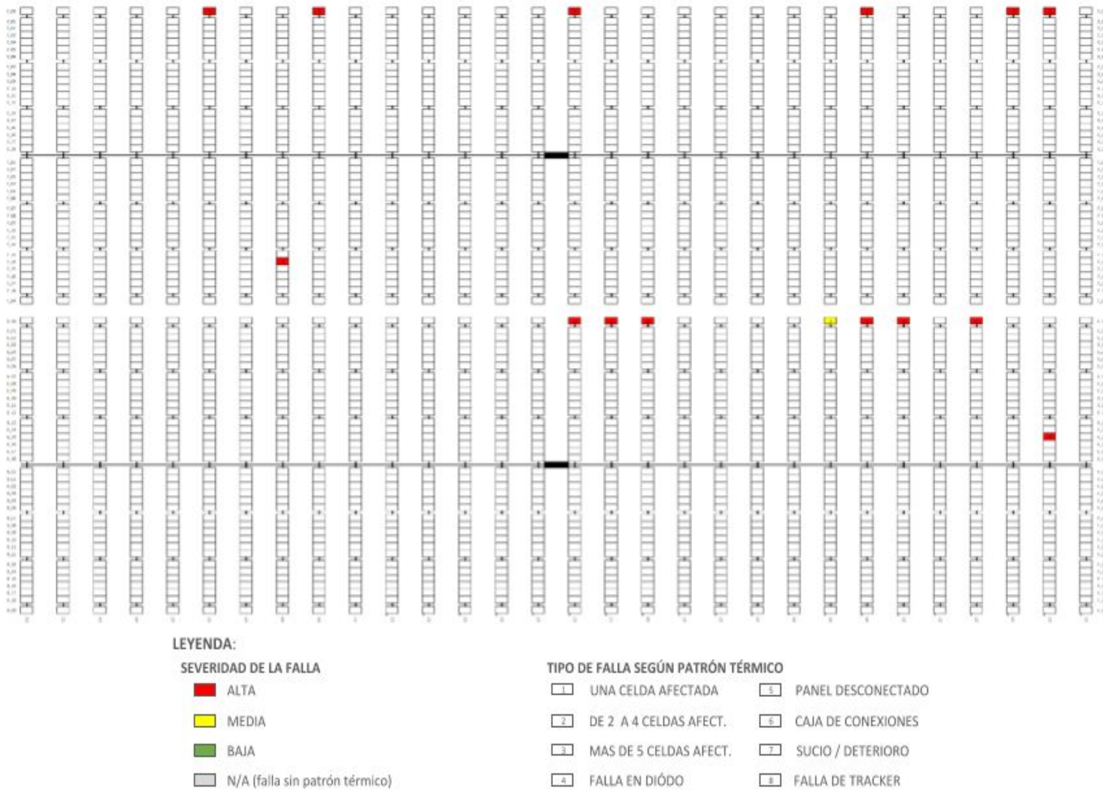
Figure 6: Precision & Recall Diagram



Results Integration

After the correct detection of the panels with faults, they must be referenced to their corresponding spatial location within the study area. To achieve this georeferencing, the detection of the Strings of the photovoltaic panels will be used in order to be able to reconstruct through the images the location of each of these Strings, and therefore the future reference of the panel in question that is desired. Allowing this way to automatically create a detailed summary of the various panel failures through a simple structure, as shown below:

Figura 7: Diagrama de Fallas



Minimum viable product and quality of results

Subsequently, the minimum viable algorithms are subdivided at least in this phase of the project, specifying their tasks and the expected minimum performance.

1. Strings Detector:
    a. Training module: code to train the model with an arbitrary database.
    b. Evaluation module: code to evaluate the model trained in arbitrary test data.
    c. Detection module: code to detect the Strings within an image.
    d. Detector trained with the current database.
    e. Expected performance: over 90% mAP

2. Panel Failure Detector :
    a. Training module: code to train the model with an arbitrary database.
    b. Evaluation module: code to evaluate the model trained in arbitrary test data.
    c. Detection module: code to detect faulty panels within an image.
    d. Detector trained with the current database.
    e. Expected performance: over 90% accuracy.

3. Map and failure report of the Panels
    a. Integration of fault detection on map of pre-established areas.
    b. Fault statistics report in each area of the plant.
    c.

Limitations of the proposed solution

The main failures and limitations that have the proposed solution is mainly due to the nature of the data, mainly there are two types:

- Resolution of thermographic images: this factor can be an obstacle when it is possible to detect more accurately the different faults of the panels, due to the lower resolution available in the images (600x500px) and the vast area covered by these Photographs. Being a panel of a small size (10x10px), which causes difficulties when detecting and correct classification of the fault.
- Reduced number of failures in the training set: although there are a large number of images of the various areas of the photovoltaic plant, the proportion of images with the various failures of the panels can cause a complication at the time of training of the fault detection models.