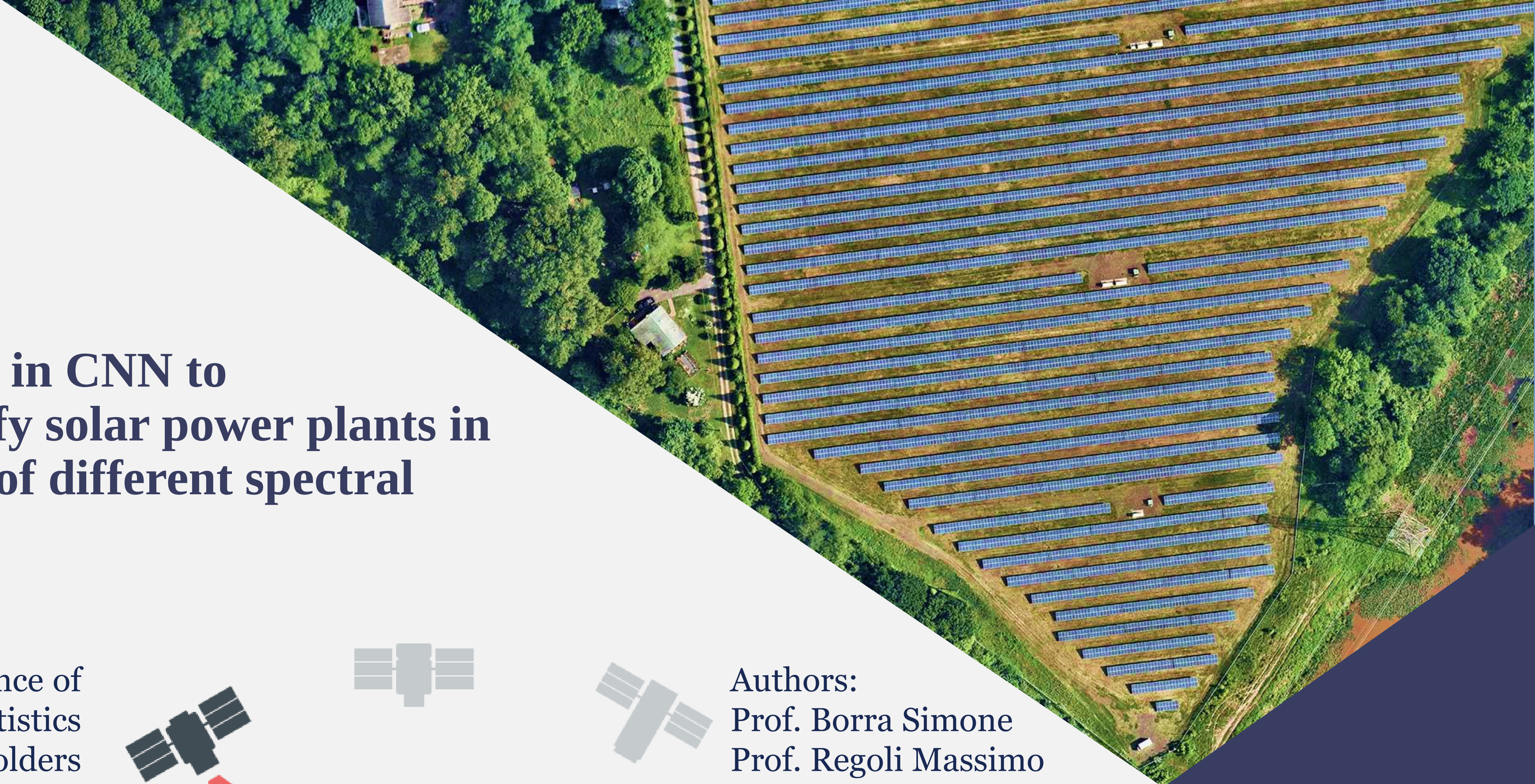

Using Sentinels data in CNN to automatically identify solar power plants in Italy: a comparison of different spectral bands combinations

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Agenda

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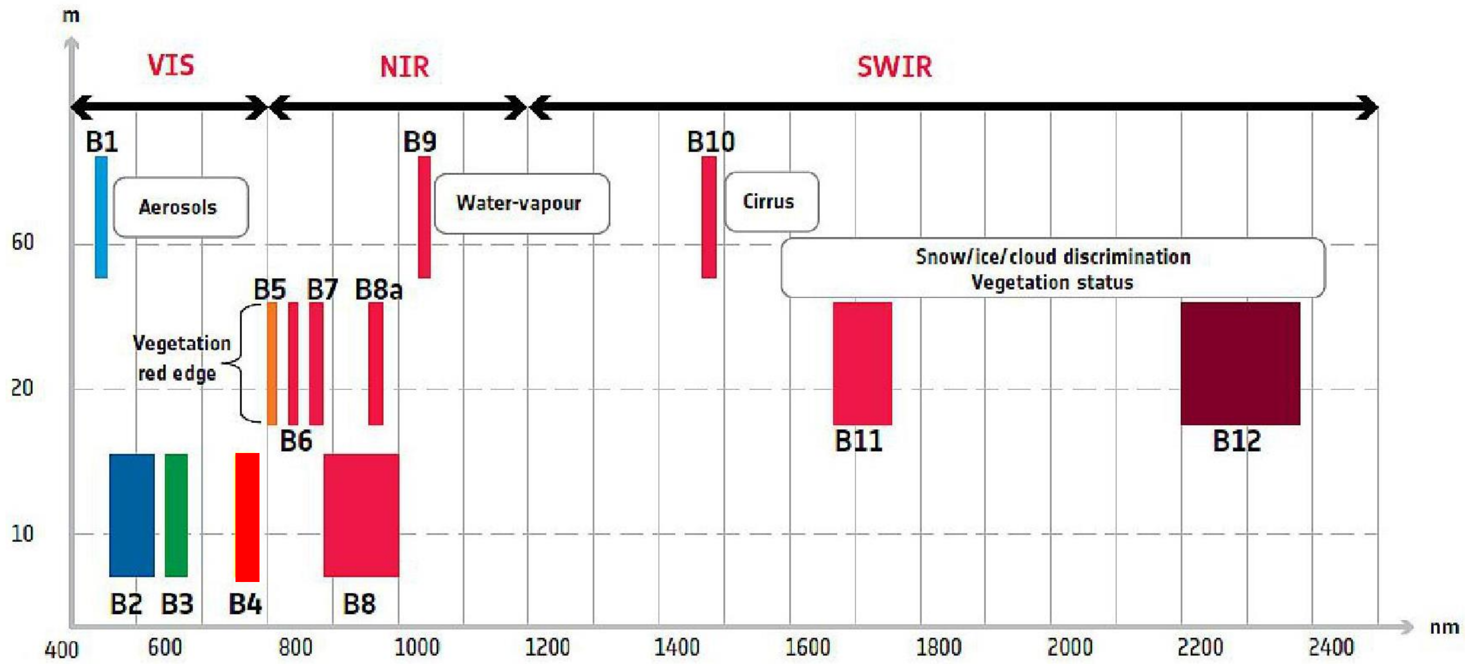
2. Literature Background
3. Research Objective
4. Methodology
5. Results
6. Conclusions

INTRODUCTION

- ***Satellite based Earth Observation (EO)*** is recognized as an innovative and complementary source of data, which combined with the current data processing trends of Machine Learning (ML) algorithms, constitute an efficient, cost-effective alternative to obtain automatized, frequent, and consistent results
- This work implements Satellite data made available **freely** by the ***European Space Agency* (ESA)** *Copernicus* project, collected by the satellites of *Sentinel 2*
- ***SENTINEL-2*** is a European imaging satellites with wide-swath, high-resolution and multi-spectral mission. It has 2 twin satellites flying in the same orbit carrying an optical instrument payload that samples *13 spectral bands*: four bands at 10 m, six bands at 20 m and three bands at 60 m spatial resolution



LITERATURE BACKGROUND

- Diffusion of renewable energy sources, in particular **solar panels**, has gradually increased in recent years and this distribution is expected to increase more rapidly until 2030 (Jang H.S. et al., 2016). It drives a growing interest in collecting data on solar energy distribution. Here it comes as a key tool the use of **satellites data** associated with **Machine Learning** and **Deep Learning** trends
- Deep learning imaging techniques present a **fast** and an **inexpensive way** for detecting distributed **photovoltaic arrays.** In particular **Deep Convolutional Neural Networks** have achieved impressive results on a variety of applications including ***image classification*** (Krizhevsky A. et.al 2012; He K., et.al 2015; He K., et.al 2016), ***object detection*** (Girshick R. et.al 2016; He K., et.al 2016; Ren S. et.al 2017) and ***image segmentation*** (Farabet C. et.al 2013; Shelhamer E. et.al 2017).
- After analyzing the body of literature of interest, we classify the main objectives of prior works in 4 main groups:

1. *SOLAR PANELS DETECTION*
2. *PHOTOVOLTAIC PLANT FAULTS*
3. *HIGH RESOLUTION SATELLITE IMAGERIES AND DEEP ALGORITHMS DEVELOPMENT*
4. *PREDICTION OF PV POWER GENERATION THROUGH SOLAR RADIATION AND CLOUDS FORECASTS*

RESEARCH OBJECTIVE

- The main goal of our research is to provide a ***Deep Learning approach to automatically detect Solar Plants in Italy through the implementation of Satellites Data from Sentinel 2***, computing various experiments testing the image augmentation effect on the prediction performance, along with different bands combinations
- The aim can be broken down in the following objectives:

OBJECT DETECTION

Verify the capability of the algorithm to detect Solar Power Plants, using the freely available Sentinels data at a spatial resolution ranging from 10 to 20m

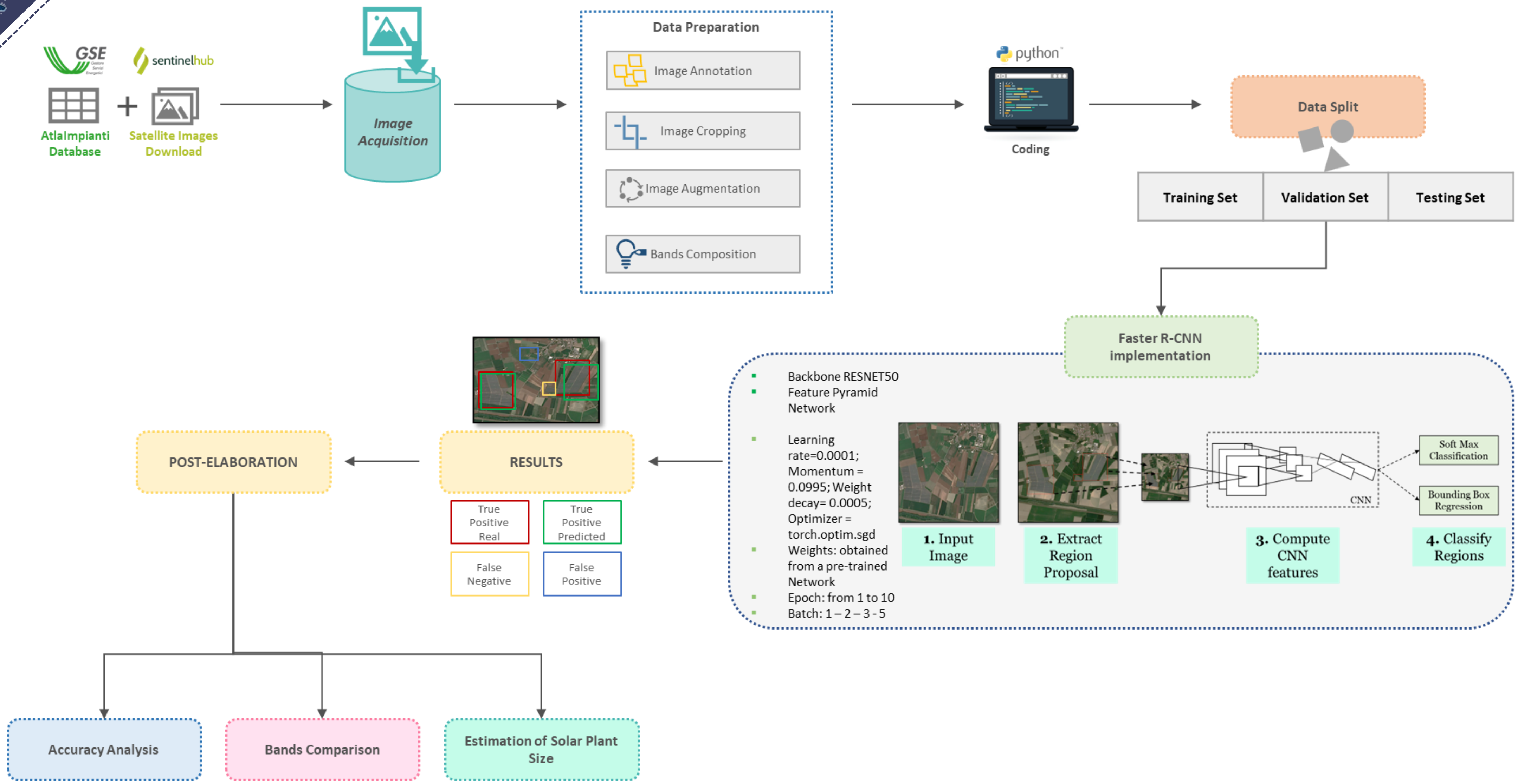
IMAGE AUGMENTATION EFFECTS

Verify whether the image augmentation in the training sample affects the predicting capacity of the algorithm in terms of average precision and detection performance

BANDS COMBINATIONS

Compare different combinations of Spectral Bands to boost the ability of classification with respect to the use of visible RGB Images (Red, Green, Blue color channels)

METHODOLOGY 1/6



METHODOLOGY 2/6

Image Acquisition

- Started from a publicly available database of the company *Atlaimpianti (GSE)* used to identify the positioning of the ***200 largest solar plants*** (>4950kw) located in ***16 Italian regions***
- Downloaded the interested images on the Satellite Images Software *EO Browser* with the following setups:
  - Sentinel 2 images Level 2A (atmospherically corrected)
  - Cloud coverage at max 10%
  - Time range 01/2022 - 05/2022
  - Altitude 500m
  - Image file format in KMZ/JPG in high resolution, both in **True Colors** and **All Sentinel 2 Spectral Bands (from B1 to B13)**
  - Average downloaded image size: 1500x700 pixels

Image Annotations

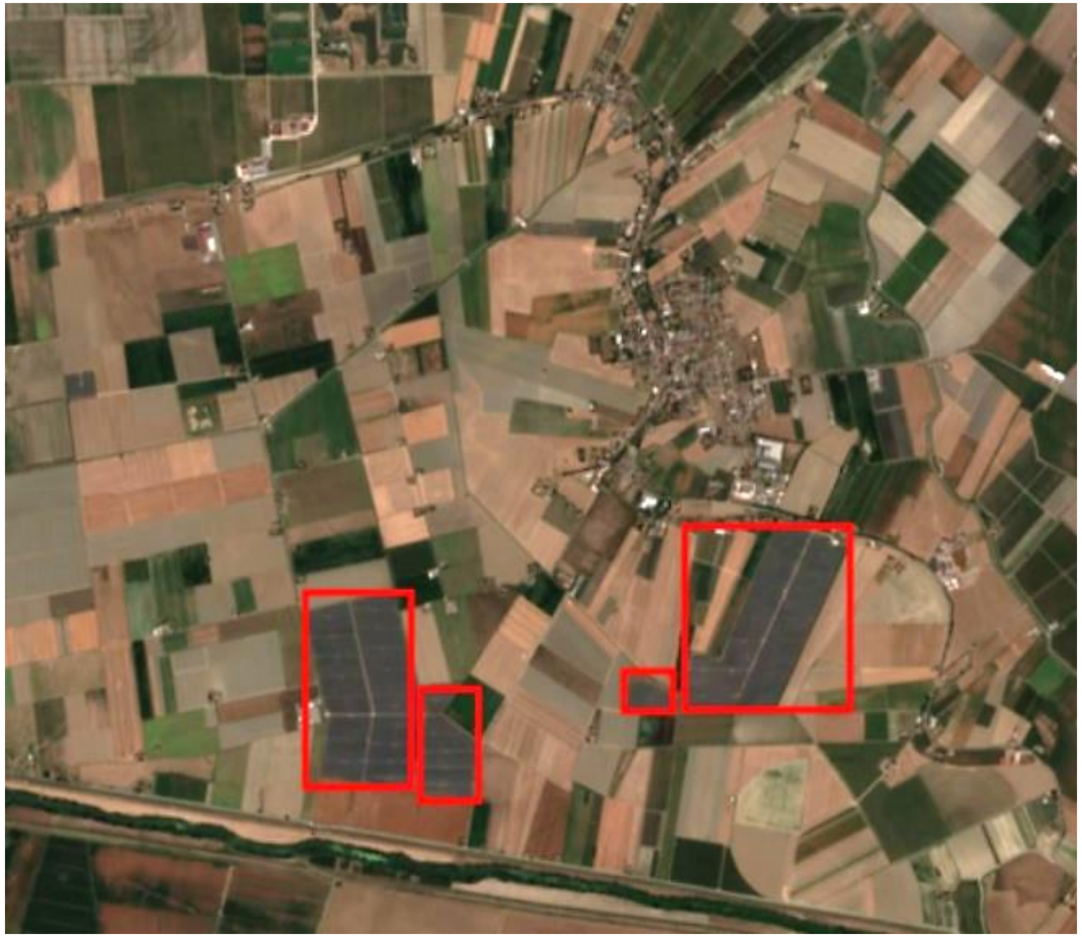
- Used an open access software called *MakeSenseAI* to manually assign **rectangular labels** to solar power plants in each downloaded image
- Saved the annotations in Pascal Visual Object Classes (VOC) format as XML file

Data Preparation

- **Cropping:** Python code to crop the original image into maximum 8 squares of 512x512 pixels, each containing at least one PV plant.
- **Image Augmentation:** image transformations to enlarge the dataset. Python code randomly applies on each cropped image, at least 2 out of these transformations: *Horizontal Flip*, *Vertical Flip* and *Image Rotation* of multiples of 90°

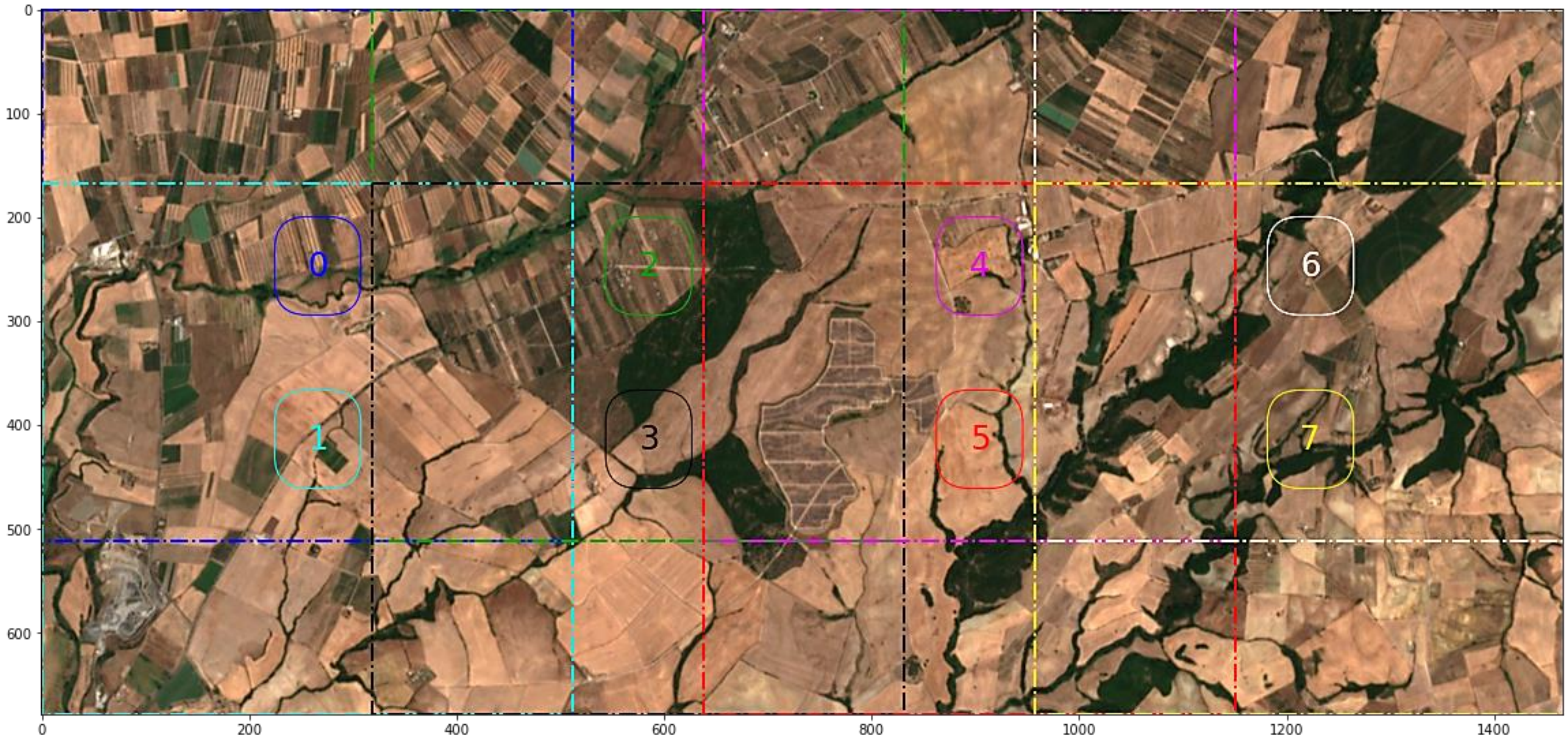
METHODOLOGY 3/6

Illustration of the labelled solar plants with the red rectangular labels manually assigned to each original image



METHODOLOGY 4/6

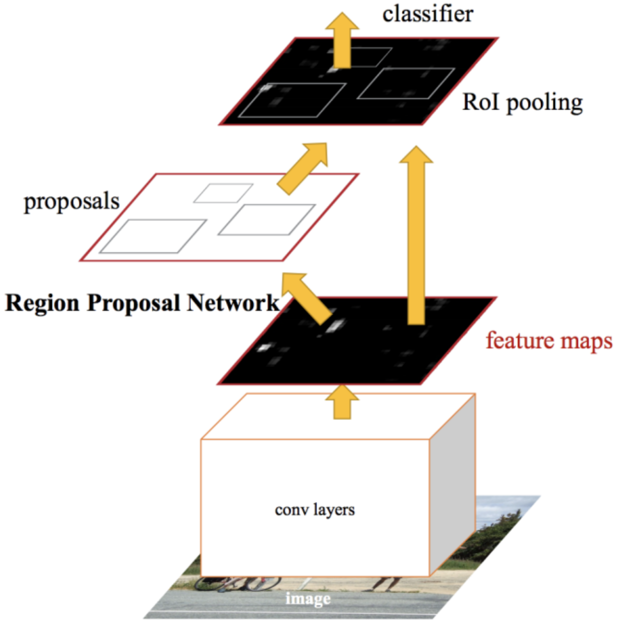
Illustration of the 8-squared cropping process to an original image



METHODOLOGY 5/6

Data Split

Set	*Original Dataset*		*With Image Augmentation*	
	N of images	% of split	N of images	% of split
Training	413	67%	826	72%
Validation	111	18%	222	19%
Test	96	15%	96	8%
Total	620	100%	1144	100%



DEEP LEARNING MODEL FOR OBJECT DETECTION

Architecture

- **Faster R-CNN** (*Region based Convolutional Neural Network*) consists in an object detection architecture that extracts a feature map of the convolution layers and predicts whether there is an object or not, and also predict the bounding box of those objects
- Backbone RESNET50
- Feature Pyramid Network

Configuration

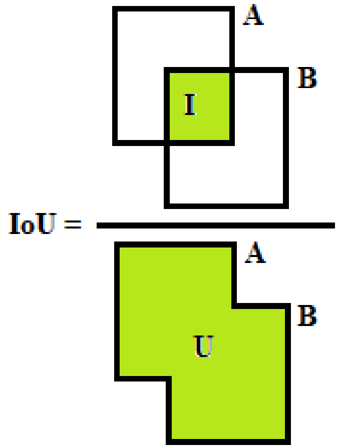
- Parameters setup:
  learning rate=0.0001; momentum = 0.0995; weight decay= 0.0005; optimizer = torch.optim.sgd
- Weights: obtained from a pre-trained Network
- Epoch: from 1 to 10
- Batch: 1 – 2 – 3 - 5

METHODOLOGY 6/6

METRICS FOR ACCURACY ANALYSIS

Intersection over Union (IOU)

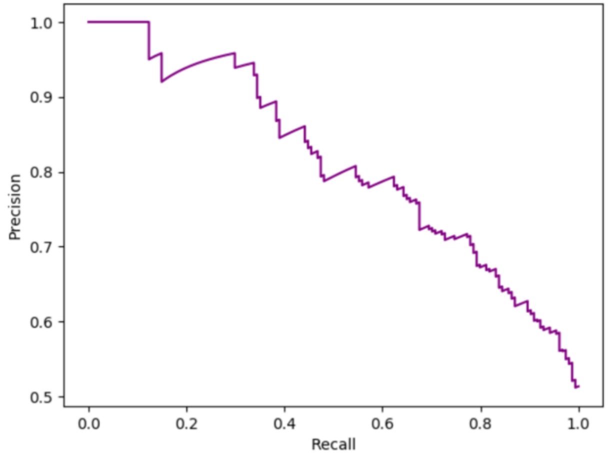
It is the ratio between the area of overlap between the True and Predicted labels over the area of their union



Precision – Recall Curve

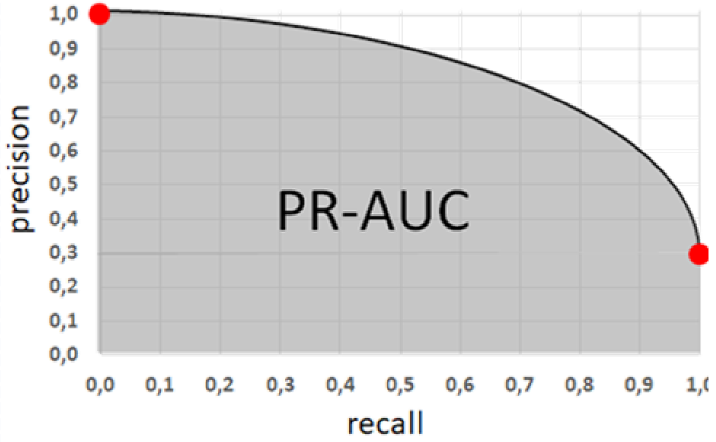
Precision: how many real PV plants among all the predicted positive are recognized
Recall: how many of PV plants are classified as positive

Sorting the scores of predicted labels in ascending order, the two values are computed for each percentile



Average Precision (AP)

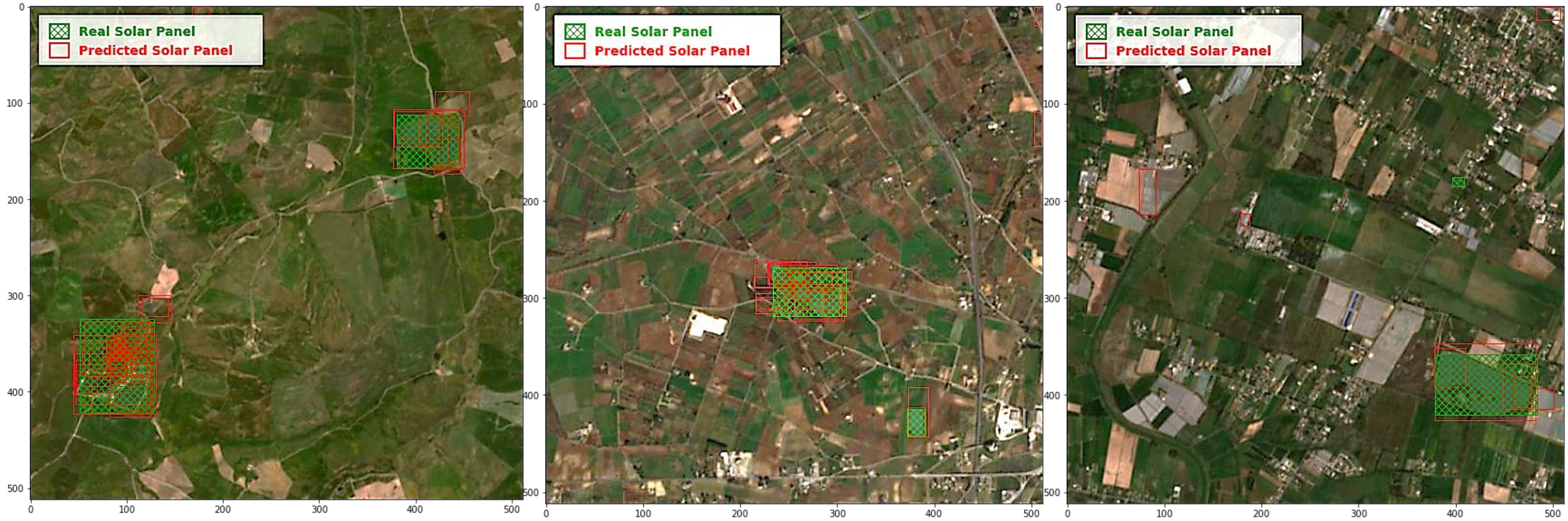
Index providing the area under the P-R Curve (PR AUC). It is computed by segmenting Recall values evenly to 11 parts and then calculate the mean of corresponding precisions. The method used is called ***11 points interpolated precision recall curve***



RESULTS 1/6

The threshold of **IoU** is necessary to define the True Positive and False Positive labels.

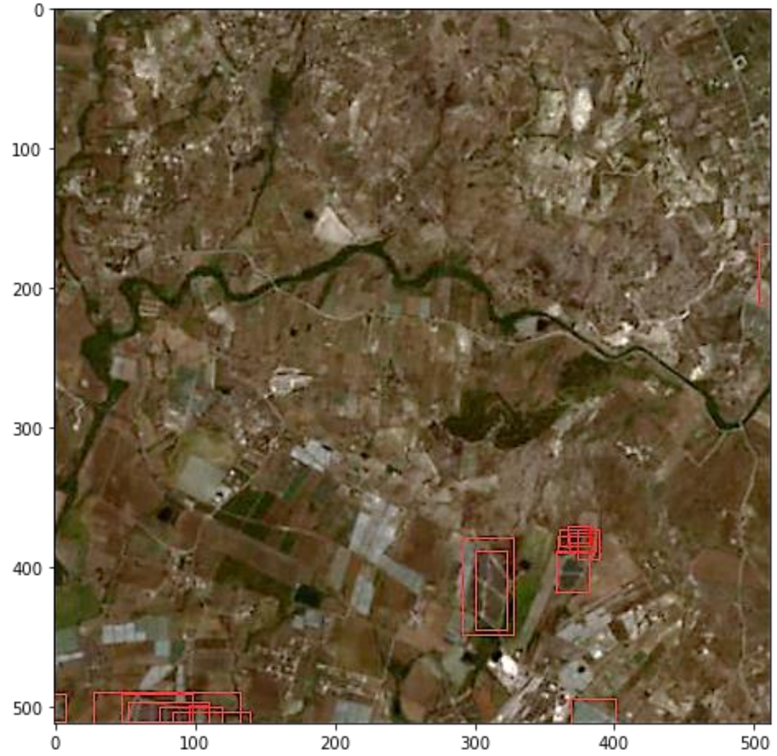
Object Detection: illustrative results of predicted labels



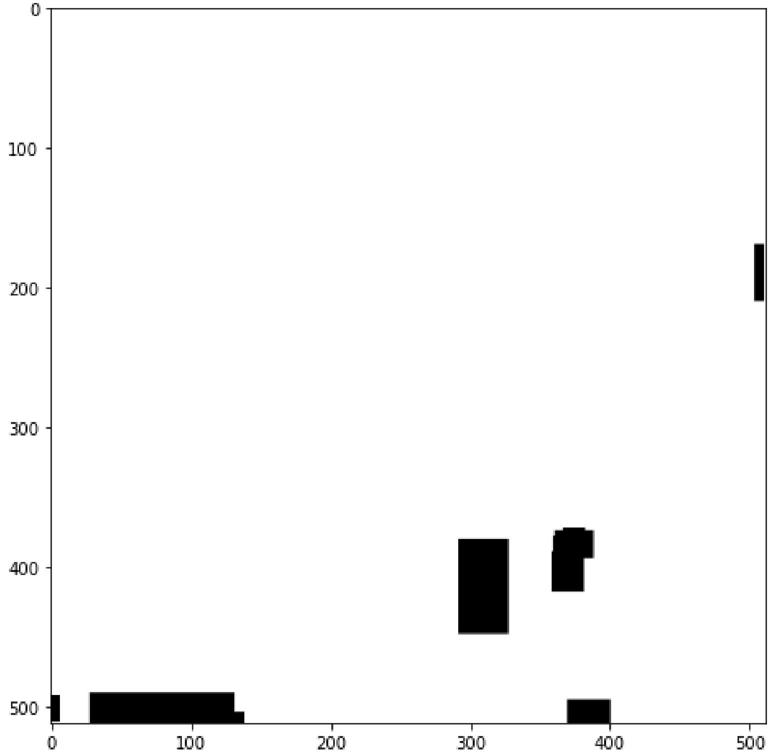
RESULTS 2/6

Post-elaboration results: to avoid redundancy and increase precision, we check the presence of multiple label boxes pointing at the same solar plant, then we set a *Score threshold* to eliminate redundant boxes. Subsequently we check for the union of remaining boxes and draw a larger overall box whose score is assigned by a weighted average of the contained boxes' scores.

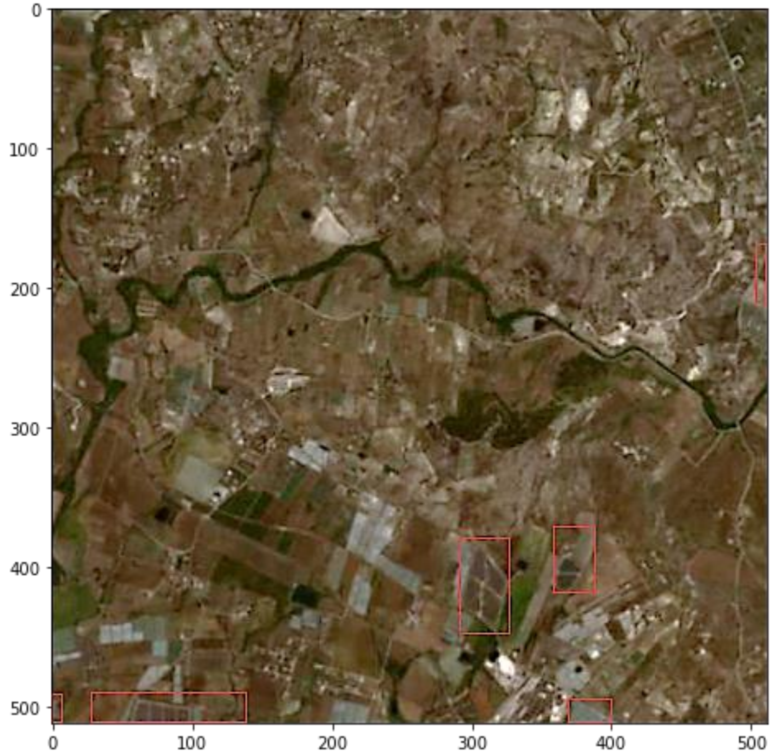
This procedure simplifies the output and it improves the overall *Average Precision*



Faster R-CNN output



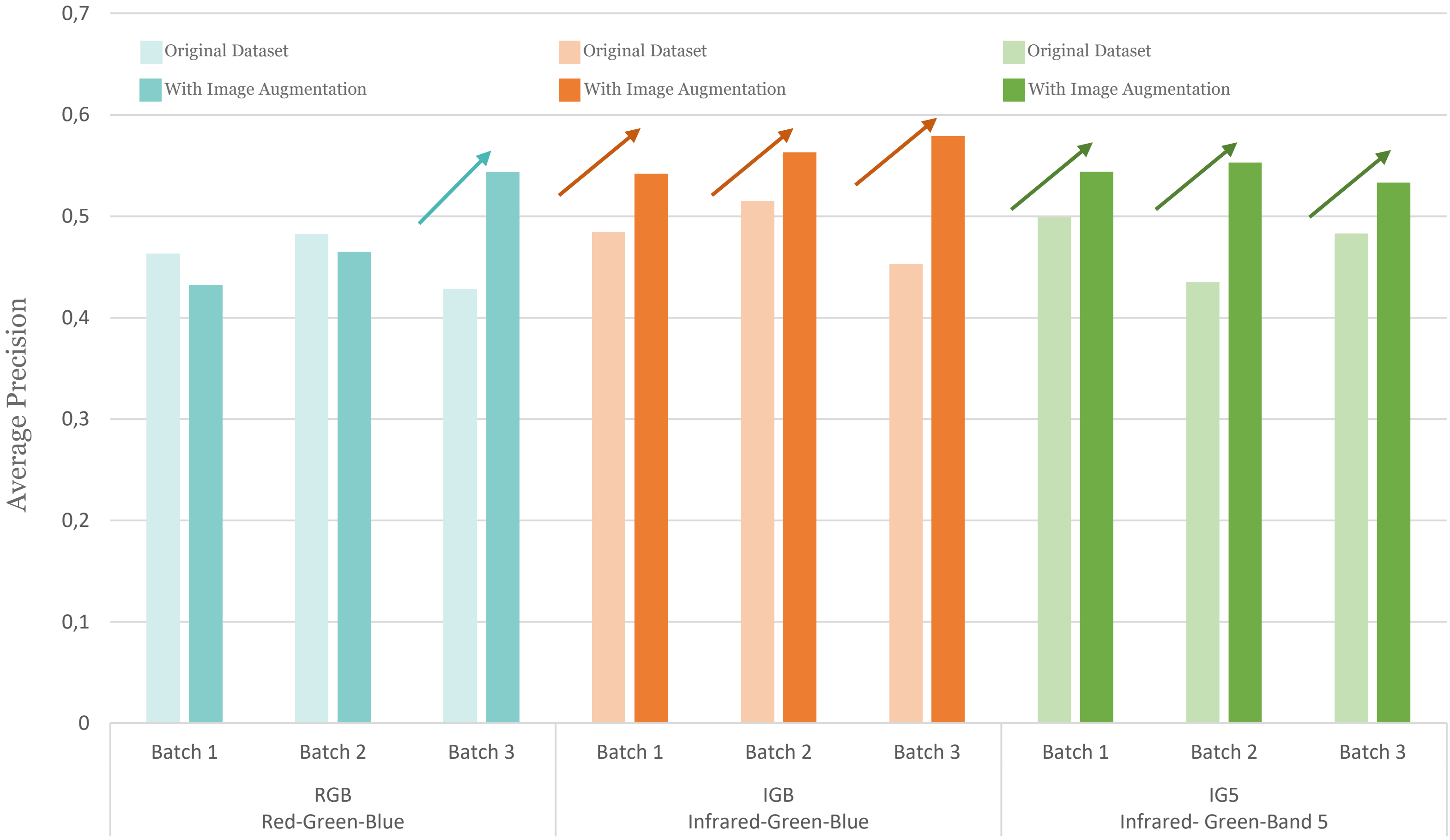
Union of boxes



Post-Elaboration result

RESULTS 3/6

Image Augmentation effect results by comparing the *Average Precision* of the original dataset, with the one containing the *Transformed* images into the *training set*



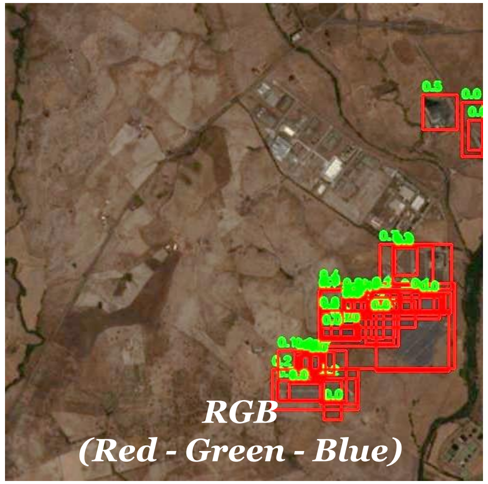
Bands Combination	*N of Batch*	*Average Precision Original Dataset*	*Average Precision with Image Augmentation*
RGB Red-Green-Blue	*Batch 1*	0,463	0,432
	Batch 2	0,482	0,465
	Batch 3	0,428	0,543
IGB Infrared-Green-Blue	*Batch 1*	0,484	0,542
	Batch 2	0,515	0,563
	Batch 3	0,453	0,579
IG5 Infrared-Green-Band 5	*Batch 1*	0,499	0,544
	Batch 2	0,435	0,553
	Batch 3	0,483	0,533

- Average Precision generally increases with Image Augmentation
- Batch 2 and Batch 3 seem to be better than Batch 1

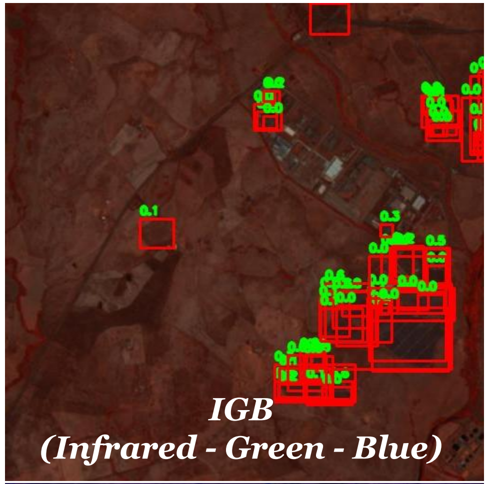
RESULTS 4/6

Bands Comparison results: visualization of images in various bands combination

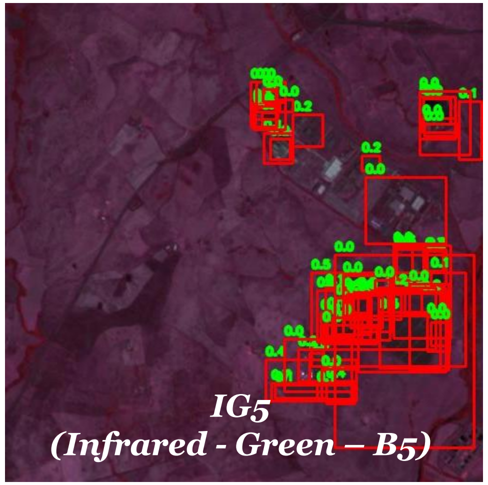
Originally assigned labels



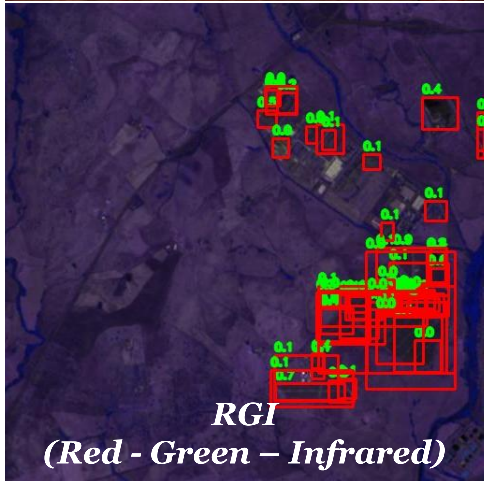
RGB
(Red - Green - Blue)



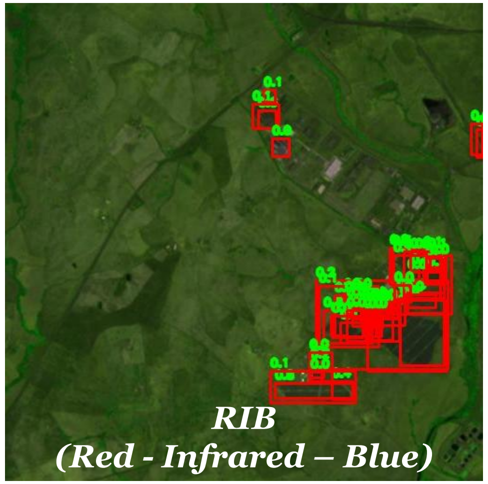
IGB
(Infrared - Green - Blue)



IG5
(Infrared - Green – B5)



RGI
(Red - Green – Infrared)

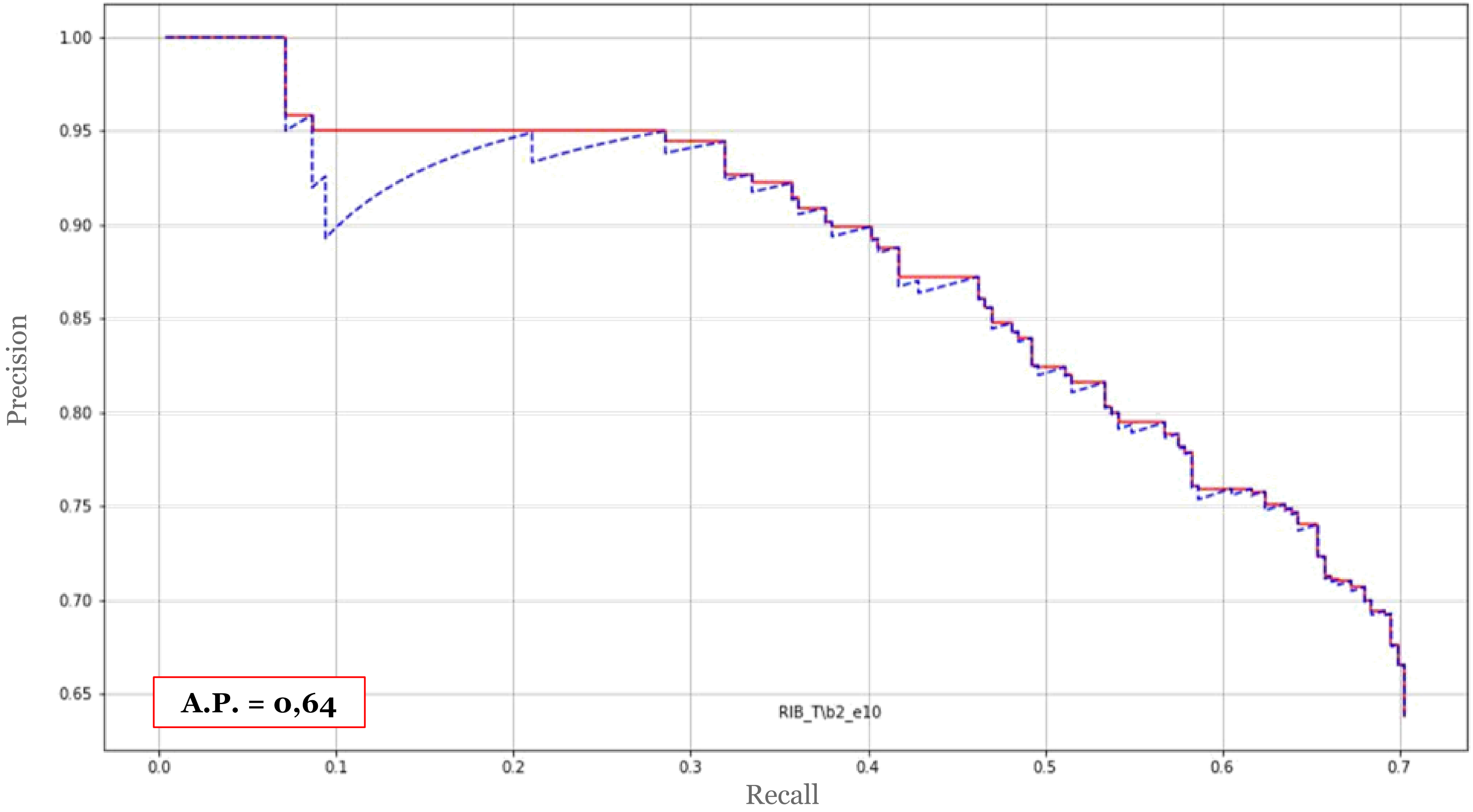


RIB
(Red - Infrared – Blue)

RESULTS 5/6

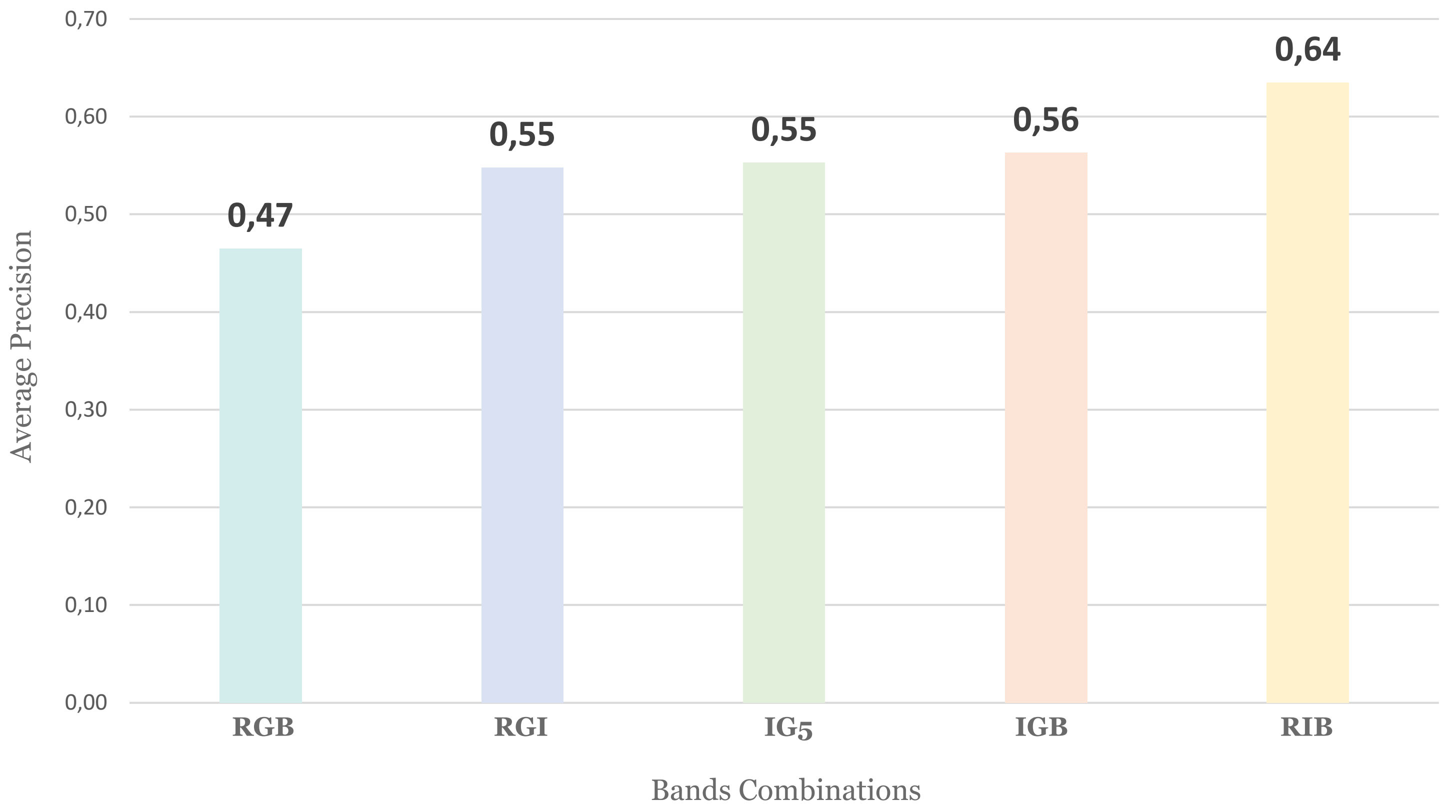
Precision-Recall Curve best performance

Batch 2 and bands combination of **RIB** (Red, Infrared, Blue bands)



RESULTS 6/6

Bands Comparison results by Average Precision



Bands Combinations	Average Precision
RGB Red-Green-Blue	0,47
RGI Red- Green-Infrared	0,55
IG5 Infrared- Green-Band5	0,55
IGB Infrared-Green-Blue	0,56
RIB Red- Infrared-Blue	0,64

- Fixed Batch at 2 and compared the performance across the bands
- RIB (Red- Infrared – Blue) Bands combination provides the best performance in terms of AP

CONCLUSIONS 1/2

- *M*any countries lack of a ***comprehensive and consistent database of the PV plants*** implemented
- The body of literature of solar panels applications reports that ***there is not much difference*** in using ***different backbones of network architectures*** in terms of performance
- Confirmation that object detection through satellites data is more of a ***data-driven problem*** than a ***model-driven problem***

- ***Image Augmentation*** is effective: inserting transformed image into the *Training Set* provided better results in the *Test Set* in terms of improved ***Average Precision*** independently from the Batch and the Bands combinations
- ***Bands Combinations do affect*** the performance of the algorithm, enhancing the characteristics of the identified objects
- Bands Combination of ***RGB (Red, Green, Blue)*** yields the lowest results in terms of Average Precision, while the best combination appears to be the Bands Combination of ***RIB (Red, Infrared, Blue)***
- The use of the ***Band Infrared*** introduces great improvements in rising the *Average Precision for PV Plants*
- The use of Infrared justifies the choice of using ***Sentinel2 Data***
- ***Post - Elaboration*** is effective in terms of reducing redundancy of labels and providing a weighted average of the Labels Score. It simplifies the visual output and it improves the overall *Average Precision*

CONCLUSIONS 2/2

LIMITATIONS

- Type of network used: we used a Faster R-CNN, we could have used a Mask R-CNN
- Rectangular labels are not so appropriate as polygons
- Used Object Detection technique, instead of Semantic Segmentation that is based on pixels
- Lower resolution of Satellite Images with respect to other studies
- Human Error derived from manually assign labels

NEXT STEPS

- Extend the number of bands to insert into bands combinations instead of using only triples
- Estimation of the size of solar plants: derive an estimate of the size of the solar plant by calculating the area of the label associated with the identified object
- Estimate of energy production that also depends on geographic location and weather conditions, merging different sources of data

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Thank you for your kind attention

&

we look forward to receive your feedbacks!

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