The rise of Artificial Intelligence for Earth Observation

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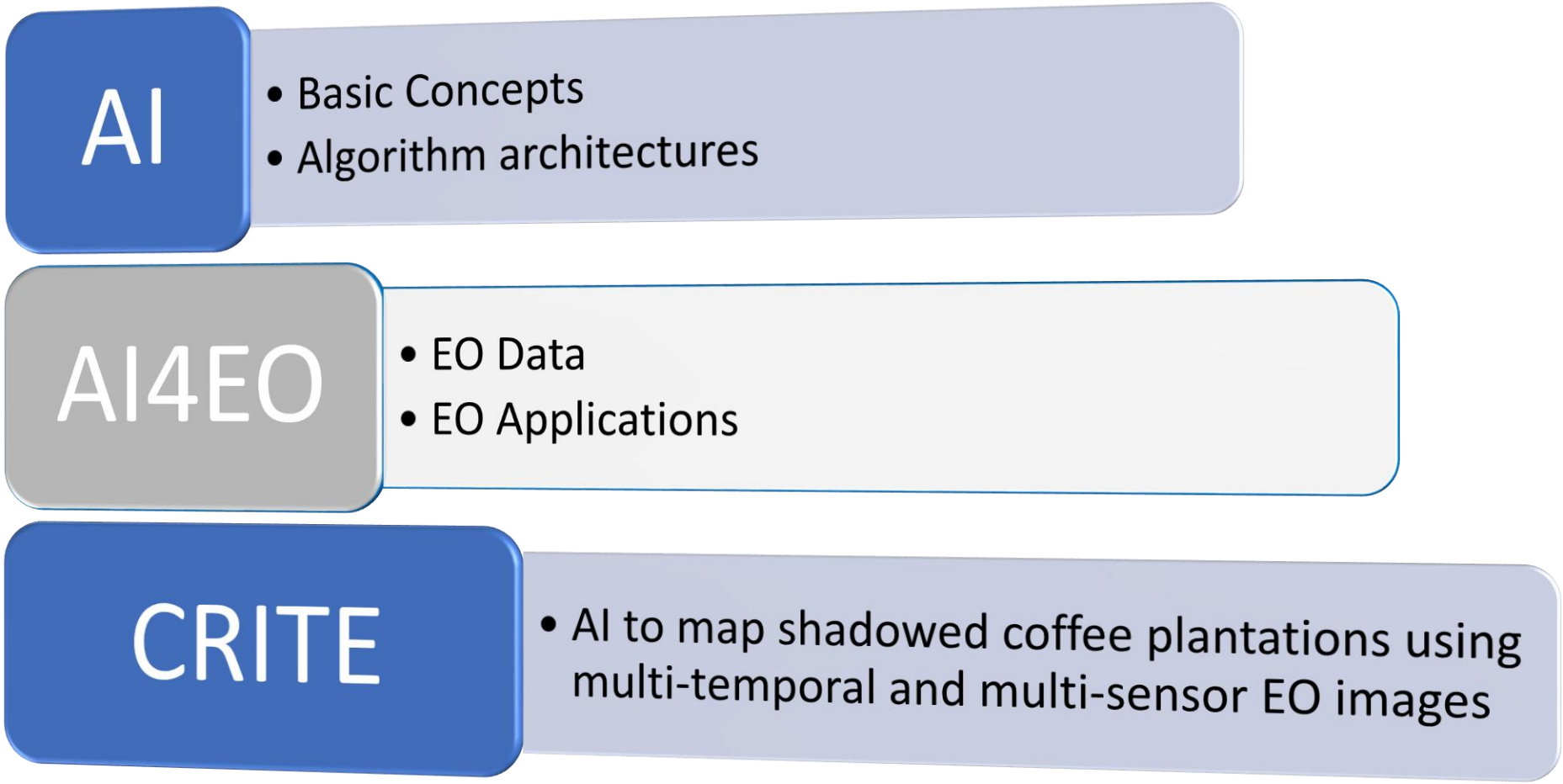
AGENDA


AI
• Basic Concepts
• Algorithm architectures
AI4EO
• EO Data
• EO Applications
CRITE
• AI to map shadowed coffee plantations using multi-temporal and multi-sensor EO images

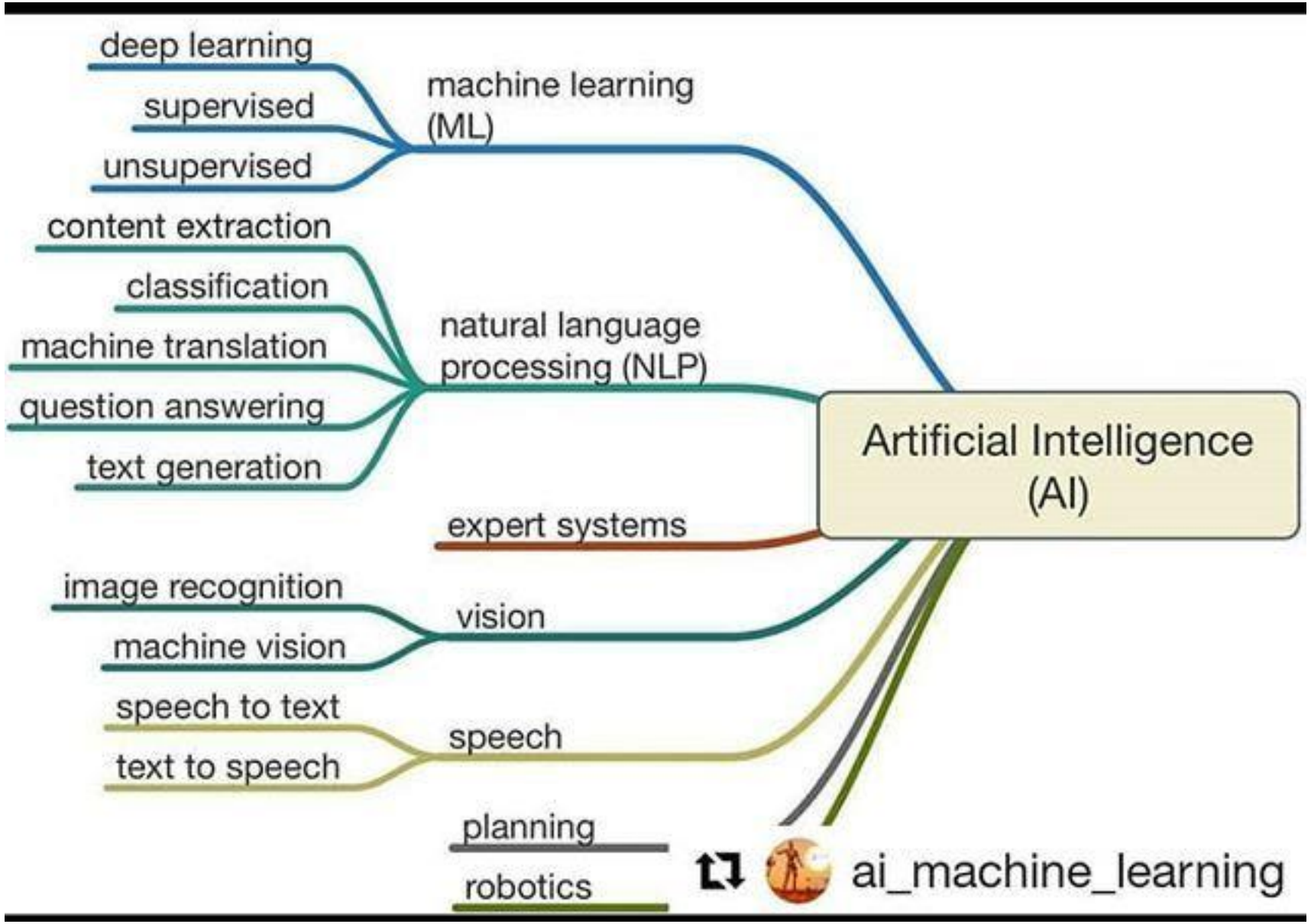


Image credits: https://www.instagram.com/p/B8qo6SWHmsD/?utm_source=ig_web_copy_link

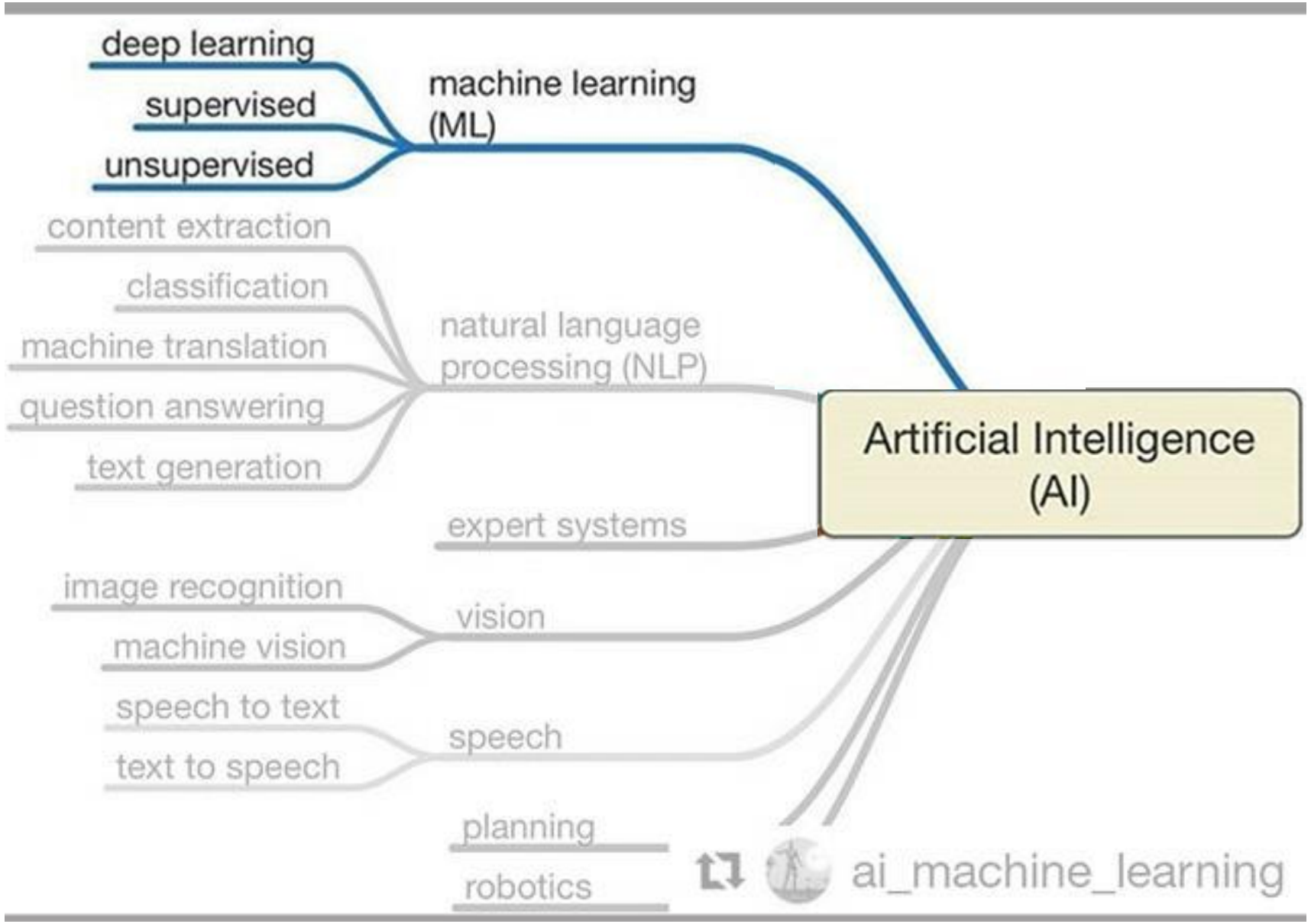


Image credits: https://www.instagram.com/p/B8qo6SWHmsD/?utm_source=ig_web_copy_link

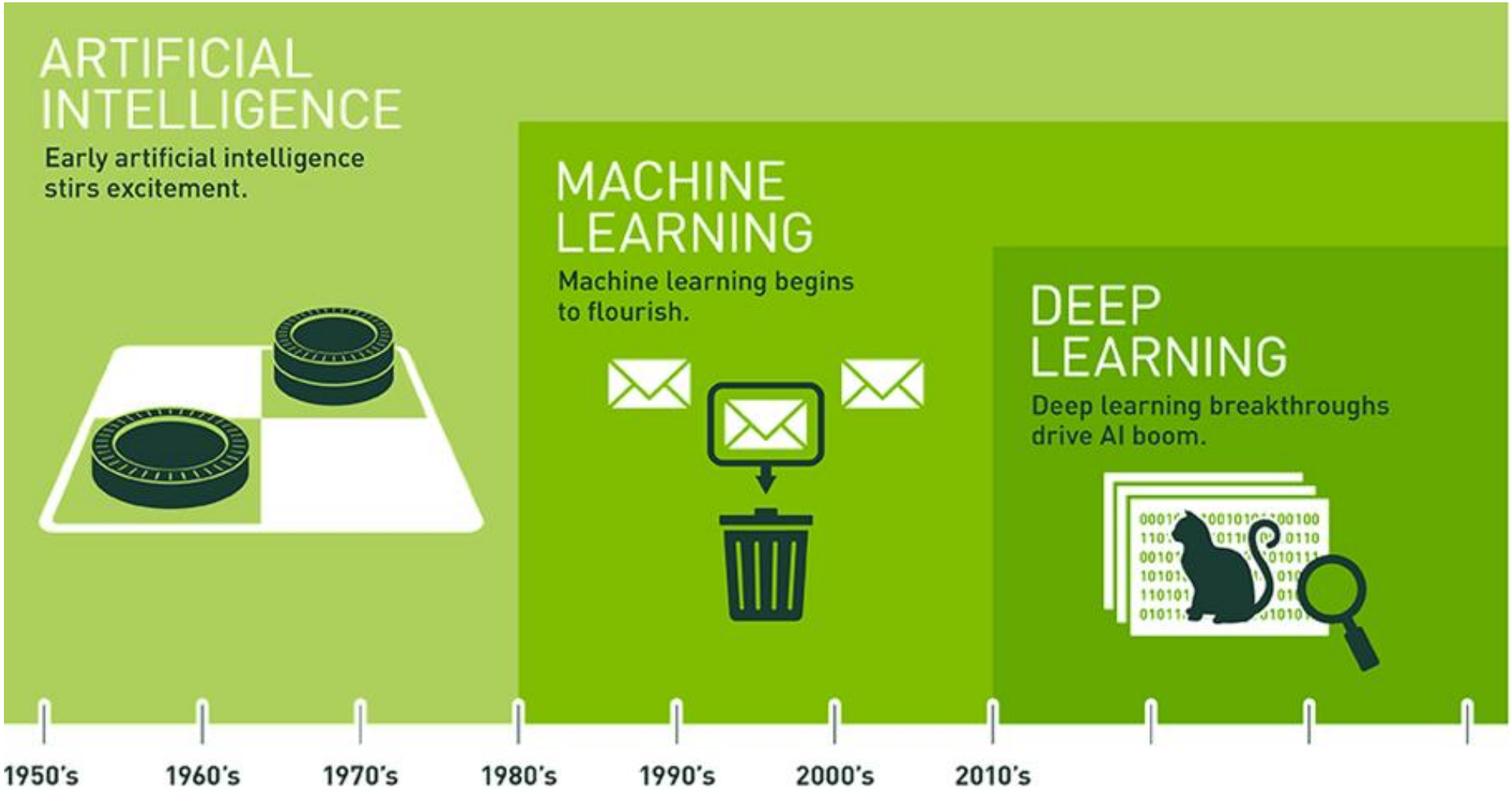


Image credits: https://blogs.nvidia.com/blog/2016/07/29/whats-difference-artificial-intelligence-machine-learning-deep-learning-ai/

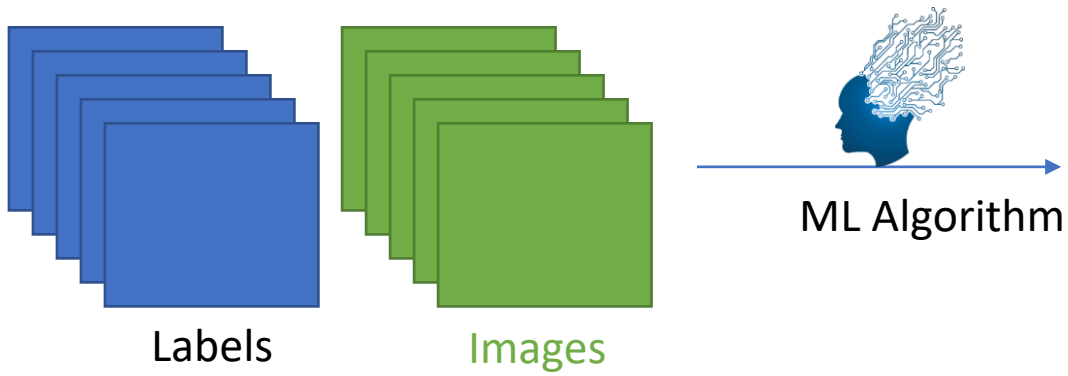
Machine Learning and Deep Learning

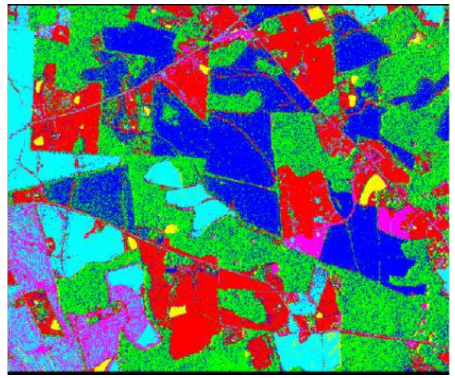
Basic concepts

Image credits : https://www.iceye.com/

Supervised Learning

In **supervised learning**, the training data that is fed to the algorithm already includes the desired solutions, called labels.
A typical supervised learning task is classification. To perform a classification of land cover, a multispectral image is used.
In this process, you select pixels that represent patterns or land cover features that you recognize, or that you can identify with help from other sources, such as aerial photos, ground truth data, or maps. Knowledge of the data, and of the classes desired, is required before classification.
The algorithm is trained with many pixels of the different desired land cover classes and, based on that training, classifies the multispectral image.





CLASSIFICATION

Supervised Learning

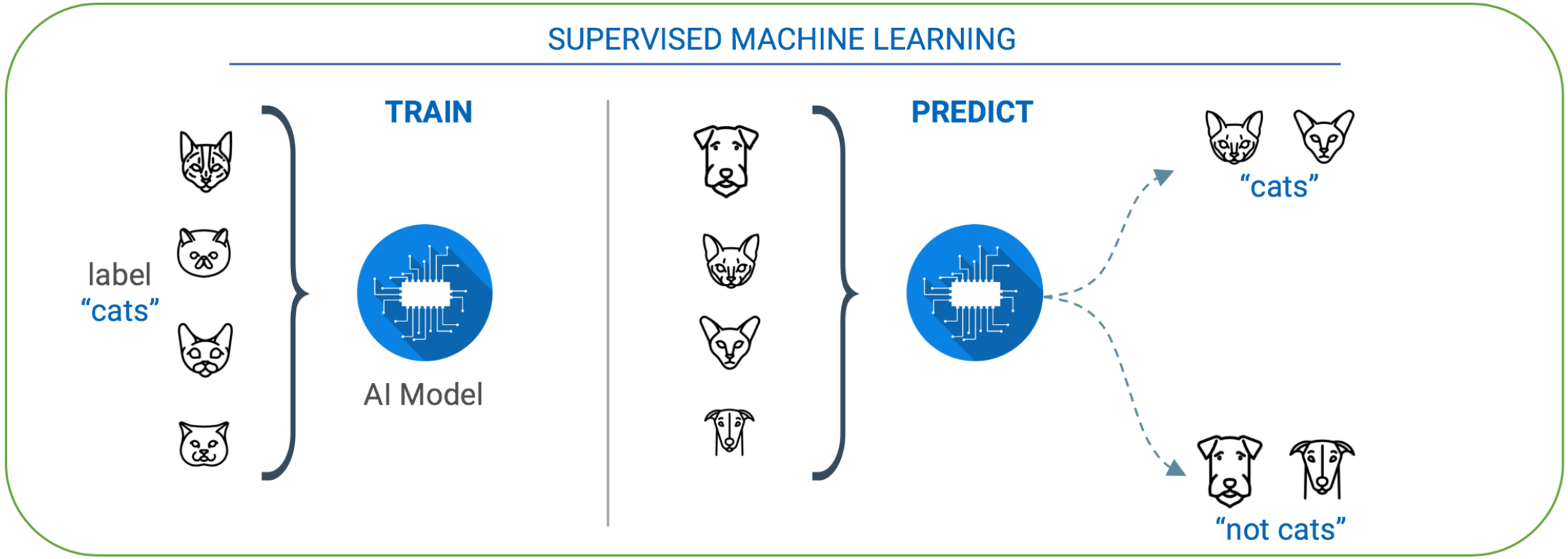
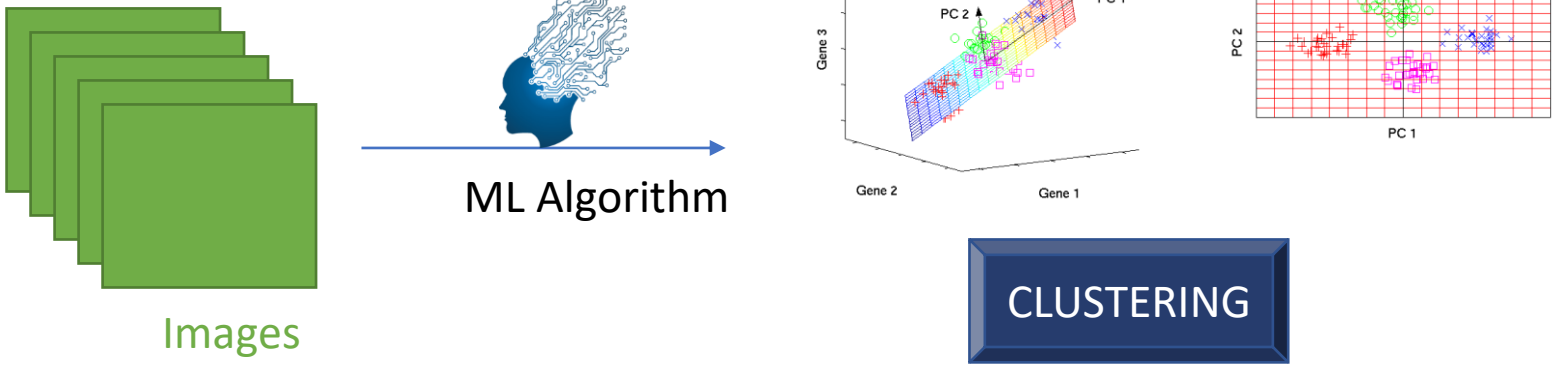


Image credits: https://www.linkedin.com/pulse/how-do-machines-learn-mallesh-murugesan/

Unsupervised Learning

In **unsupervised learning**, the system tries to learn without first training the data.
In the land cover classification example, the algorithm attempts to divide the multispectral image into a set number of classes based solely on the data in the image.
The output classes are determined by the distribution of the data in the image, not by the training data of desired land cover classes that is provided in Supervised learning. The analyst then attaches meaning to the resulting classes.
Unsupervised training is dependent upon the data itself for the definition of classes.
This method is usually used when less is known about the data before classification.



Unsupervised Learning

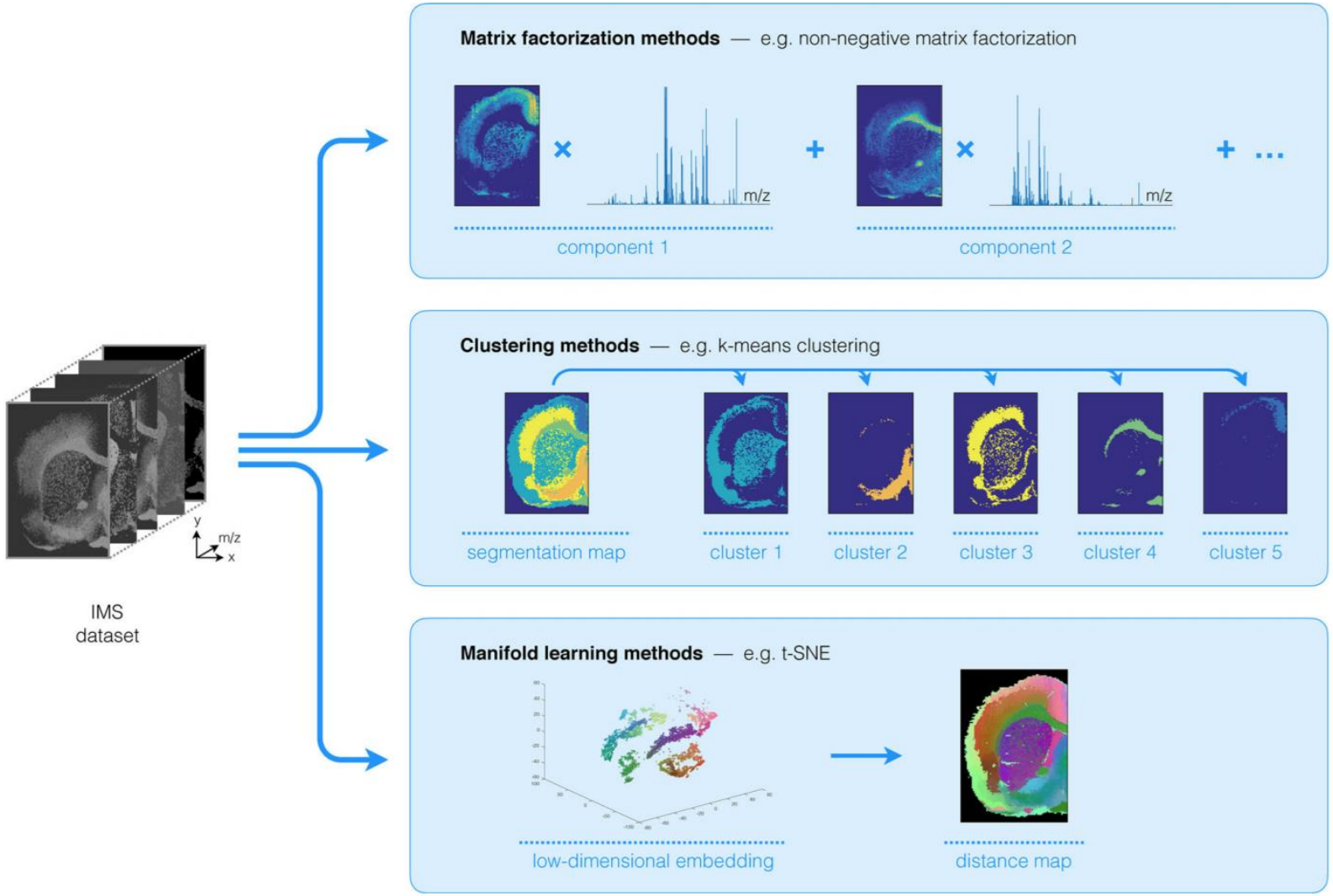
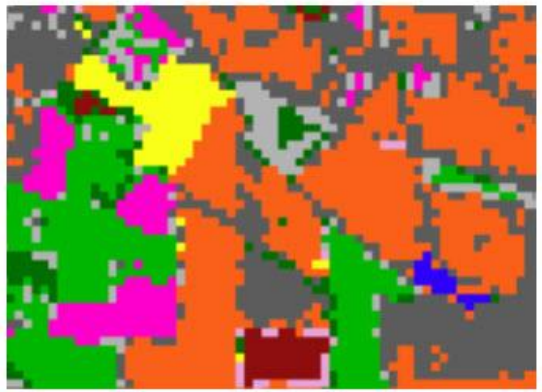
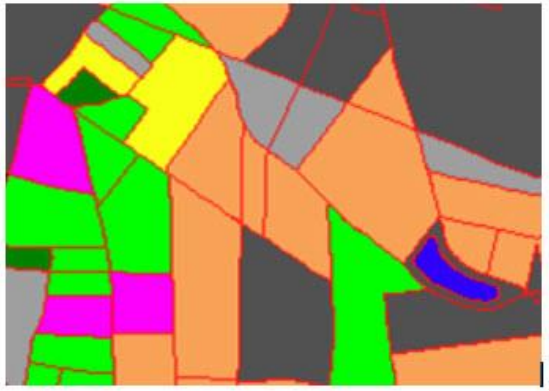


Image credits: https://www.aspect-analytics.com/media/publications/2019-10-11-unsupervised-review/

Pixel Based and Object Based



Pixel based



Object based

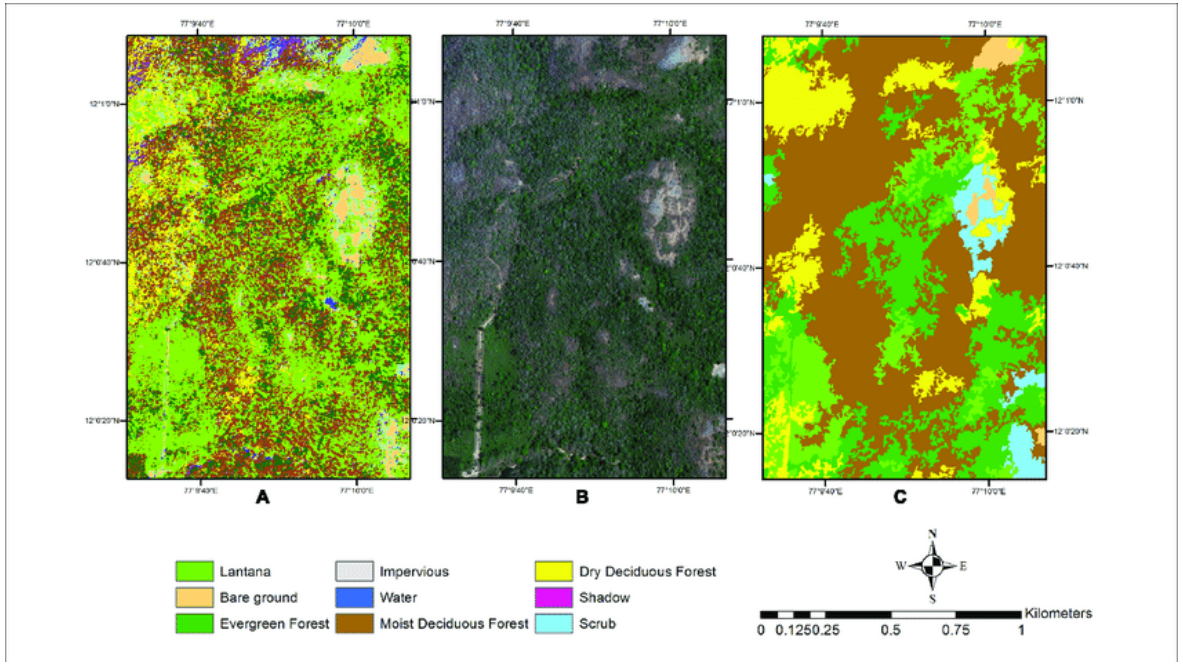


Image credits: Comparing Pixel and Object-Based Approaches to Map an Understorey Invasive Shrub in Tropical Mixed Forests

Classification tasks

Image Recognition

Image Segmentation

Object Detection

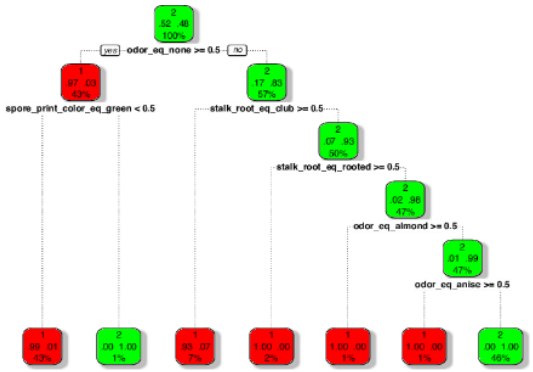
Instance Segmentation

Machine Learning and Deep Learning

Algorithm architectures

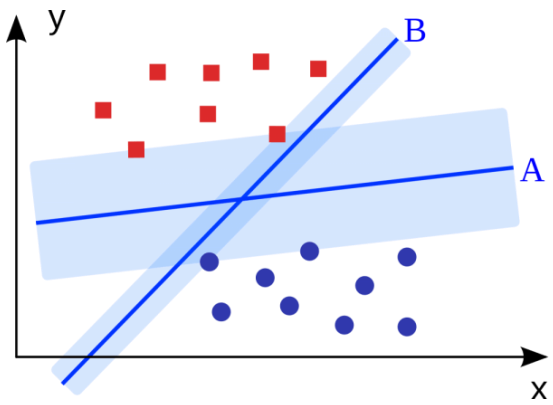
Image credits : https://www.iceye.com/

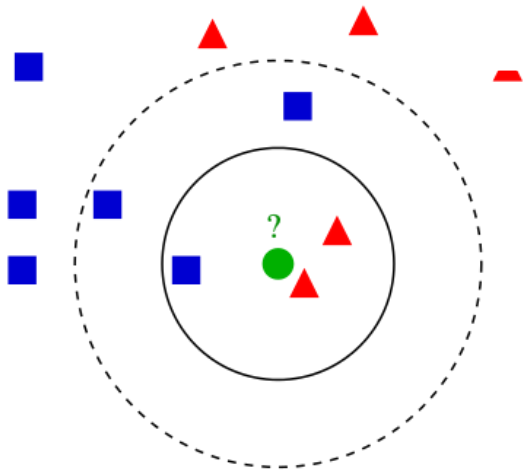
Machine Learning Methodologies



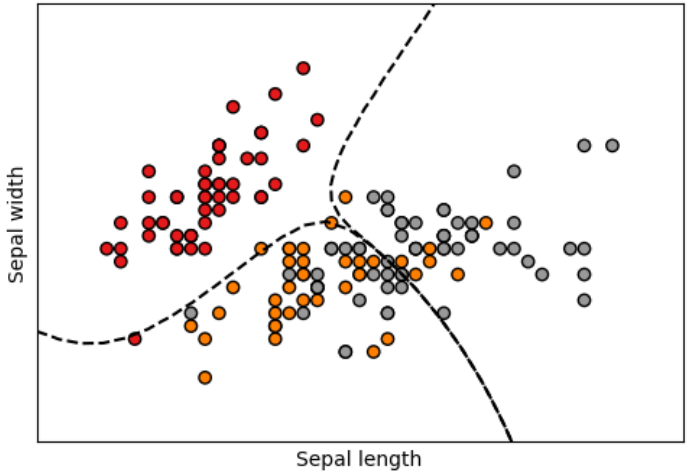
CART Decision Tree

Support Vector Machine

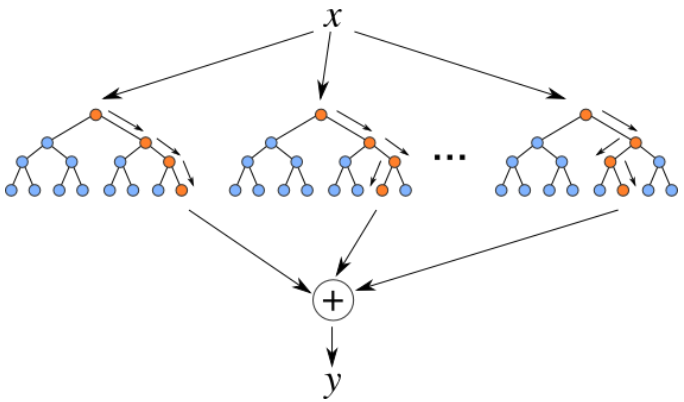




K-Nearest Neighbors

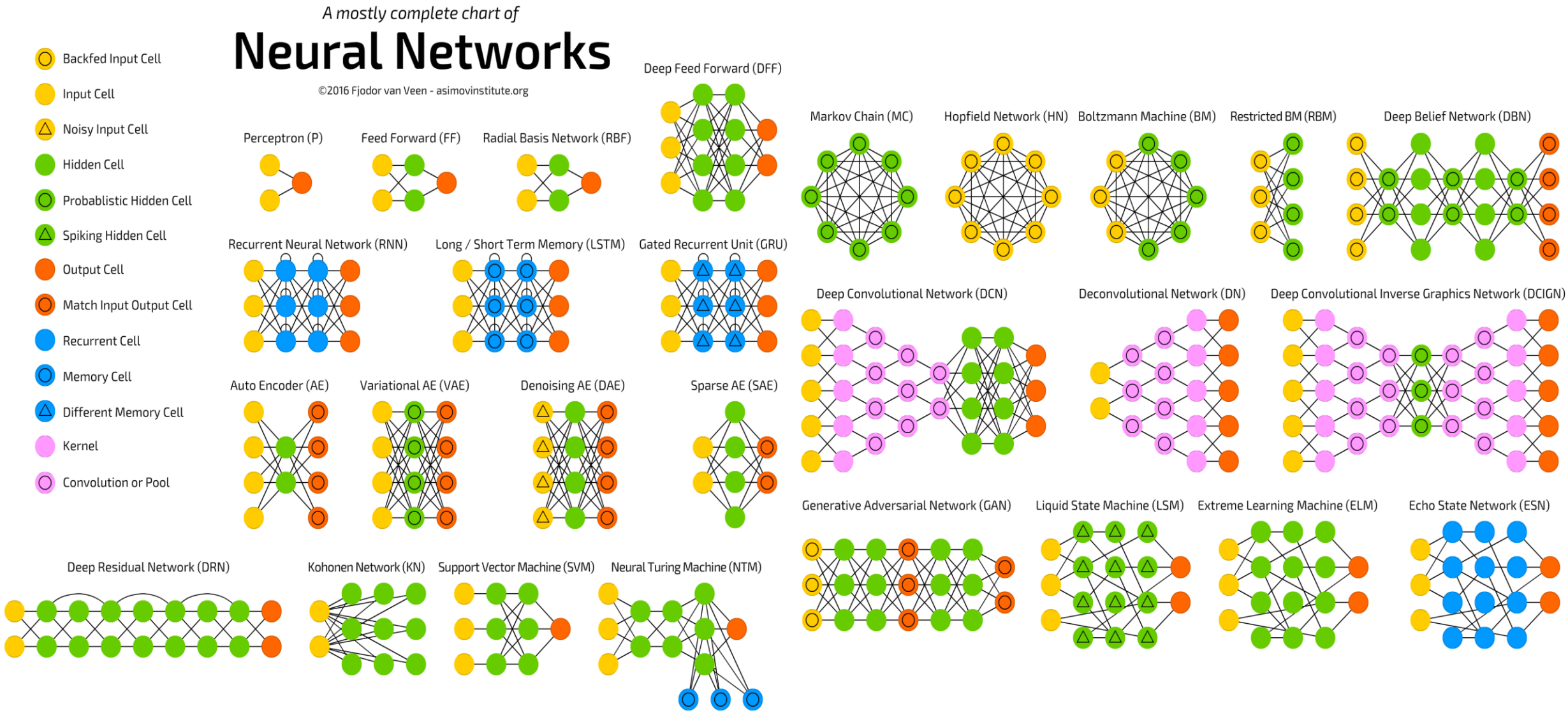


Naive Bayes



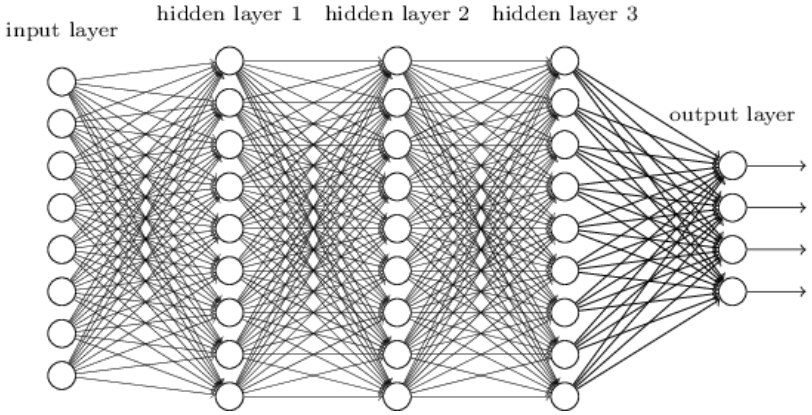
Random Forest

NN architectures

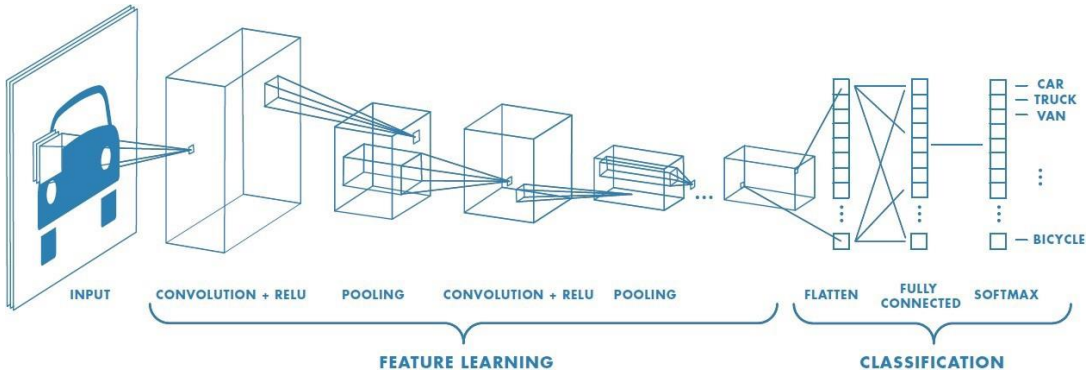


Artificial Neural Network architectures

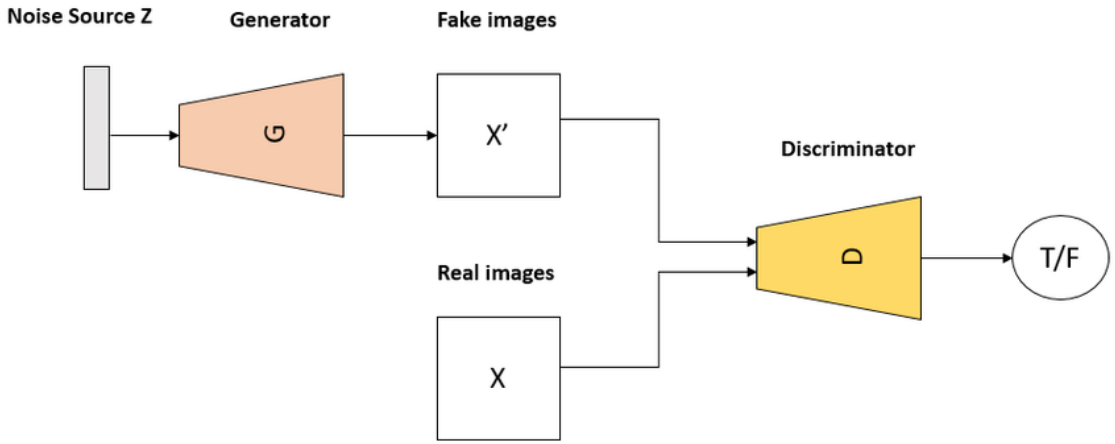
Multi Layer Perceptron



Convolutional NN



Generative Adversarial NNs



Training MLP

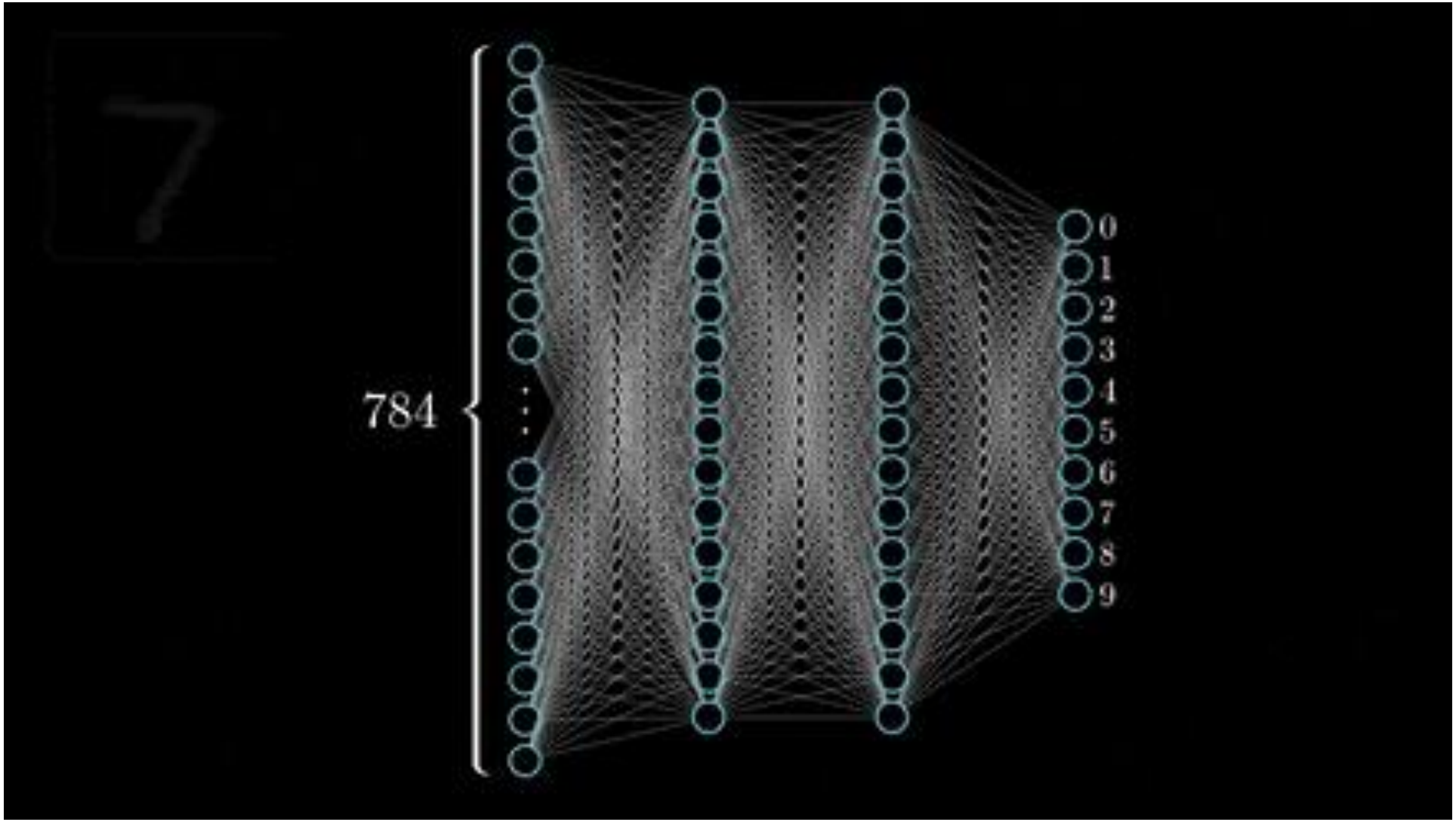


Image credits: Convolutional Neural Networks : More Dogs, cats, and frogs and cars. https://www.linkedin.com/pulse/convolutional-neural-networks-gaurav-jain/

Training MLP

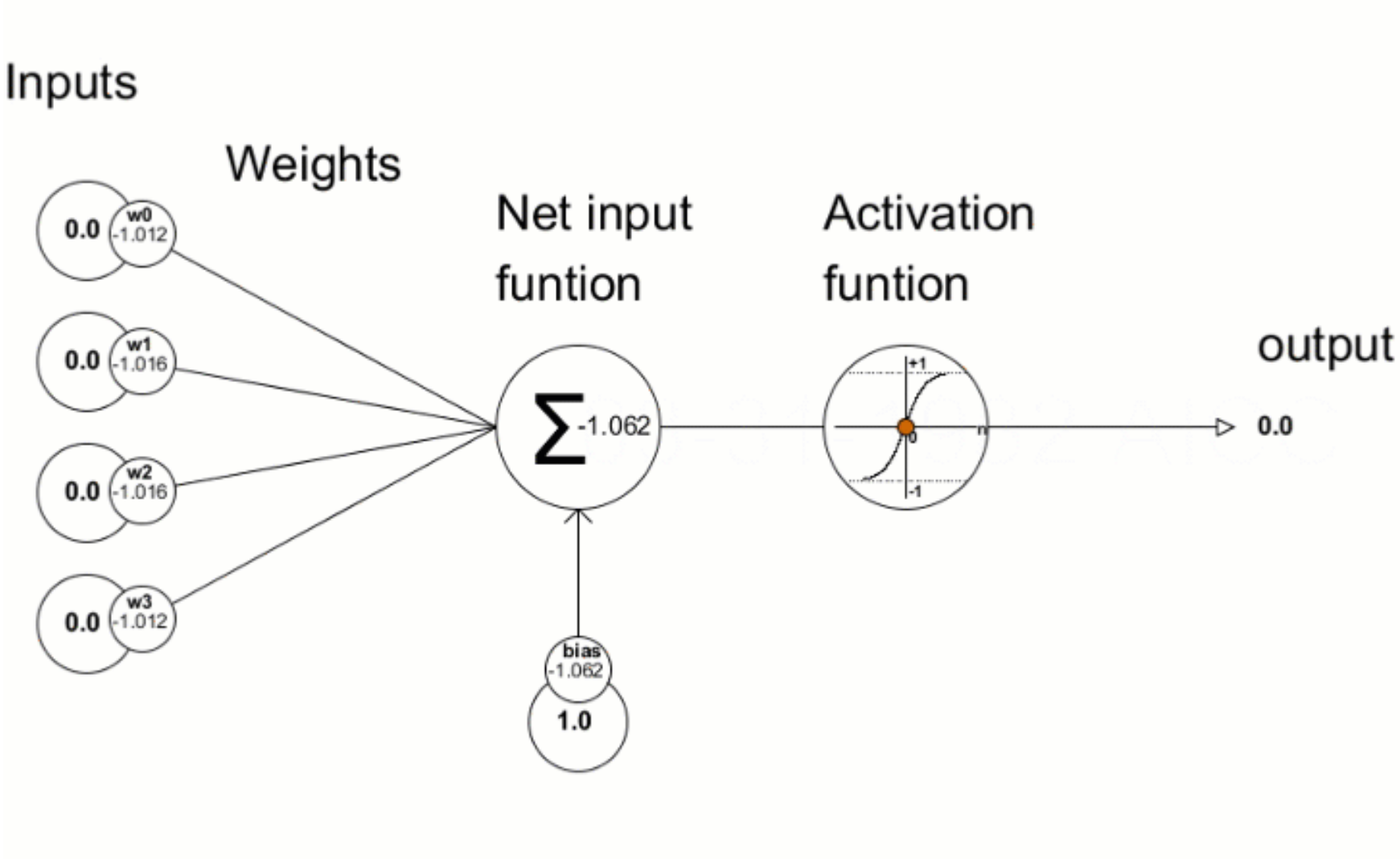
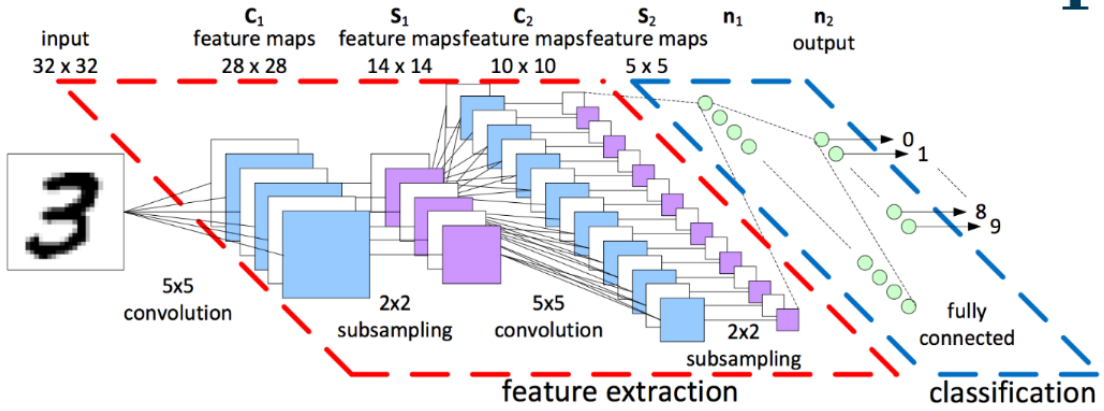
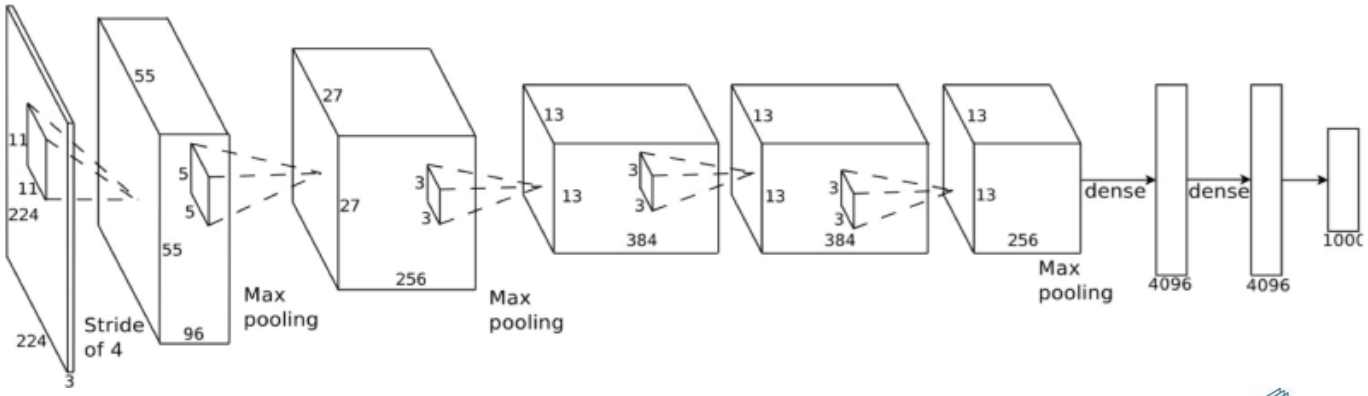
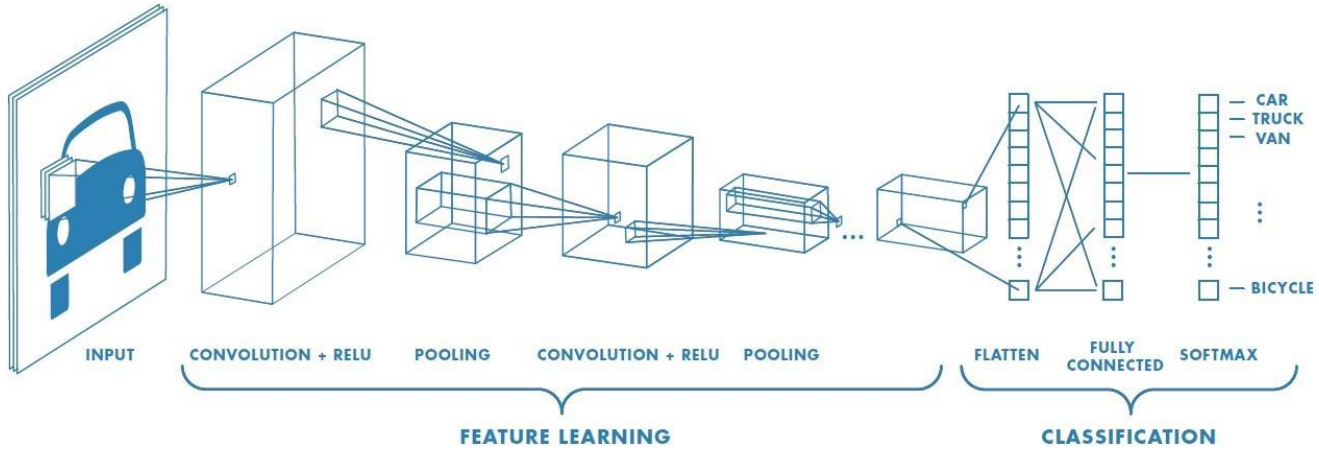


Image credits: Programming a deep neural network from scratch using mql language : https://www.mql5.com/en/blogs/post/724245

Different architectures of CNN







Convolutional NNs

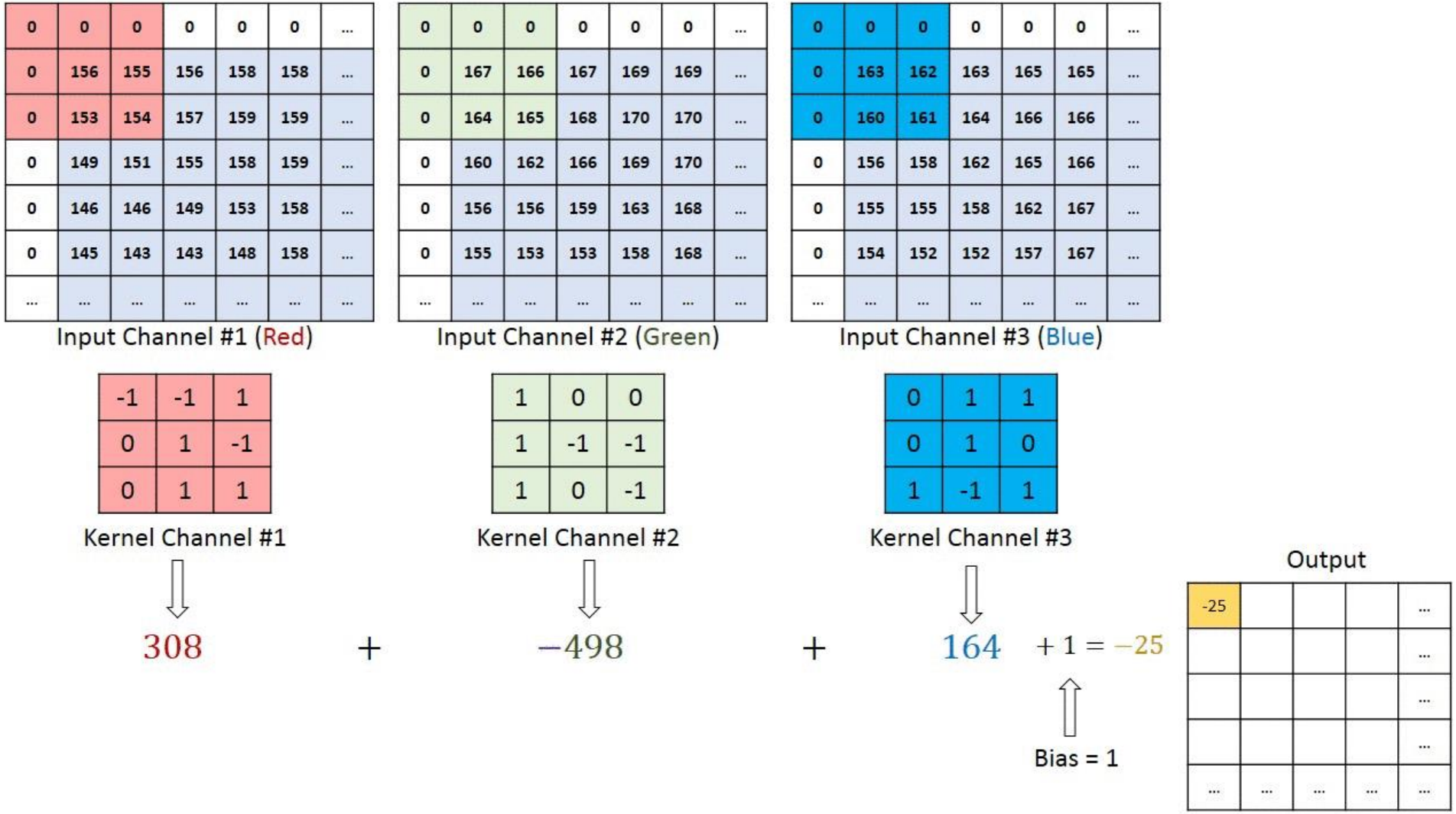


image credits: A Comprehensive Guide to Convolutional Neural Networks –https://towardsdatascience.com/a-comprehensive-guide-to-convolutional-neural-networks-the-eli5-way-3bd2b1164a53

Convolutional NNs

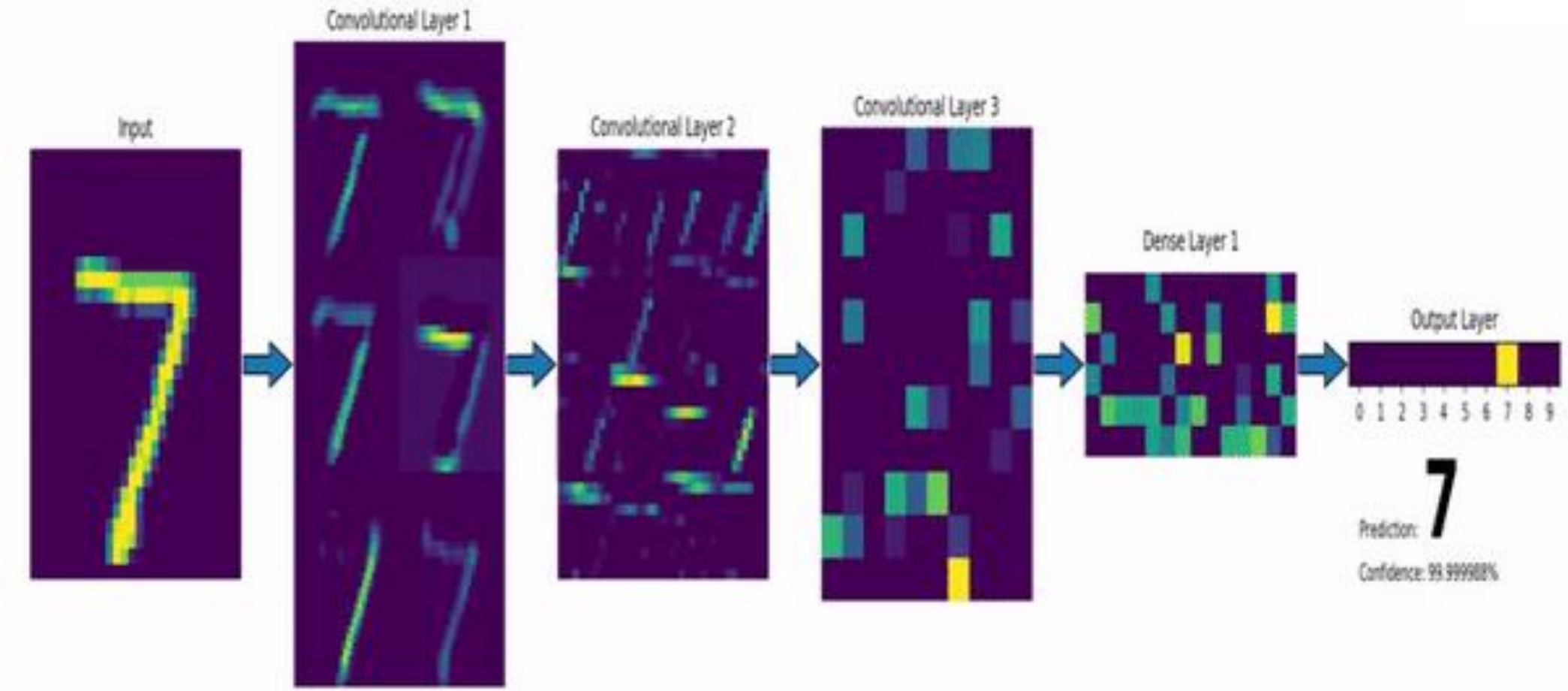
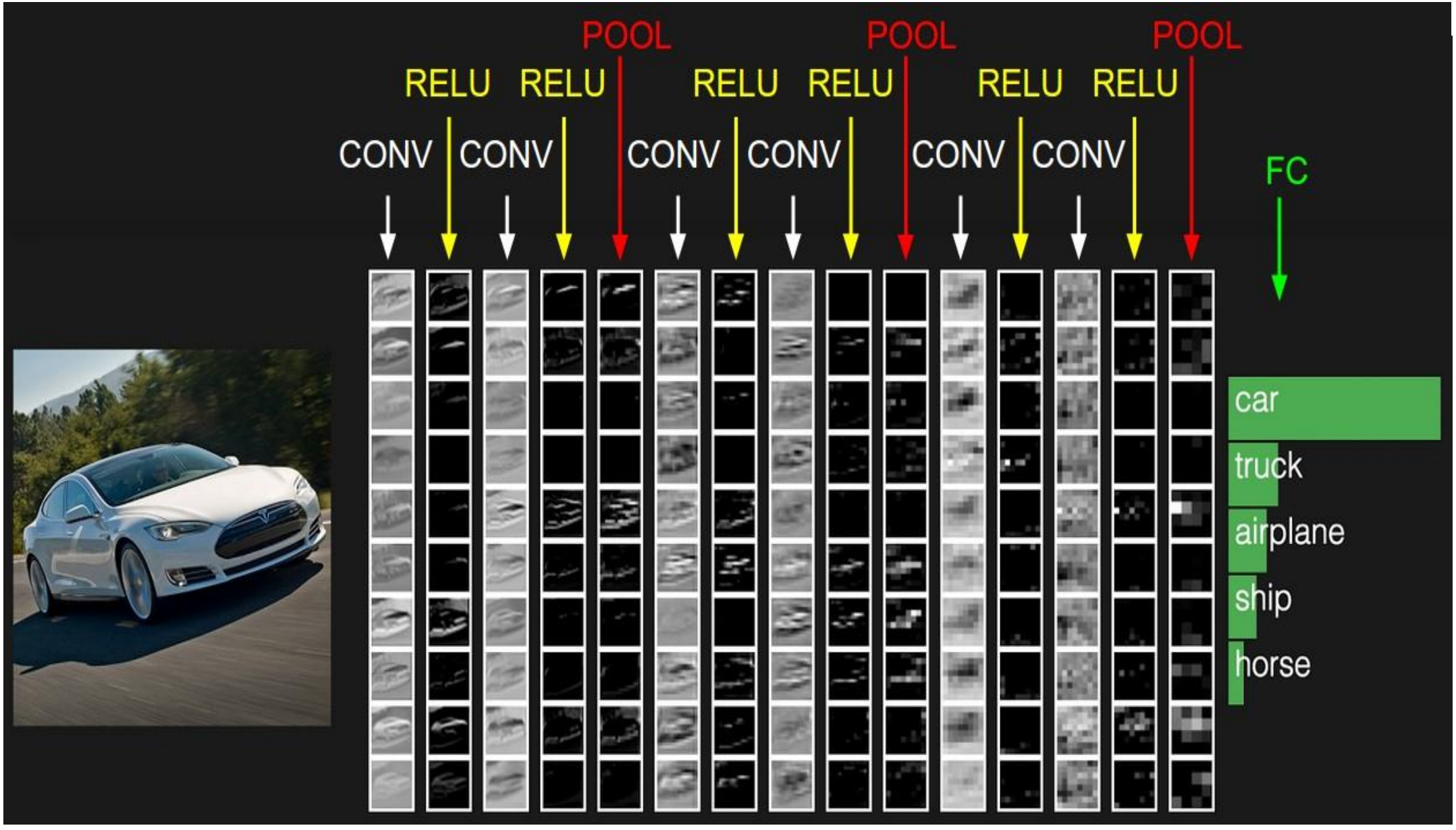


Image credits: State-of-the-Art Convolutional Neural Networks Explained — DenseNets


POOL
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CONV
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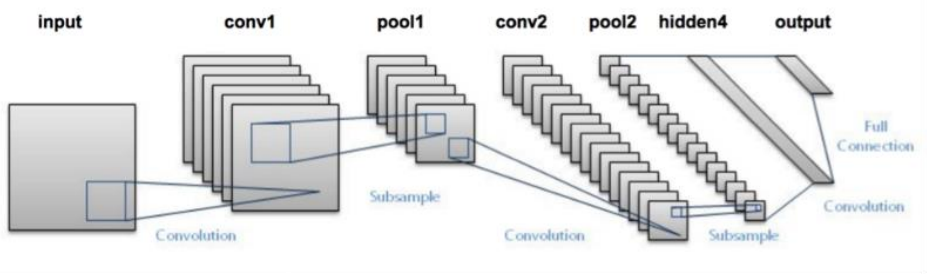
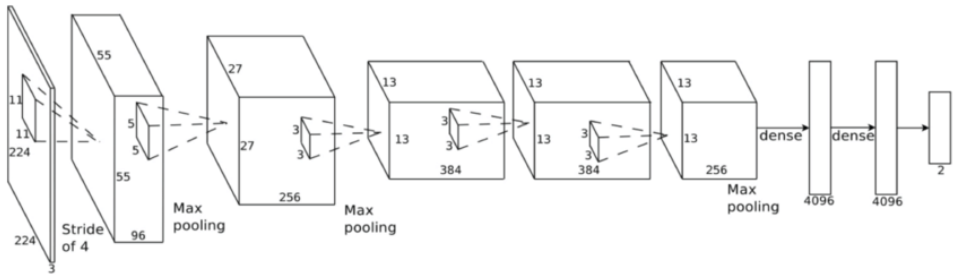
CONV
FC
car
truck
airplane
ship
horse

Most Famous CNN Architectures

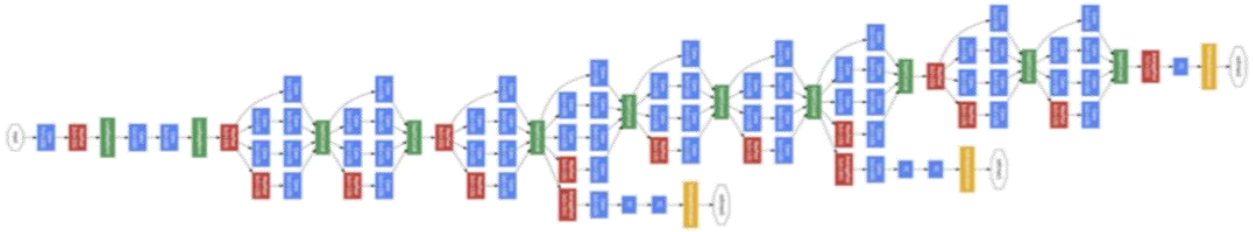
LeNet-5 (1998)



AlexNet (2012)

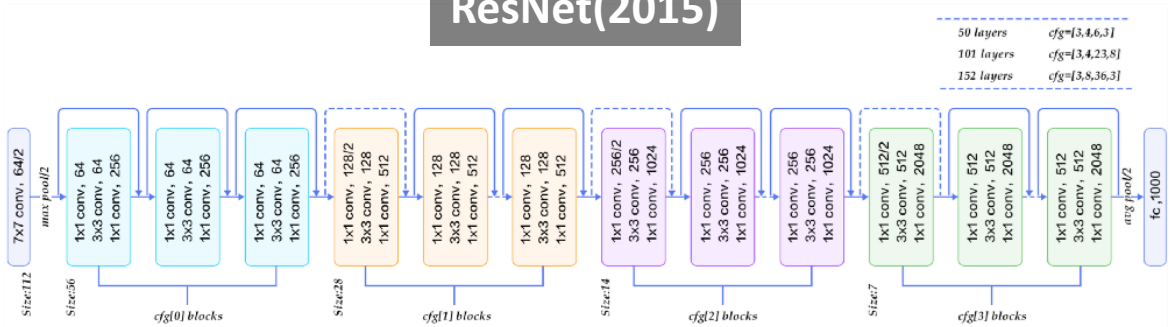


GoogleNet/Inception(2014)



VGGNet (2014)

ResNet(2015)



Generative Adversarial Neural Networks

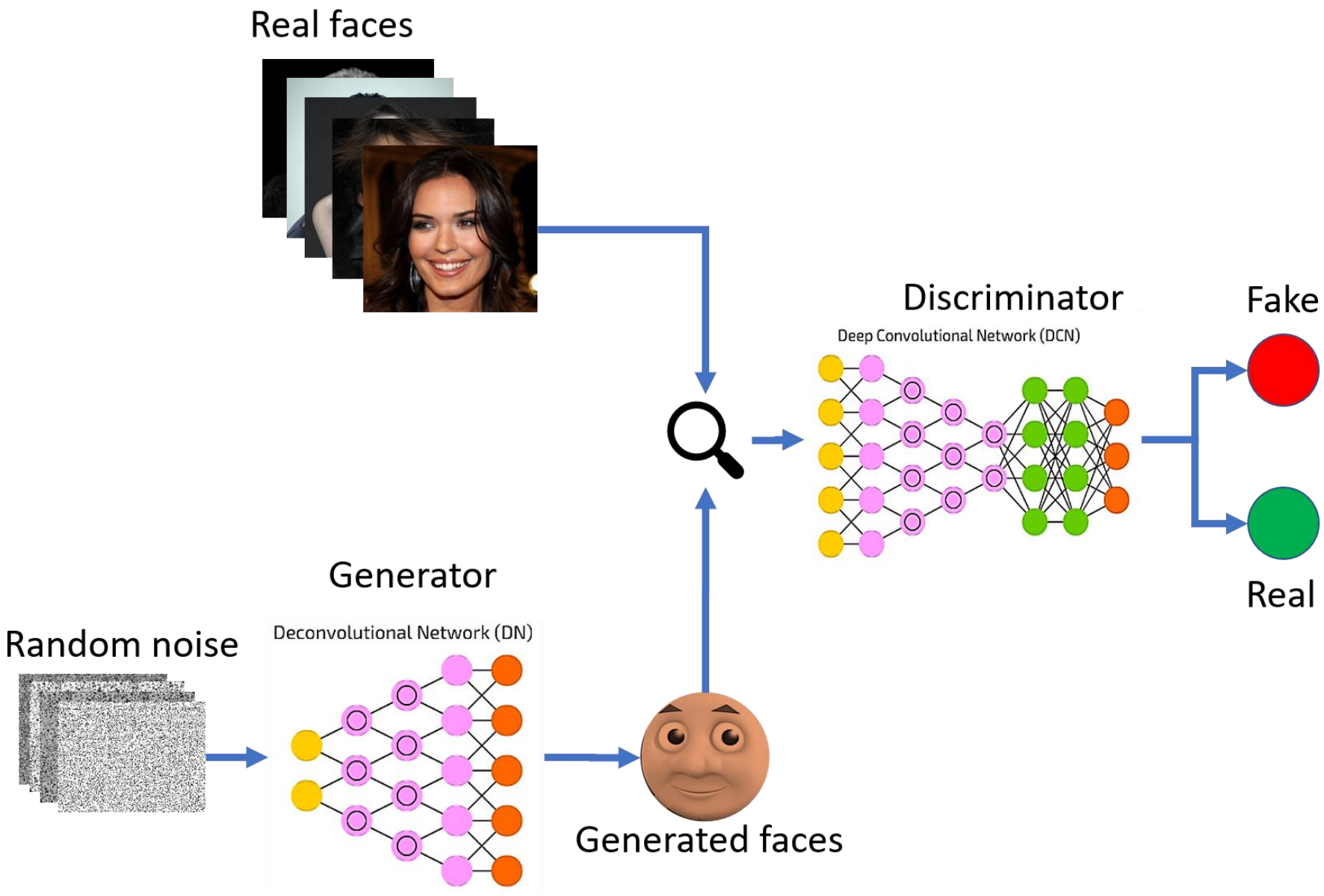


Image credits: https://www.spindox.it/en/blog/generative-adversarial-neural-networks/

Generative Adversarial Neural Networks

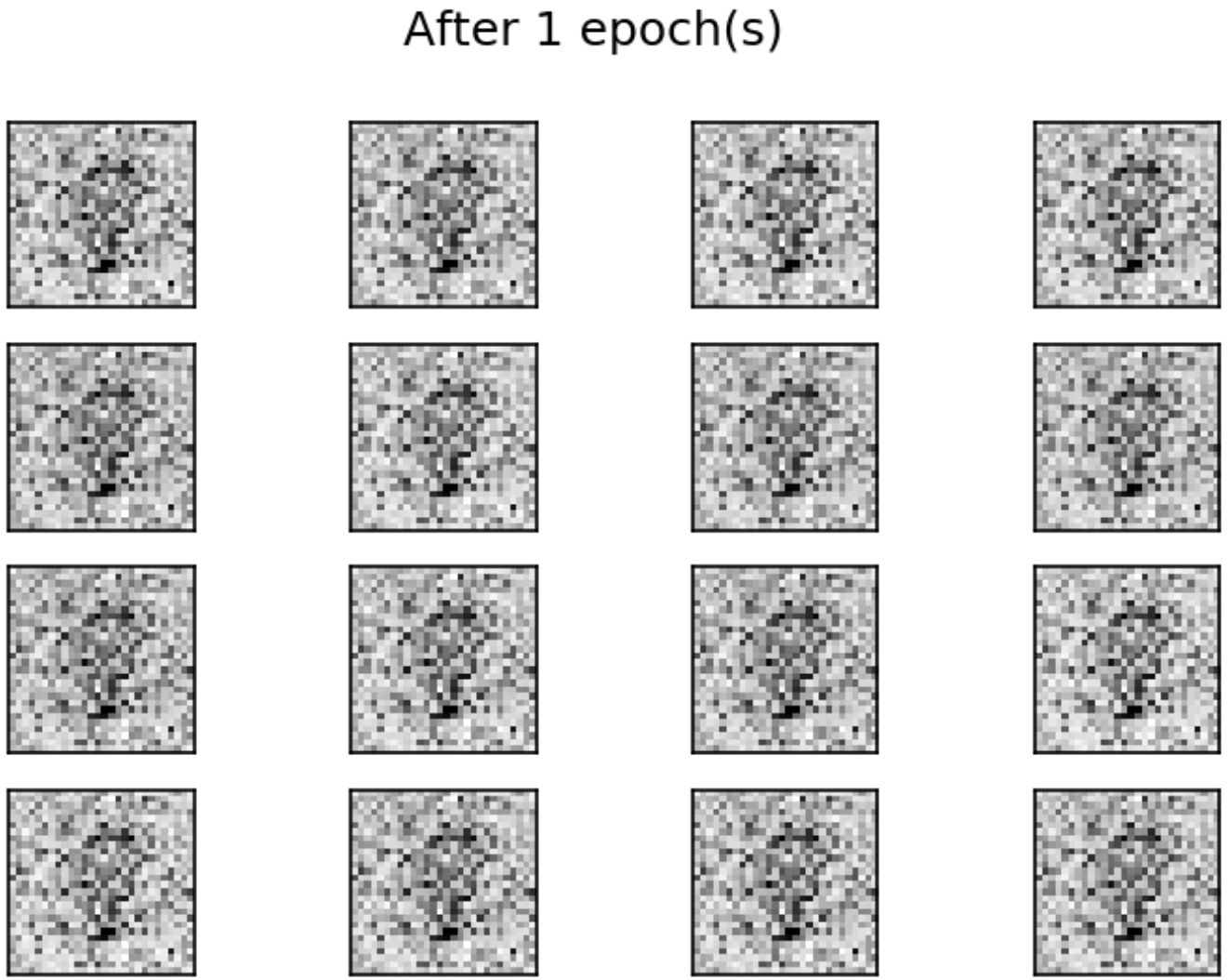


Image credits: Write your first Generative Adversarial Network Model on PyTorch

Machine Learning and Deep Learning

EO DATA

Image credits : https://www.iceye.com/

DATA

Image credits : ESA

DATA

Image credits : Copernicus

DATA

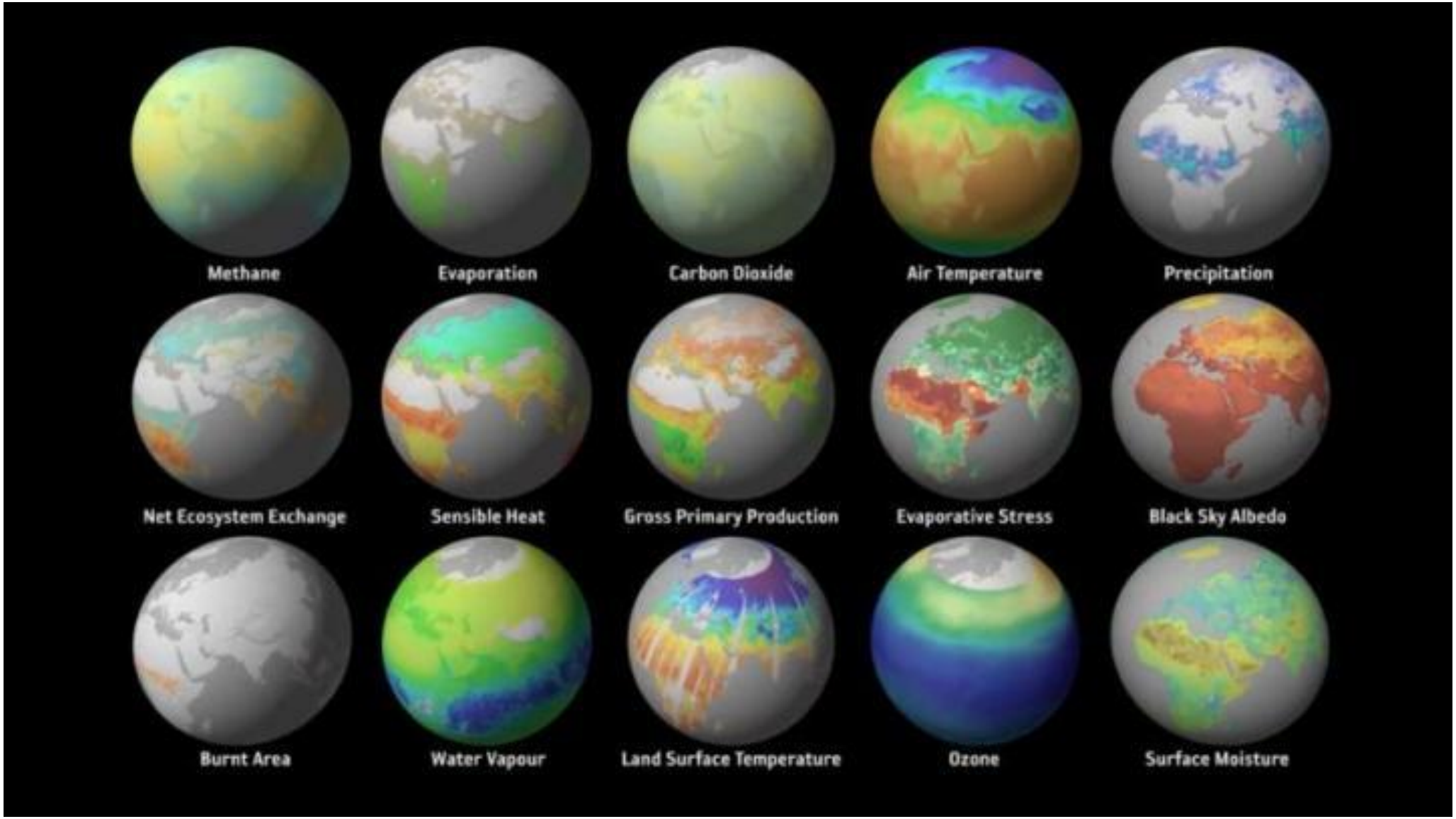


Image credits: HTTP://EARTHSYSTEMDATALAB.NET/

DATA

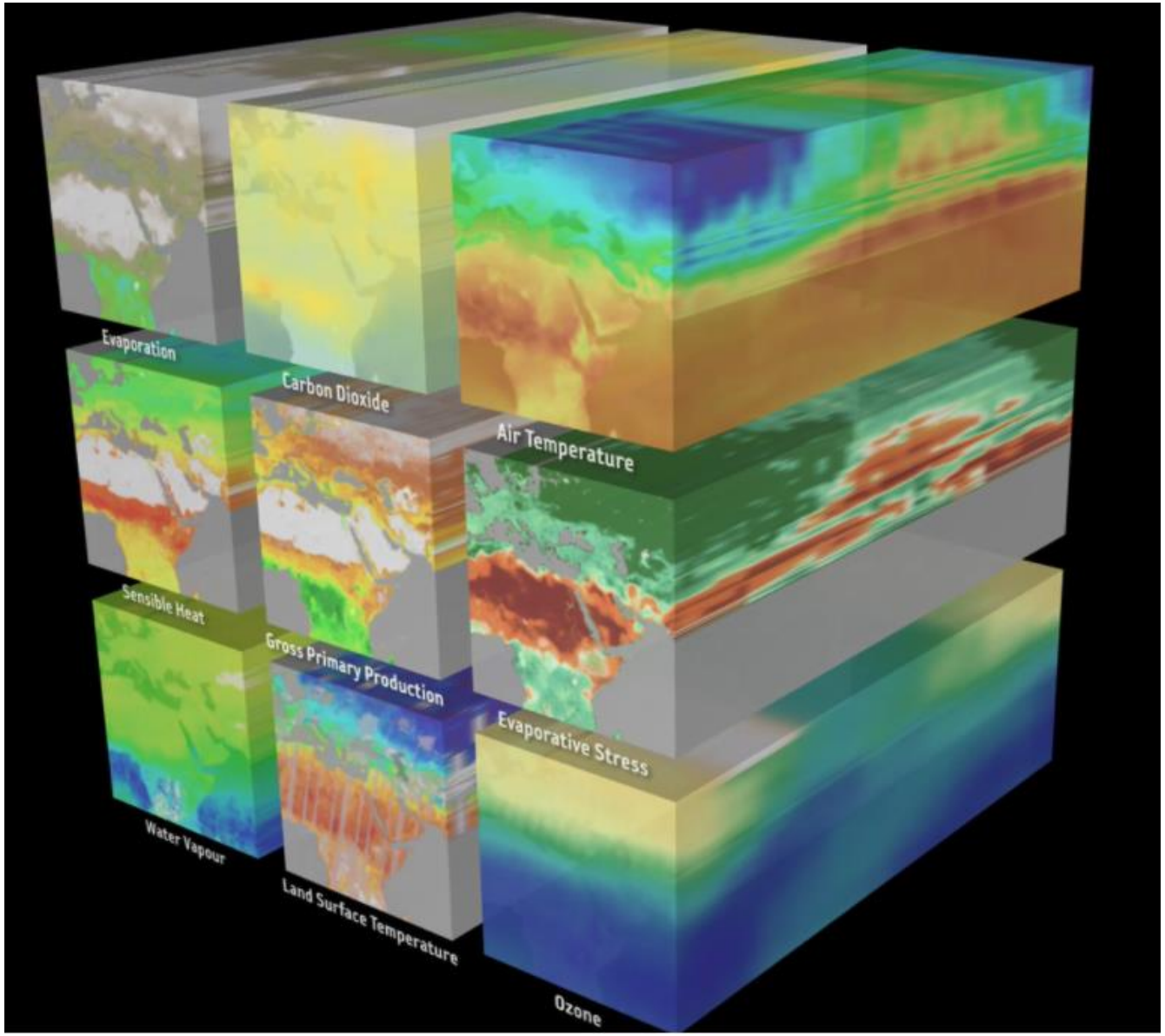
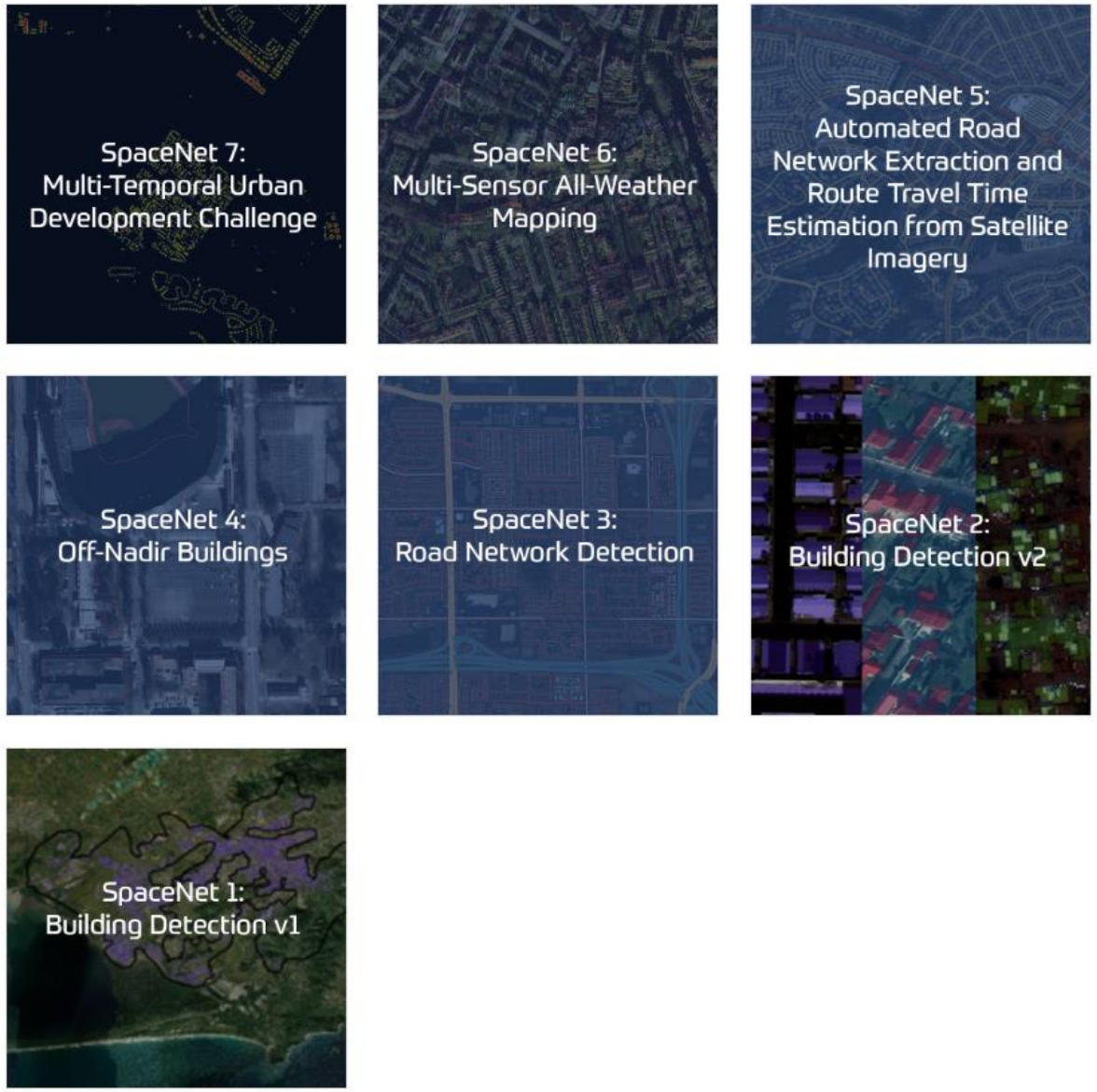


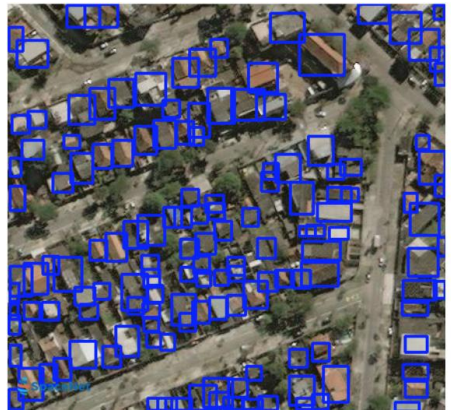
Image credits: HTTP://EARTHSYSTEMDATALAB.NET/

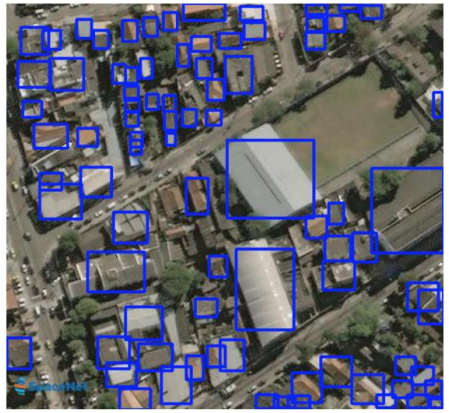
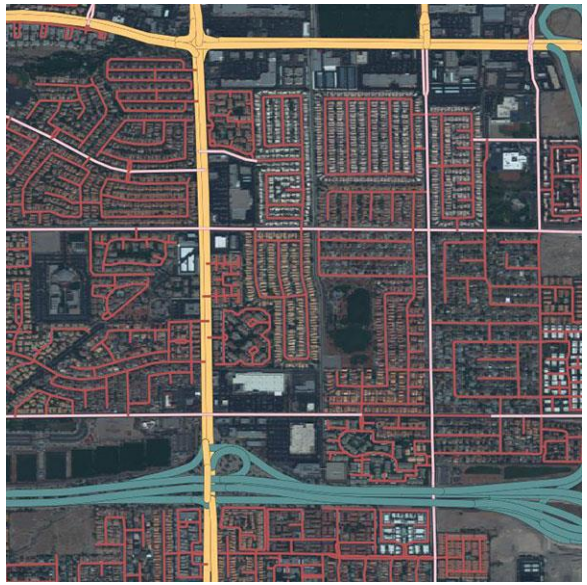
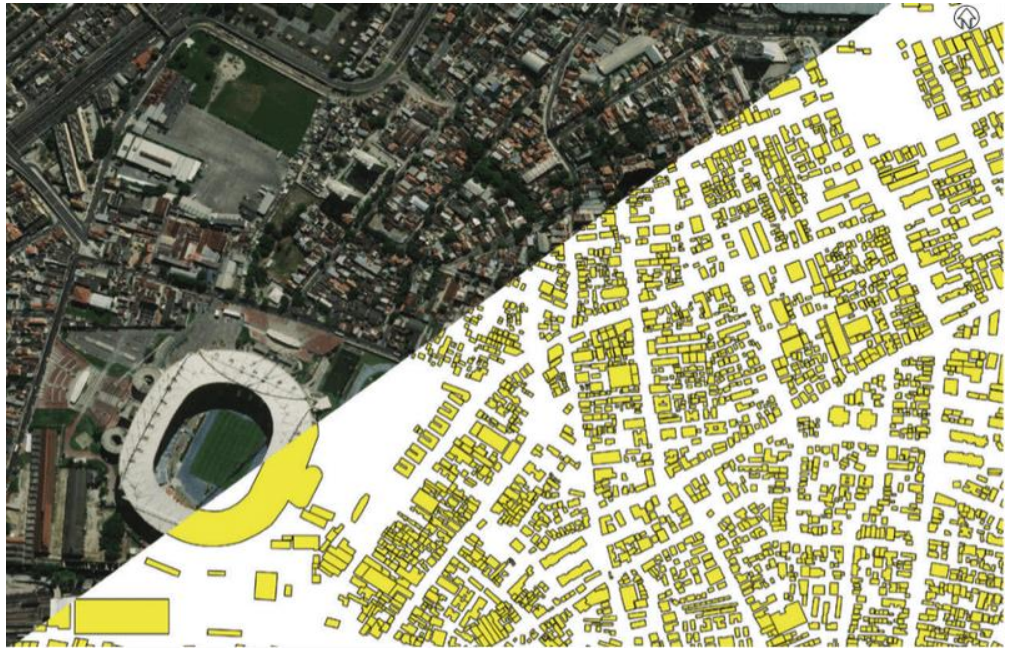
DATASET

SpaceNet Challenge Datasets



DATASET

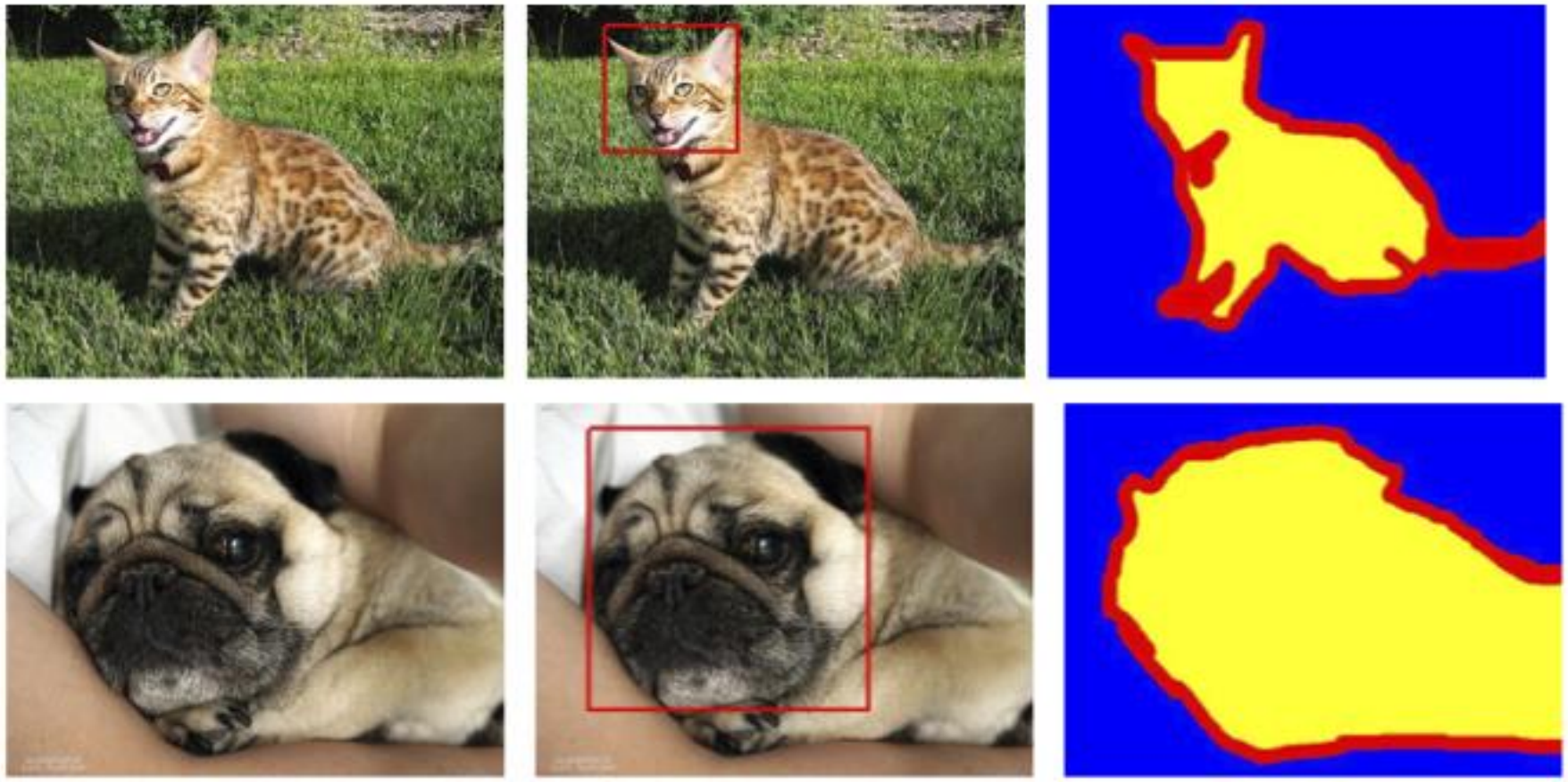


Dataset	Task	Topic	Platform	Sensor	Resolution	Example Application by Architectures
NWPU RESISC45 [155]	IR	LULC	multiple platforms	optical	high	VGG-16 [155]
EuroSAT [156]	IR	LULC	Sentinel 2	multispectral	medium	Inception-V1 and ResNet-50 [156]
BigEarthNet [116,117]	IR	LULC	Sentinel 2	multispectral	medium	ResNet-50 [117]
So2Sat LCZ42 [157]	IR	local climate zones	Sentinel 1+2	mltspectr+SAR	medium	ResNeXt-29 + CBAM [157]
SpaceNet1 [158]	IS	building footprints	-	multispectral	low	VGG-16 + MNC [158,159]
SpaceNet2 [160]	IS	building footprints	WorldView3	multispectral	high	U-Net (modified: inputdepth = 13) [160]
SpaceNet3 [161]	IS	road network	WorldView3	multispectral	high	ResNet-34 + U-Net [161]
SpaceNet4 [162]	IS	building footprints	WorldView2	multispectral	high	SE-ResNeXt-50/101 + U-Net [162]
SpaceNet5 [163]	IS	road network	WorldView3	multispectral	high	ResNet-50 + U-Net [164], SE-ResNeXt-50 + U-Net [163]
SpaceNet6 [165,166]	IS	building footprints	WordView2 + Capella36	mltspectr + SAR	high	VGG-16 + U-Net [166]
ISPRS 2D Sem. Lab. [126]	IS	multiple classes	plane	multispectral	very high	U-Net, DeepLabV3+, PSPNet, LANet (patch attention module) [167], MobileNetV2(with atrous conv) + Dual path encoder + SE modules [168]
DeepGlobe-Road [169]	IS	road network	WorldView3	multispectral	high	D-LinkNet (ResNet-34 + U-Net with atrous decoder) [170], ResNet-34 + U-Net [171]
DeepGlobe-Building [169]	IS	building footprints	WorldView3	multispectral	high	ResNet-18 + Multitask U-Net [172], WideResNet-38 + U-Net [173]
DeepGlobe-LCC [169]	IS	LULC	WorldView3	multispectral	high	Dense Fusion Classmate Network (DenseNet + FCN varaint) [174], Deep Aggregation Net (ResNet + DeepLabV3 + variant) [175]
WHU Building [176]	IS	building footprints	multiple platforms	optical	high	VGG-16 + ASPP + FCN [177]
INRIA [178]	IS	building footprints	multiple platforms	multispectral	very high	ResNet-50 + SegNet variant [179], U-Net variant [180]
DLR-SkyScapes [181]	IS	multiple classes	helicopter	optical	very high	SkyScapesNet (custom design [181])
NWPU VHR-10 [182]	OD	multiple classes	airborne platforms	optical	very high	DarkNet + YOLO (modified: VaryBlock) [183], ResNet-101 + FPN (modified: Densely connected top-down path) + fully convolutional detector head [184]
COWC [185]	OD	vehicle detection	airborne platforms	optical	very high	VGG16 + SSD + correlation alignment domain adaptation [186]
CARPK [187]	OD	vehicle detection	drone	optical	very high	VGG16 + LPN (Layout Proposal Net) [187]
DLR 3K Munich [188]	OD	vehicle detection	airborne platform	optical	very high	ShuffleDet (ShuffleNet + modified SSD) [189]
DOTA [100]	OD	multiple classes	airborne platforms	optical	very high to high	ResNet-50+improved Cascade R2CNN see leader board of [100], ResNet-101/FPN + Fater R-CNN OBB + RoI transformer [138]
DIOR [24]	OD	multiple classes	multiple platforms	optical	heigh to medium	ResNet-101 + PAnet and ResNet-101 + RetinaNet [24]

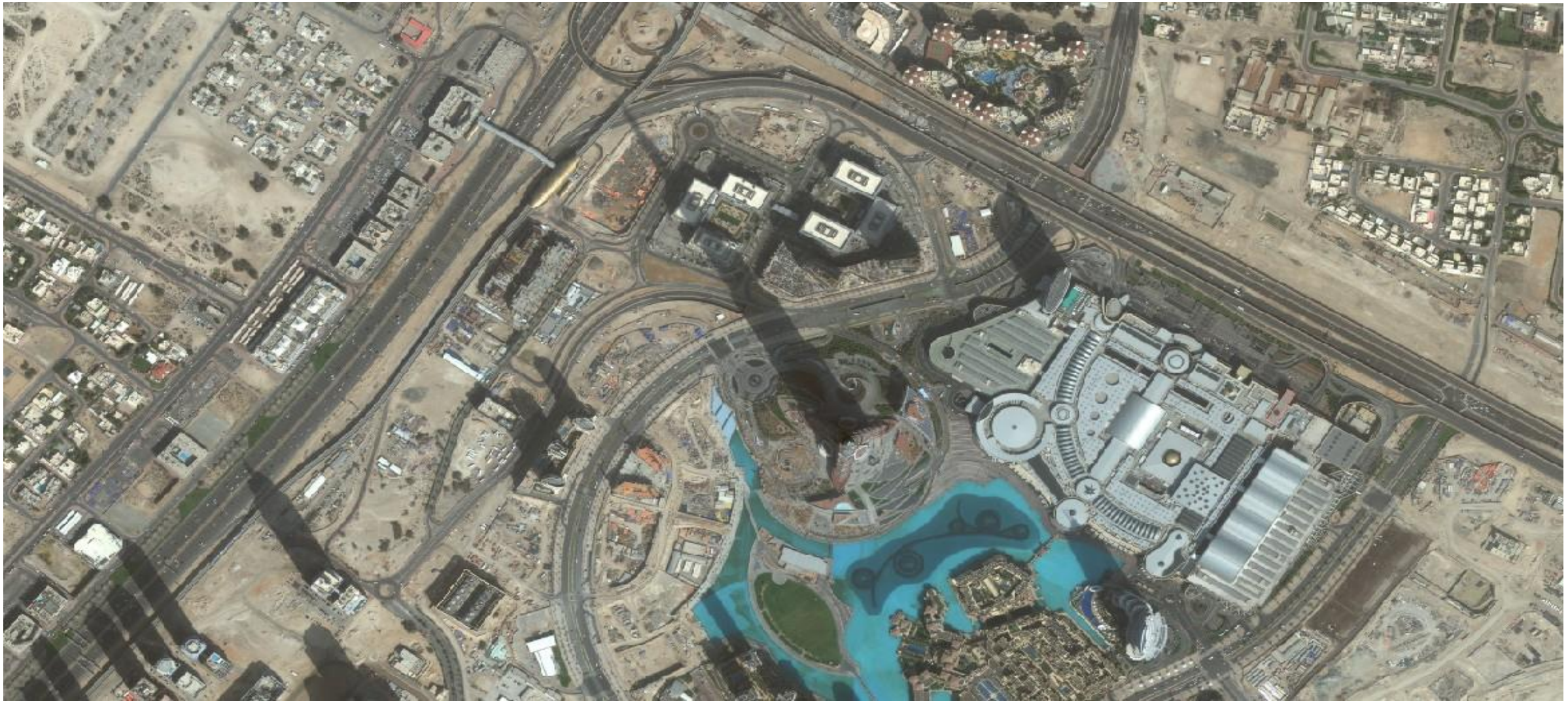
Credits: Object Detection and Image Segmentation with Deep Learning on Earth Observation Data: A Review-Part I: Evolution and Recent Trends

Satellite Images (NO DOGS NO CATS)



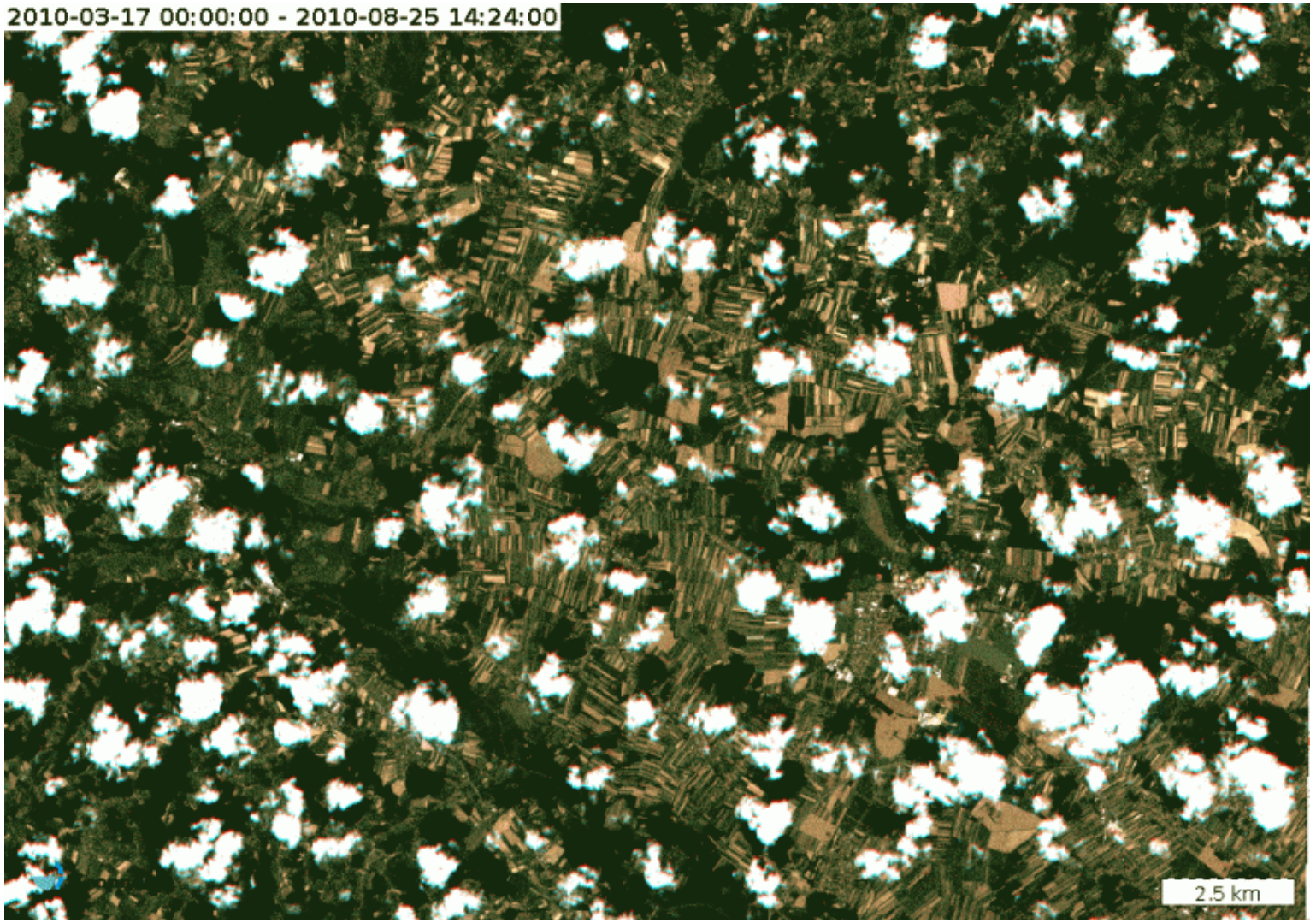
CHALLENGES

Satellite Images (SHADOWS and OFF-NADIR angles)



CHALLENGES

Satellite Images (CLOUDS)

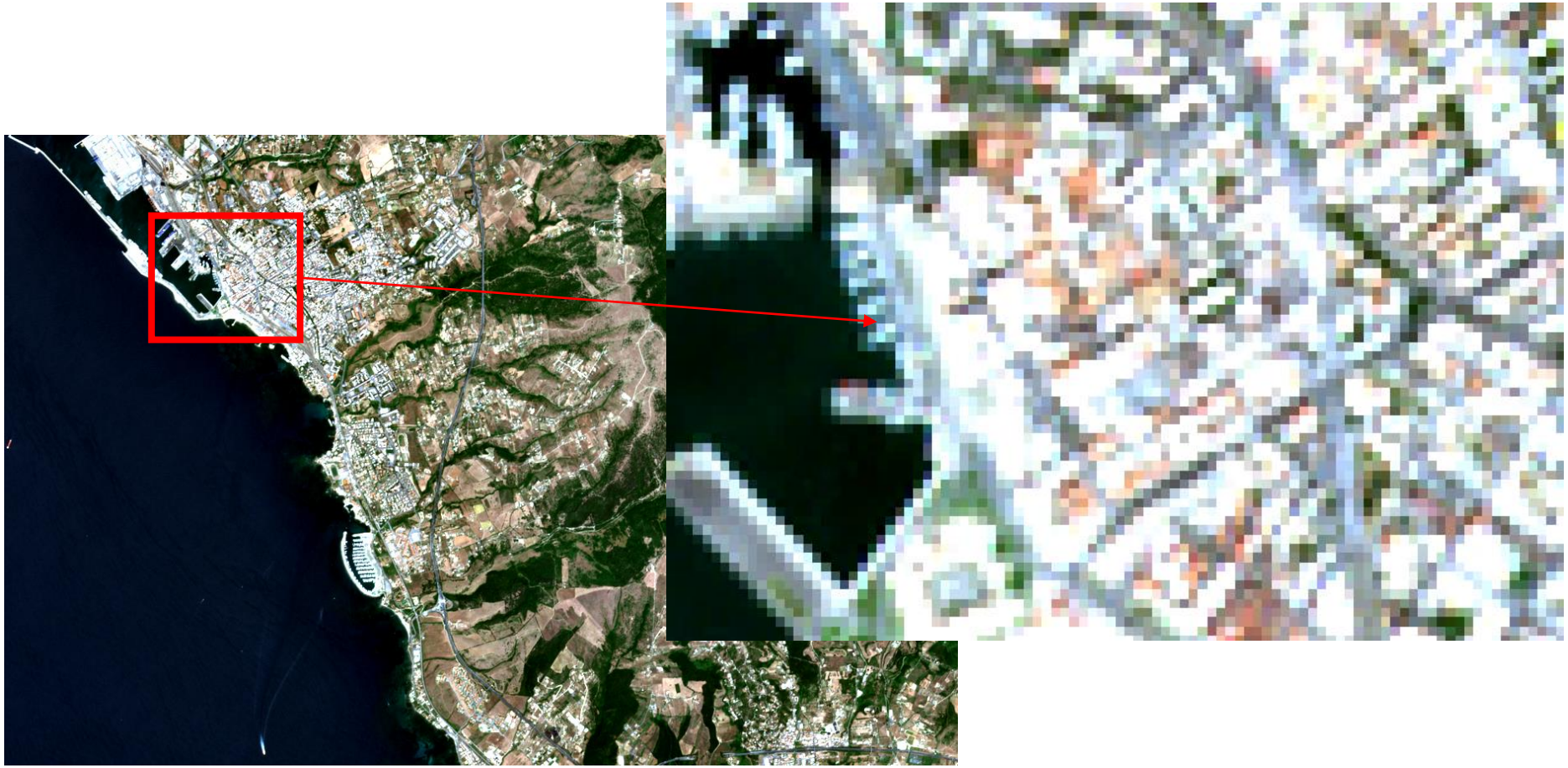


CHALLENGES

Satellite Images (PIXEL RESOLUTION)

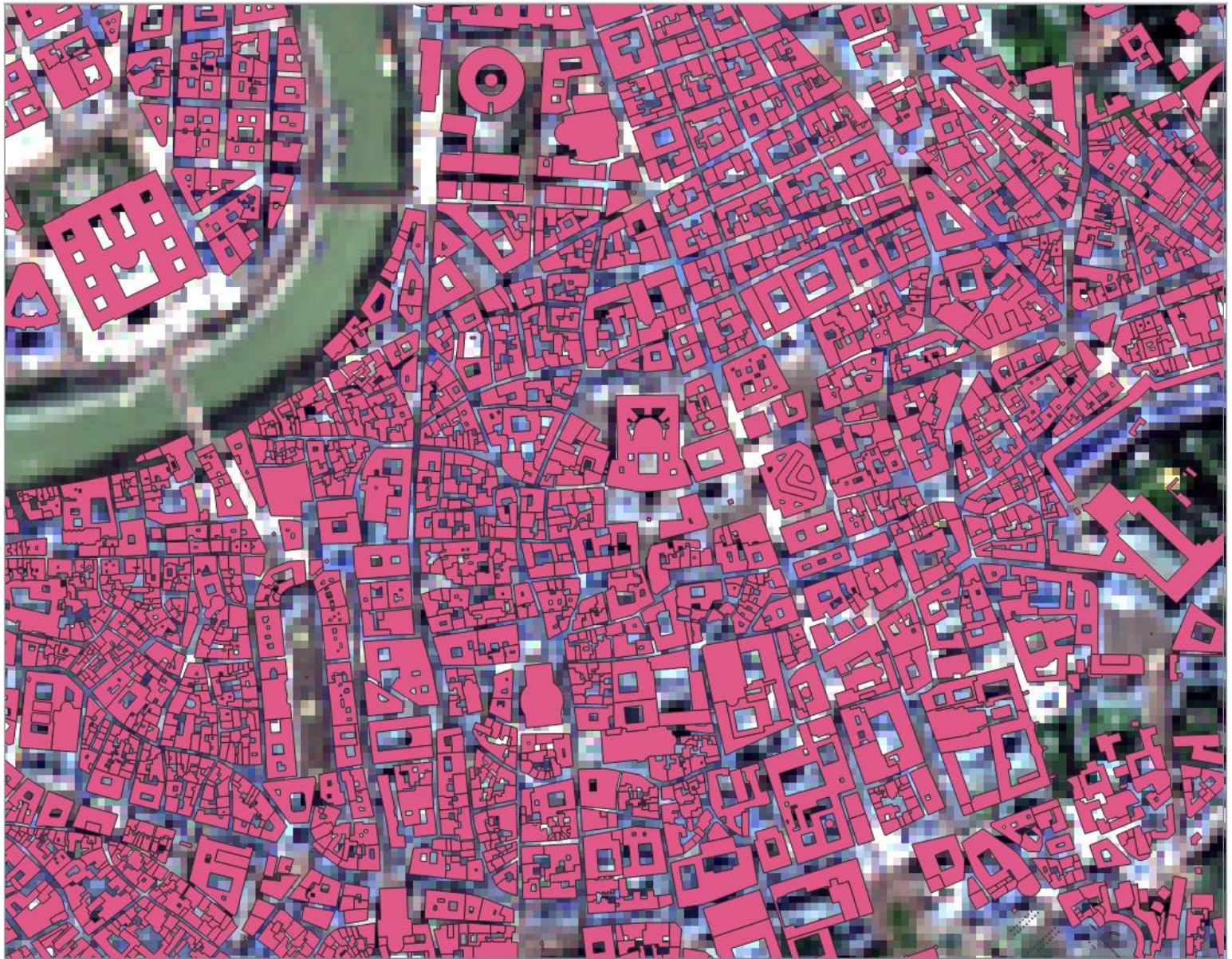
CHALLENGES

Satellite Images (PIXEL RESOLUTION)



CHALLENGES

Misalignment between GT and satellite images



CHALLENGES

Time series challenges

- Coregistration
- Different light condition
- No-data interpolation

AI4EO tools

neat-EO

Efficient AI4EO OpenSource framework

eo-learn

eo-learn makes extraction of valuable information from satellite imagery easy.

candela

COPERNICUS ACCESS PLATFORM INTERMEDIATE LAYERS SMALL SCALE DEMONSTRATOR

openEO

openEO develops an open API to connect R, Python, JavaScript and other clients to big Earth observation cloud back-ends in a simple and unified way.

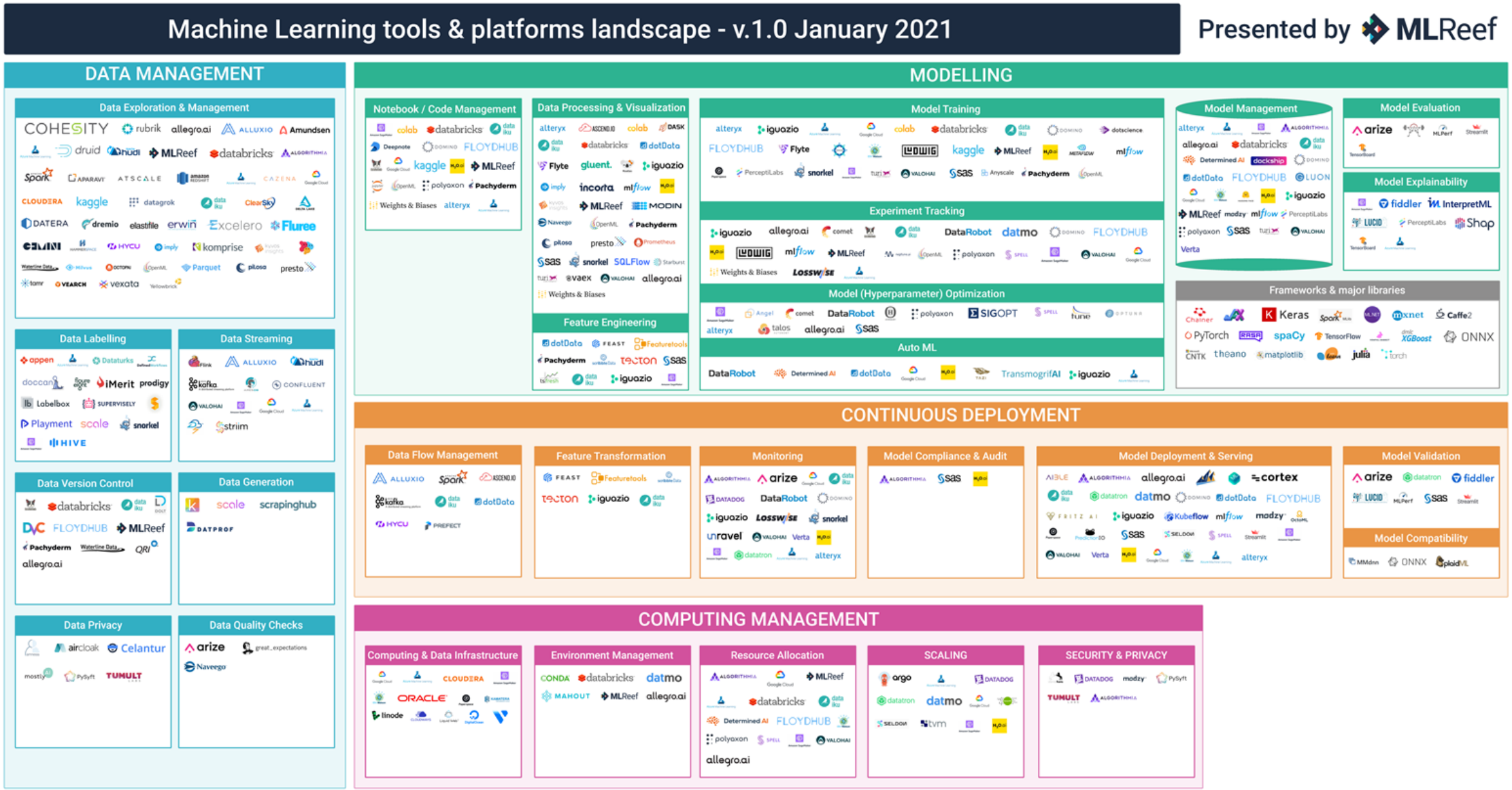
EOPEN

Open Interoperable platform for unified access and analysis of earth observation data

WEkEO

Copernicus and Sentinel data at your fingertips alongside cloud computing resources and tools

ML tools and Platforms



Machine Learning and Deep Learning

EO Applications

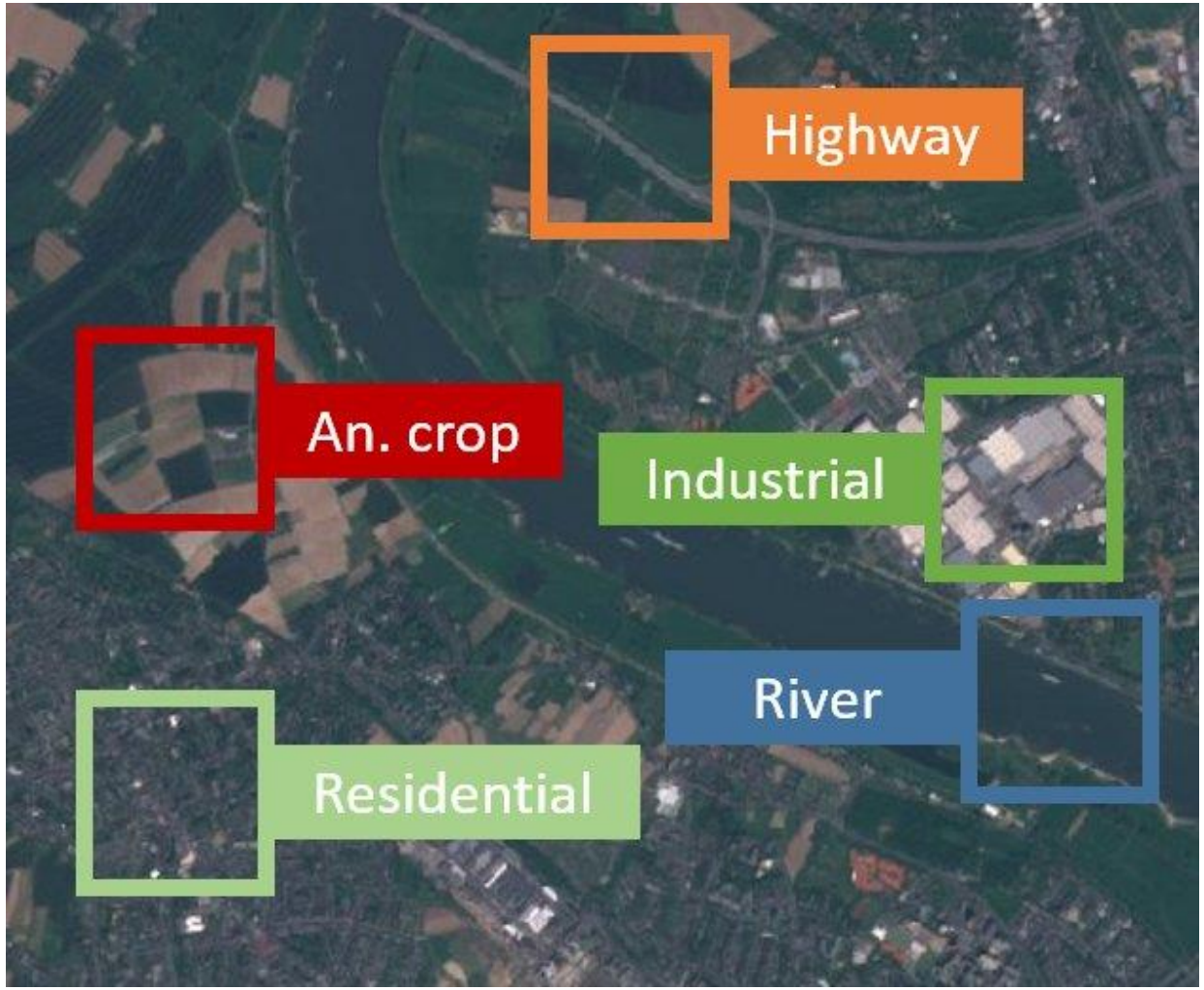
Image credits : https://www.iceye.com/

Building Detection

Topic:	**Object Detection**
Sensor:	**Optical -WV3**
Resolution:	**VHR-0.5m**
Bands:	**RGB**
Training:	**SpaceNet**
Method:	**MaskRCNN**

More information: https://github.com/Mstfakts/Building-Detection-MaskRCNN

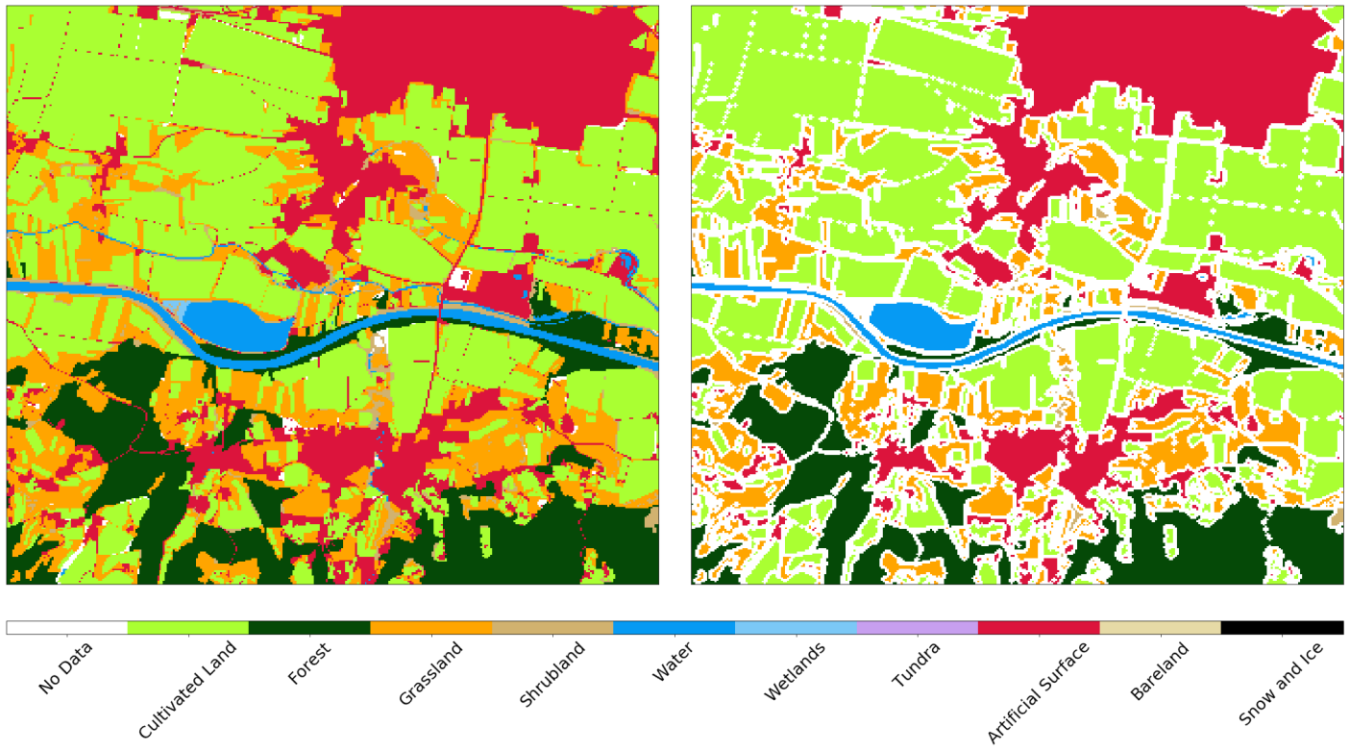
Tile based - LCLU



Topic:	**LULC (tile based)**
Sensor:	**multispectral-S2**
Resolution:	**medium-10m**
Bands:	**13**
Training:	**EuroSAT**
Method:	**ResNet-50**

More information: EuroSAT: A Novel Dataset and Deep Learning Benchmark for Land Use and Land Cover Classification

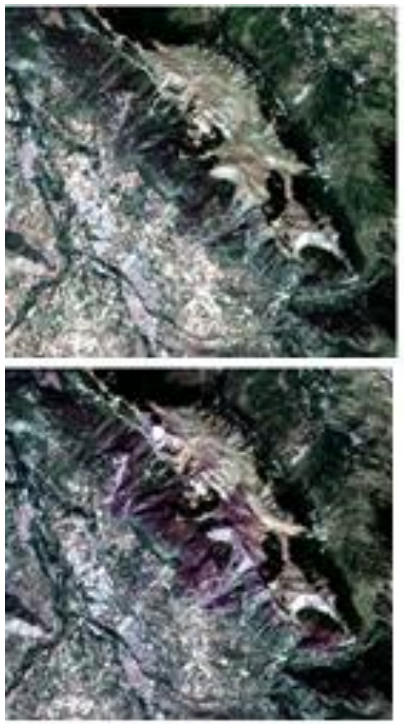
Pixel based - LCLU

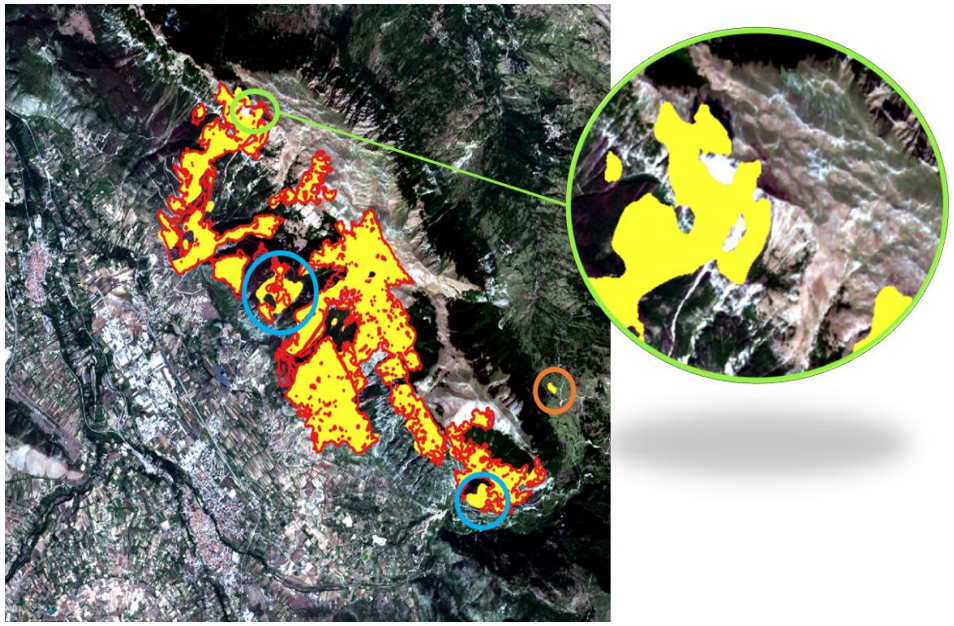


Topic:	**LCLU (pixel based)**
Sensor:	**multispectral - S2 TS**
Resolution:	**medium - 10m**
Training:	**provided by government**
Method:	**LGBM-UNet**

More information: https://medium.com/sentinel-hub/land-cover-classification-with-eo-learn-part-2-bd9aa86f8500

Change detection



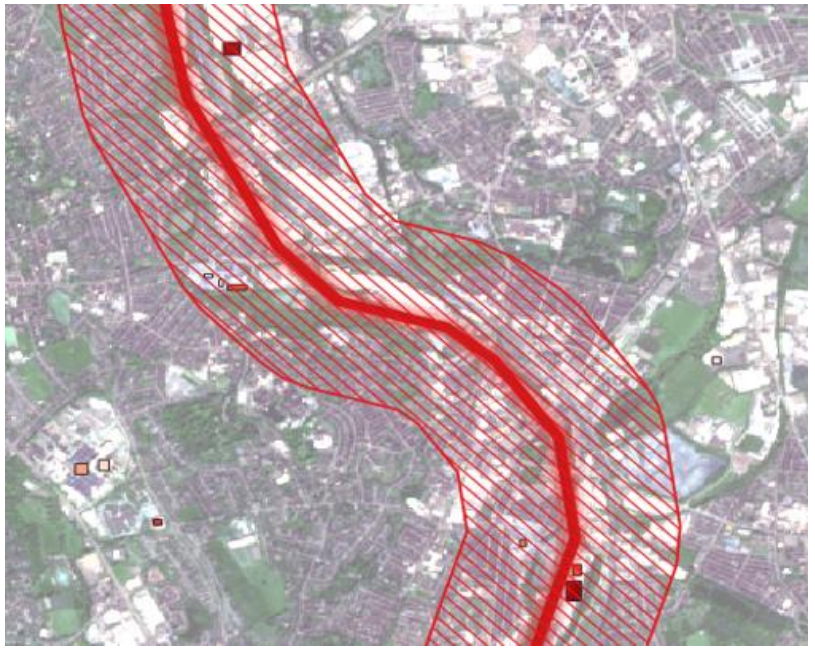


Topic:	**uns. Change detection**
Sensor:	**multispectral - S2 pre-post**
Resolution:	**medium - 10m**
Bands:	**12**
Method:	**Autoencoder**

Collaboration with UNIBA - Submitted to Remote Sensing Letters

Change detection

ML+DL



Topic:	**uns/sup Change detection**
Sensor:	**multispectral - S2 TS and pre-post**
Resolution:	**medium - 10m**
Bands:	**12**
Bands:	**Onera Satellite Change Detection**
Method:	**RF + change point det + Unet**

OneAtlas - AIRBUS

17 May 2019

5 April 2018

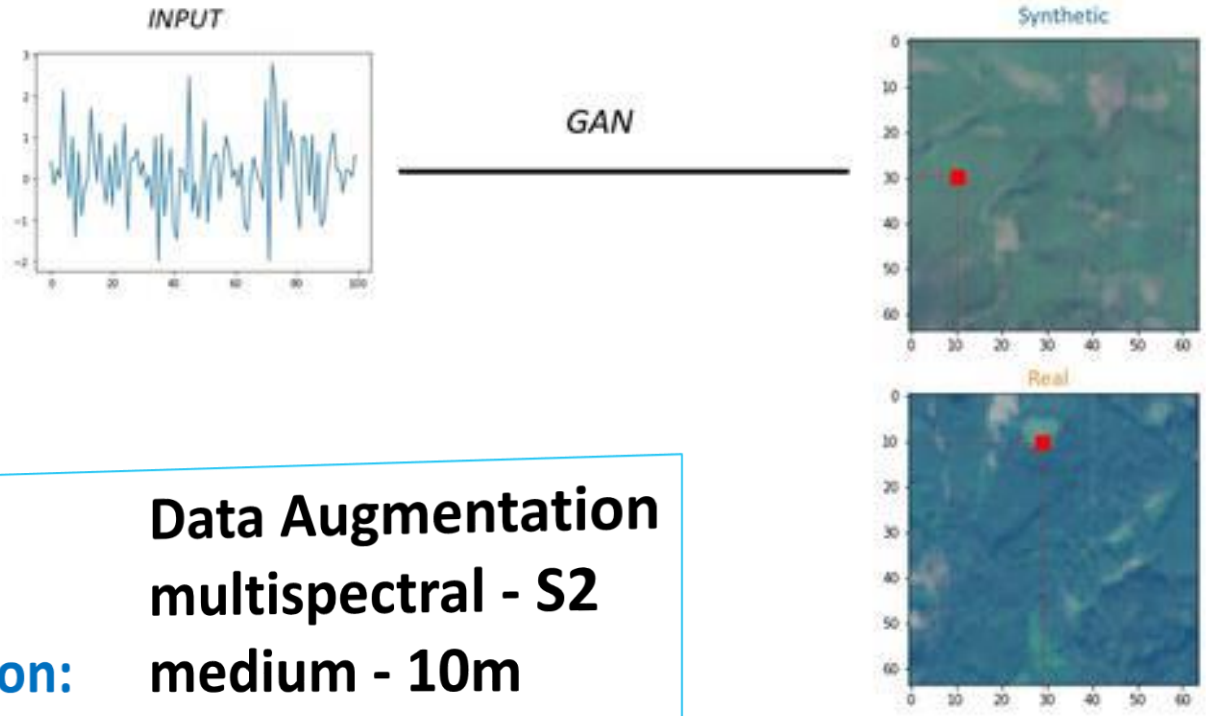
ONE ATLAS

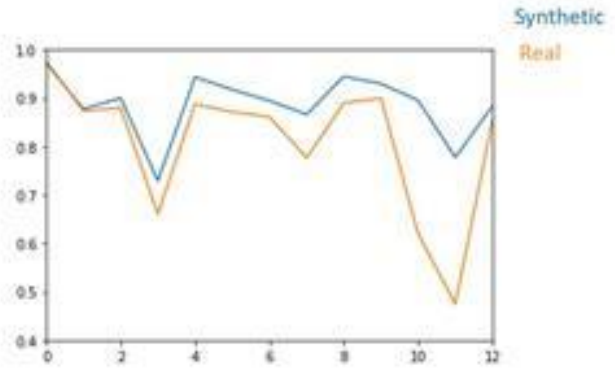
AIRBUS

Topic:	sup. Change Detection
Data:	VHR - Pléiades - SPOT
Method	: Machine Learning + human check

More information: https://oneatlas.airbus.com/home

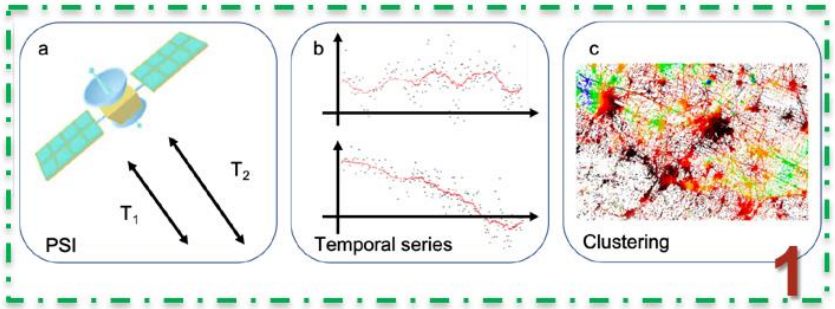
Use of GANs

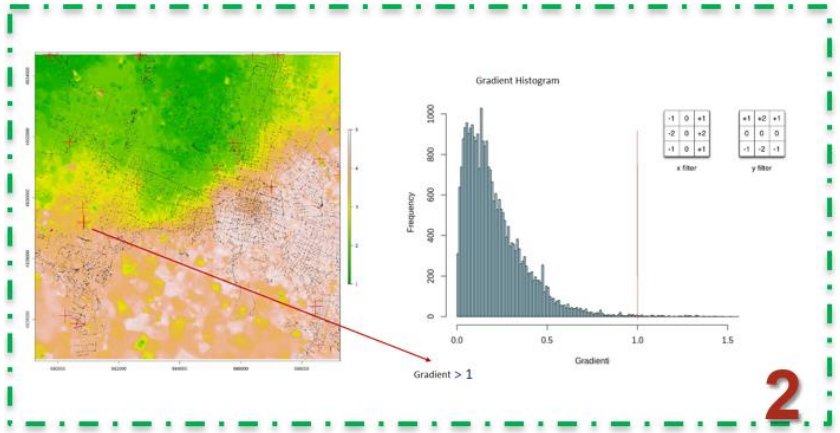


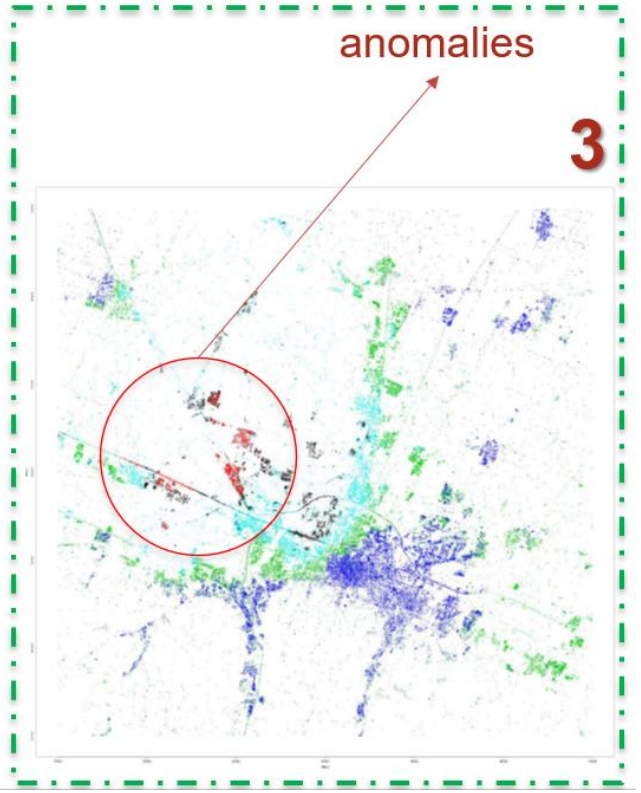


Topic:	**Data Augmentation**
Sensor:	**multispectral - S2**
Resolution:	**medium - 10m**
Bands:	**12**
Training:	**EuroSAT**
Method:	**GANs**

1D Time series data: Persistent Scatterers



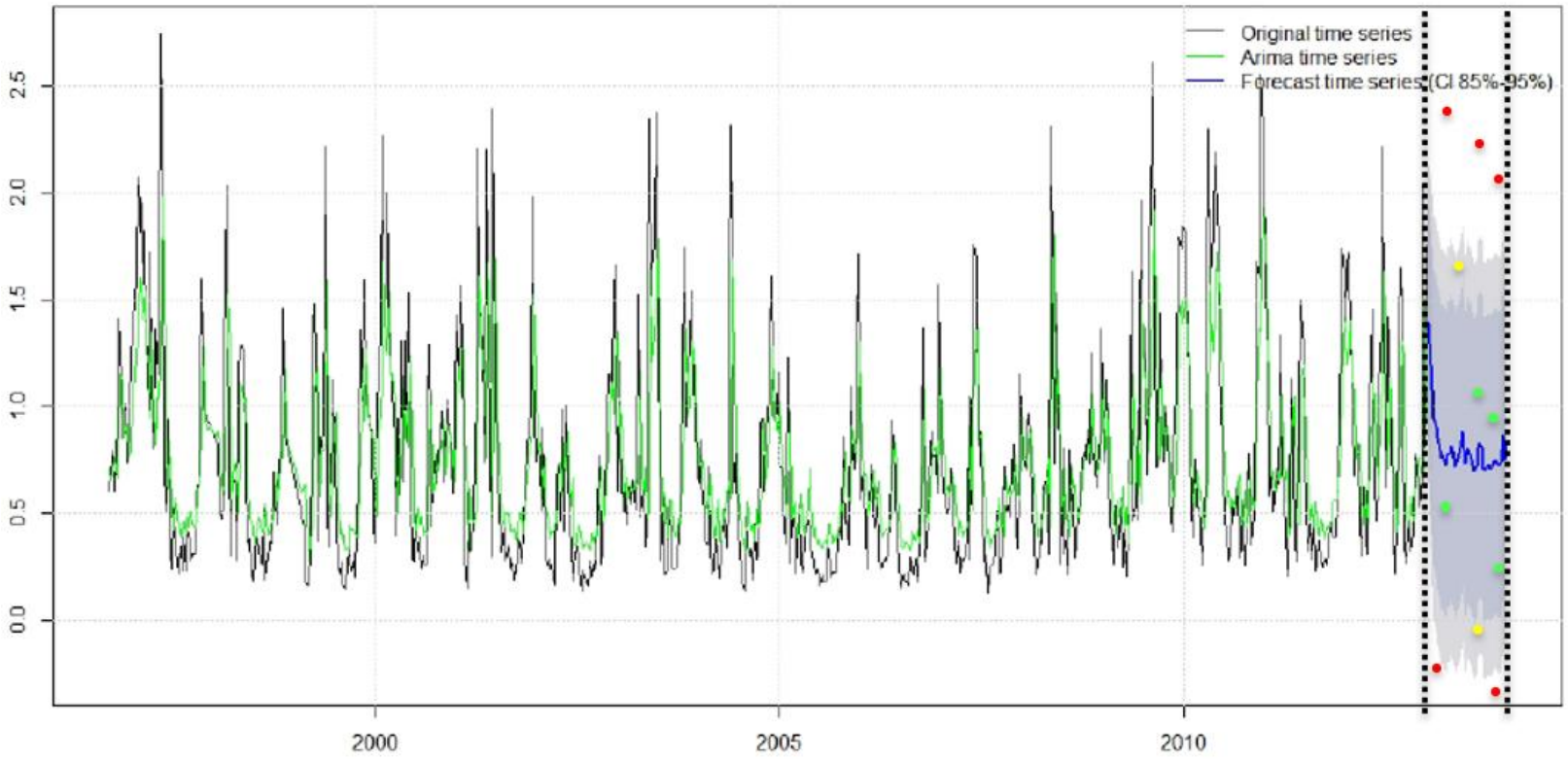




Topic:	**Clustering PS**
Data:	**PS from S1**
PS Num:	**~10M**
Clusters:	**5**
Method:	**K-Means**

MDPI and ACS Style
Amoroso, N.; Cilli, R.; Bellantuono, L.; Massimi, V.; Monaco, A.; Nitti, D.O.; Nutricato, R.; Samarelli, S.; Taggio, N.; Tangaro, S.; Tateo, A.; Guerriero, L.; Bellotti, R. PSI Clustering for the Assessment of Underground Infrastructure Deterioration. *Remote Sens.* **2020**, *12*, 3681.

Chlorophyll TS data



Topic:	**Anomaly detection**
Data:	**Marine data**
Rate:	**Weekly**
Method:	**LSTM+ARIMA**

AI on board

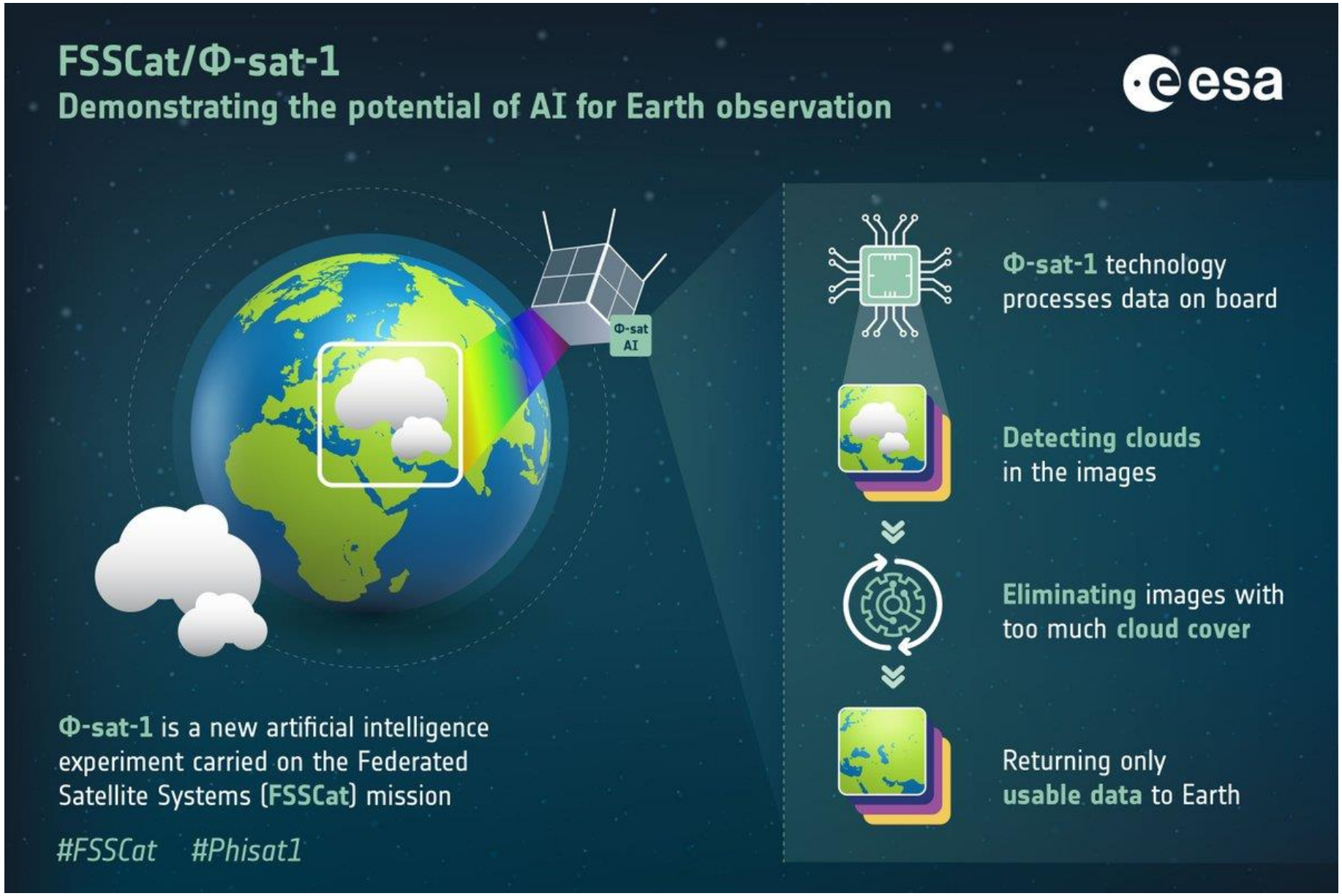


Image credits: https://twitter.com/ESA_EO/status/1274991895706570753

CRITE:
AI to map shadowed coffee plantations using multi-temporal and multi-sensor EO images

CRITE - Project

Image credits : https://www.iceye.com/