Successful case studies of DL

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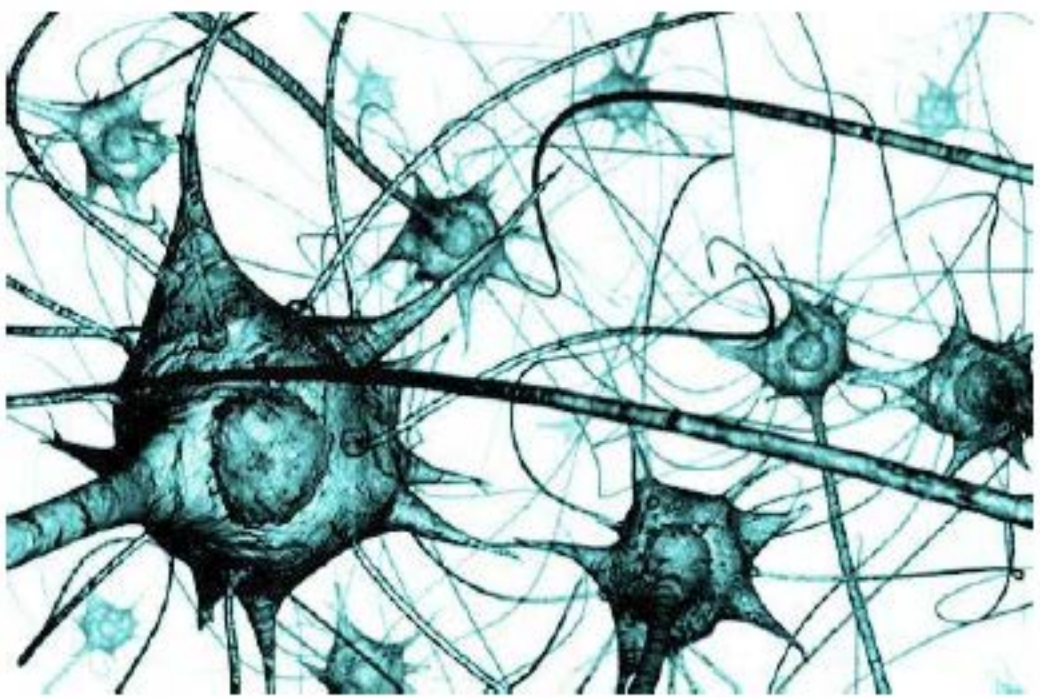
Outline

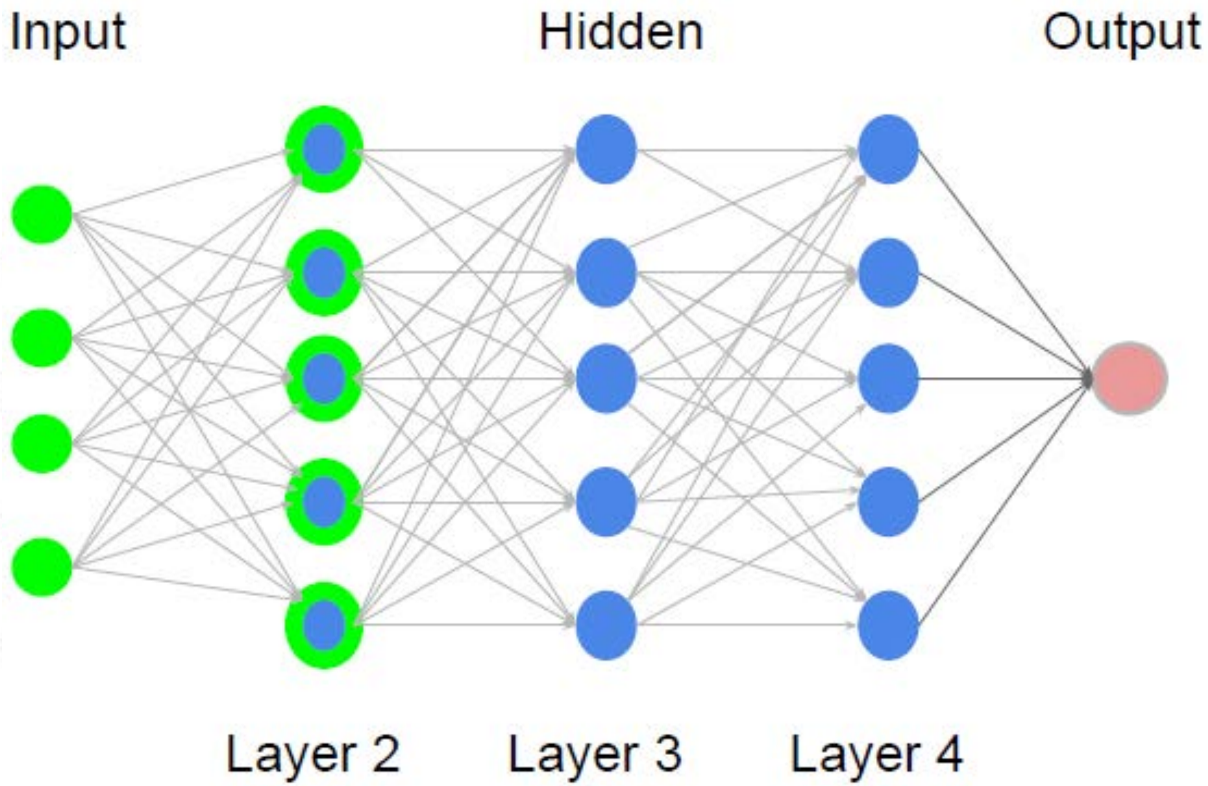
- Deep CNNs
- Four fundamental computer visions tasks
- Receipt for addressing each case study
- Case studies:
  - Protected plant species detection
  - Whale counting
  - Electrical sub-stations

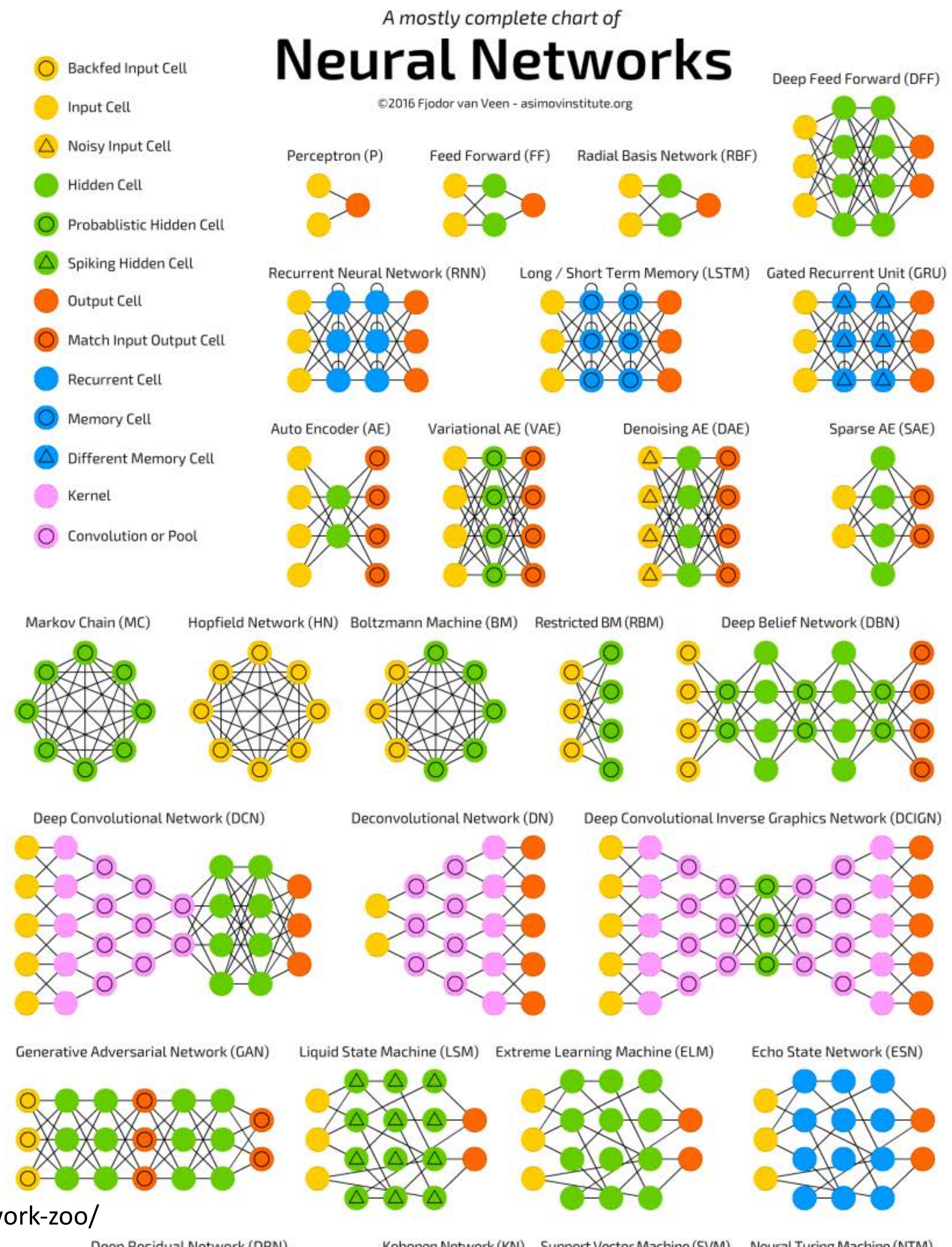
¿What are Artificial Neural Networks?

Artificial Neural Networks

Learn from data to make predictions

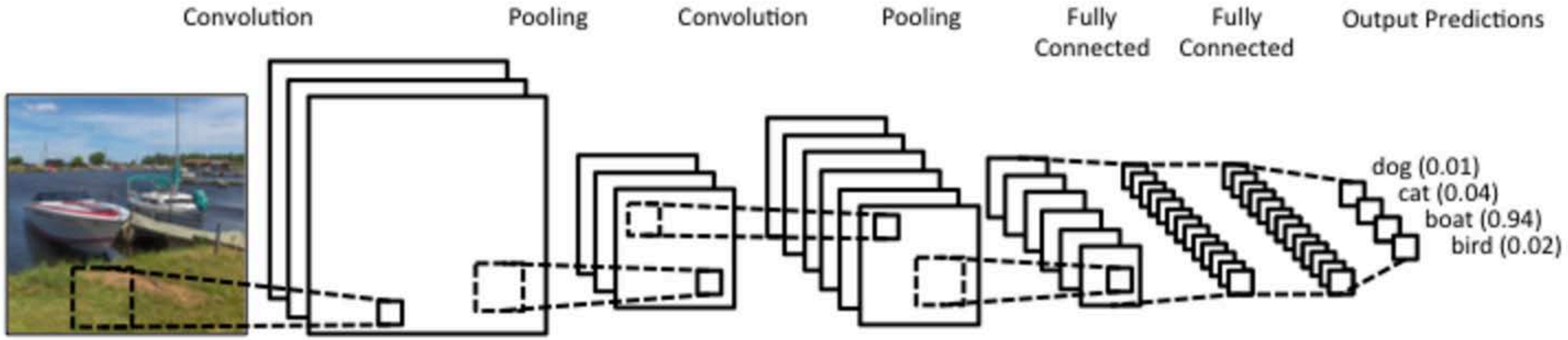






Source: http://www.asimovinstitute.org/neural-network-zoo/

Convolutional Neural Networks (CNN)



By the way ...

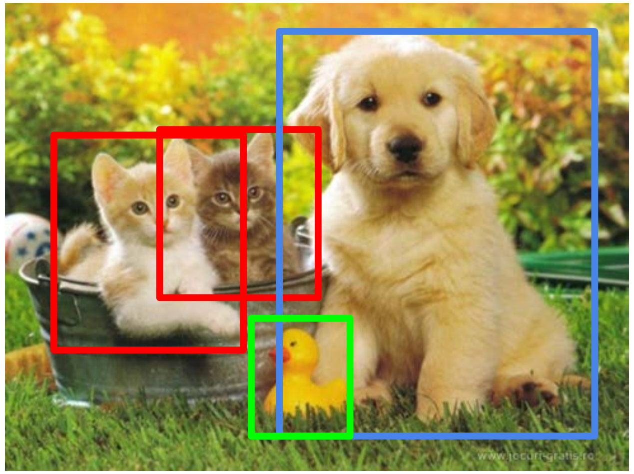
Classification

CAT

Classification + Localization

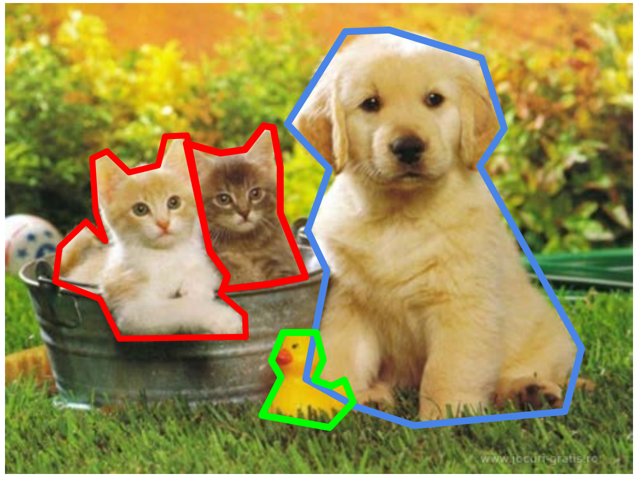
CAT

Object Detection



CAT, DOG, DUCK

Instance Segmentation



CAT, DOG, DUCK

Single object

Multiple objects

State-of-the art CNN-models

Classification

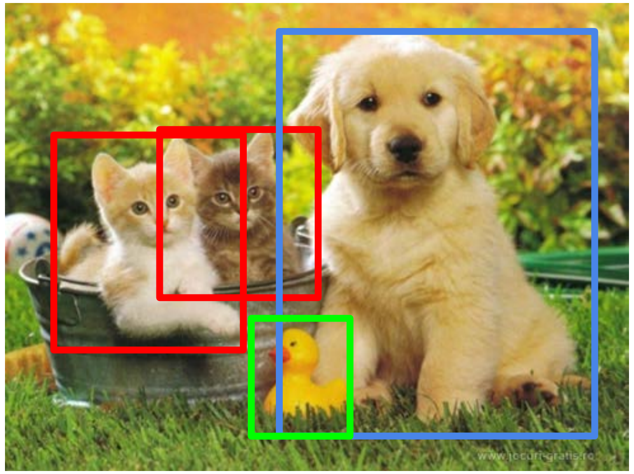
CAT

ResNet
Inception
Inception-ResNet
EfficientNet

Classification + Localization

CAT

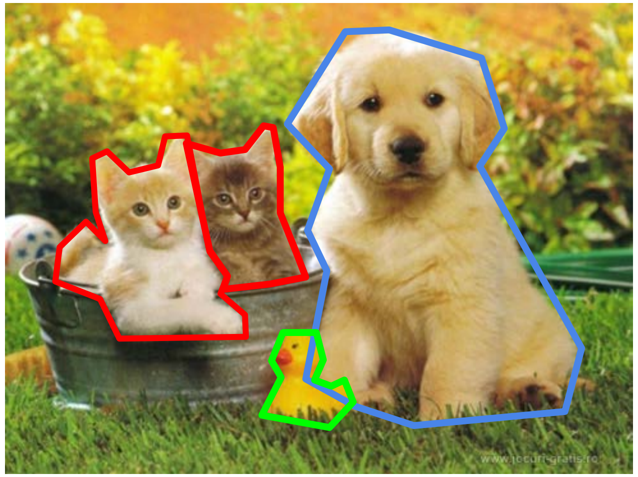
Object Detection



CAT, DOG, DUCK

Faster RCNN
SSD
Yolo

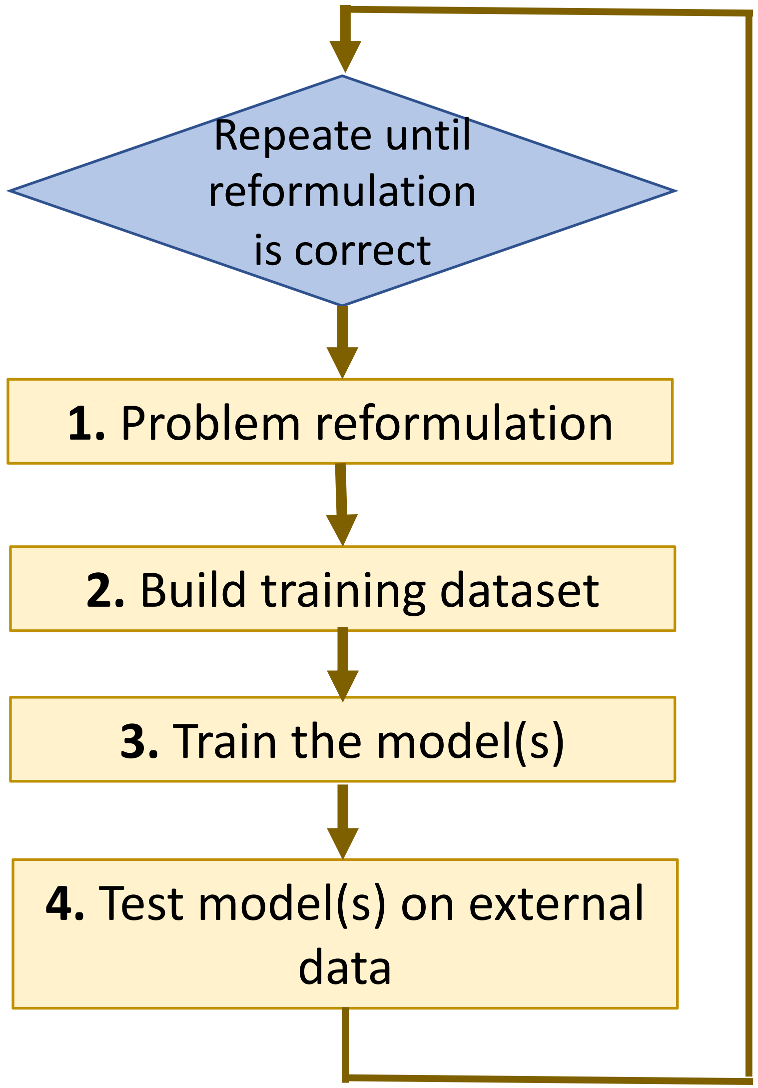
Instance Segmentation



CAT, DOG, DUCK

Mask-RCNN
UNet

How do we address new problem with Deep NN



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  - ❑ **Protected plant species detection**
  - ❑ Whale counting
  - ❑ Electrical sub-stations detection

Protected plant species detection in Google-Earth images

Objective: build a tool to monitor the conservation state of the Mediterranean area

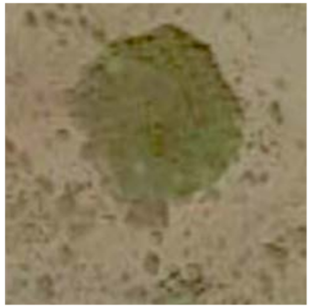
Zizphus Lotus

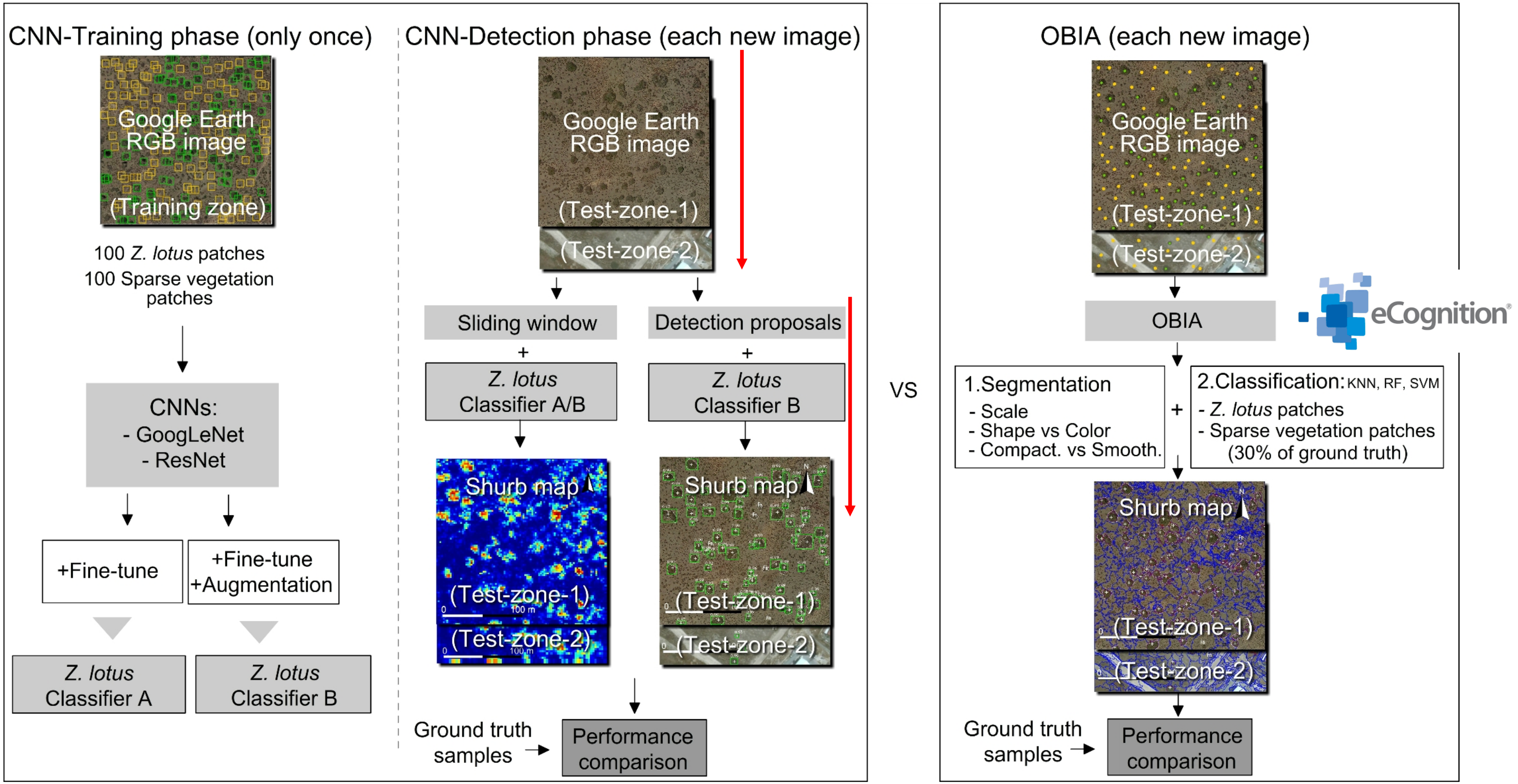
Deep-Learning Convolutional Neural Networks for scattered shrub detection with Google Earth Imagery E Guirado, S Tabik, D Alcaraz-Segura, J Cabello, F Herrera. Remote Sensing 9(12): 1220 (2017)

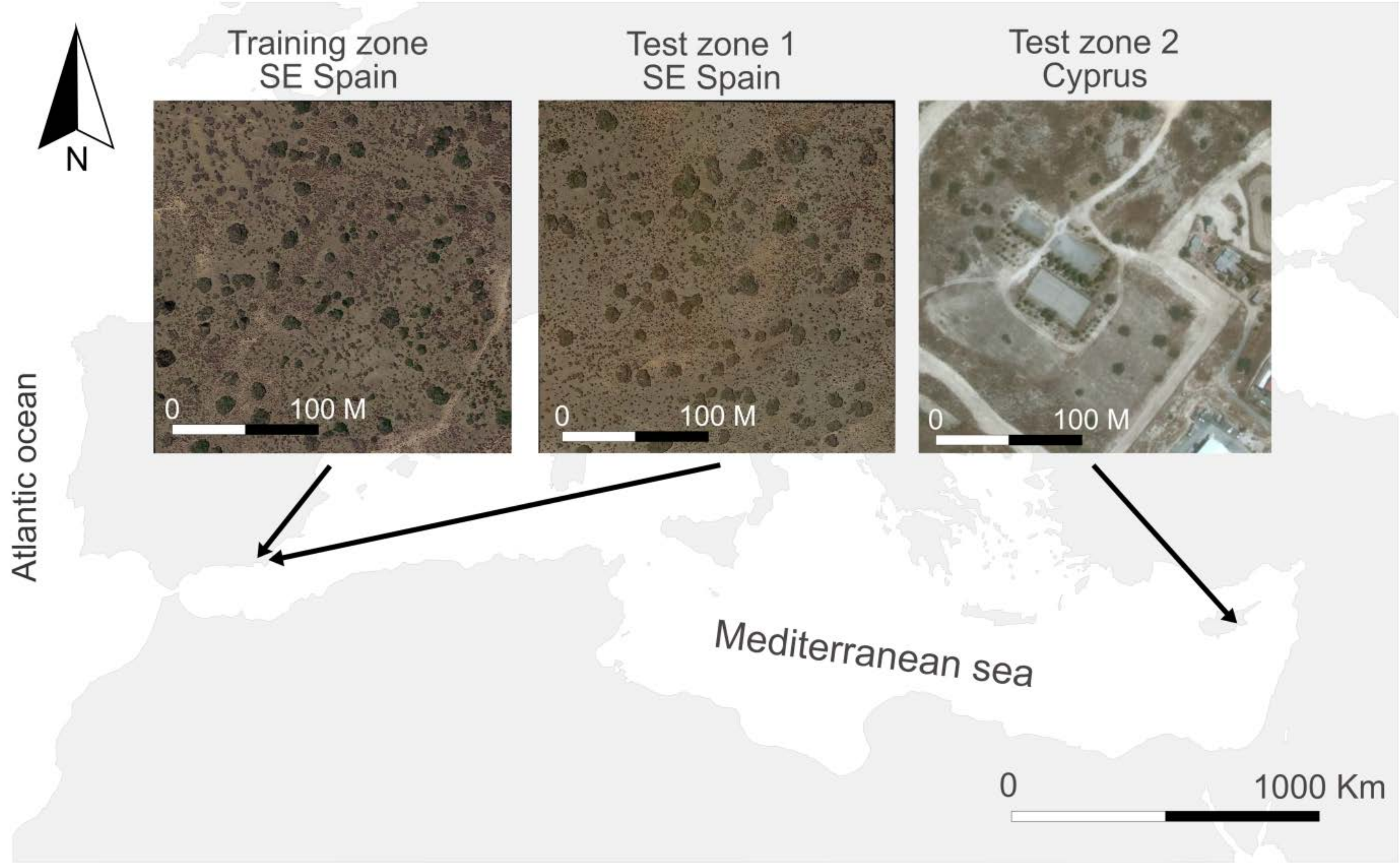
Problem	Model	Database	Results

Chalenges: Zizphus Lotus has not a clear pattern for the human eye

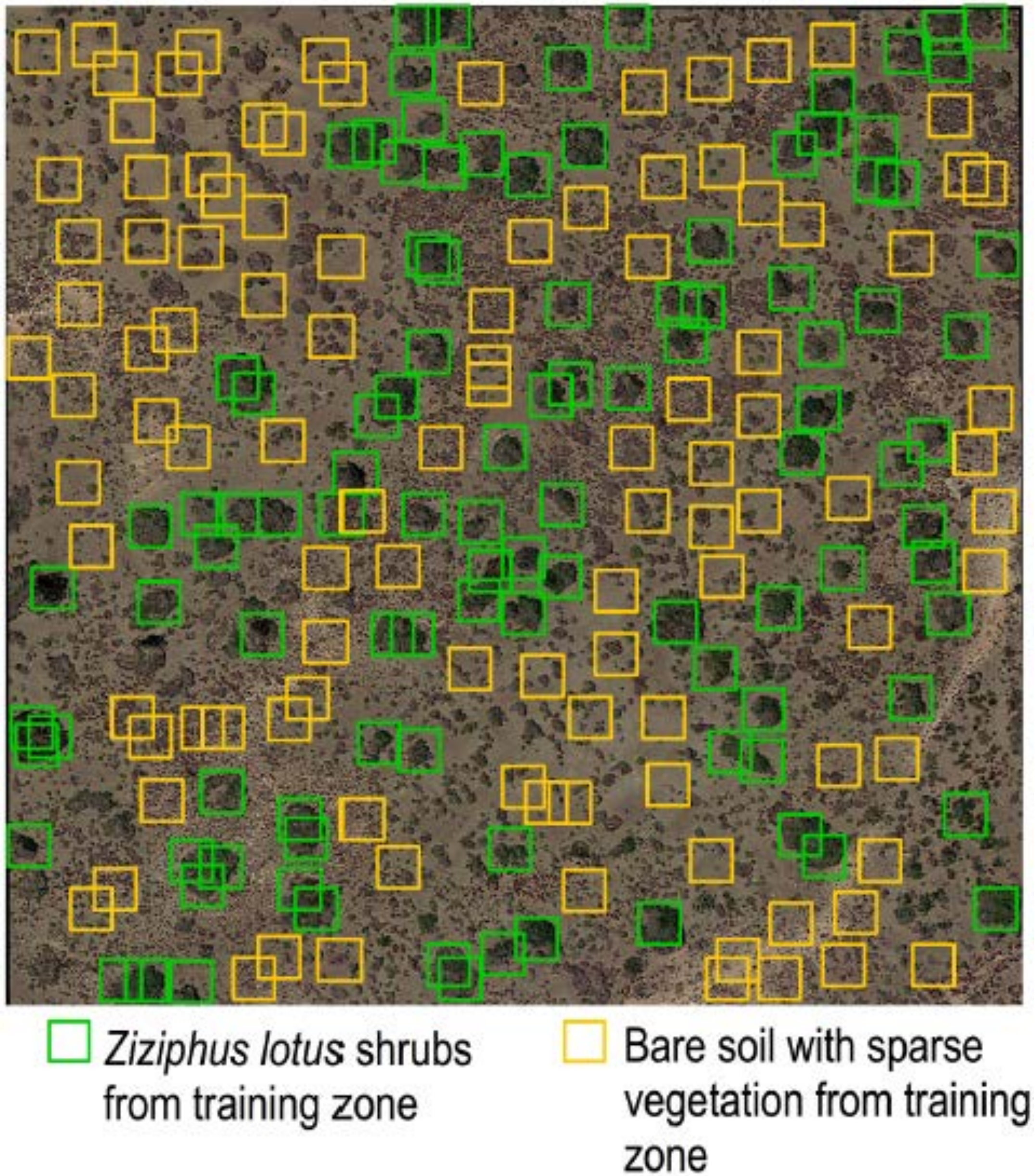
1900 × 1900 pixeles with 0.5 m/pixel



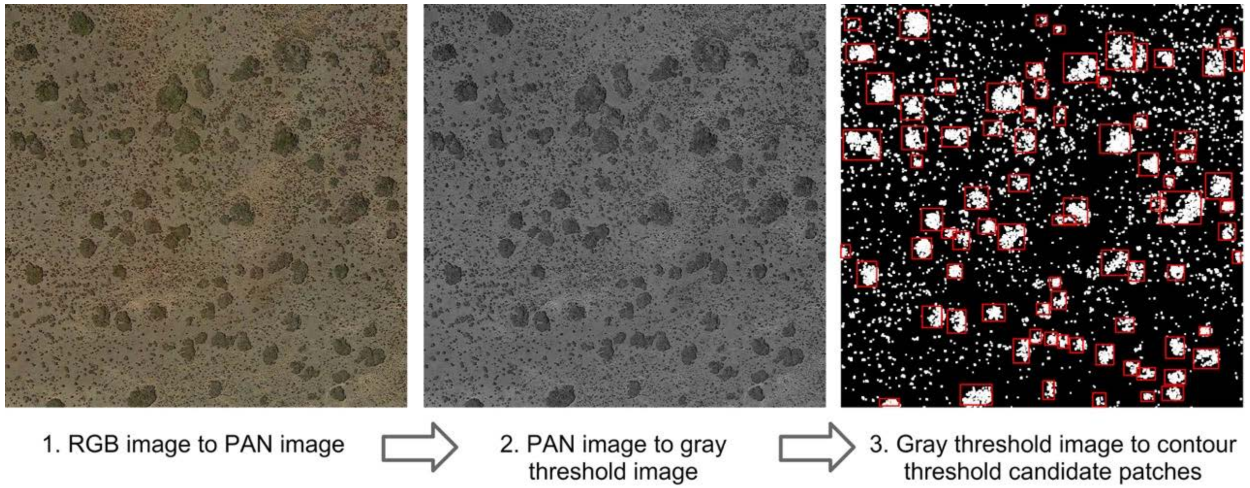

CNN-Training phase (only once)
Google Earth RGB image
(Training zone)
100 Z. lotus patches
100 Sparse vegetation patches
CNNs:
- GoogLeNet
- ResNet
+Fine-tune
+Fine-tune
+Augmentation
Z. lotus Classifier A
Z. lotus Classifier B
CNN-Detection phase (each new image)
Google Earth RGB image
(Test-zone-1)
(Test-zone-2)
Sliding window
+
Z. lotus Classifier A/B
Detection proposals
+
Z. lotus Classifier B
Shurb map
(Test-zone-1)
(Test-zone-2)
Shurb map
(Test-zone-1)
(Test-zone-2)
Ground truth samples
Performance comparison
VS
OBIA (each new image)
Google Earth RGB image
(Test-zone-1)
(Test-zone-2)
OBIA
eCognition
1.Segmentation
- Scale
- Shape vs Color
- Compact. vs Smooth.
+
2.Classification: KNN, RF, SVM
- Z. lotus patches
- Sparse vegetation patches
(30% of ground truth)
Shurb map
(Test-zone-1)
(Test-zone-2)
Ground truth samples
Performance comparison


Training zone
SE Spain
Test zone 1
SE Spain
Test zone 2
Cyprus
N
0
100 M
0
100 M
0
100 M
Atlantic ocean
Mediterranean sea
0
1000 Km

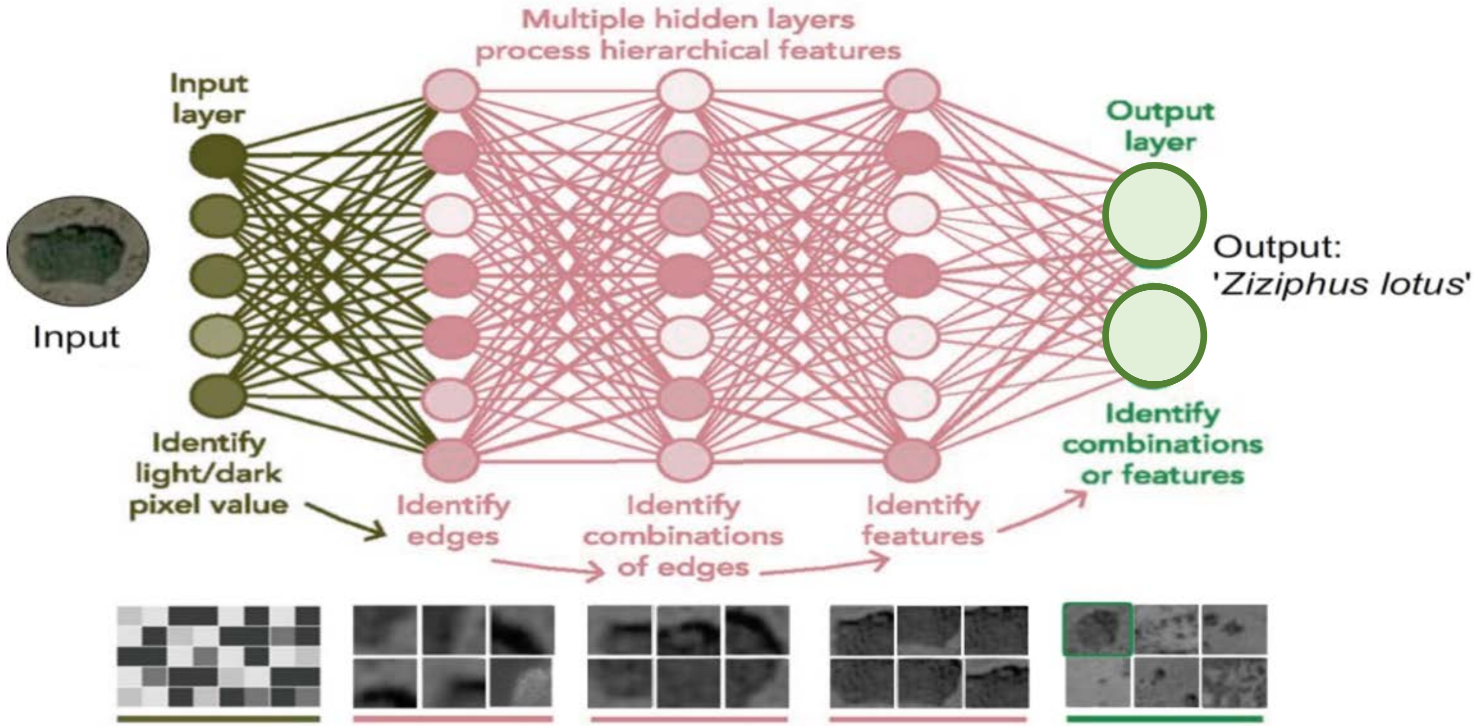
Two class problem



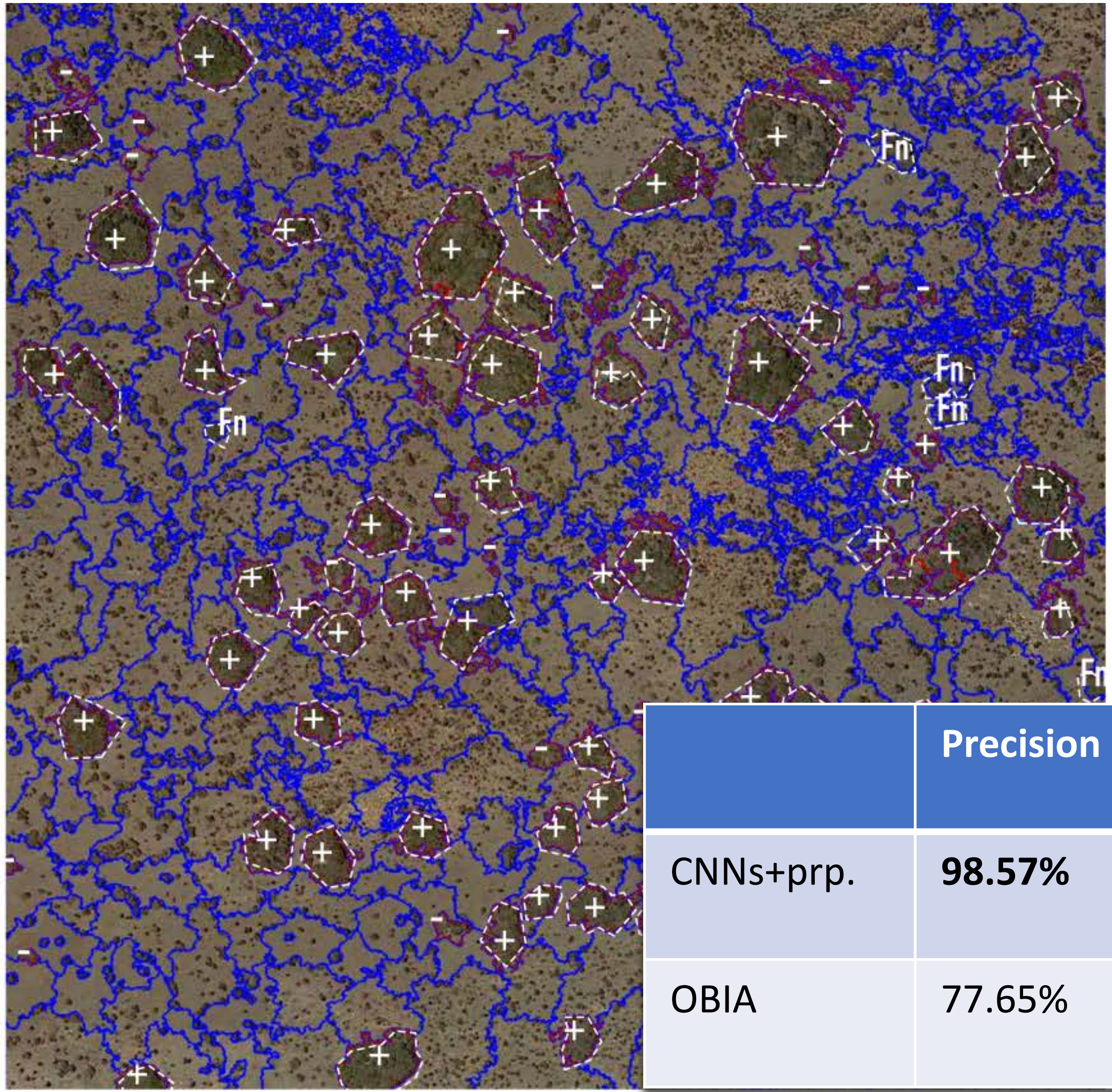
Step 1:

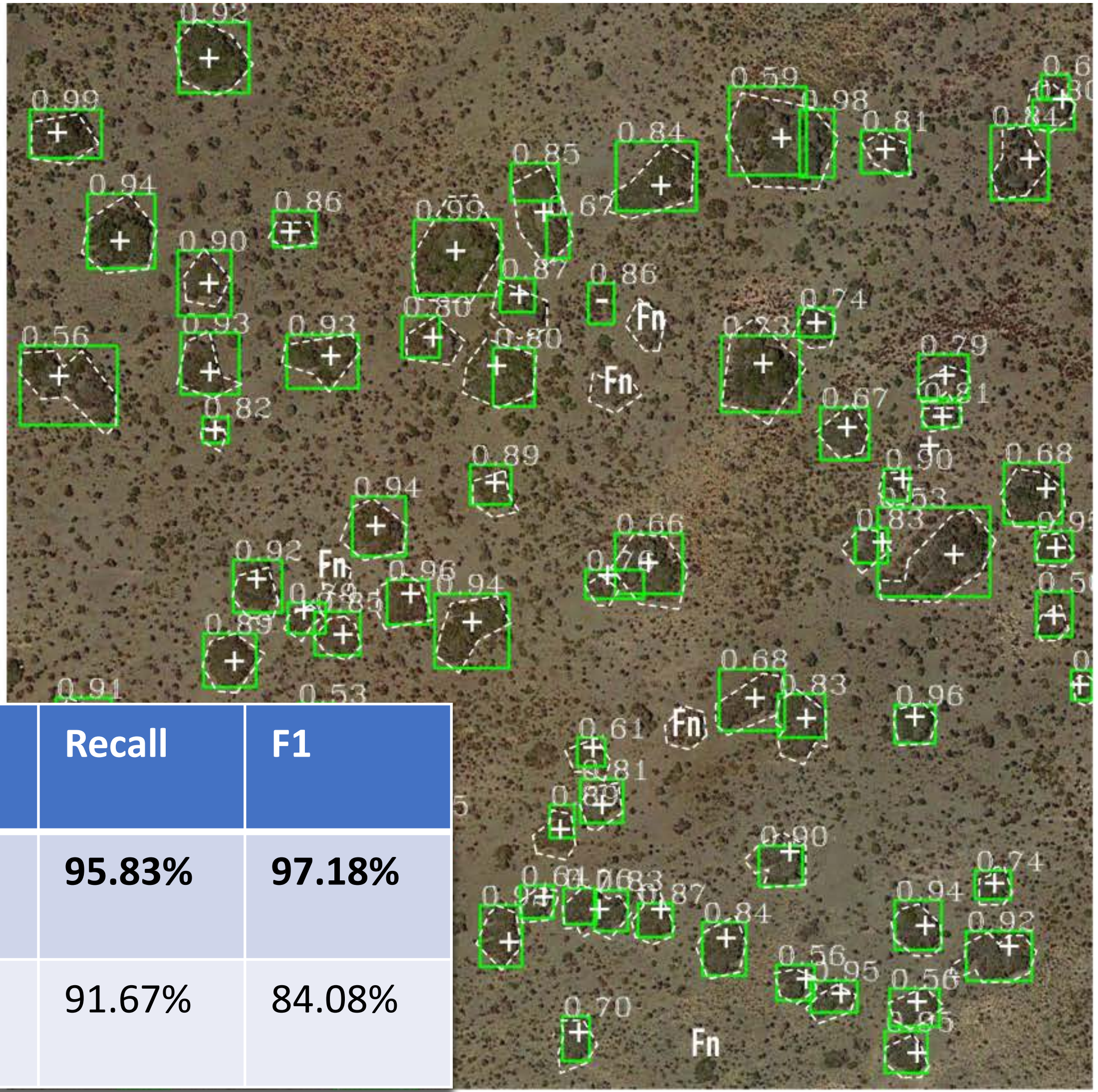

1. RGB image to PAN image
2. PAN image to gray threshold image
3. Gray threshold image to contour threshold candidate patches

Step 2:


Multiple hidden layers process hierarchical features
Input layer
Output layer
Input
Output: 'Ziziphus lotus'
Identify light/dark pixel value
Identify edges
Identify combinations of edges
Identify features
Identify combinations or features

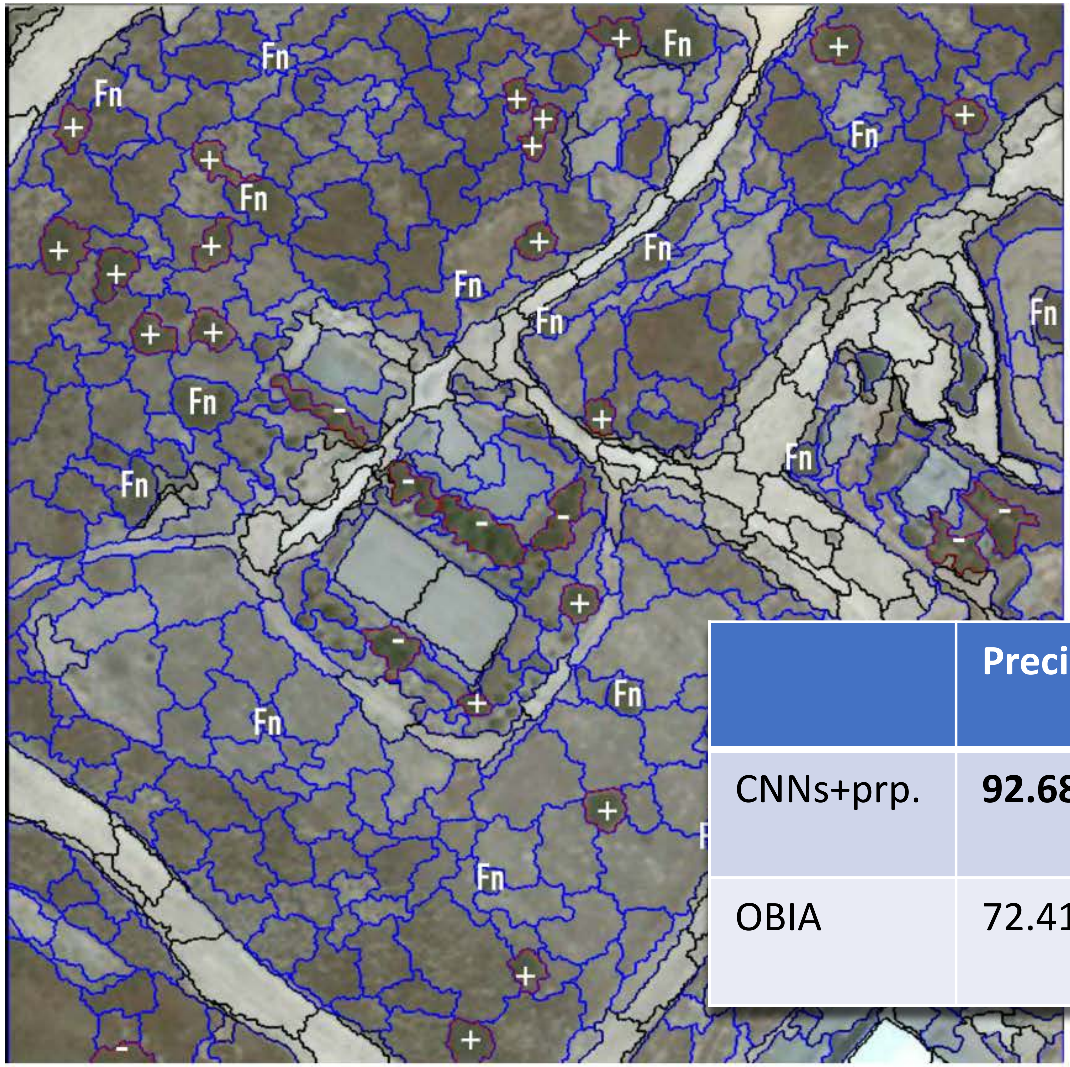
OBIA(12 hours) vs CNNs(35.4seconds)

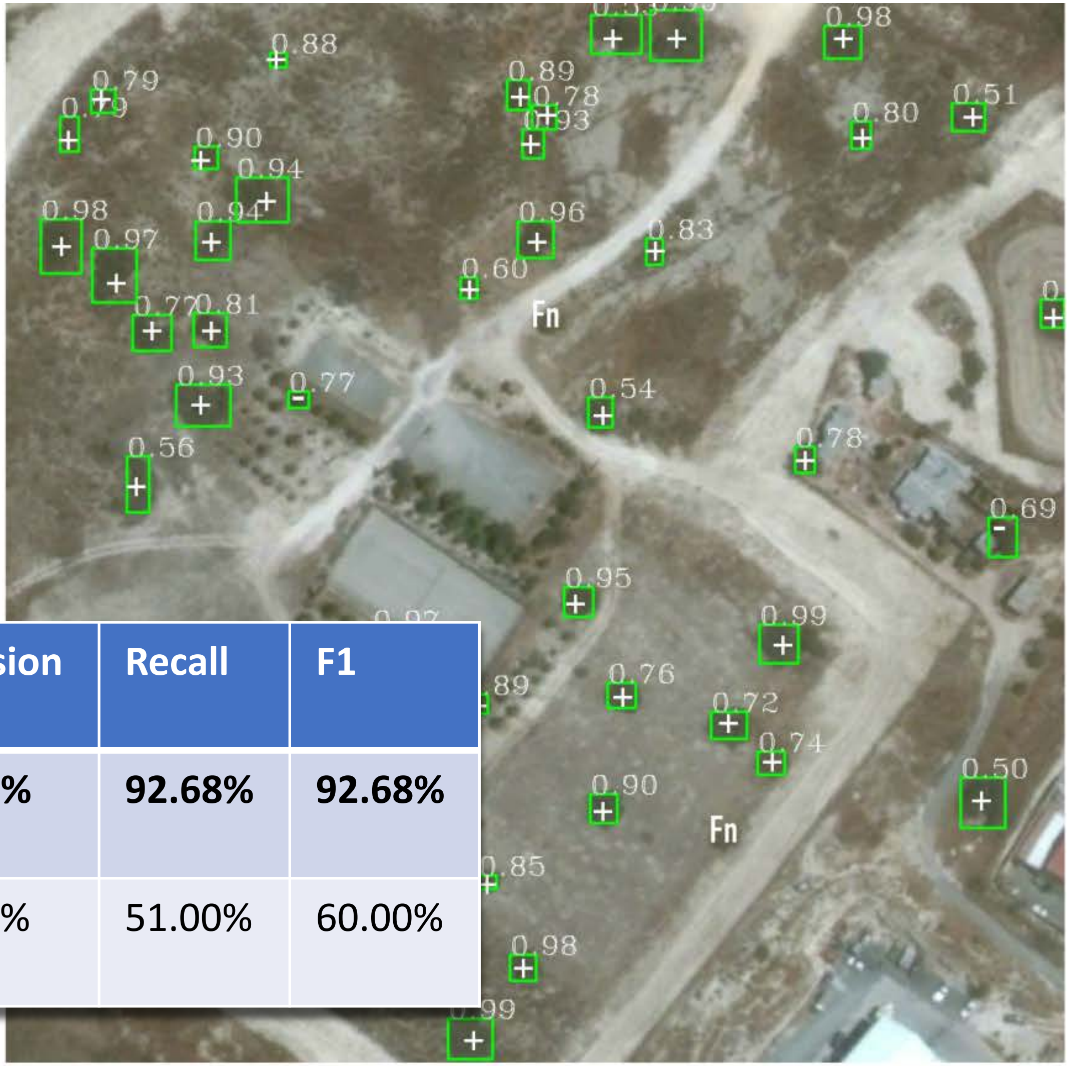




	Precision	Recall	F1
CNNs+prp.	**98.57%**	**95.83%**	**97.18%**
OBIA	77.65%	91.67%	84.08%

OBIA(12 hours) vs CNNs(24.1seconds)





	Precision	Recall	F1
CNNs+prp.	**92.68%**	**92.68%**	**92.68%**
OBIA	72.41%	51.00%	60.00%

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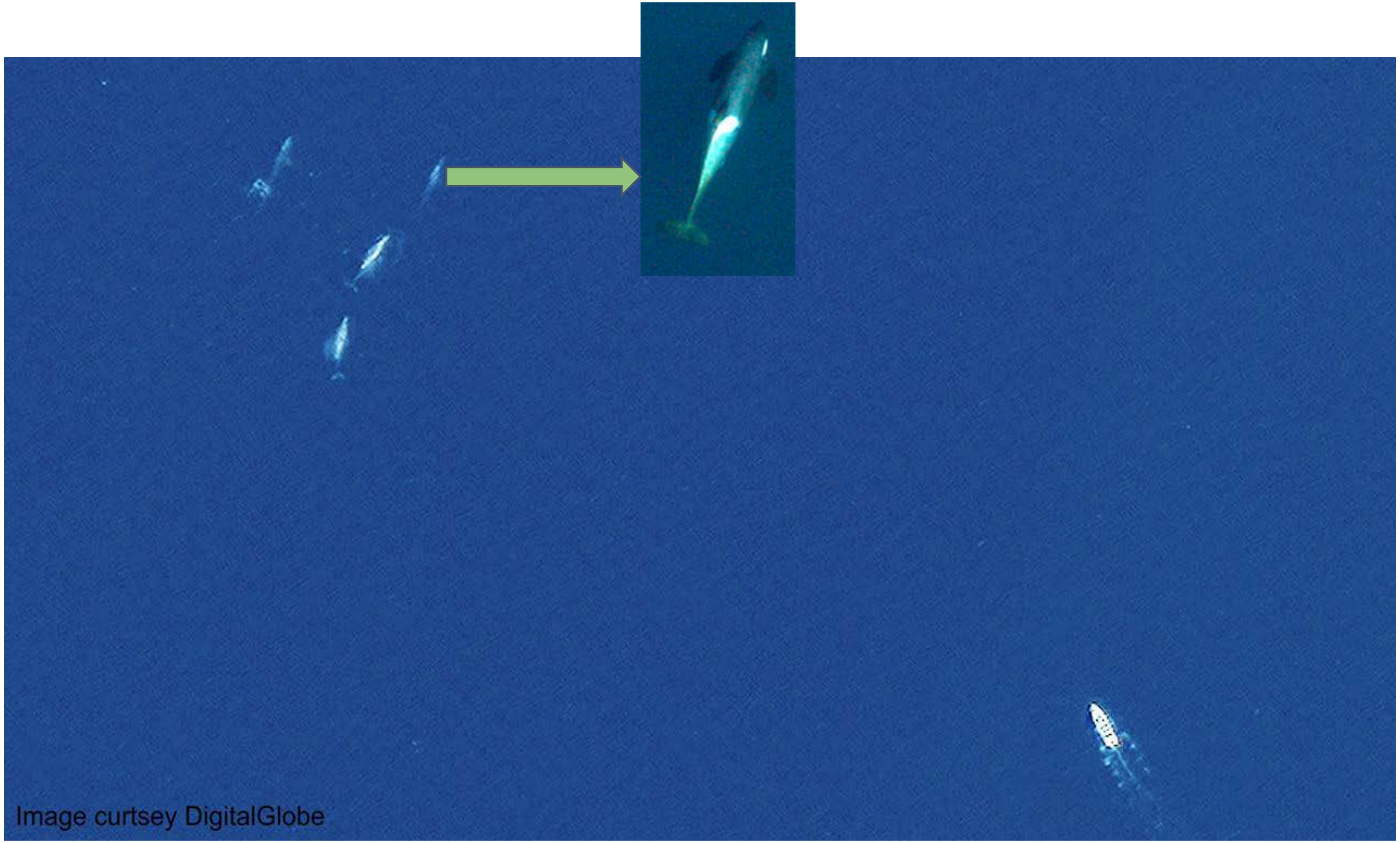
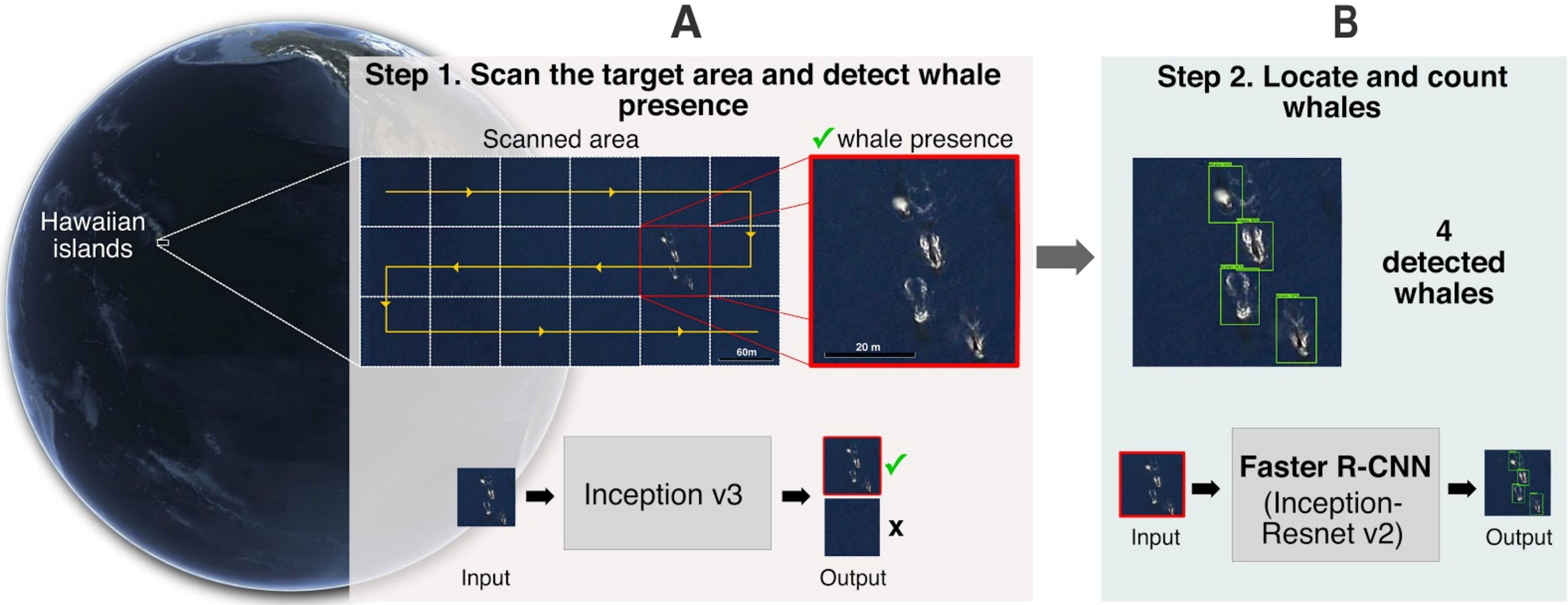
Whale counting in aerial and satellite images

Objective: build an automatic tool to count whales at a global scale

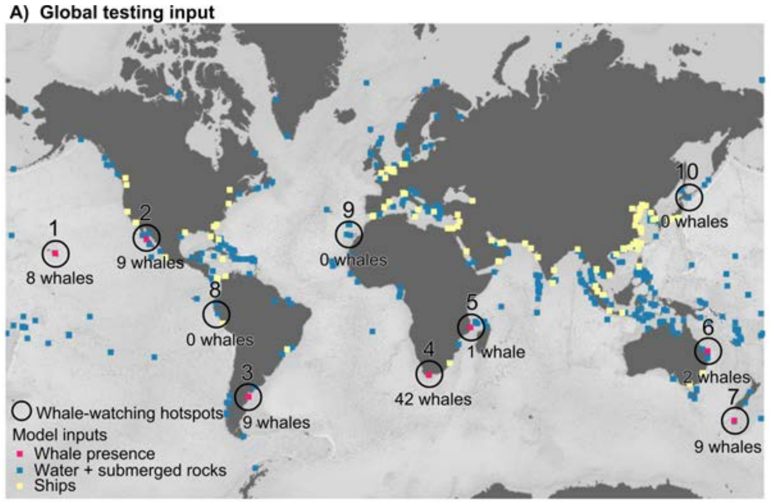


[Whale counting in satellite and aerial images with deep learning](). E Guirado, S Tabik, ML Rivas, D Alcaraz-Segura, F Herrera. [Scientific Reports]()9 (1), 1-12

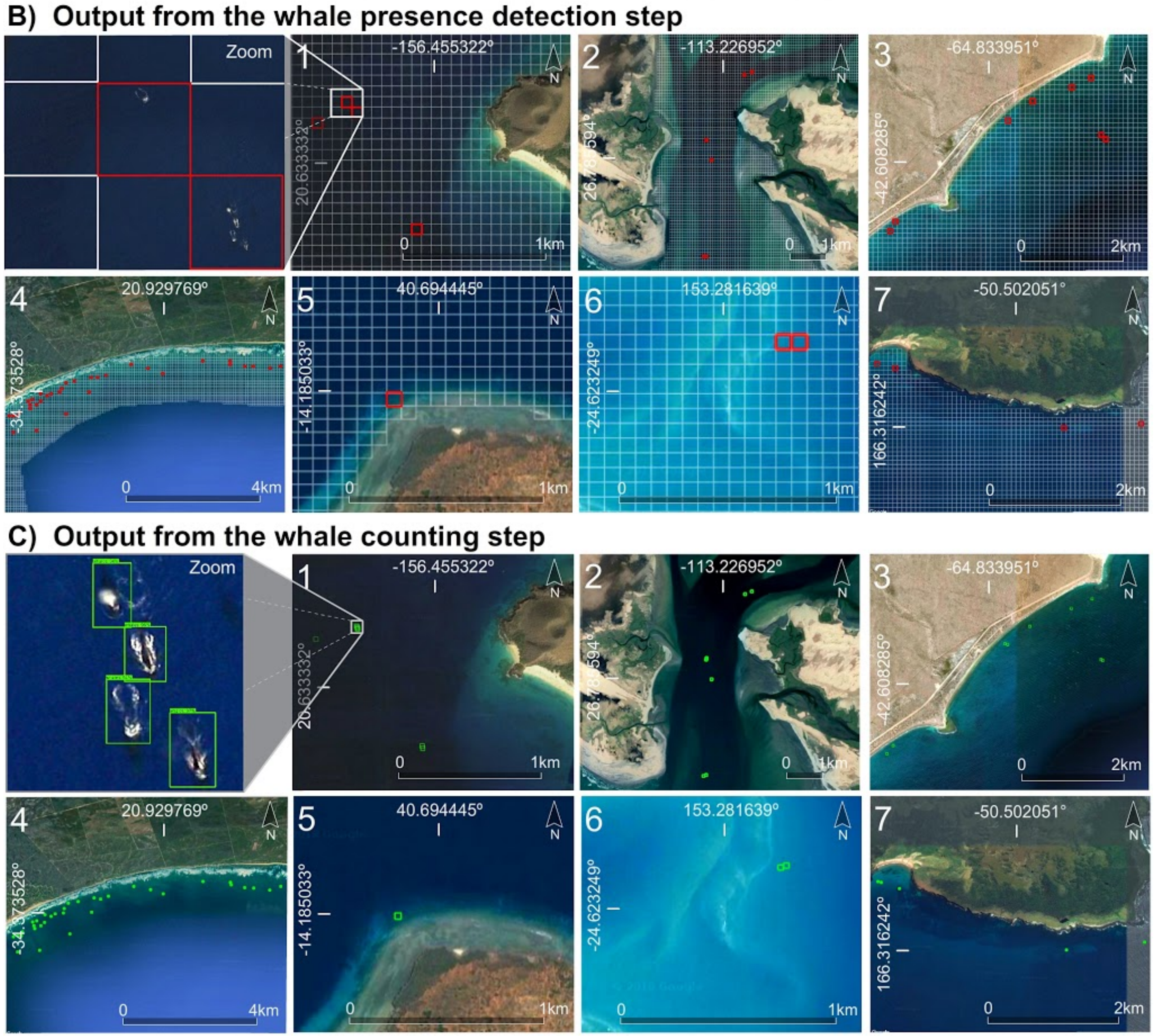

A
B
Step 1. Scan the target area and detect whale presence
Hawaiian islands
Scanned area
✓ whale presence
60m
20 m
Input
Inception v3
Output
x
Step 2. Locate and count whales
4 detected whales
Input
Faster R-CNN (Inception-Resnet v2)
Output

- Base de datos para entrenar: 700 (con 900 ballenas) aéreas imágenes extraídas de Google Earth, free Arkive, NOAA Photo Library y NWPU-RESISC45 dataset.

- Base de datos para testear:

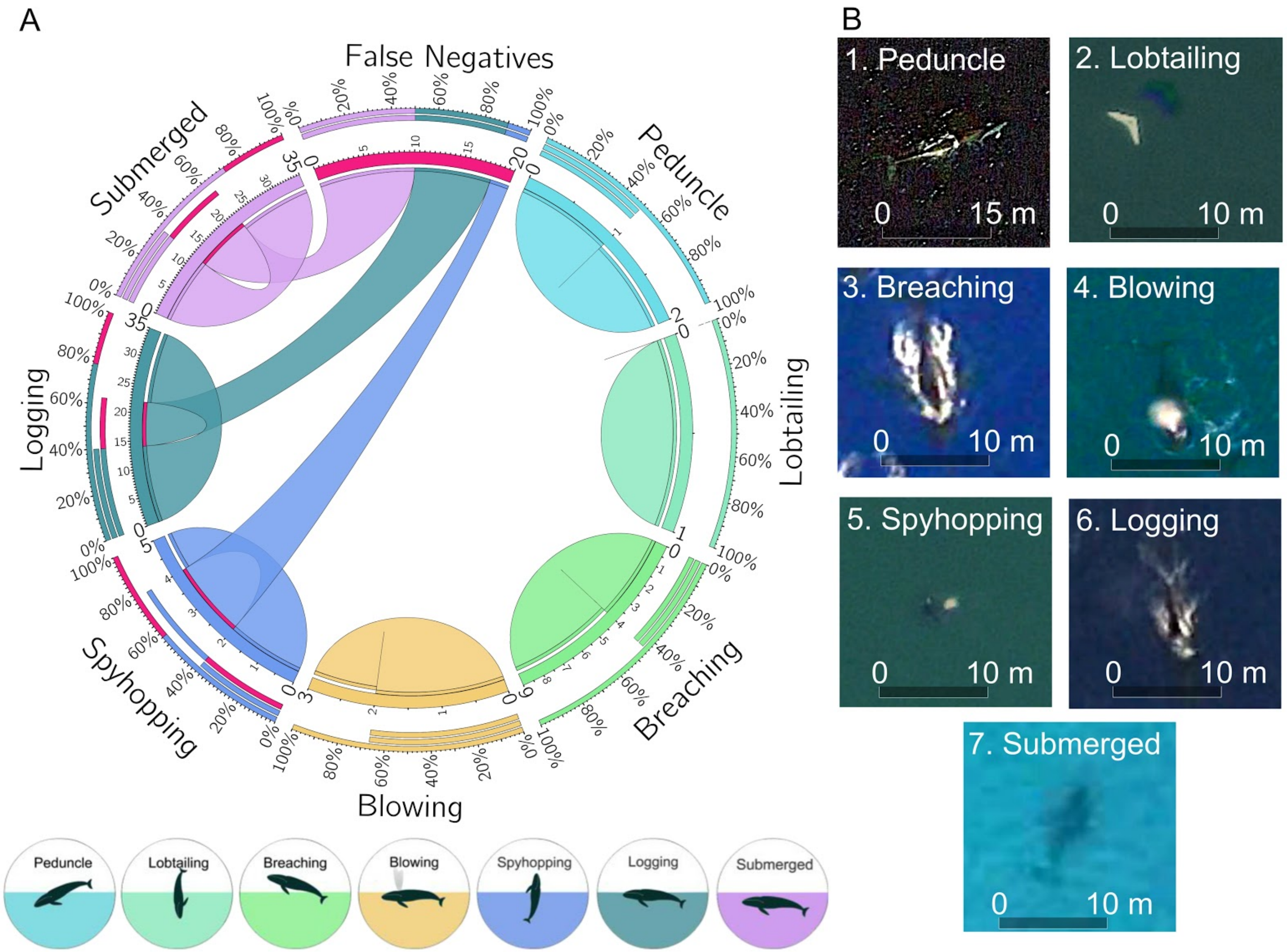


- The first step detects the presence of whales with 84% accuracy
- The second step counts whales with 97% accuracy

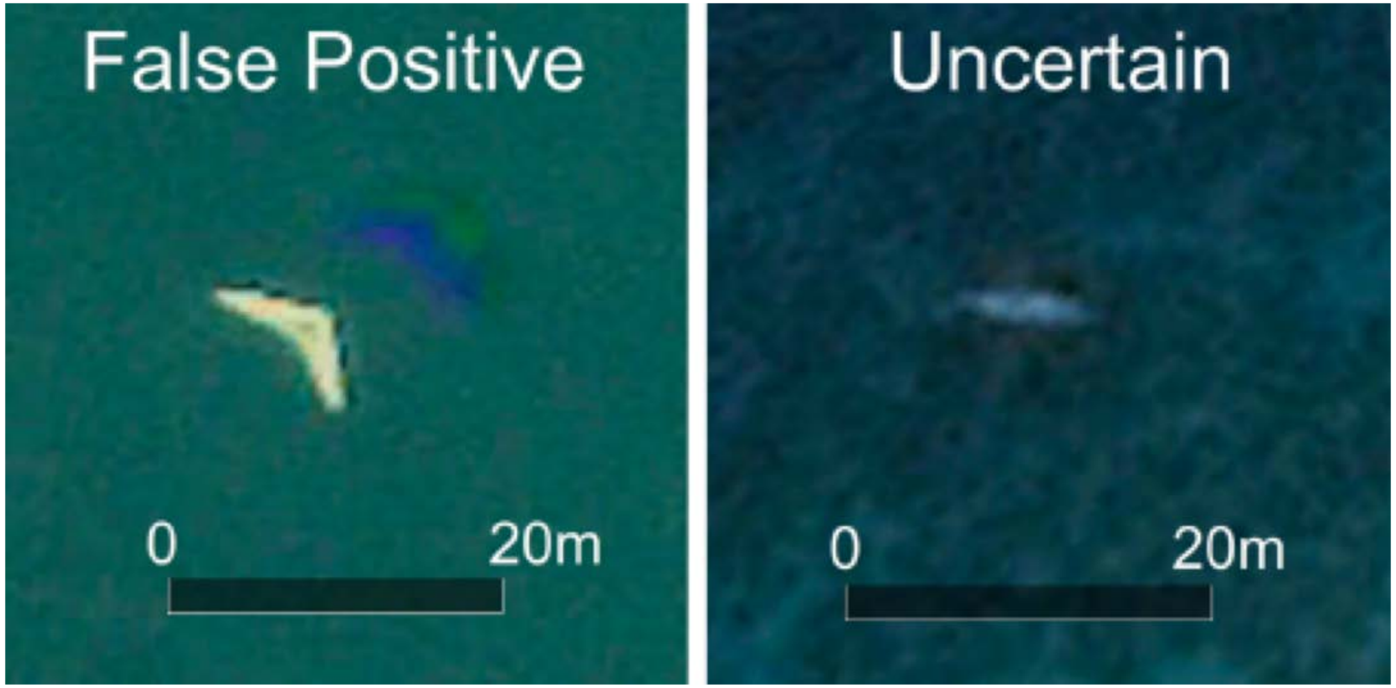


Problem	Model	Database	**Results**

- Impact of whale posture of whales on the performance of the model



Example of false positives of a hang-glider



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    - ❑ **Electrical sub-stations detection**

Detection of electrical substations

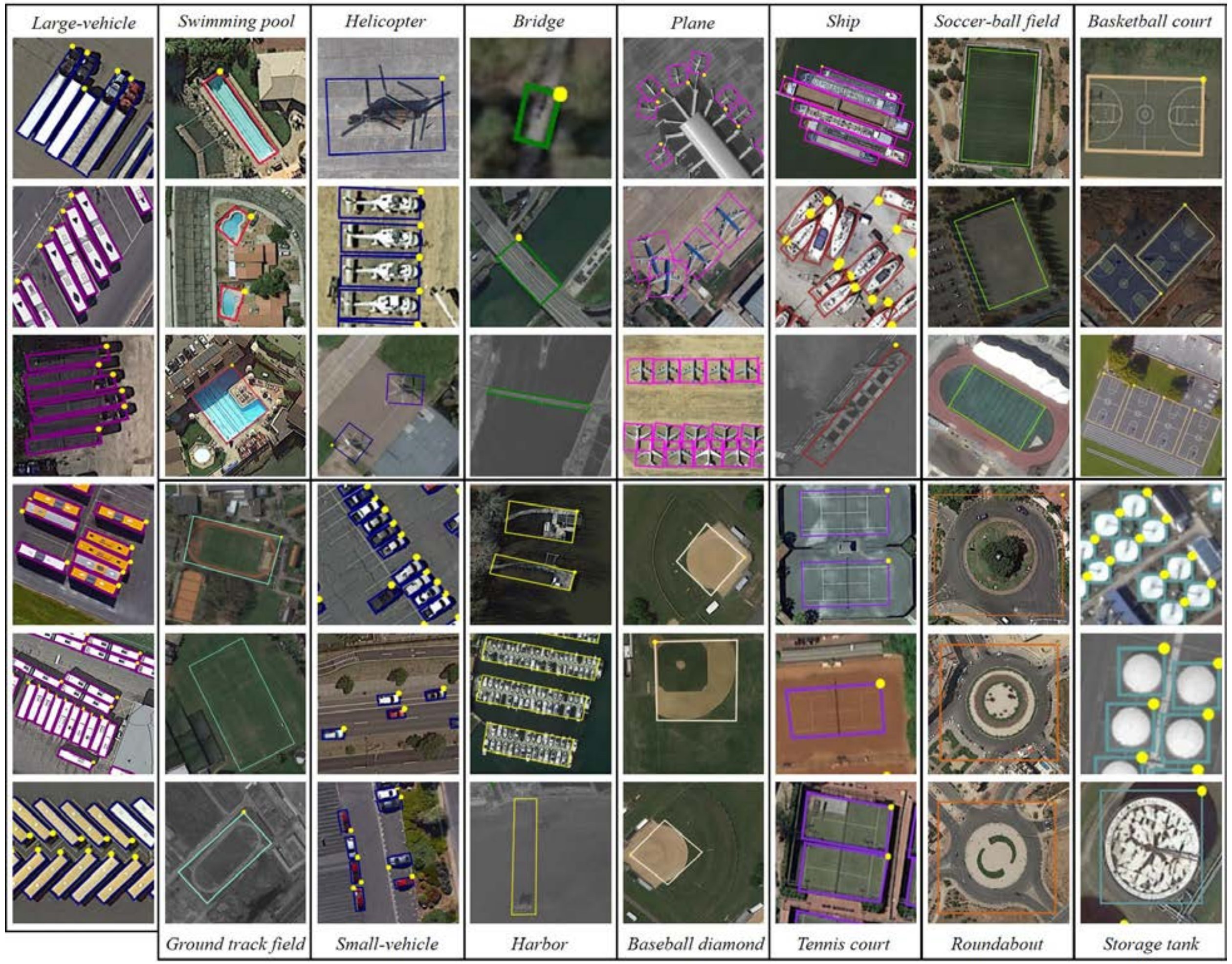
Objective: build a tool to detect electrical substations

(Upper part) Images with zoom 18, 19 and 20 one tile from Google Maps and (lower part) zoom 18, 19, 20 and 21 when combining 9 tiles from Bing maps.

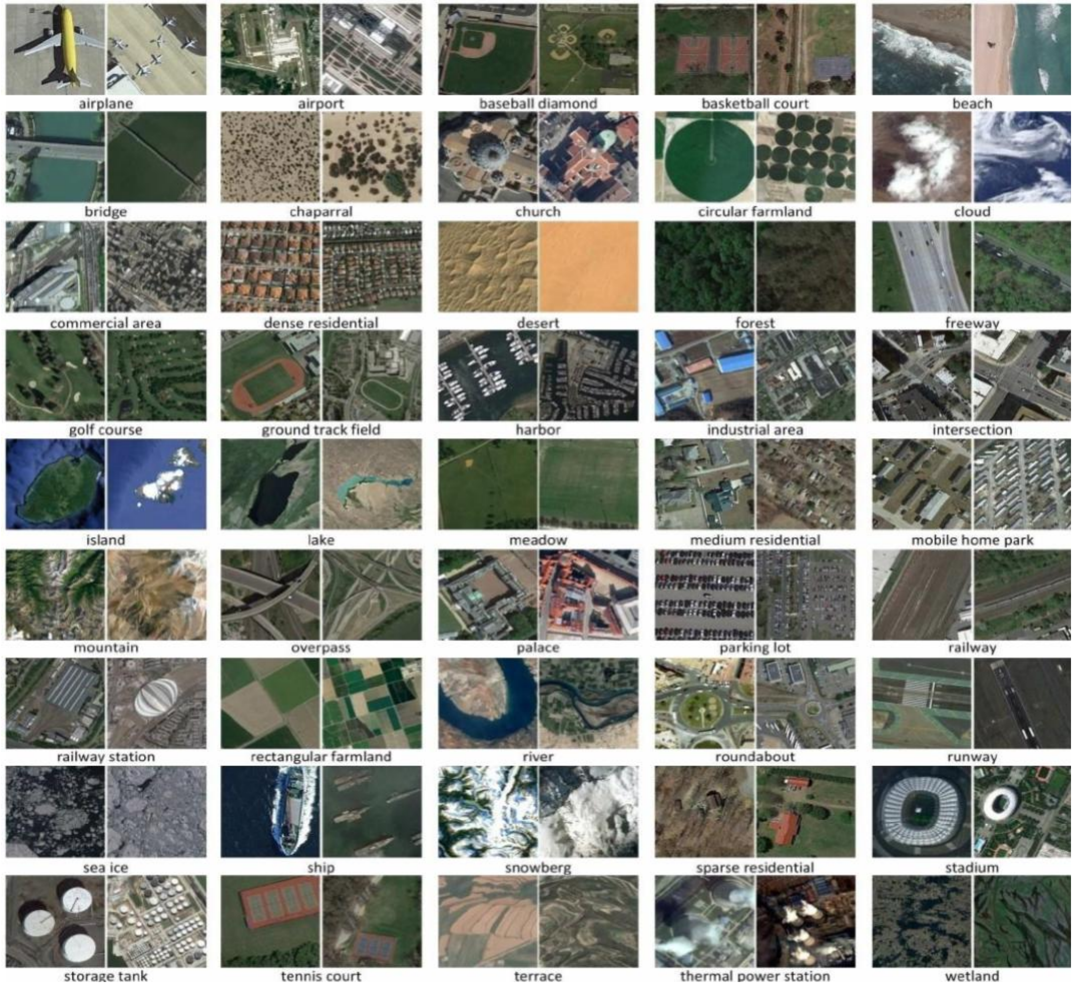
Zoom 18	19	20	21	22	23
0.475m	0.237m	0.119m	0.059m	0.0297m	0.015m

Problem	**Model**	**Database**	Results

DOTA



RESISC45



Problem	**Model**	**Database**	Results

Zoom level	Electrical substation	Swiming											
pool	Helicopter	Bridge	Plane	Soccer-ball field	Basketball court	Ground track court	Port	Beisbol court	Tenis court	Roundabout	Storage tank		
18	103	111	0	19	0	4	0	0	0	0	6	25	23
19	278	911	20	88	13	146	91	4	1	2	126	103	538
20	271	370	17	39	8	65	49	0	0	0	46	38	249
21	247	141	17	19	2	40	35	0	0	0	27	8	73
22	103	2	0	0	0	0	0	0	1	0	0	0	0
23	52	0	0	0	0	0	0	0	0	0	0	0	0
DOTA	0	1732	630	2041	7944	311	509	307	5937	412	2325	385	5024
Total	1054	3267	684	2206	7967	566	684	311	5939	414	2530	559	5907

Problem	Model	Database	**Results**

mAP 0.5	Average	65,98 %	68,97 %	63,16 %	65,39 %	65,83 %	63,96 %
	Electrical substation	85,00 %	85,19 %	83,05 %	87,55 %	82,73 %	87,78 %
	Plane	85,30 %	84,43 %	85,81 %	80,91 %	86,29 %	84,96 %
	Helicopter	10,39 %	23,14 %	6,83 %	12,48 %	48,03 %	6,23 %
	Bridge	63,16 %	62,38 %	48,45 %	50,31 %	60,54 %	39,71 %
	Storage tank	92,28 %	88,97 %	91,01 %	90,89 %	90,93 %	91,82 %
	Port	59,75 %	69,70 %	63,82 %	70,22 %	69,71 %	73,29 %

Conclusions

- Good quality data are essential for building good quality models
- Data scientists and experts must works together to reformulate and annotate data

Questions?