How Deep Learning could help to improve OSM Data Quality ?

@o_courtin

@sotm 2018

Purpose

Detect inconsistencies between two datasets :   Imagery and Vector

TOOLS

development SEED

BY DREW BOLLINGER ON JAN 11, 2018

Quickly plug satellite imagery into your favorite machine learning framework

Creating labelled image chips doesn't have to be hard

https://developmentseed.org/blog/2018/01/11/label-maker/

https://github.com/developmentseed/label-maker

Pinpointing the power grid

Saturday 17:10, De Donato

Sajjad Anwar 30 minutes

Development Seed

Over 1.2 billion people around the world lack access to electricity, most of them in rural areas of Sub Saharan Africa and Asia. An accurate map of infrastructure is critical to expand access to these people. Yet, the electricity network is often under-mapped and the schematics that do exist are not publicly available, or lack geospatial accuracy.

In this talk, we'll describe our work with the World Bank to map the grid network in OpenStreetMap in an efficient and repeatable manner. We developed an approach using machine learning to identify areas likely to contain high-voltage towers and used this information to speed up human mappers more than 10-fold. We will highlight this strategy of augmenting human effort with machine learning and provide perspective on how this workflow might be applied to other challenges facing the mapping community.

RoboSat

Generic ecosystem for feature extraction from aerial and satellite imagery

Berlin aerial imagery, segmentation mask, building outlines, simplified GeoJSON polygons

Slippy Tile

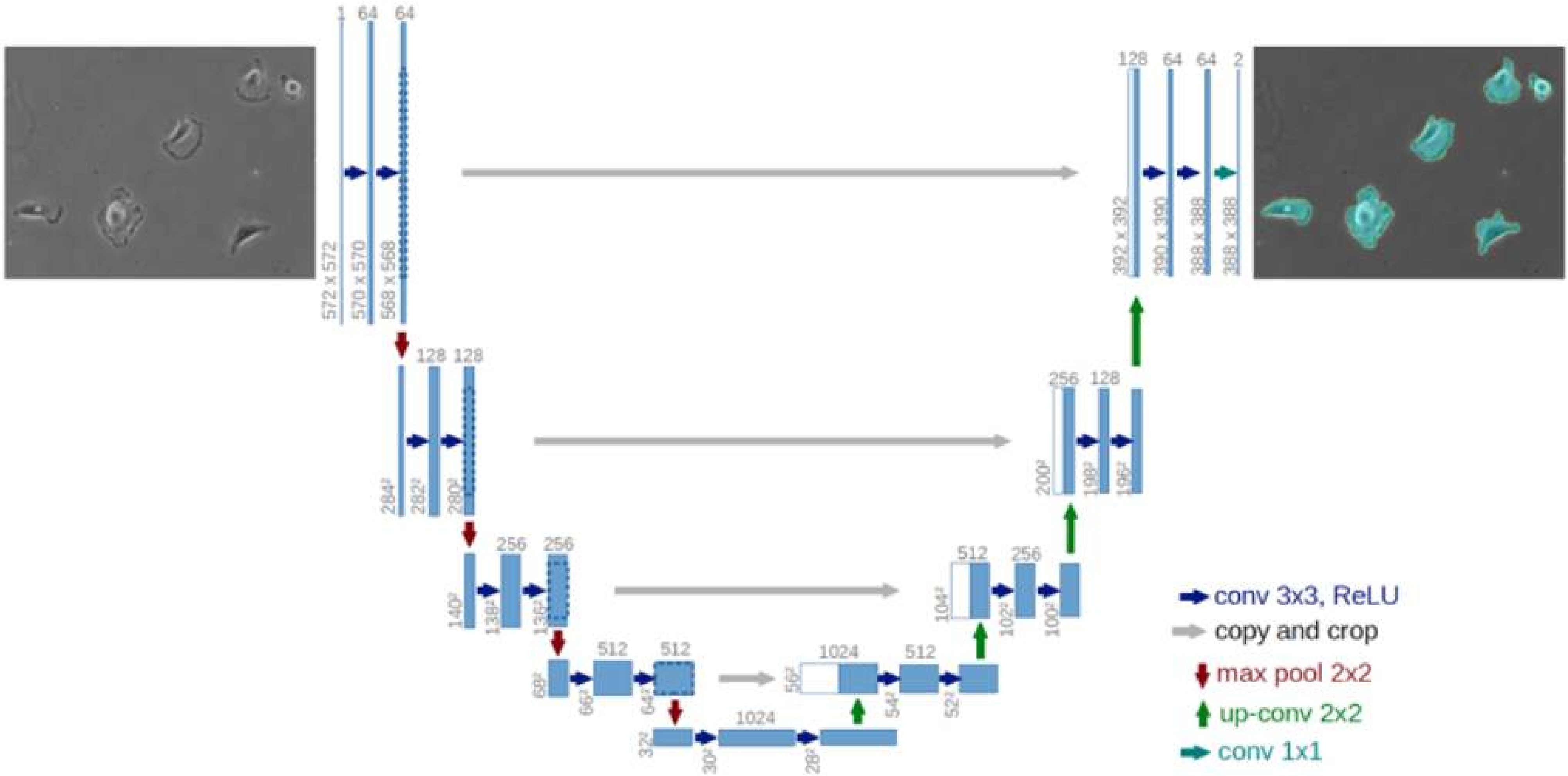
Modular and extensible

State of art SemSeg

OSM and MapBox ecosystem integration

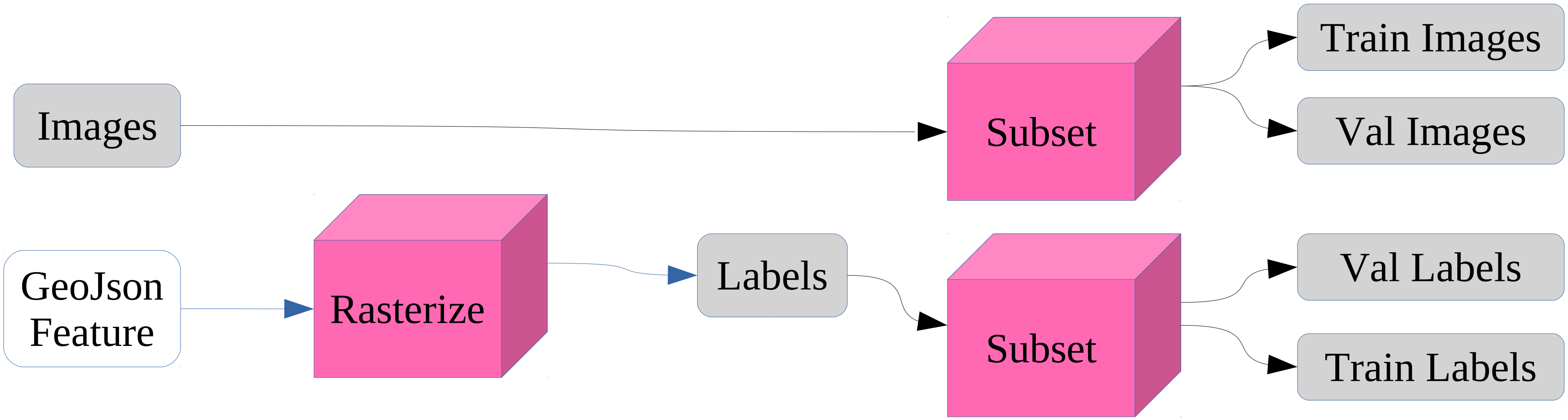
Licence MIT

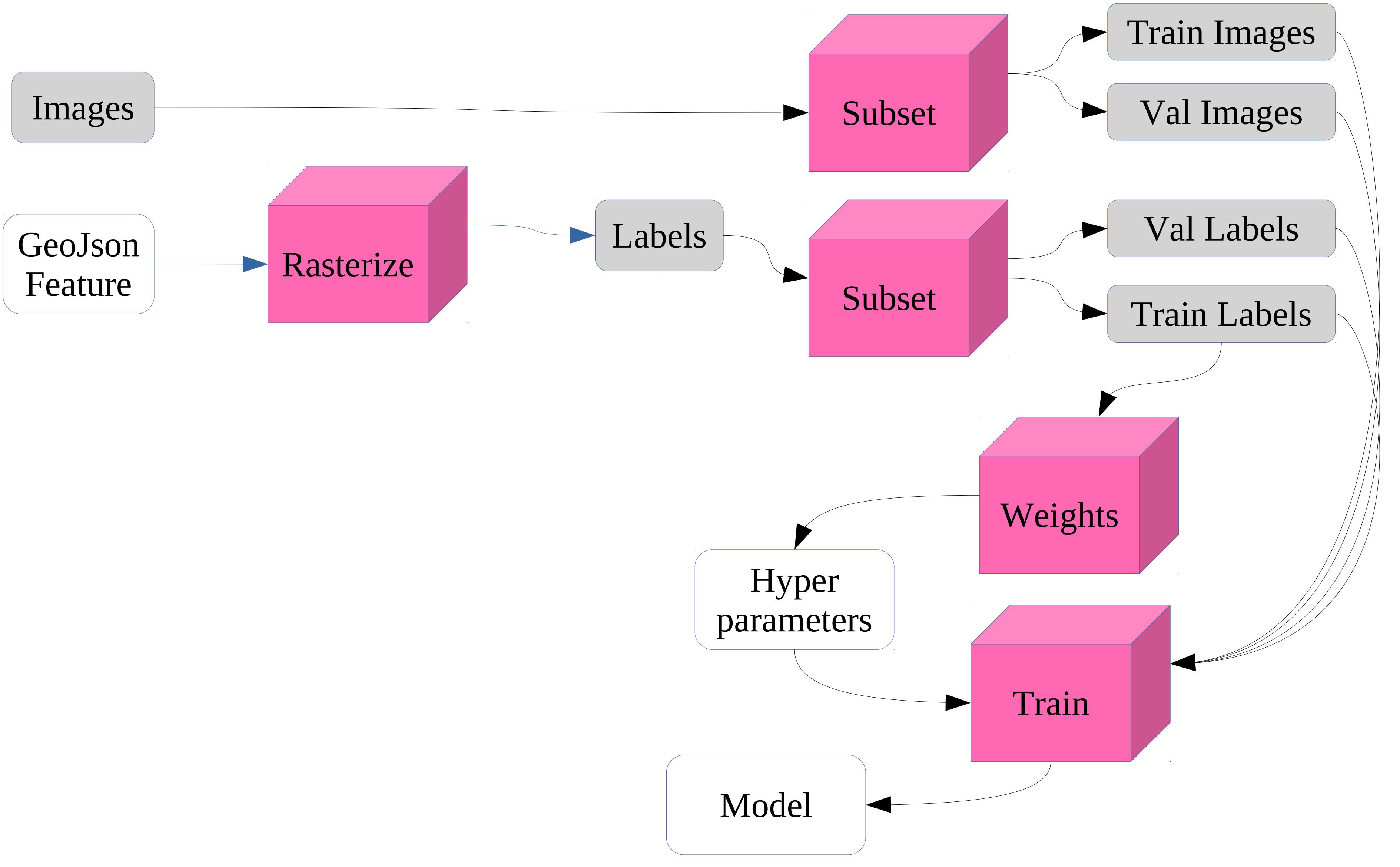
https://github.com/mapbox/robosat



U-Net: Convolutional Networks for Biomedical Image Segmentation

https://arxiv.org/abs/1505.04597


Images
Subset
Train Images
Val Images
GeoJson Feature
Rasterize
Labels
Subset
Val Labels
Train Labels


Images
GeoJson Feature
Rasterize
Labels
Subset
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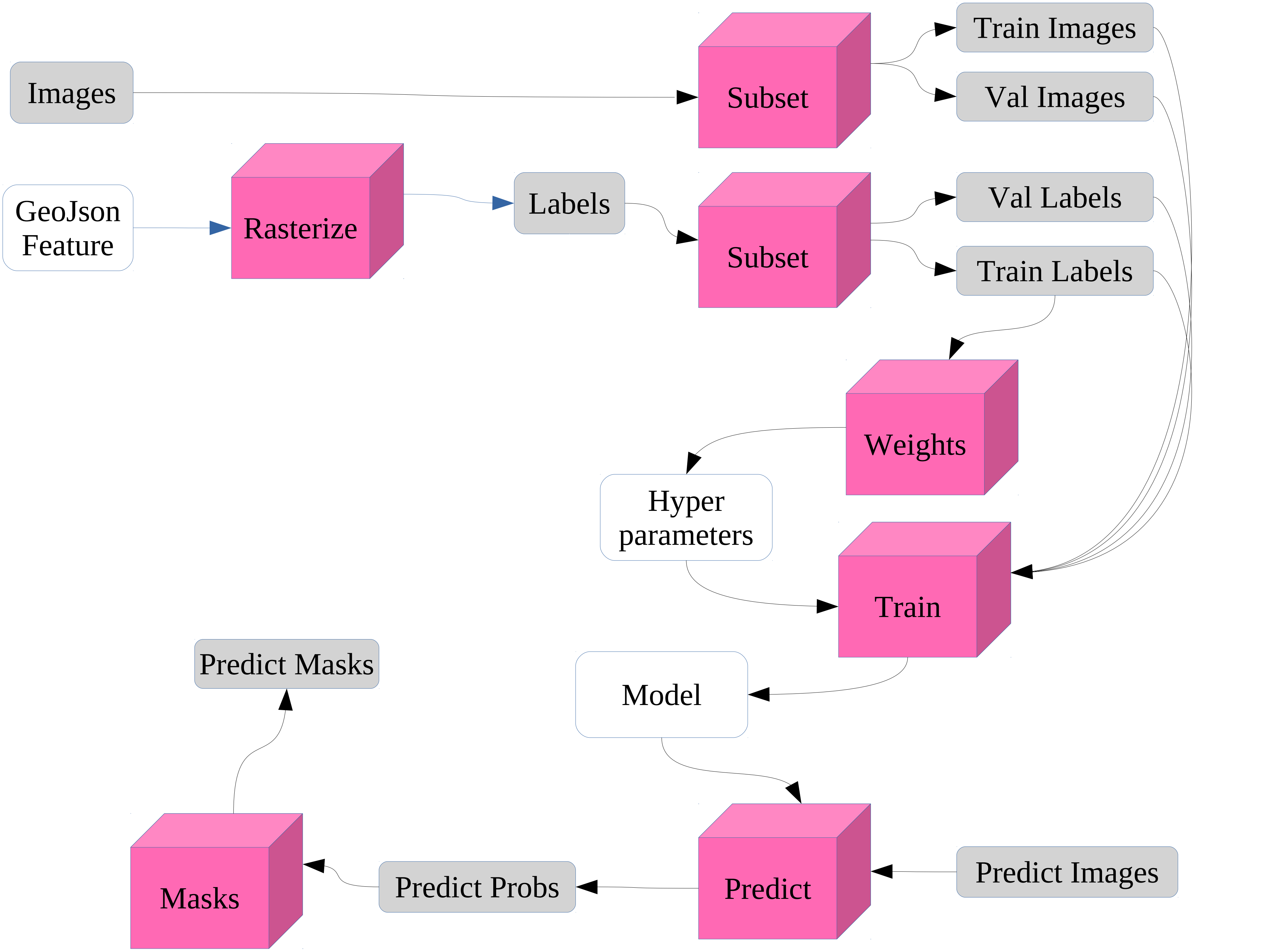
Train Images
Val Images
Val Labels
Train Labels
Weights
Hyper parameters
Train
Model


Images
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Val Images
GeoJson Feature
Rasterize
Labels
Subset
Val Labels
Train Labels
Weights
Hyper parameters
Train
Model
Predict Masks
Masks
Predict Probs
Predict
Predict Images

NGI Belgium DataSet on Building features

RGB 0.25 cm

Zoom level : 18

10 epochs

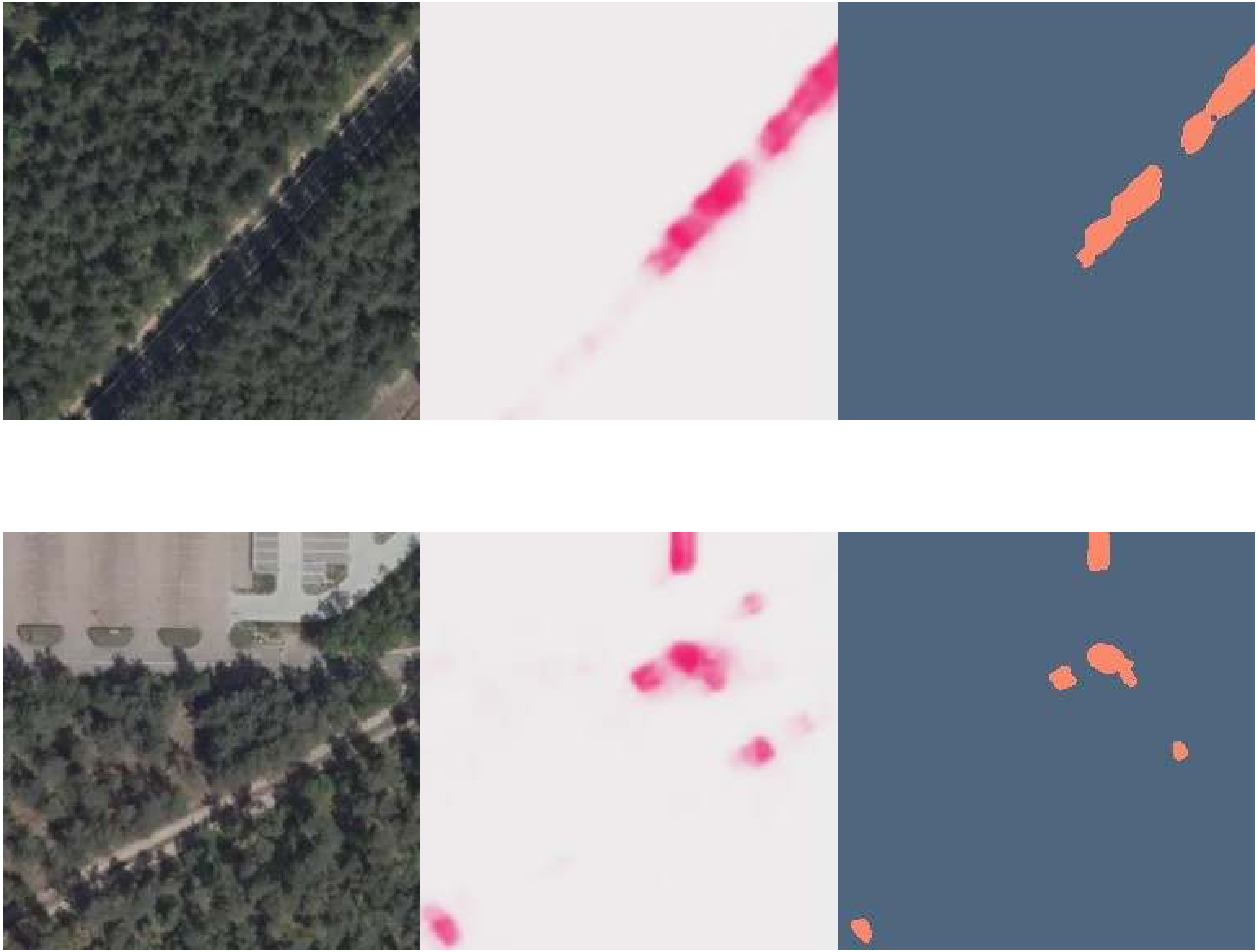
Batch Size : 16

Tile Size : 256px

Train: 2000 tiles

Validation : 500 tiles

IoU : 77.4



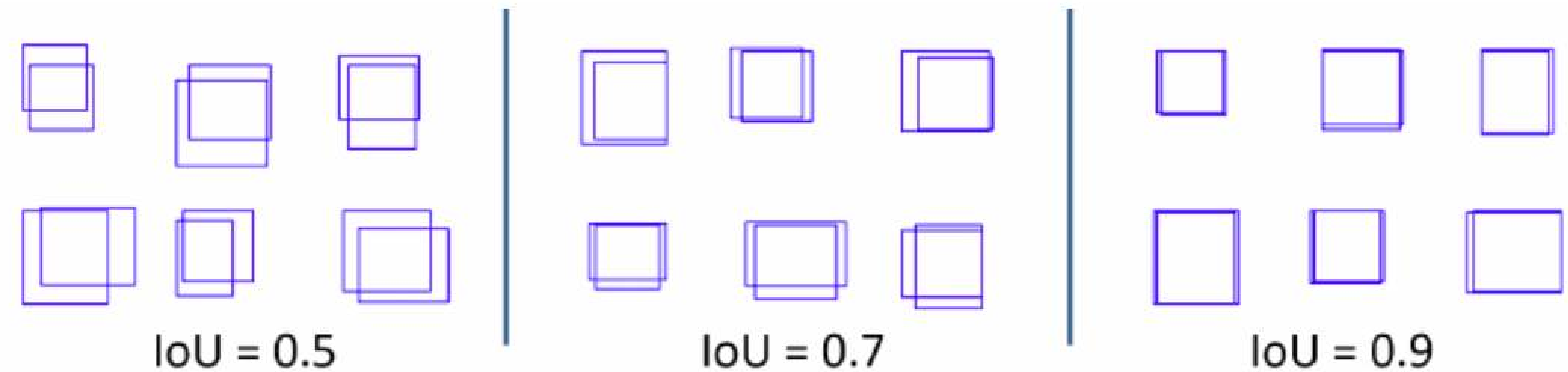
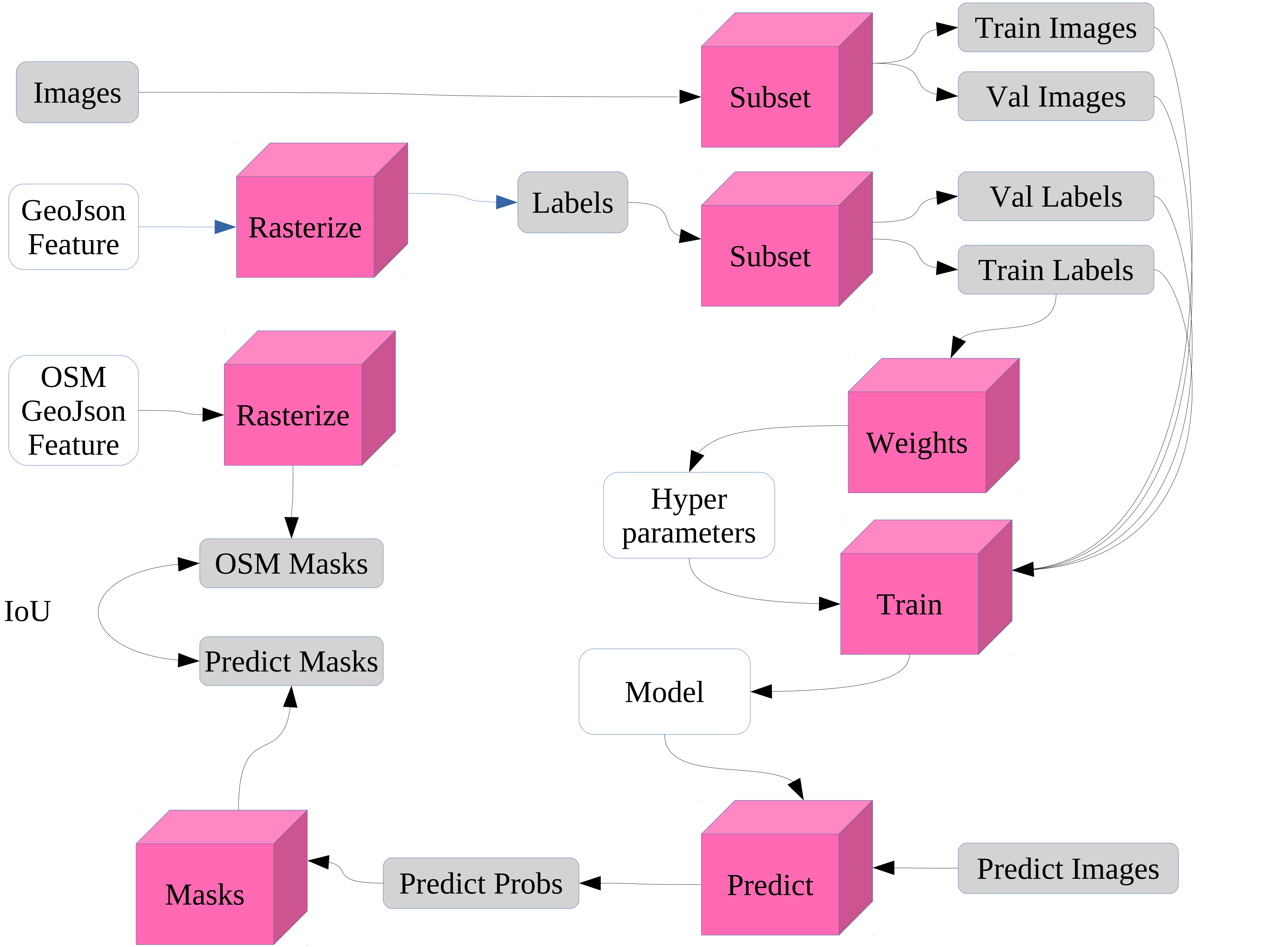


Fig. 2. An illustration of random bounding boxes with Intersection over Union (IoU) of 0.5, 0.7, and 0.9. An IoU of 0.7 provides a reasonable compromise between very loose (IoU of 0.5) and very strict (IoU of 0.9) overlap values.

Source : Lawrence Zitnick, Charles & Dollár, Piotr. (2014). Edge Boxes : Locating Object Proposals from Edges. 8693. 10.1007/978-3-319-10602-1_26.



Images
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Rasterize
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Subset
Val Labels
Train Labels
OSM GeoJson Feature
Rasterize
Weights
Hyper parameters
Train
OSM Masks
IoU
Predict Masks
Model
Masks
Predict Probs
Predict
Predict Images


IoU 0.37
IoU 0.41
IoU 0.79

Is it ‘that’ simple ?

Coverage about 5500 km²

Aerial orthorectified RGB 0.30m resolution
+ 8 bands MultiSpectral

Buildings and Linear Routes labels

5 big cities

Licence : CC-BY-NC

AOI	Area of Raster (Sq. Km)	Building Labels (Polygons)	Road Labels (LineString)
AOI_1_Rio	2,544	382,534	N/A
AOI_2_Vegas	216	151,367	3685 km
AOI_3_Paris	1,030	23,816	425 km
AOI_4_Shanghai	1,000	92,015	3537 km
AOI_5_Khartoum	765	35,503	1030 km

https://spacenetchallenge.github.io/

Coverage about 810 km²

Aerial orthorectified RGB 0.30m resolution

Buildings labels

Several cities in the world (bigs and smalls)

Licence : Public Domain ?

https://project.inria.fr/aerialimagelabeling/

NATIONAAL GEOGRAFISCH INSTITUUT
INSTITUT GEOGRAPHIQUE NATIONAL

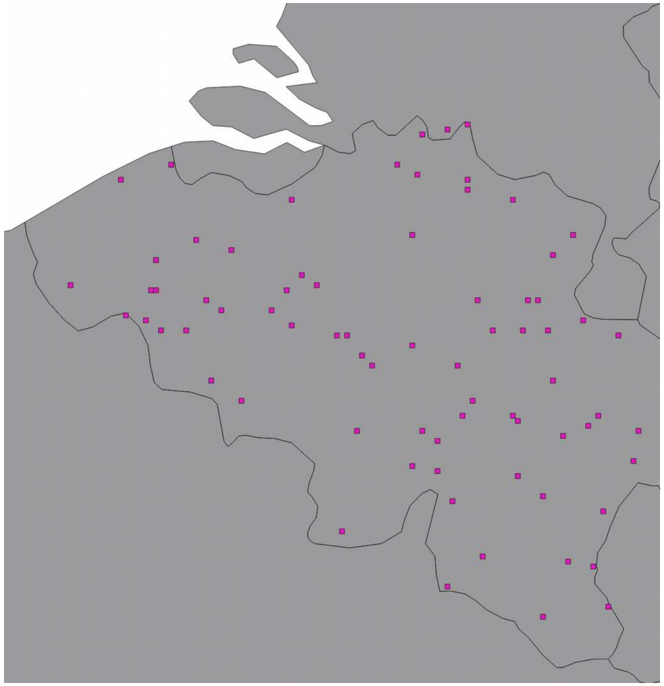
Coverage about 300 km²

Aerial orthorectified RGB 0.25m resolution

Some extra IR band on few tiles

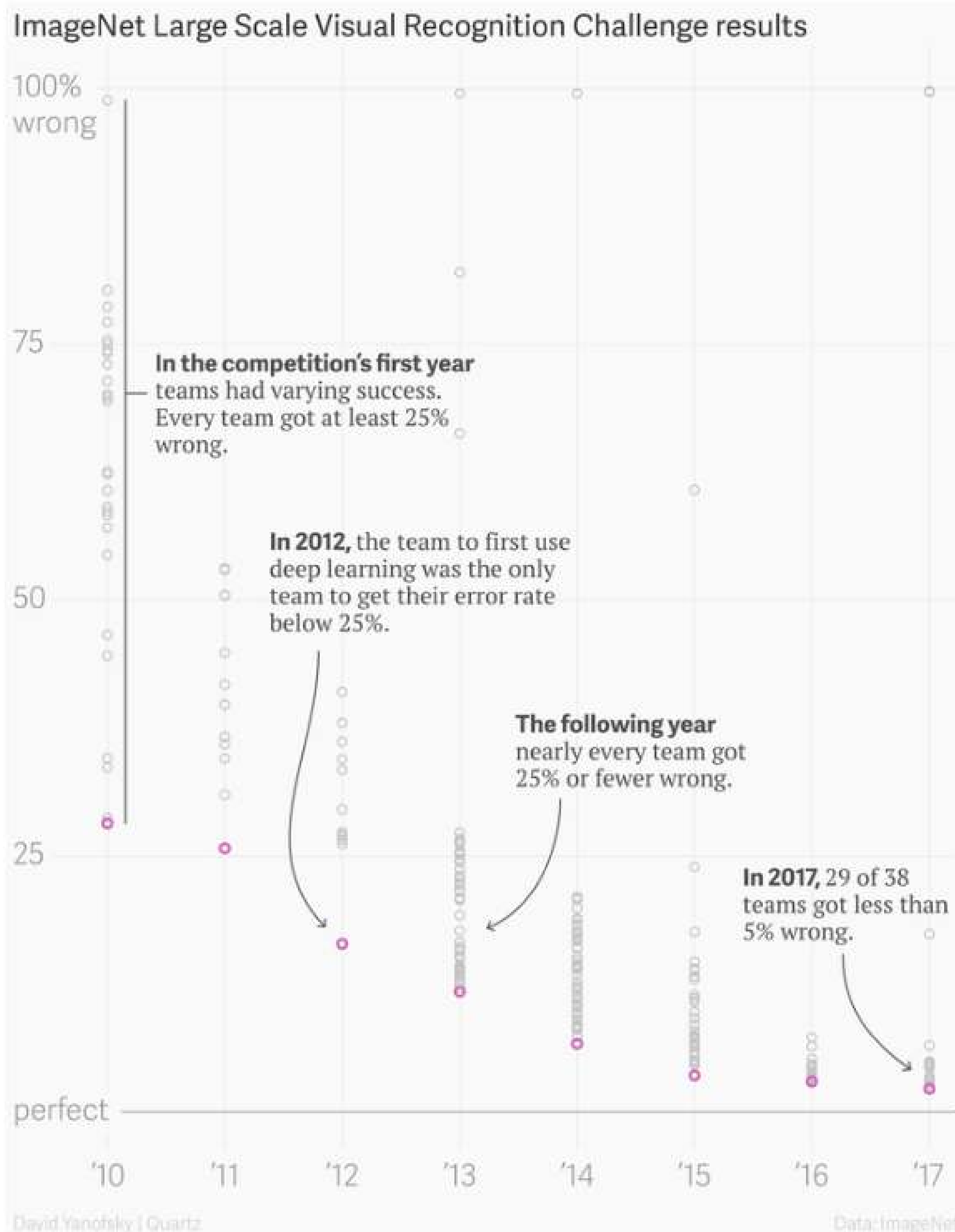
Vectors features labels (roads, buildings, water surface)

Belgium area, countryside mostly



Licence: research project only

https://ac.ngi.be/catalogue


ImageNet Large Scale Visual Recognition Challenge results
100% wrong
75
50
25
perfect
In the competition's first year teams had varying success. Every team got at least 25% wrong.
In 2012, the team to first use deep learning was the only team to get their error rate below 25%.
The following year nearly every team got 25% or fewer wrong.
In 2017, 29 of 38 teams got less than 5% wrong.
'10
'11
'12
'13
'14
'15
'16
'17
David Yanofsky | Quartz
Data: ImageNet

Structuration by OpenDataSet

#1 – DIY stage

#2 – Good Training DataSet publicly available

#3 – Efficient PreTrained model publicly available

#4 – Out of the box app

An Ideal OpenDataSet

OpenData Licence compliant

World’s landscapes representative

Mixed resolutions, and mixed sensors

Cloudless OrthoRectified RGB at least, and MultiSpectral if available

High quality Vector coverage masks (buildings, roads, vegetation, water...)

TileSize 512px

Not too small but not too big ^^

Metadata: acquisition date, sensor type

Radiant.Earth
@OurRadiantEarth

We're thrilled to announce a new tech working group on #MachineLearning for global development! They will collaborate on community standards, labeled training catalogs & a schema for global #LandCover classification. Interested in the results? Read more: bit.ly/REITechWG

Hamed Alemohammad and 7 others

6:50 PM · Jun 27, 2018

https://medium.com/radiant-earth-insights/creating-a-machine-learning-commons-for-global-development-256ef3dd46aa

So now,

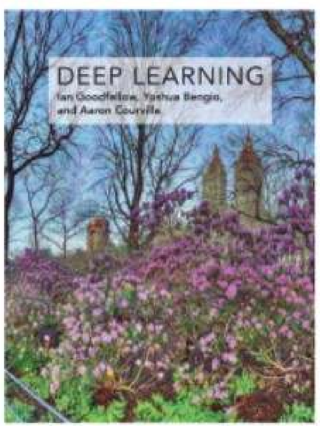
You want to play ?

https://www.openstreetmap.org/user/daniel-j-h/diary44321

http://cs231n.stanford.edu/syllabus.html

https://raw.githubusercontent.com/mrgloom/Semantic-Segmentation-Evaluation/master/README.md

https://arxiv.org/abs/1802.01528v2



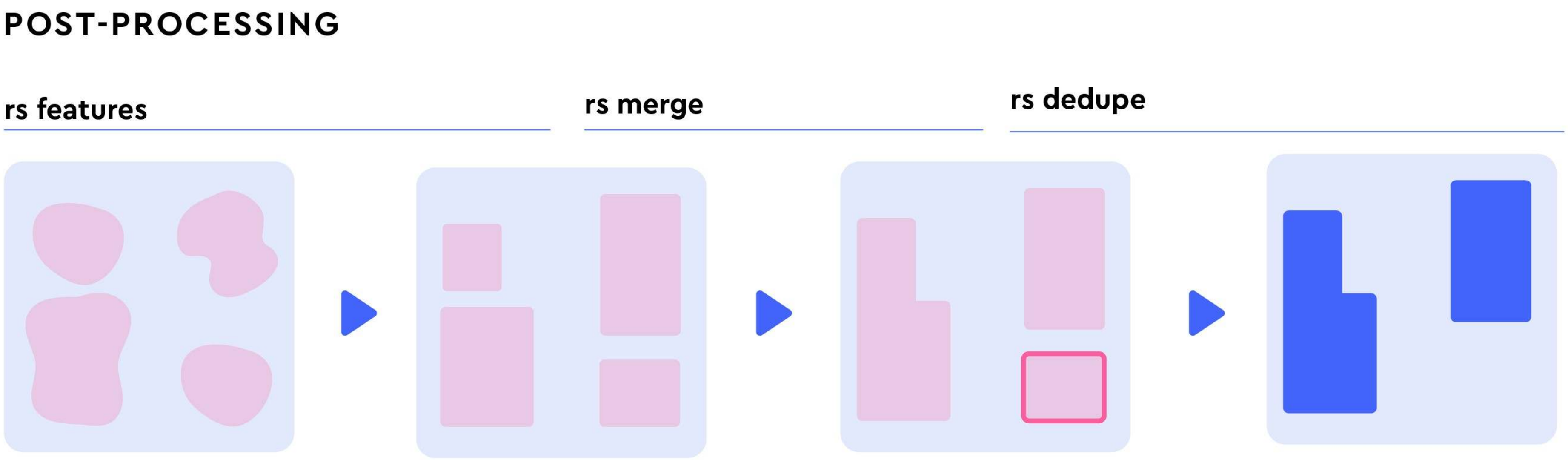
You want to contribute ?

#1 Labeling

- SpaceNet clean roads labeling

- OpenAerialMap labeling

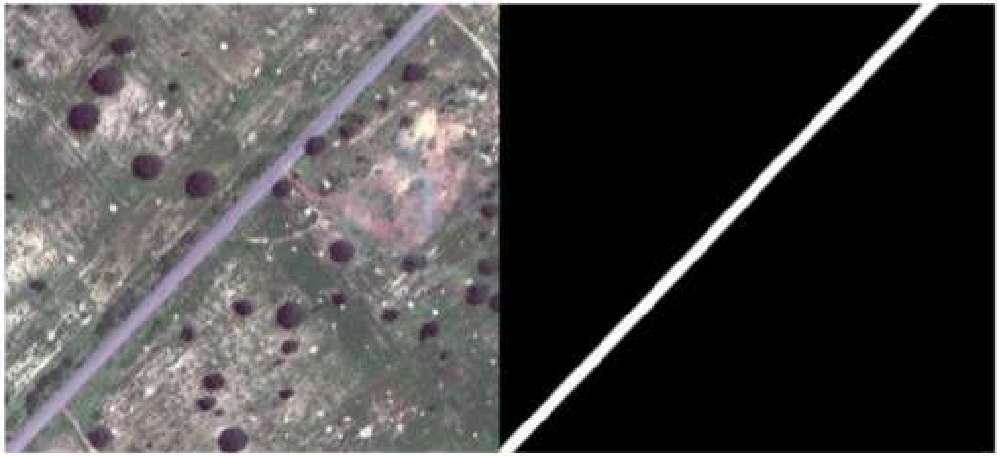
#2 Robosat features extraction :



Final results

Below we present a small sample of the final results from our models:

Buildings



Type	Wavebands	Pixel resolution	#channels	Size
grayscale	Panchromatic	0.31 m	1	3348 x 3392
3-band	RGB	0.31 m	3	3348 x 3392
16-band	Multispectral	1.24 m	8	837 x 848
	Short-wave infrared	7.5 m	8	134 x 136

https://blog.deepsense.ai/deep-learning-for-satellite-imagery-via-image-segmentation/

Next Disruptive ?

Lower resolution Imagery SemSeg: Sentinel-2 or PlanetLab

Sensors Data Fusion

Conclusions

Tools available

OpenDataSet current bottleneck

DATA PINK

@data_pink

www.datapink.com