DaSCI
Instituto Andaluz Interuniversitario en
Data Science and Computational Intelligence

Successful case studies of DL

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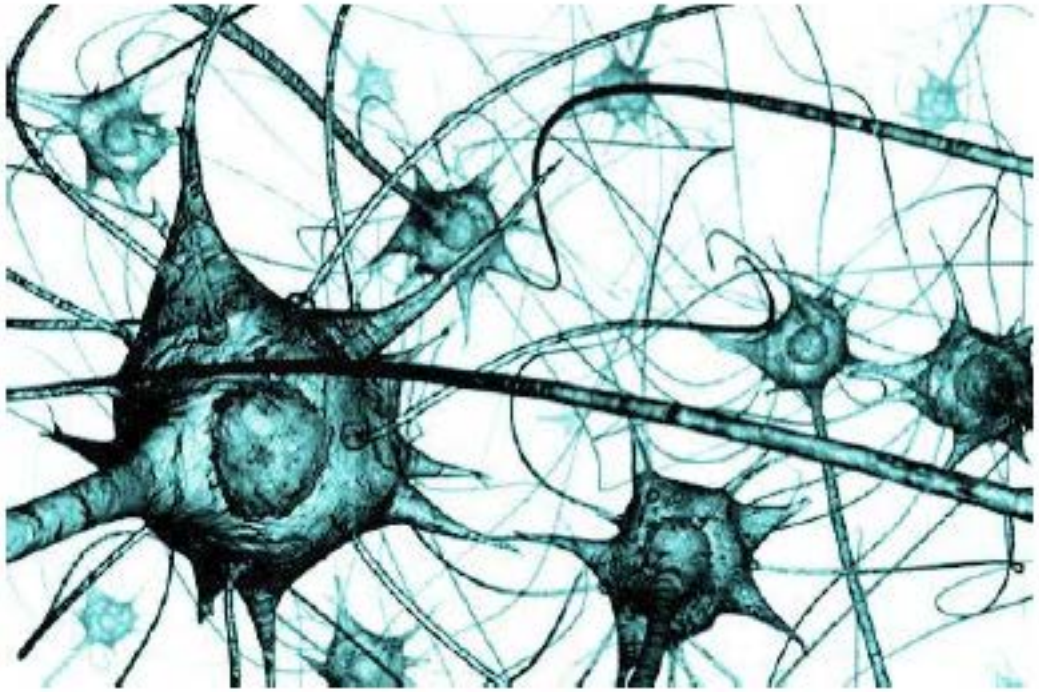
Outline

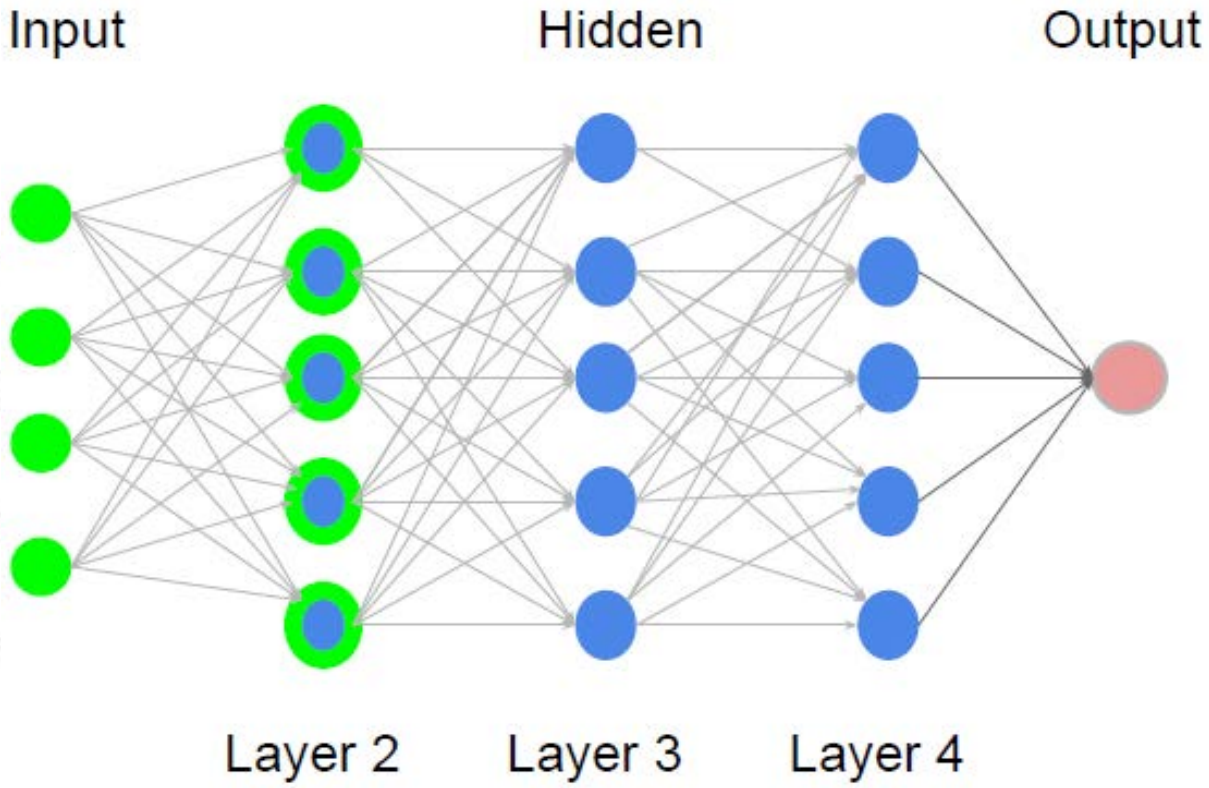
- ❑ Deep CNNs
- ❑ Four fundamental computer visions tasks
- ❑ How object detection models work?
- ❑ Receipt for addressing each case study
- ❑ Case studies:
  - ❑ Protected plant species detection
  - ❑ Whale counting
  - ❑ Critical-infrastructures

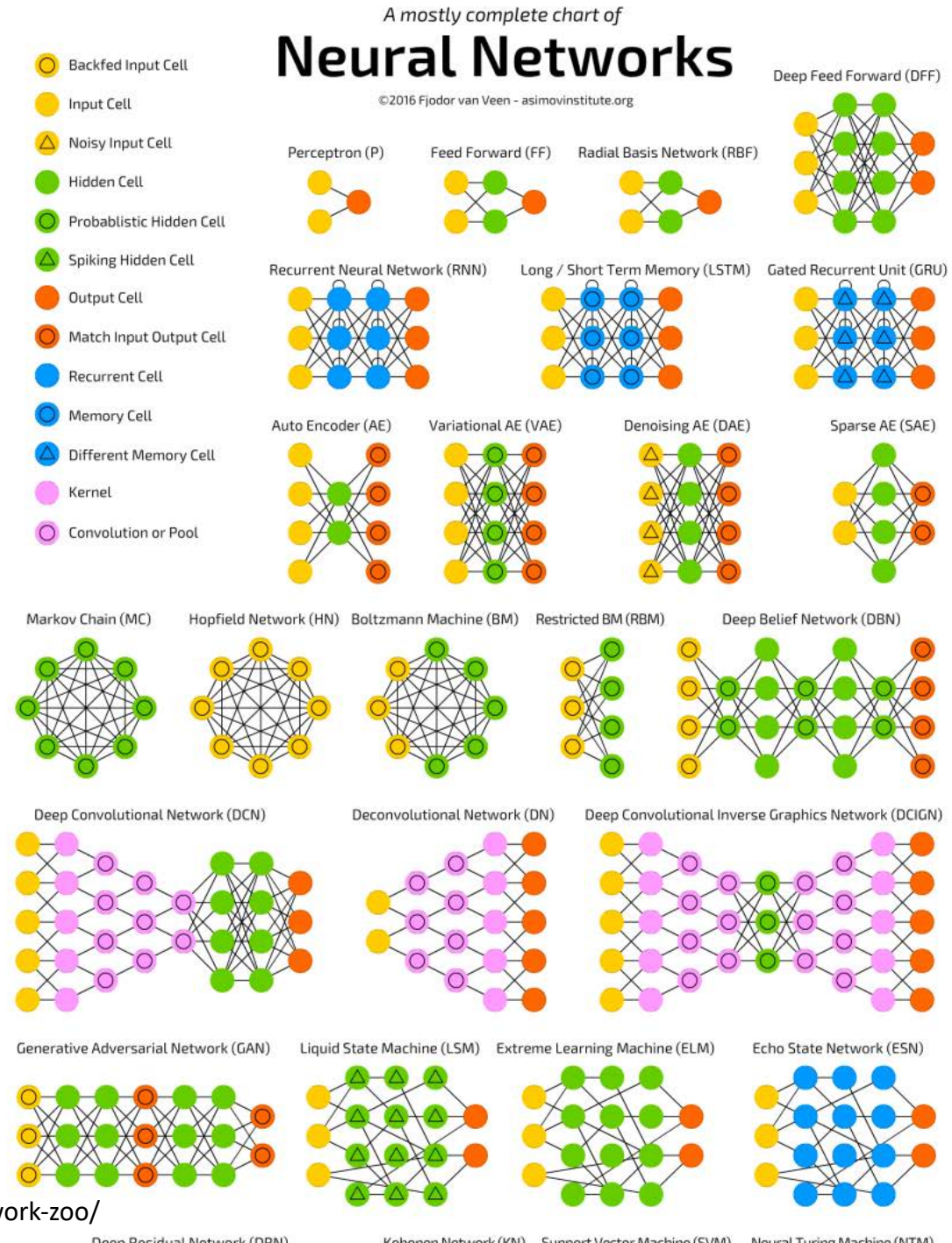
¿What are Artificial Neural Networks?

Artificial Neural Networks

Learn from data to make predictions

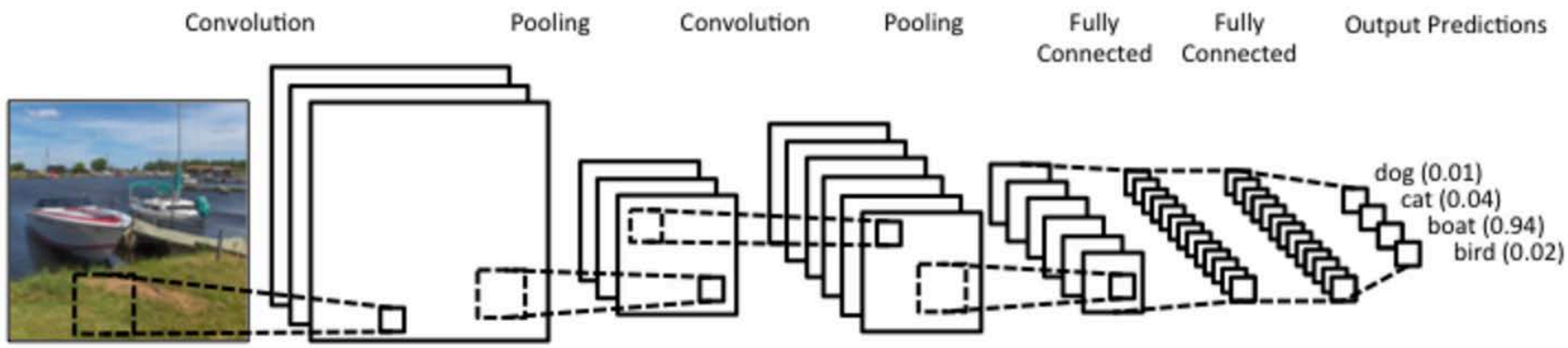






Source: http://www.asimovinstitute.org/neural-network-zoo/

Convolutional Neural Networks (CNN)



CNNs pros and cons

- Requires large training dataset to achieve good results

Solution

- Data-augumentation
- Transfer learning

By the way …

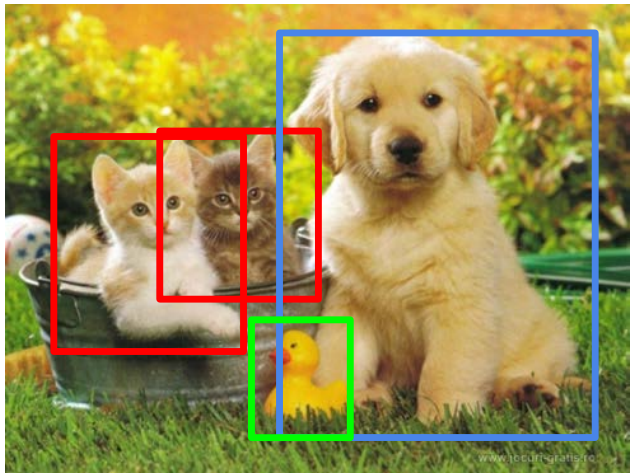
Classification

CAT

Classification + Localization

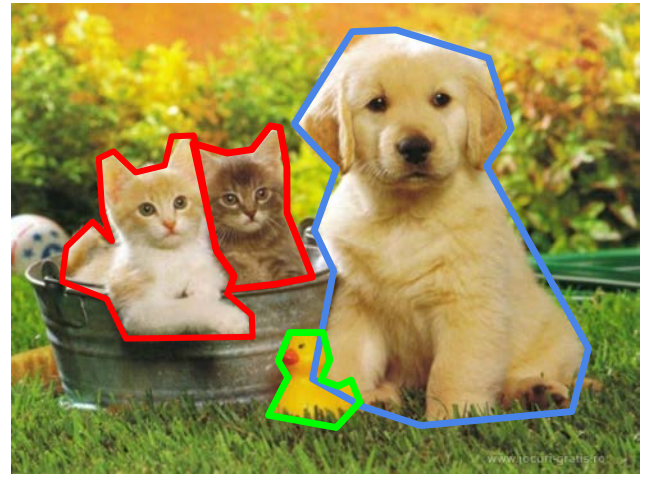
CAT

Object Detection



CAT, DOG, DUCK

Instance Segmentation



CAT, DOG, DUCK

Single object

Multiple objects

State-of-the art CNN-models

Classification

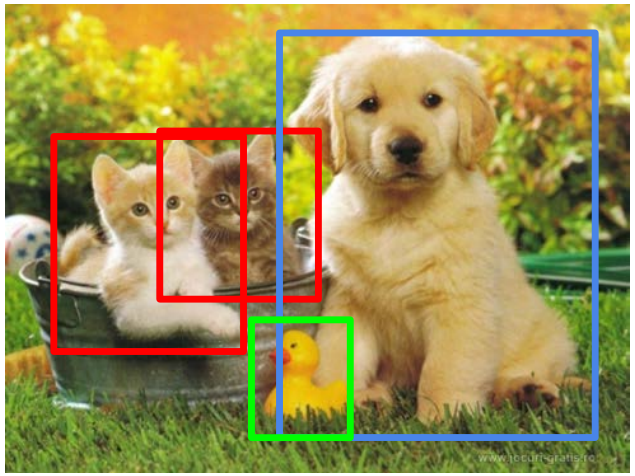
CAT

ResNet
Inception
Inception-ResNet
EfficientNet

Classification + Localization

CAT

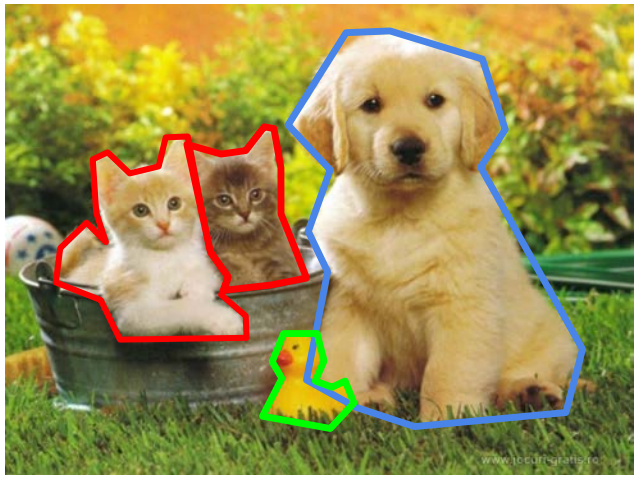
Object Detection



CAT, DOG, DUCK

Faster RCNN
SSD
Yolo

Instance Segmentation

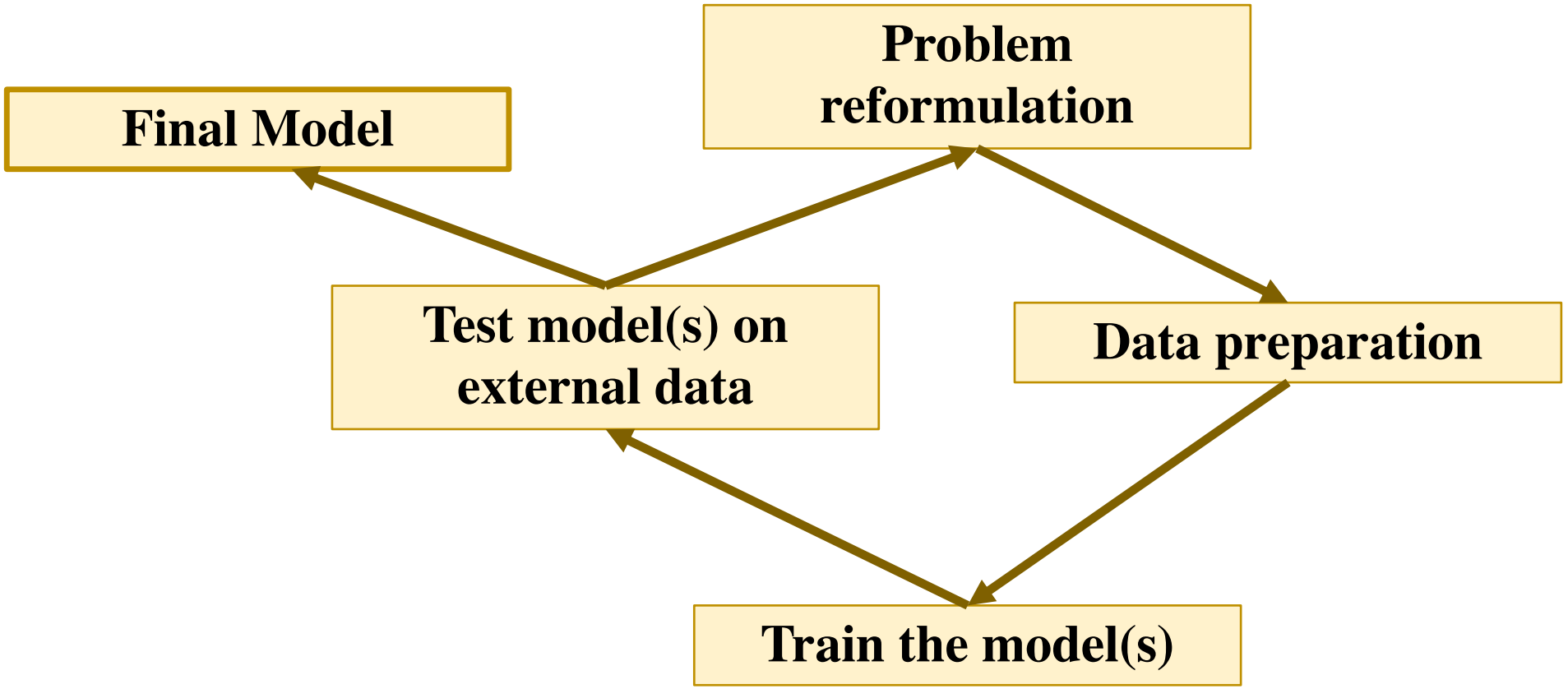


CAT, DOG, DUCK

Mask-RCNN
UNet

How object detection Works?

How do we address new problem with Deep NN?



Outline

- ❑ Deep CNNs
- ❑ Four fundamental computer visions tasks
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  - ❑ **Protected plant species detection**
  - ❑ Whale counting
  - ❑ Critical-infrastructures

Protected plant species detection in Google-Earth images

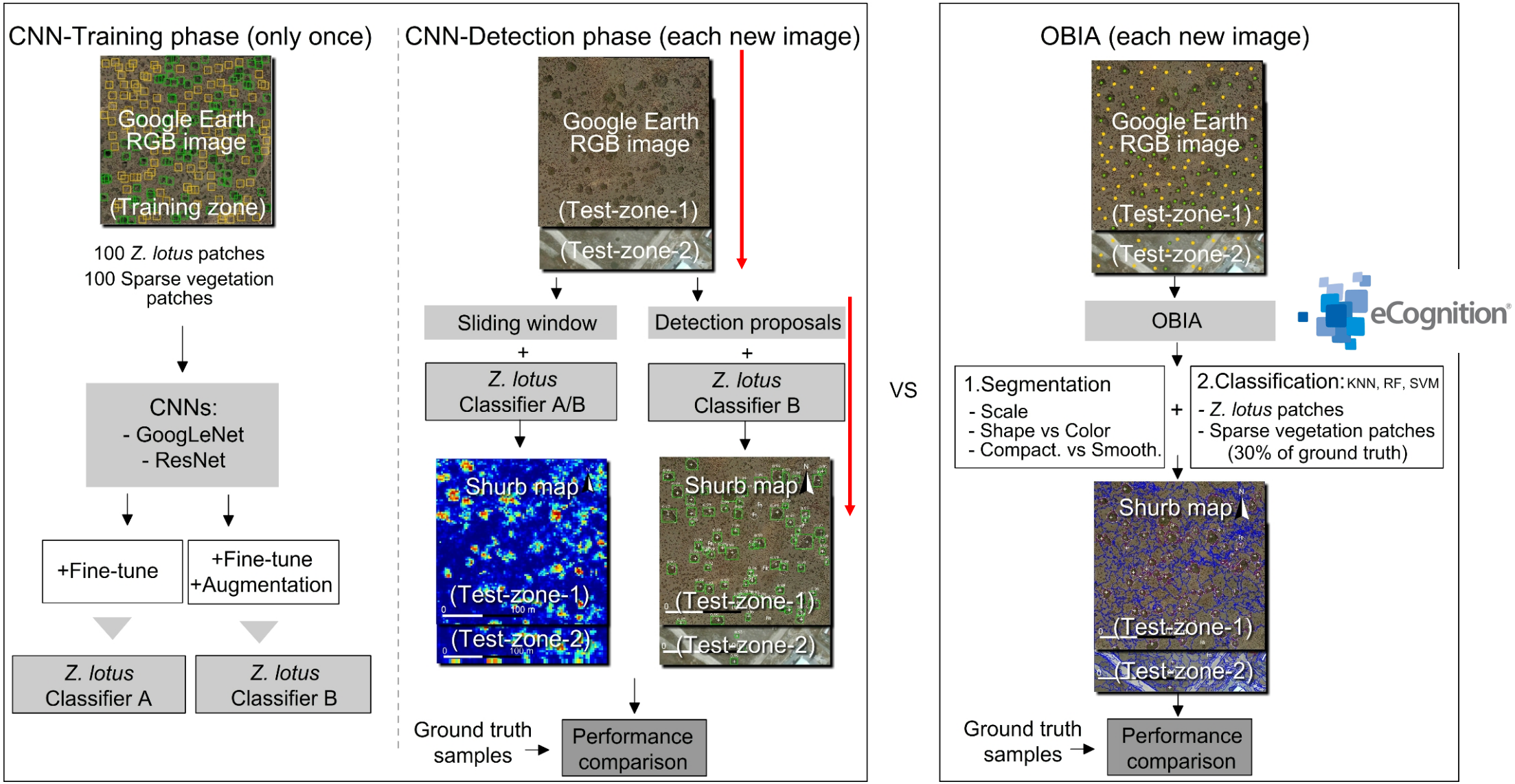
Objective: build a tool to monitor the conservation state of the Mediterranean area

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)

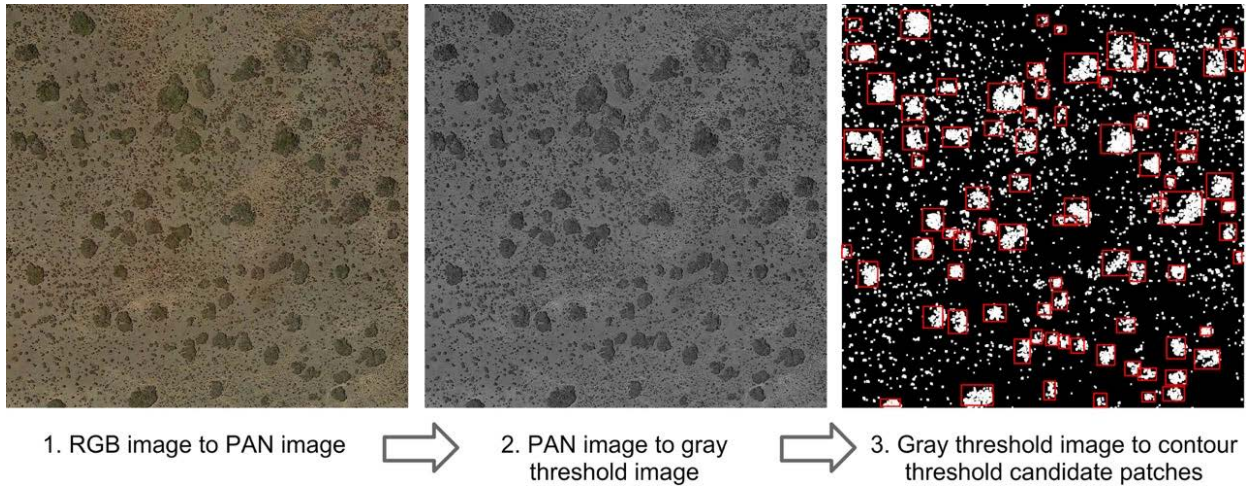
Chalenges: Zizphus Lotus has not a clear pattern for the human eye

1900 × 1900 pixeles with 0.5 m/pixel

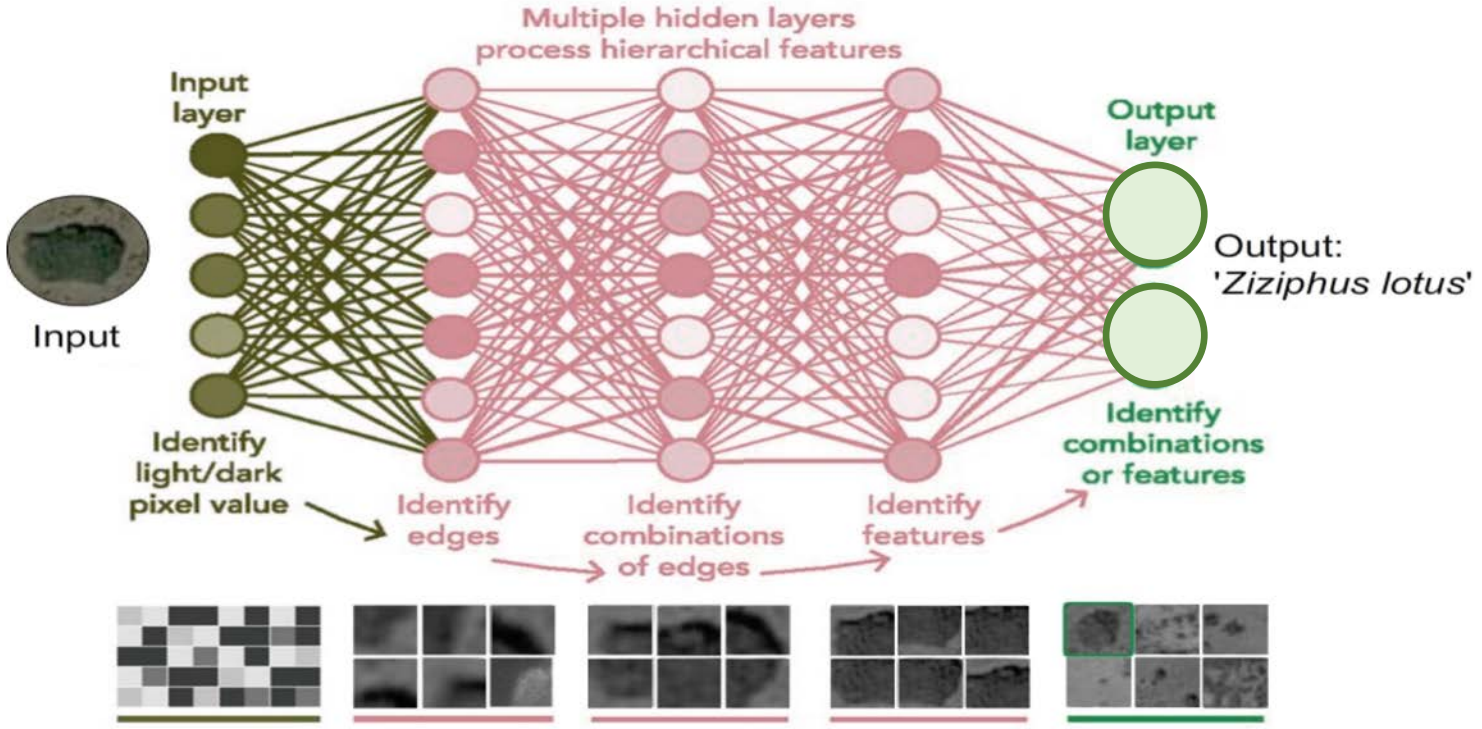

CNN-Training phase (only once)
Google Earth RGB image
(Training zone)
100 Z. lotus patches
100 Sparse vegetation patches
CNNs:
- GoogLeNet
- ResNet
+Fine-tune
+Fine-tune +Augmentation
Z. lotus Classifier A
Z. lotus Classifier B
CNN-Detection phase (each new image)
Google Earth RGB image
(Test-zone-1)
(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

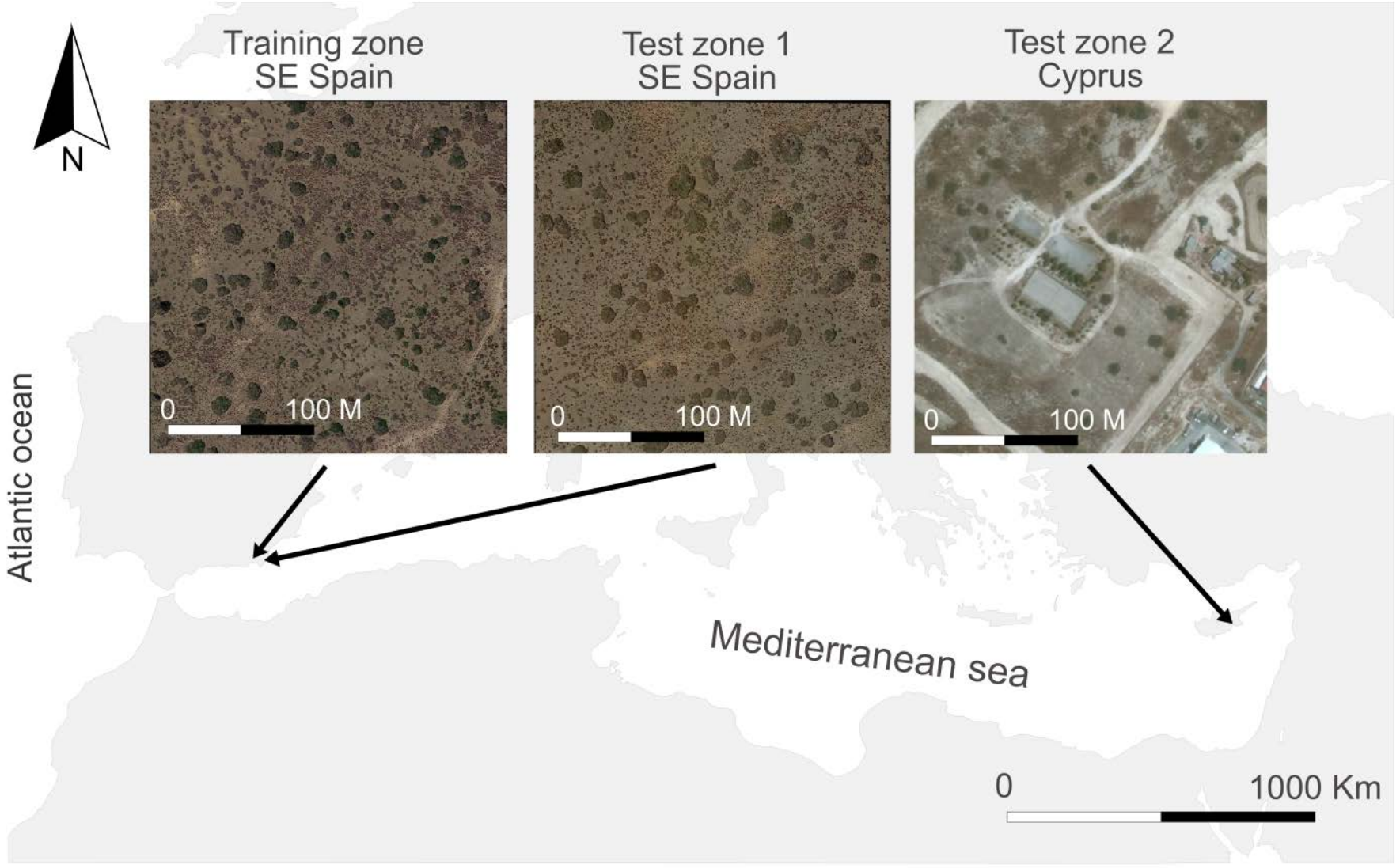
Problem	Database	**Model**	Results

Step 1:



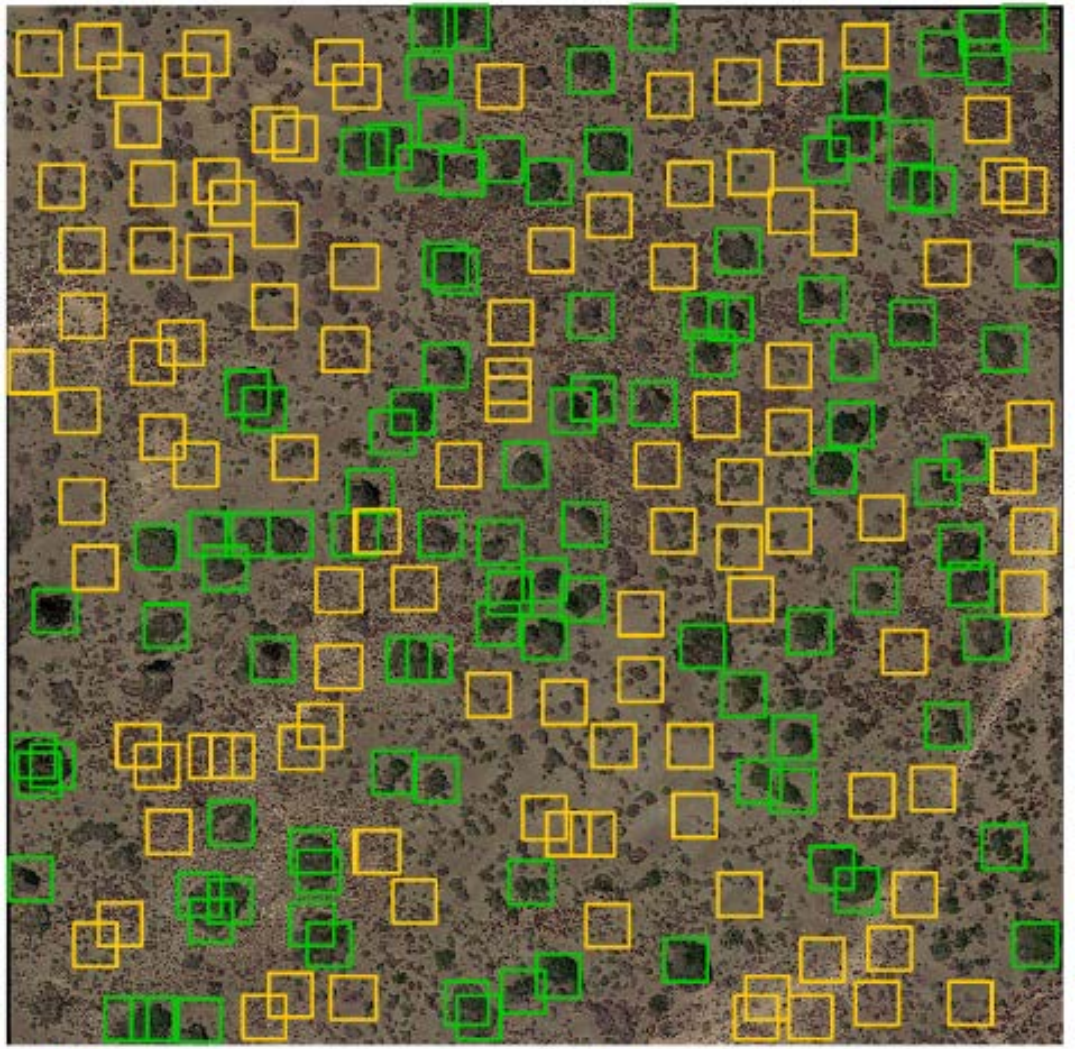
Step 2:




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

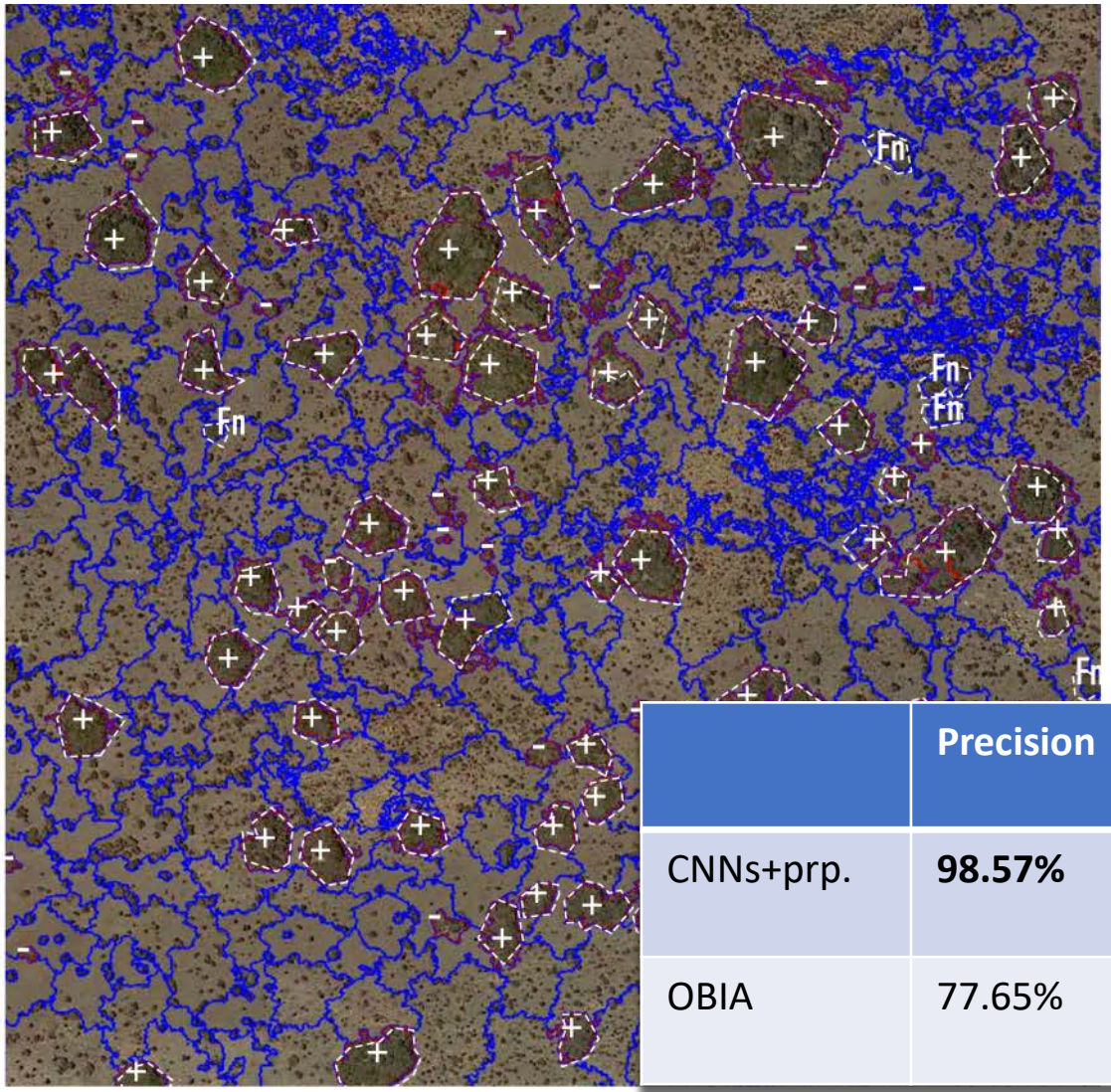
Problem	**Database**	Model	Results

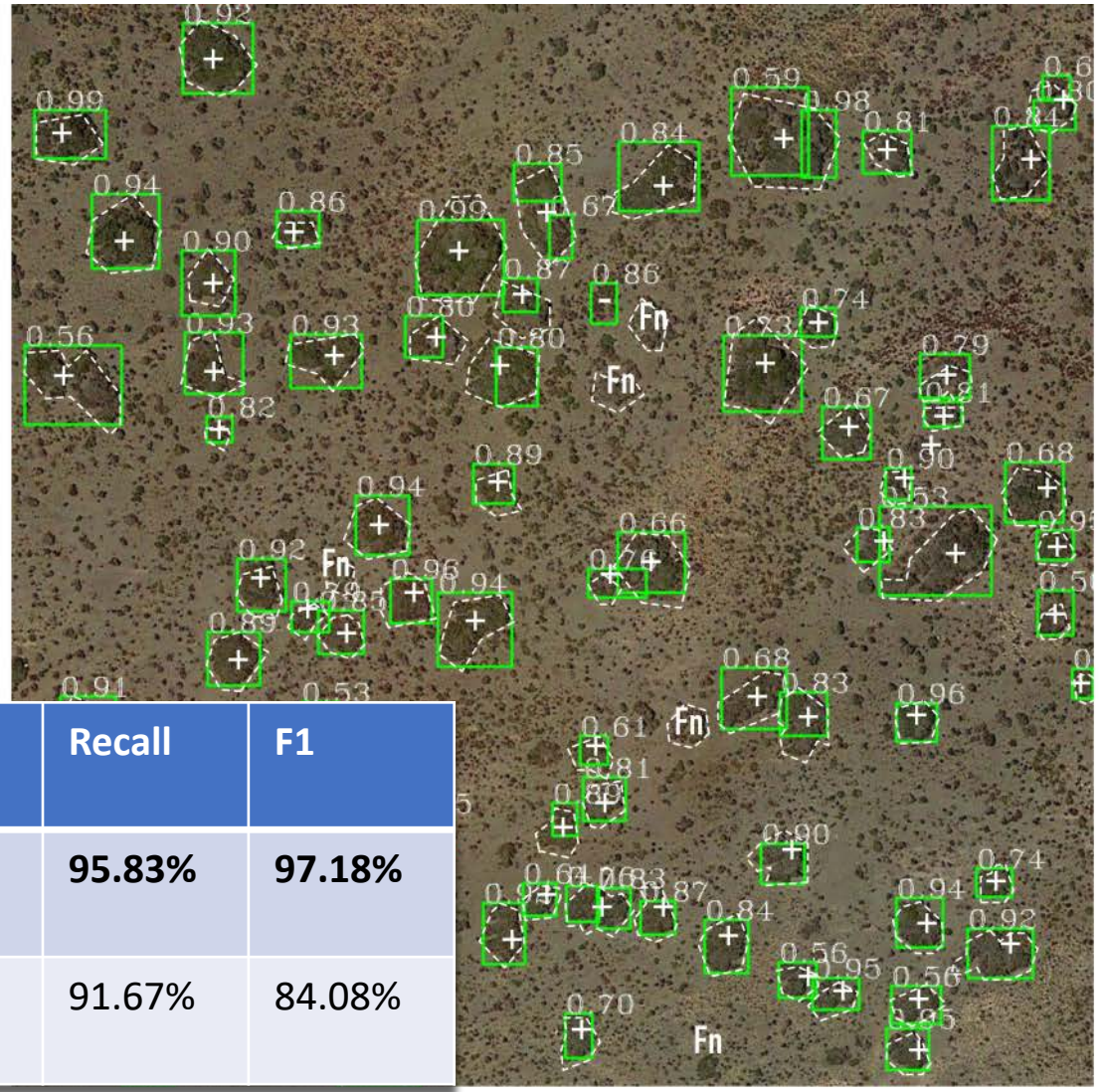
Two class problem



Problem	Database	Model	**Results**

OBIA(12 hours) vs CNNs(35.4seconds)

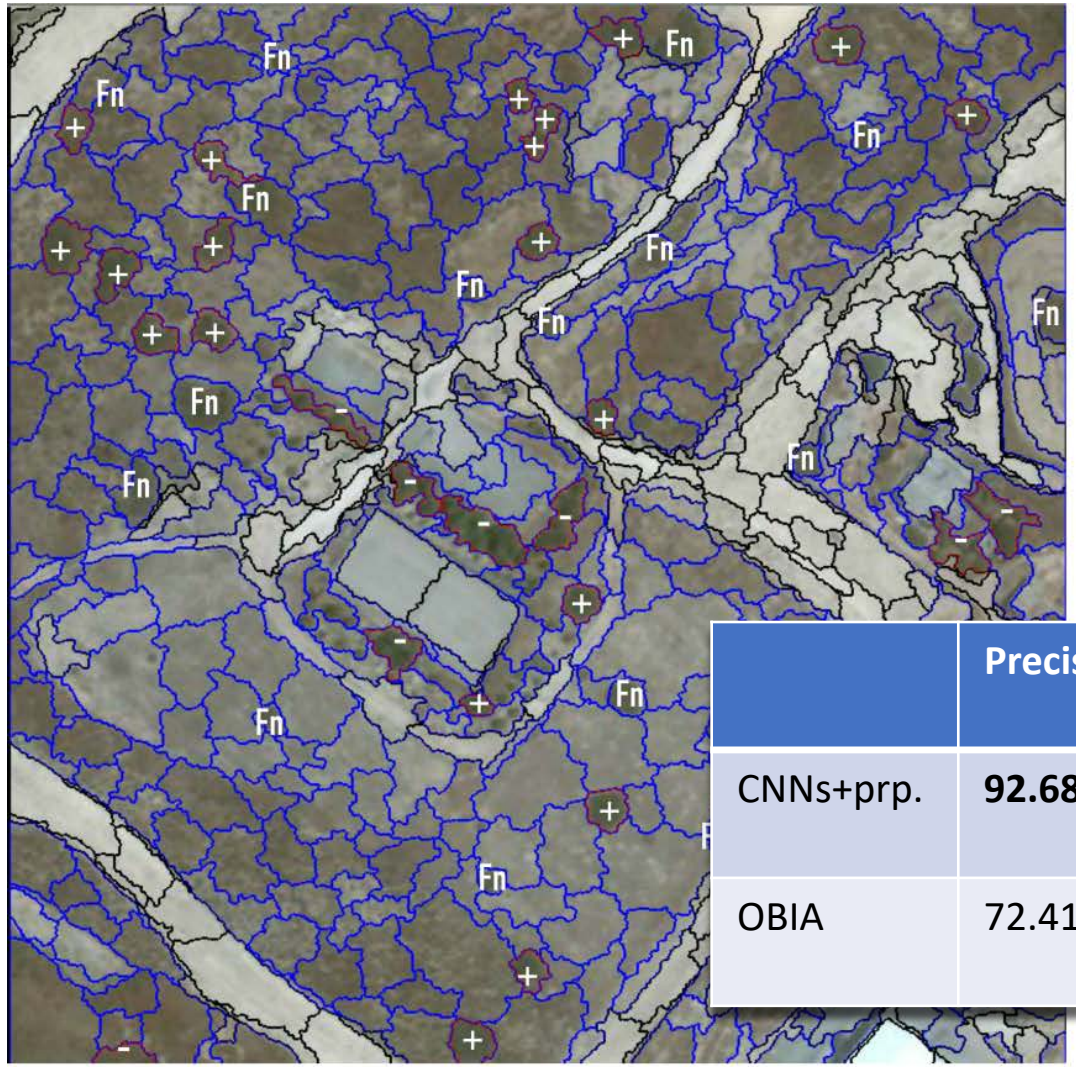


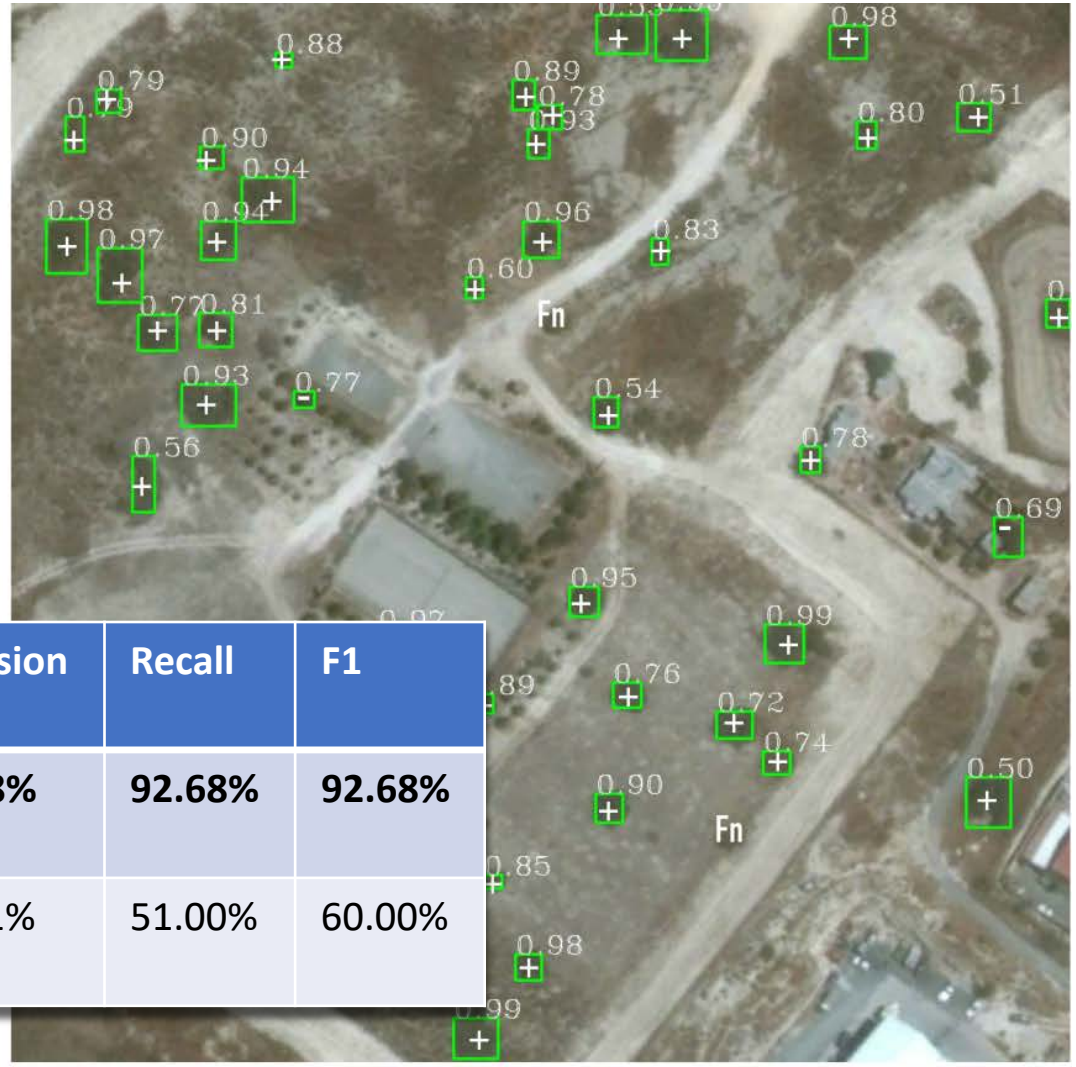


	Precision	**Recall**	**F1**
CNNs+prp.	**98.57%**	**95.83%**	**97.18%**
OBIA	77.65%	91.67%	84.08%

Problem	Database	Model	**Results**

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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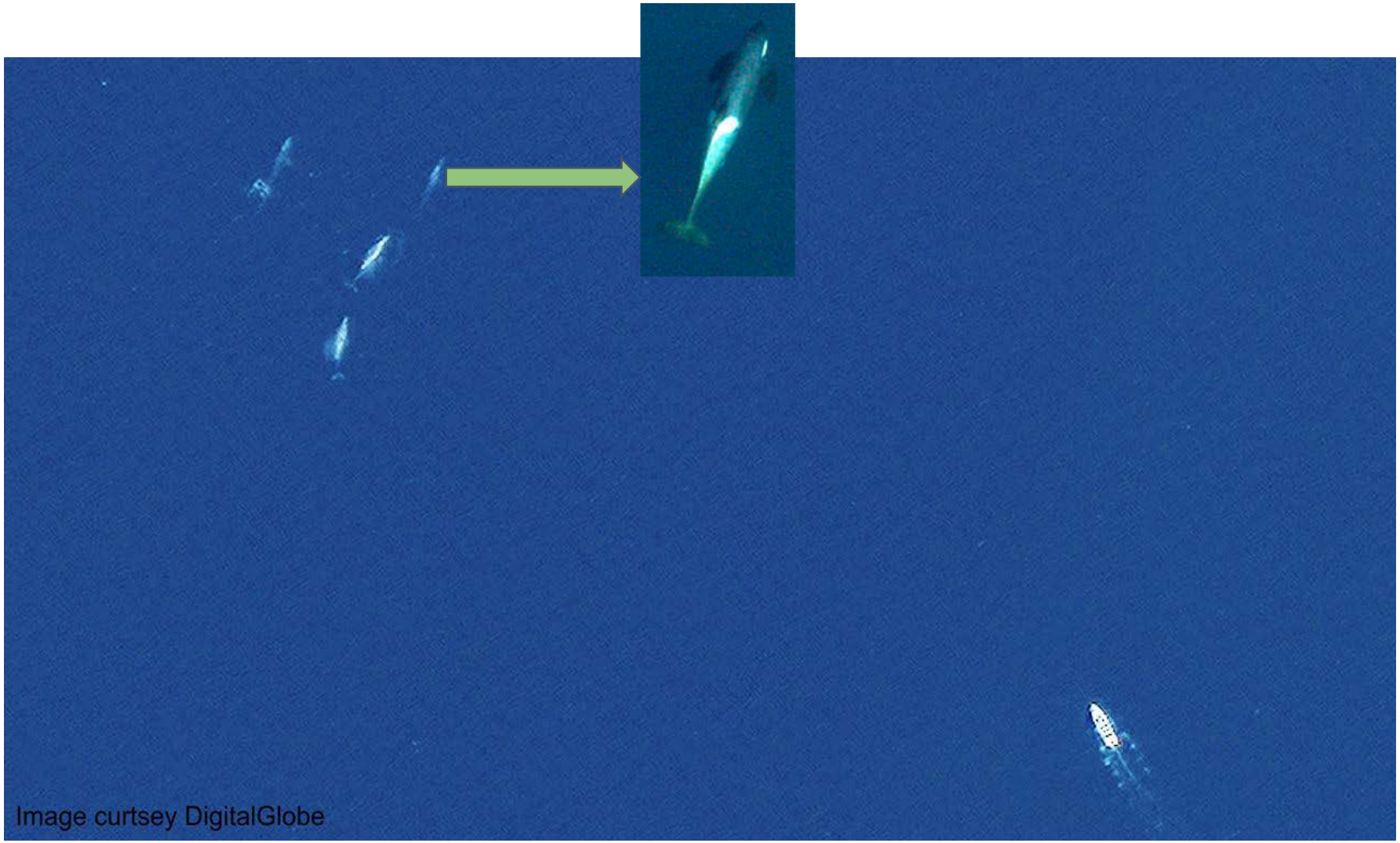
  - ❑ **Whale counting**
  - ❑ Critical-infrastructures

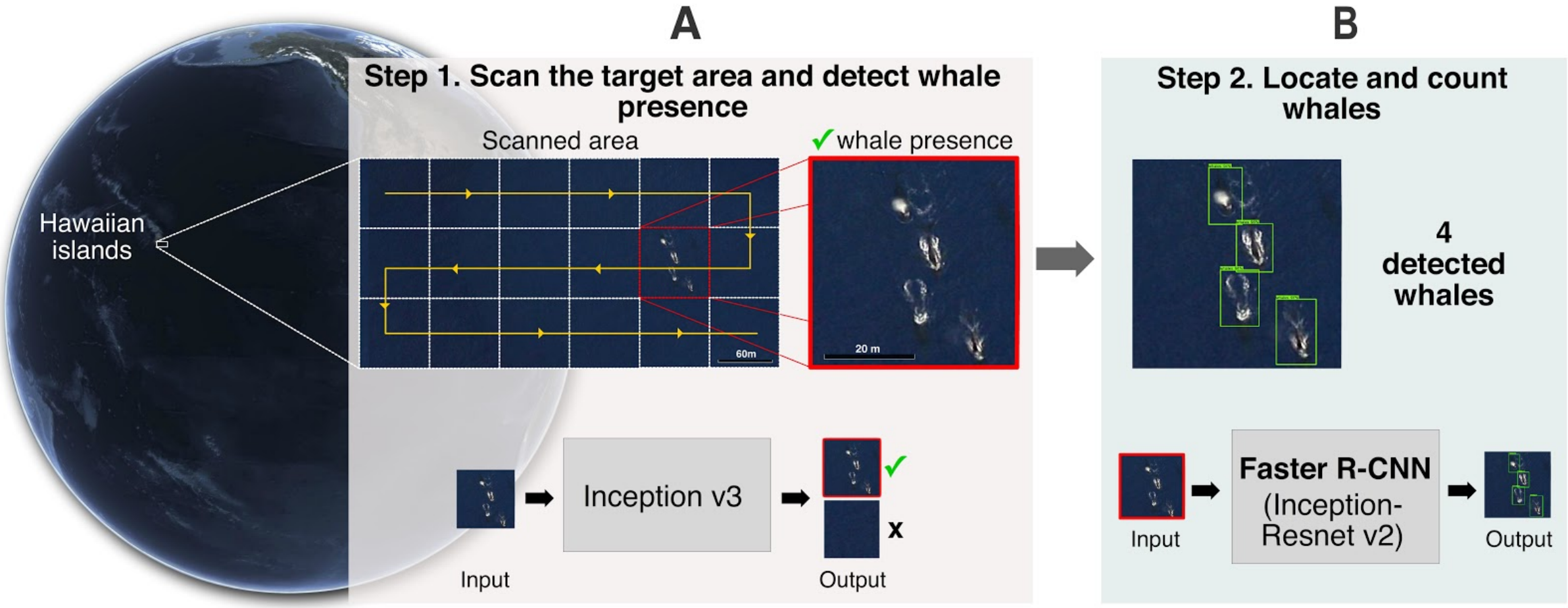
Whale counting in aerial and satellite images

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

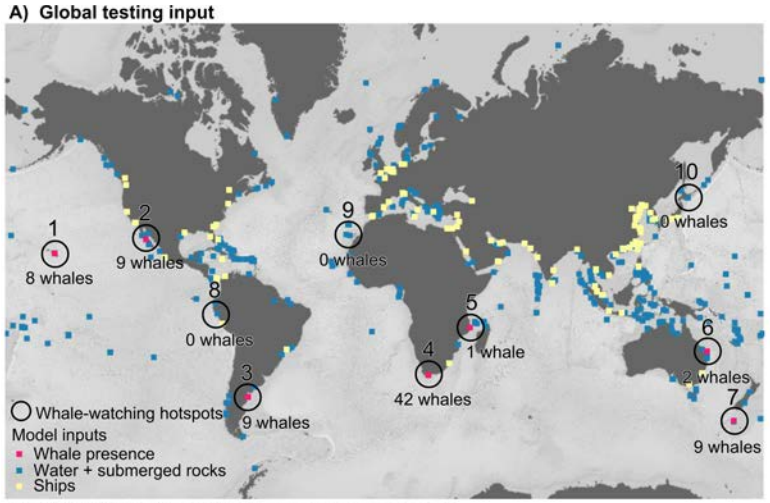
Problem	**Model**	Database	Results



Problem	Model	**Database**	Results

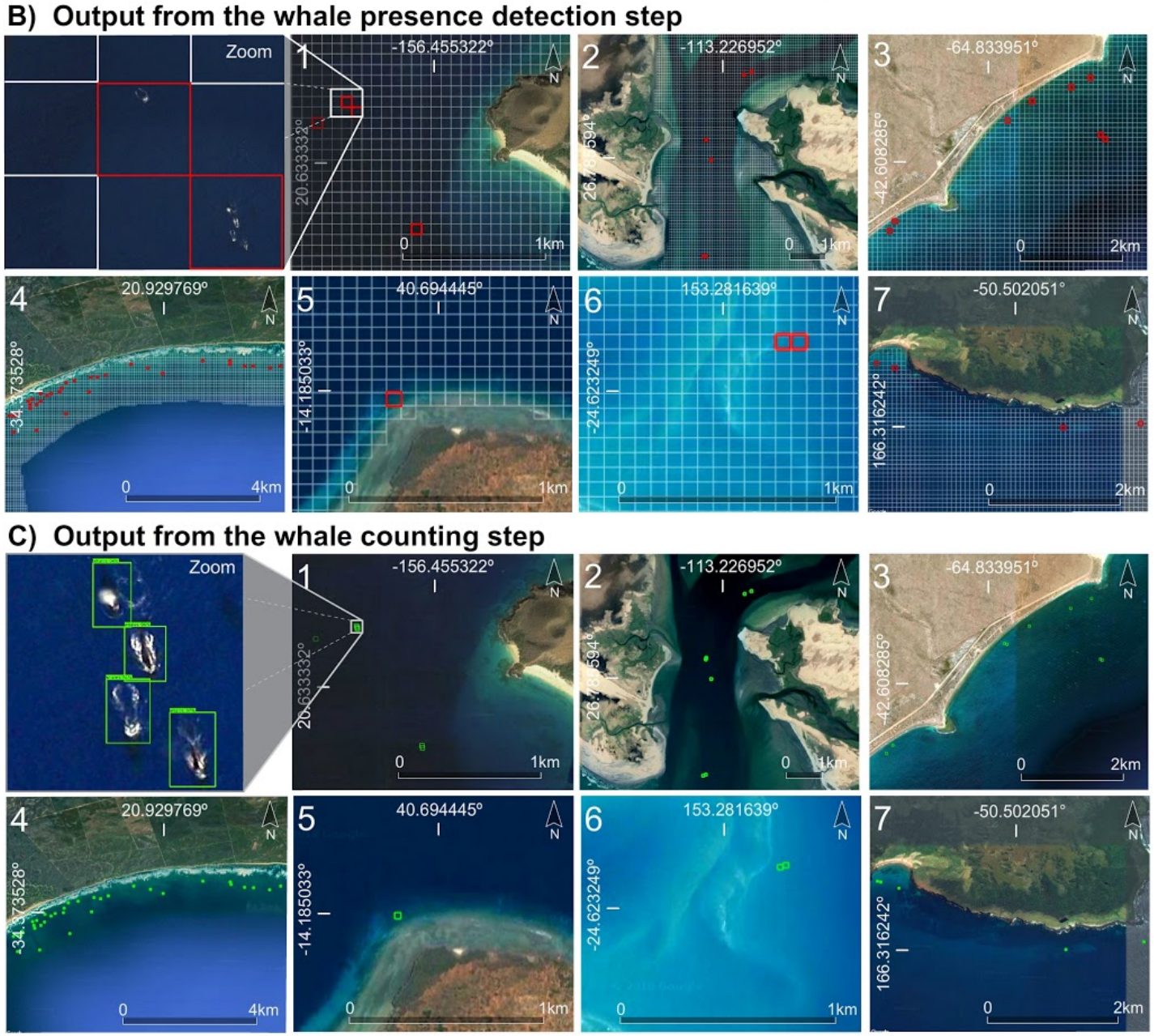
- Base de datos para entrenar: 700 (con 900 ballenas) aéreas imágenes extraídas de Google Earth, free Arkive, NOAA Photo Library y NWPU-RESISC45 dataset.

- Base de datos para testear:



Problem	Model	Database	**Results**

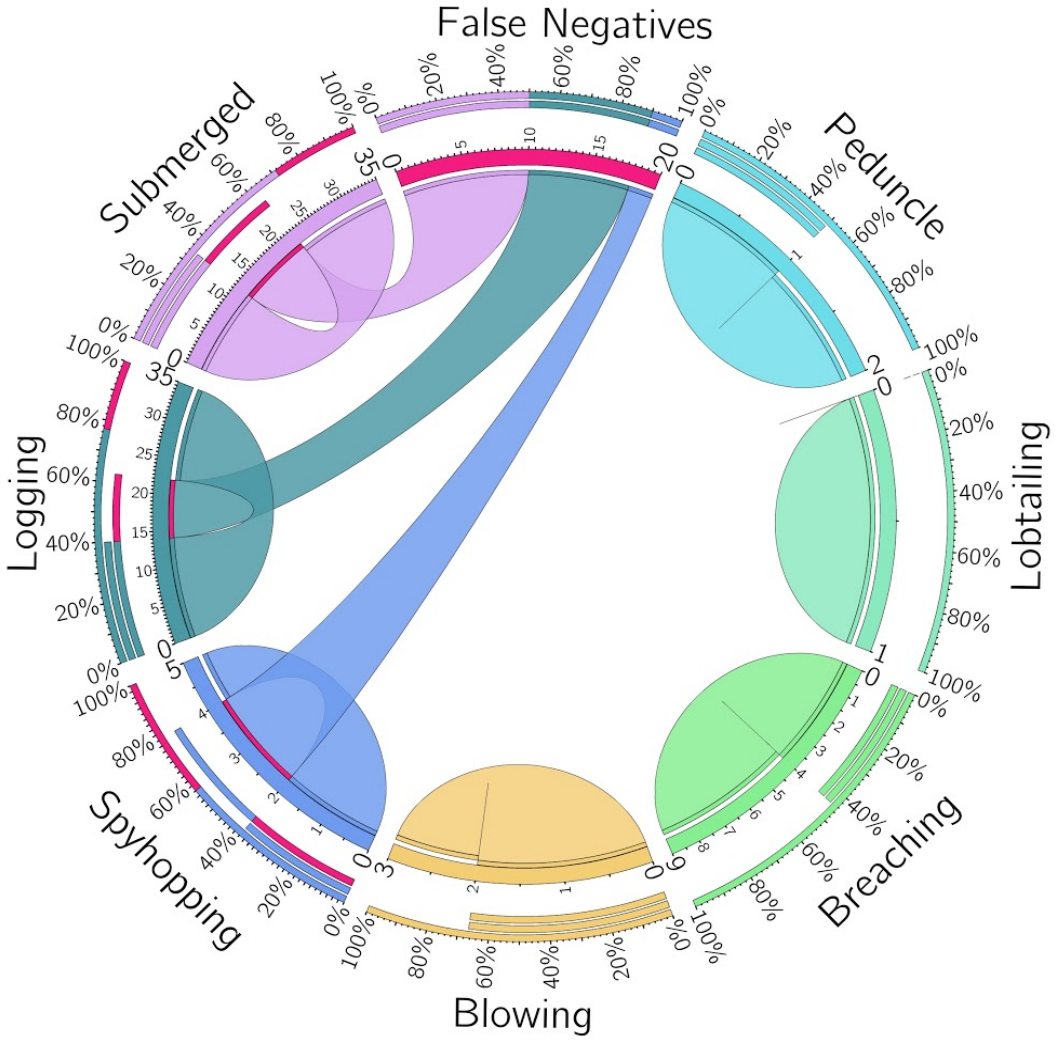
- The first step detects the presence of whales with 84% accuracy
- The second step counts whales with 97% accuracy

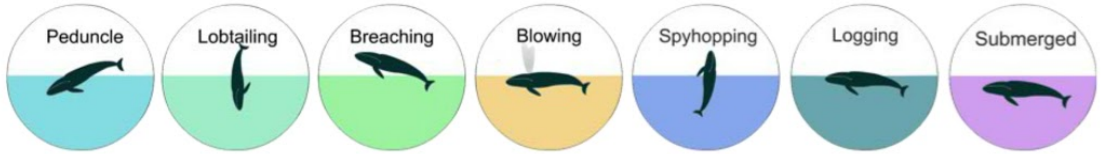


Problem	Model	Database	**Results**

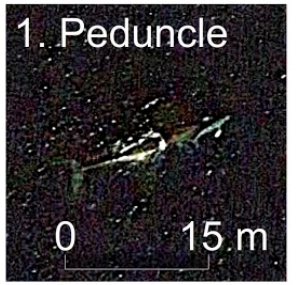
- Impact of whale posture of whales on the performance of the model

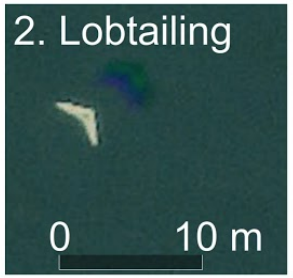
A

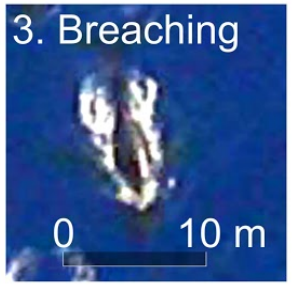


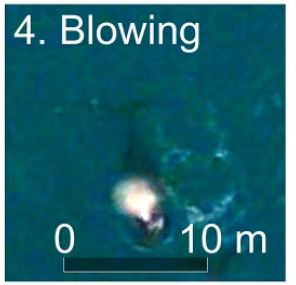


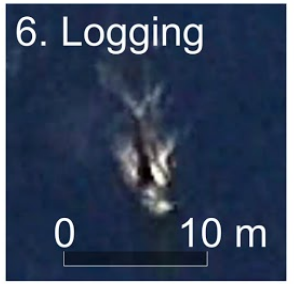
B





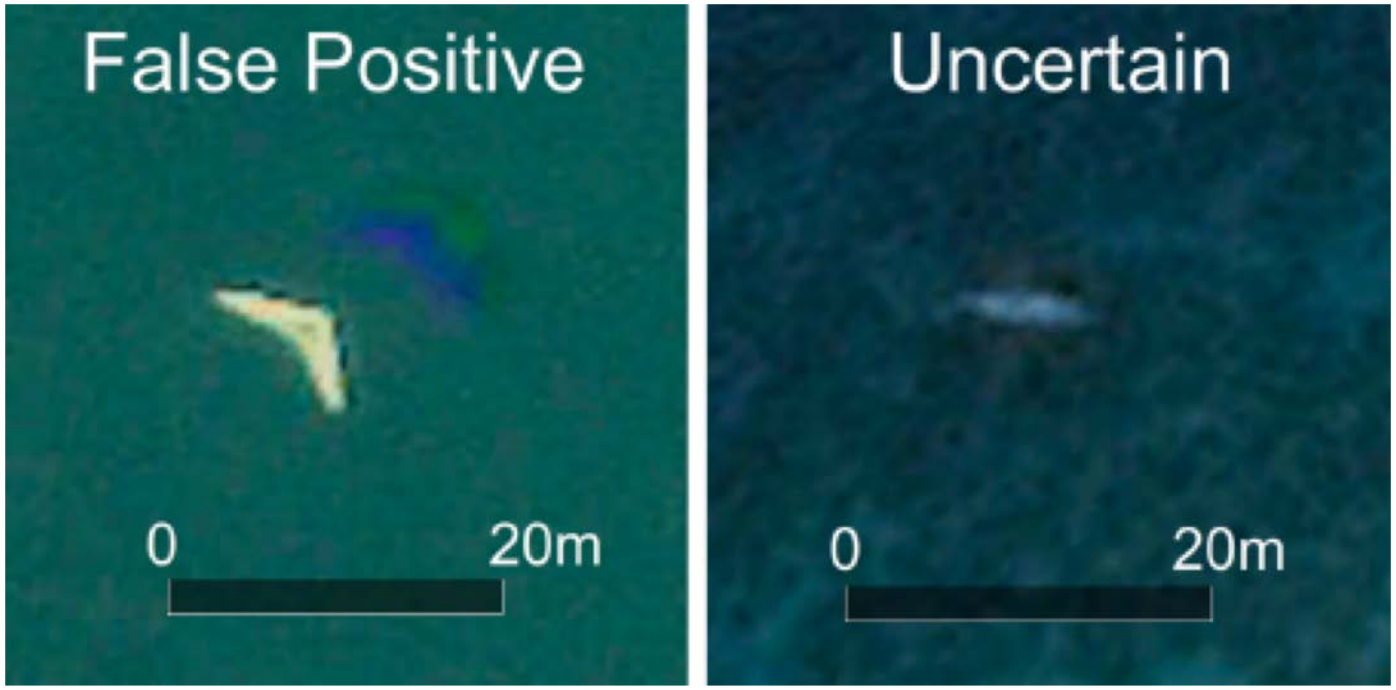






Problem	Model	Database	**Results**

Example of false positives of a hang-glider



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Detection of critical-infrastructures

Objective: build a tool to detect electrical substations and airports

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

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

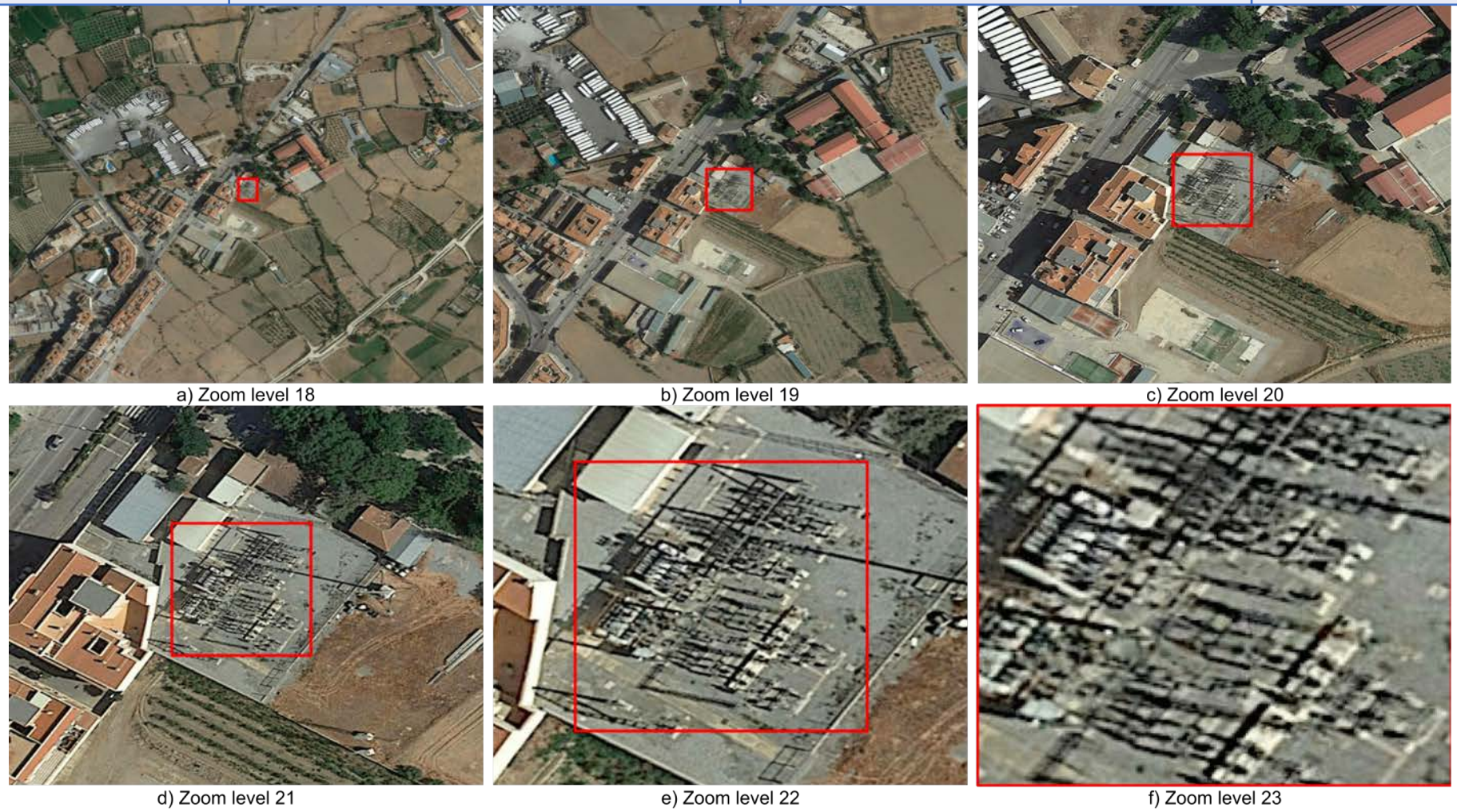
a) Zoom level 14

b) Zoom level 15

c) Zoom level 16

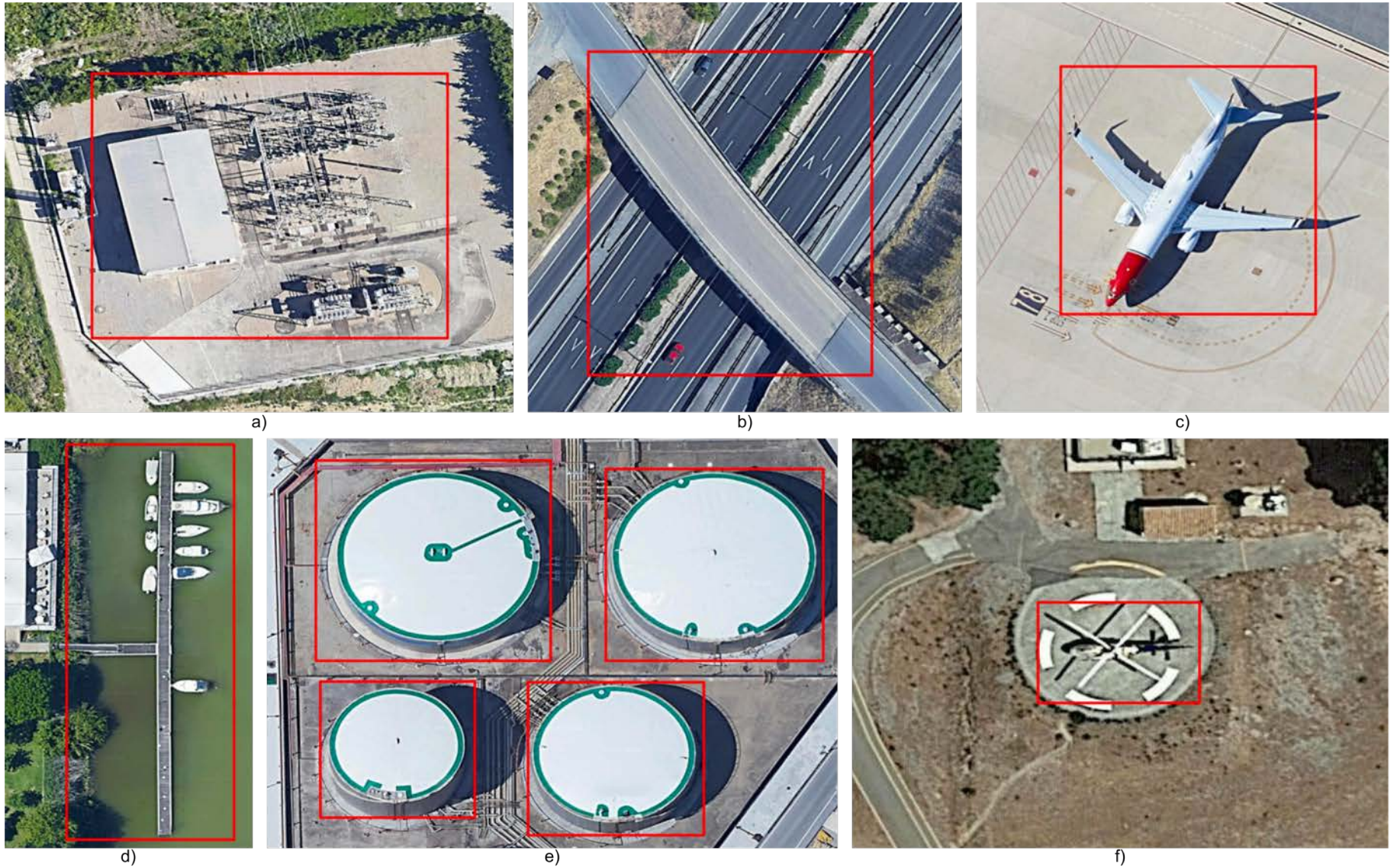
d) Zoom level 17

Comparison of images with different zoom levels 14 to 17 (one tile from Google Maps) El Hierro airport, Canary Islands, Spain



Comparison of images with different zoom levels 18, 19, 20, 21, 22 and 23 (one tile from Google Maps) Guadix electrical substation, Granada, Spain

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



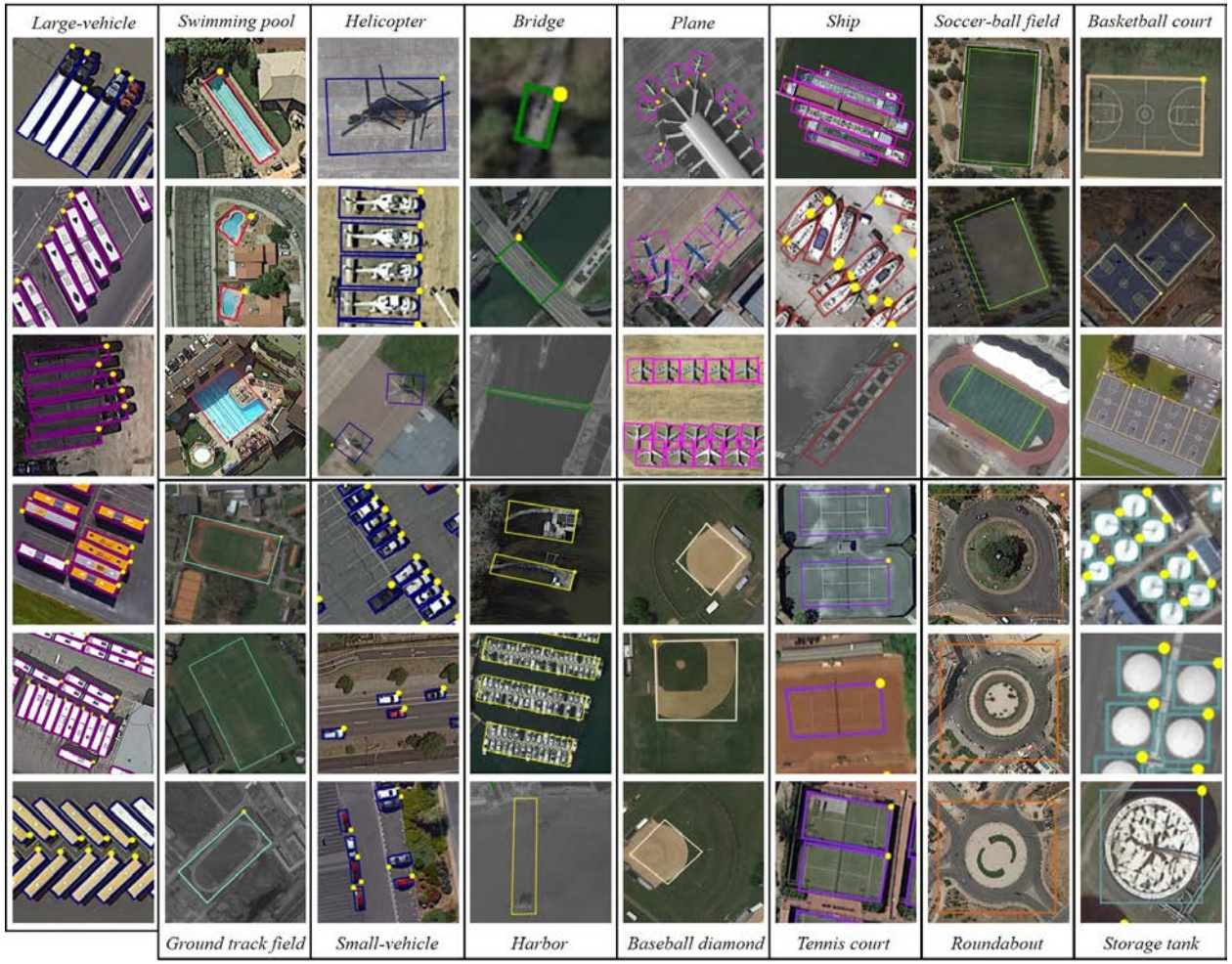
Object classes that help improving the performance of the detection: a) Electrical substation, b) bridges, c) plane, d) harbou
e) storage tanks and g) helicopter

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

Object classes that help improving the performance of the detection: a) Airport, b) bridges, c) harbour, d) industrial áreas, e) motorway and f) train station

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

DOTA



RESISC45

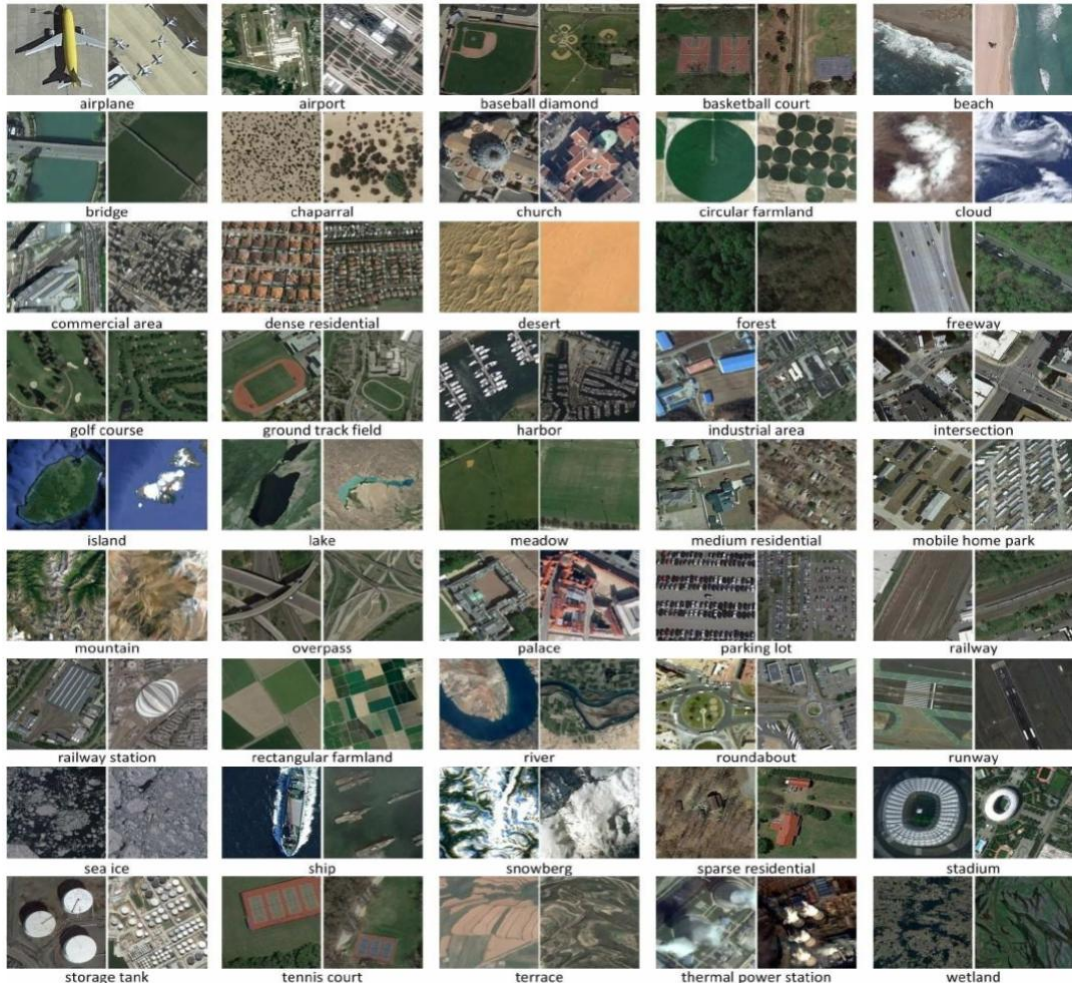


Table 14: Number of instances for small scale critical infrastructures, SSCI_train_stable dataset.

Zoom level	Electrical substation	Swimming pool	Helicopter	Bridge	Plane	Soccer ball field	Basketball court	Ground track field	Harbour	Baseball diamond	Tennis court	Roundabout	Storage tank
18	103	111	0	19	0	4	0	0	0	0	6	25	23
19	103	104	0	18	0	4	0	0	0	0	6	26	39
20	103	62	0	5	0	1	0	0	0	0	1	13	36
21	103	11	0	0	0	0	0	0	0	0	0	1	12
22	103	2	0	0	0	0	0	0	1	0	0	0	0
23	103	0	0	0	0	0	0	0	0	0	0	0	0
DOTA	-	1732	630	2041	7944	311	509	307	5937	412	2325	385	5024
19	175	807	20	70	13	142	91	4	1	2	120	77	499
20	164	308	17	34	8	64	49	0	0	0	45	25	213
21	144	130	17	19	2	40	35	0	0	0	27	7	61
Total	1101	3267	684	2206	7967	566	684	311	5939	414	2530	559	5907

Table 17: Number of instances for large scale critical infrastructures, LSCI_train_stable dataset.

Zoom level	Source	Airport	Train station	Motorway	Bridge	Industrial	Harbour
14		60	5	1012	37	69	17
15	SAS	69	6	1280	37	71	17
16	Planet	251	6	3947	57	116	27
17		124	27	4805	168	291	23
	DIOR	1327	1011	0	3967	0	5509
Total		1831	1055	11044	4266	547	5593

Input image

First stage

Zoom level classifier

Zoom level: [14,17]

Zoom level: [18,23]

Second stage

Detector

SSCI_Det_stable

LSCI_Det_stable

- **Electrical substation**
- Bridge
- Harbour
- Helicopter
- Plane
- Storage tank

- **Airport**
- Train station
- Motorway
- Bridge
- Industrial area
- Harbour

Problem	Model	Database	**Results**

Table 16: TP, FP, FN, Recall, Precision and F1 in SSCI_test_stable. SSCI_Det_stable is trained on SSCI_train_stable and SSCI_Det_beta is trained on SSCI_train_beta. For comparison purposes, SSCI_Det_alpha is trained only at airports.

	TP	FP	FN	Precision	Recall	F1
SSCI_Det_alpha(only ele. sub.)	117	449	7	20,67%	**94,35%**	33,91%
SSCI_Det_beta(six classes)	75	124	49	37,69%	60,48%	46,44%
SSCI_Det_stable(six classes)	112	62	12	**64,37%**	90,32%	**75,17%**

Conclusions

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

Questions?