Comparing different deep learning architectures for automatic detection of the agricultural field boundaries from Sentinel-2 and aerial photography

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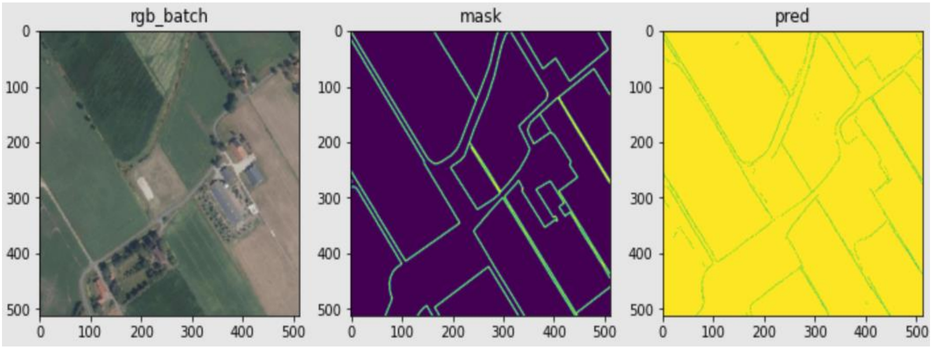
Field Boundaries Information Is an Enabler for Agricultural Applications

Existing maps are based on historic administrative maps or on observational data with low accuracy.

Solve complex tasks due to the limited number of available data and lack of detection methodology benchmark.



Why An Automatic Detection?

- It removes inefficiencies associated with low accuracy maps and error-prone manual insertion;
- Integrated Administration and Control System (IACS) with an accuracy better than 1:5000 is a prerequisite to monitor the EU's Common Agricultural Policy (CAP) subsidy expenditures;
- It produces relevant input for crop monitoring and yield forecasting applications;
- It provides a foundation in countries without cadastral data [1].

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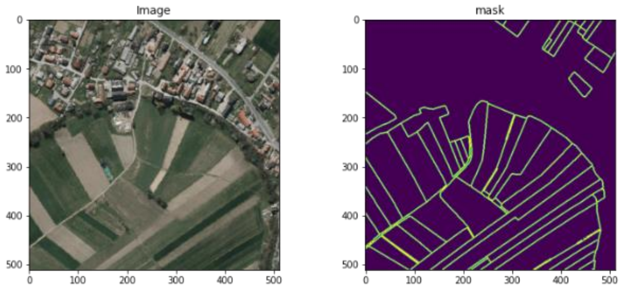
1. *Wang, S., Waldner F., Lobell, D. (2022).* Unlocking large-scale crop field delineation in smallholder farming systems with transfer learning and weak supervision. *Under submission.*

Main Purpose: A Reusable Framework

1 An open **AI-ready data set** to map field boundaries with Sentinel-2 and aerial photography (*AI4Boundaries*).



open source

2 **Open-source** TensorFlow scripts for creating an optimised data set, coding and running Deep Learning (DL) **architectures**.

TensorFlow Open-source Scripts

TFRecord Files

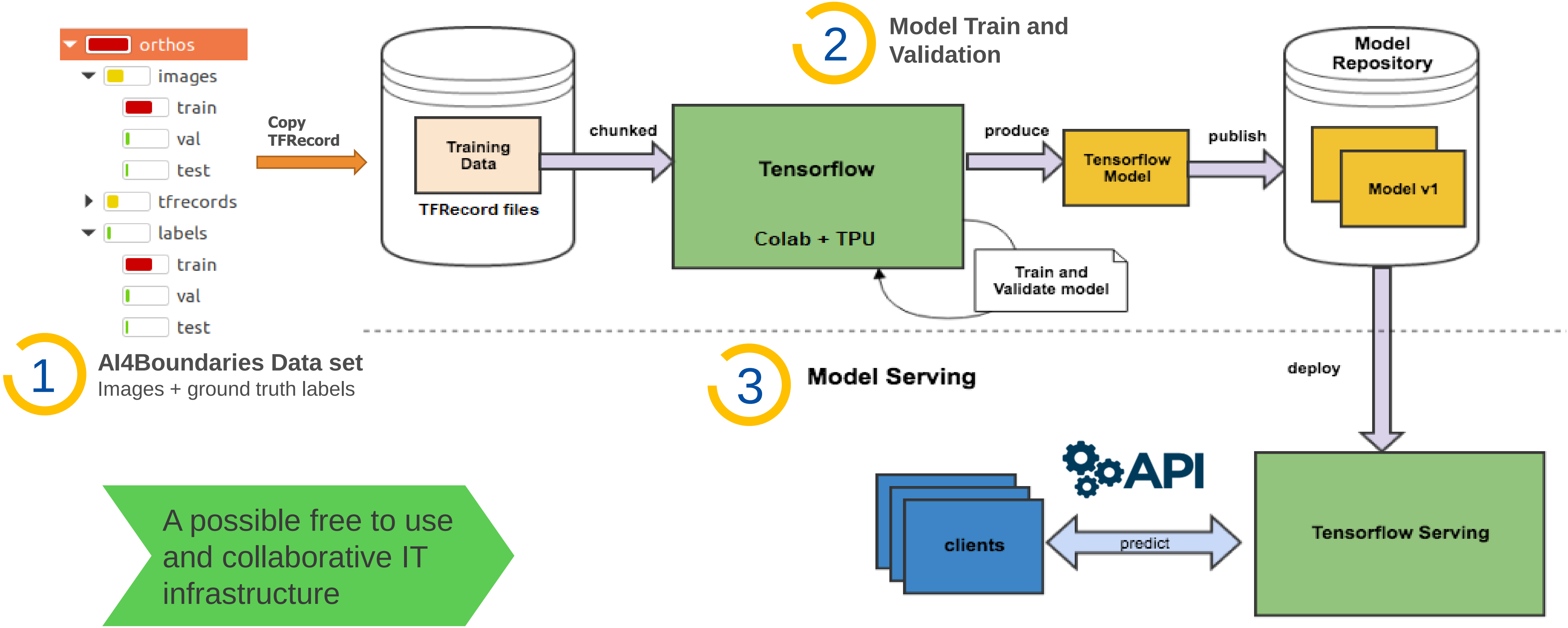
Google colab

Models Training on Tensor Processing Unit (TPU)

3 Flexible, high-performance **serving system** for deep learning models.

TensorFlow Serving

From Images to Model Training & Serving



A possible free to use and collaborative IT infrastructure

AI4Boundaries: An open AI-ready dataset to map field boundaries with Sentinel-2 and aerial photography.

Look at our poster!

Motivations

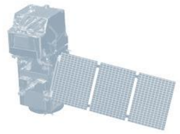
- Recent advances on Deep Learning methods have highlighted the capacity to extract field boundaries from satellite and aerial images.
- Deep Learning requires accurate data to be calibrated and assessed.
  ➡ No benchmark data set currently exists to easily achieve comparisons.
- To foster the sense of community in this research topic.

How can we know as scientific community what works best?

- *Wang, S., Waldner F., Lobell, D. (2022).* Unlocking large-scale crop field delineation in smallholder farming systems with transfer learning and weak supervision. *Under submission.*
- *Waldner, F., et al, (2021),* Detect, Consolidate, Delineate: Scalable Mapping of Field Boundaries Using Satellite Images. *Remote Sensing.*
- *Waldner F., et al., (2020),* Deep learning on edge: Extracting field boundaries from satellite images with a convolutional neural network. *Remote Sensing of Environment.*

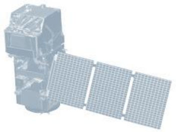
AI4Boundaries Data set - Samples

AI4Boundaries consists of 7,831 samples of 512x512 pixels for 3-specific data sets along with the corresponding ground-truth parcel.



Single date / 10 m

A set of cloud free images centered around June 19



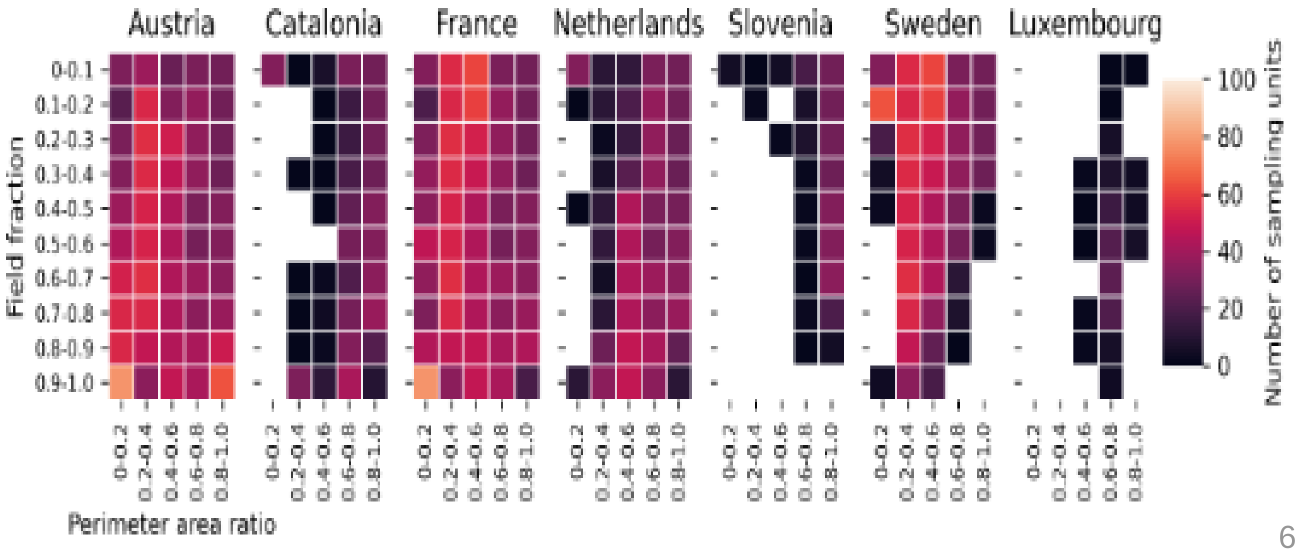
Multi date / 10 m

A set of monthly composites

Single date / 1 m

A set of cloud free orthophotos

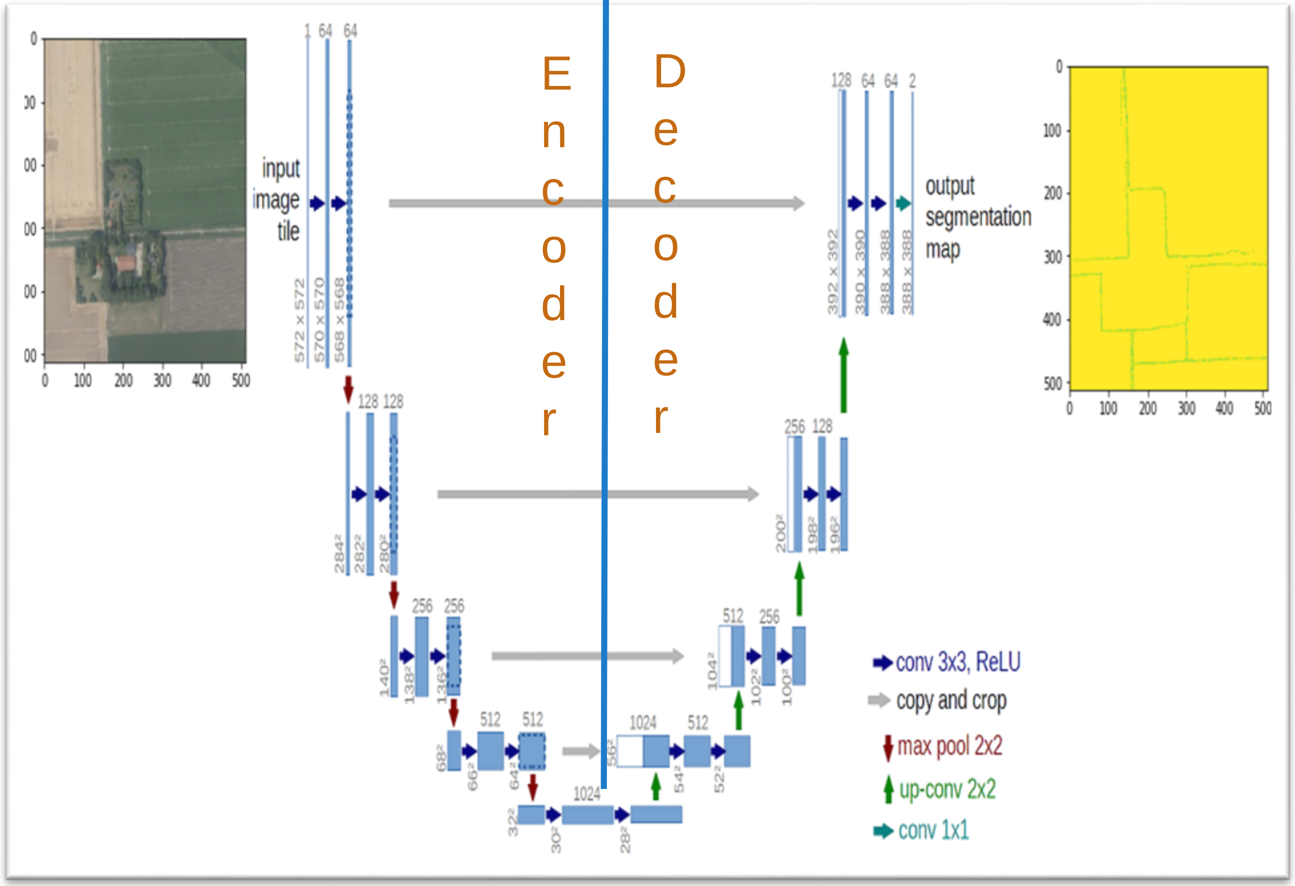
Country/Region	Number of sampling units
Austria	2091
Catalonia	652
France	2078
Luxembourg	132
Netherlands	1157
Slovenia	301
Sweden	1420
Total	7831

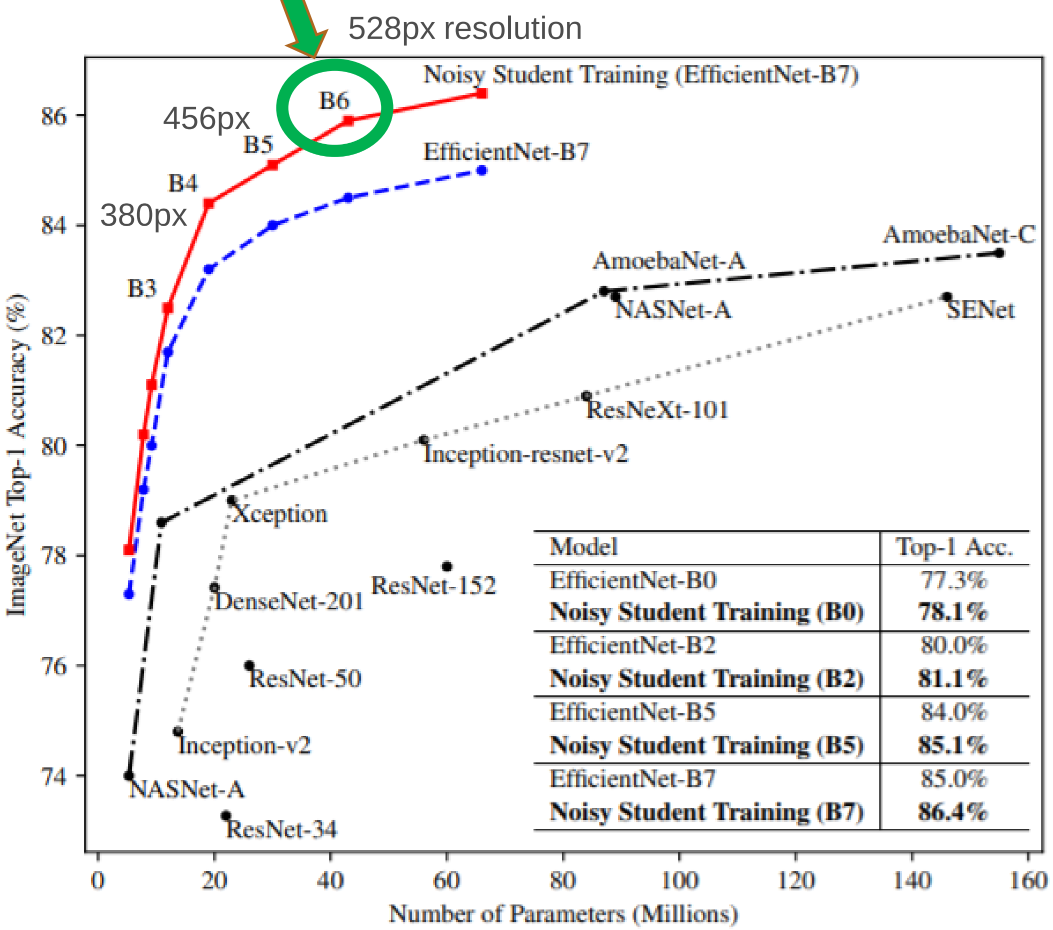


Samples available to download:

https://jeodpp.jrc.ec.europa.eu/ftp/jrc-opendata/DRLL/AI4BOUNDARIES/

Base Model: U-Net + EfficientNetB6 + Noisy Student Learning Approach





- T. Agrawal, et al., *EfficientUNet: Modified encoder-decoder architecture for the lung segmentation in chest x-ray images*, Expert Systems, April 2022
- B Baheti et al., *Eff-UNet: A Novel Architecture for Semantic Segmentation in Unstructured Environment,* Conference on Computer Vision and Pattern Recognition Workshops (CVPRW), June 2020.

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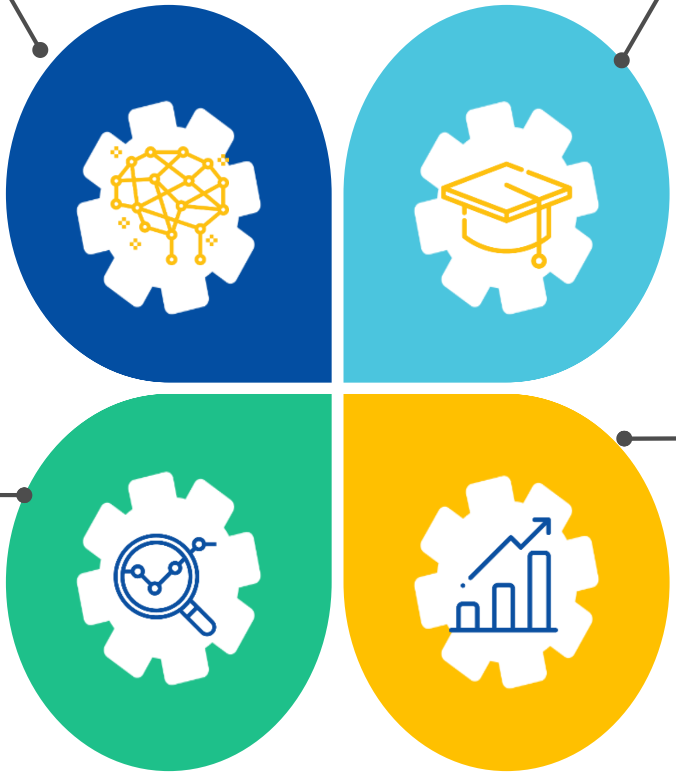
Just to Start: Loss function, Callbacks, Cyclical Learning Rate and Metrics.



Loss Function

Segmentation Boundary Loss

Only the beginning:

$$\mathcal{L}_{GDL}(\theta) = 1 - 2\frac{w_G \int_{p\in\Omega} g(p)s_\theta(p)dp + w_B \int_{p\in\Omega}(1-g(p))(1-s_\theta(p))dp}{w_G \int_\Omega [s_\theta(p) + g(p)]dp + w_B \int_\Omega [2 - s_\theta(p) - g(p)]dp} \quad (1)$$

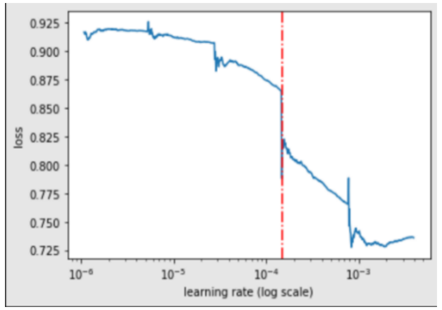
H. Kervadec et al., *Boundary loss for highly unbalanced segmentation*, Medical Image Analysis, 2021.

Callbacks & Live Tracking

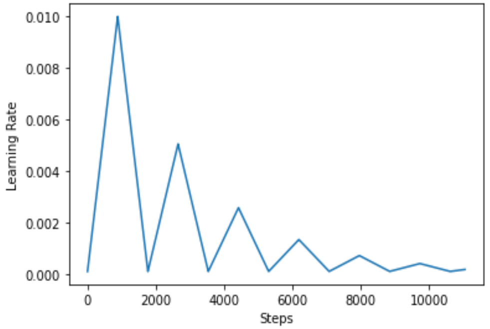
- EarlyStopping
- ModelCheckpoint
- TensorBoard

Building Deep Learning models without callbacks is like driving a car with no functioning brakes.

Cyclical Learning Rate (CLR)



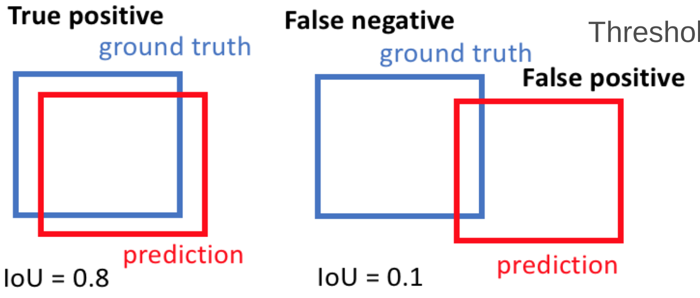
Optimal initial learning rate



Learning rate variations

CLR types: Linear, Parabolic and Sinusoidal.

Metric: Intersection over Union



Threshold: 0.5

$$accuracy = \cancel{\frac{TP + TN}{TP + TN + FP + FN}}$$

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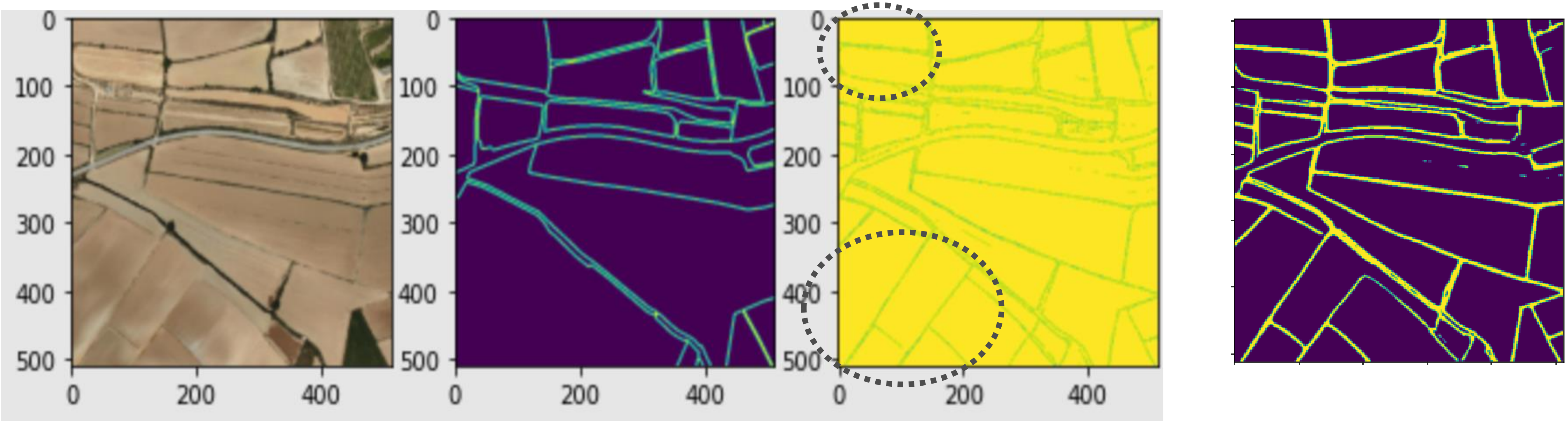
The Model Predicts Boundaries Missing in the Mask



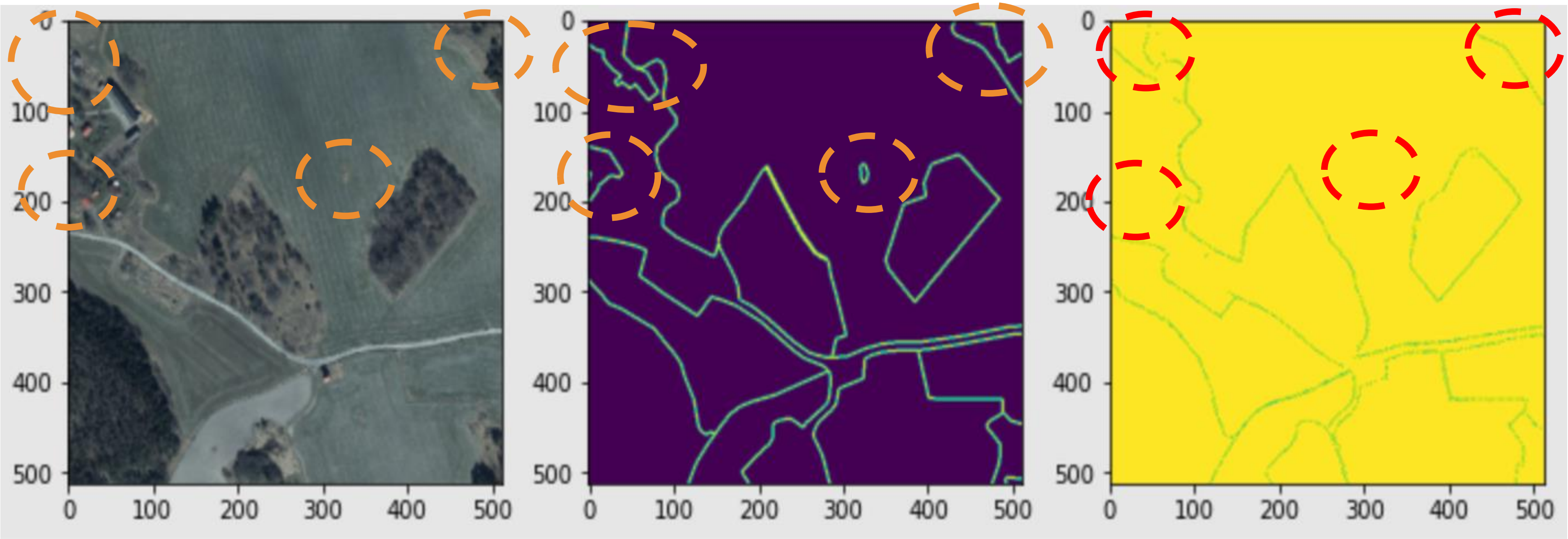
Test input image

Mask

Model predictions with pixel probability > 95%

Model predictions with pixel probability > 50%

The Model Fails to Detect Small Features

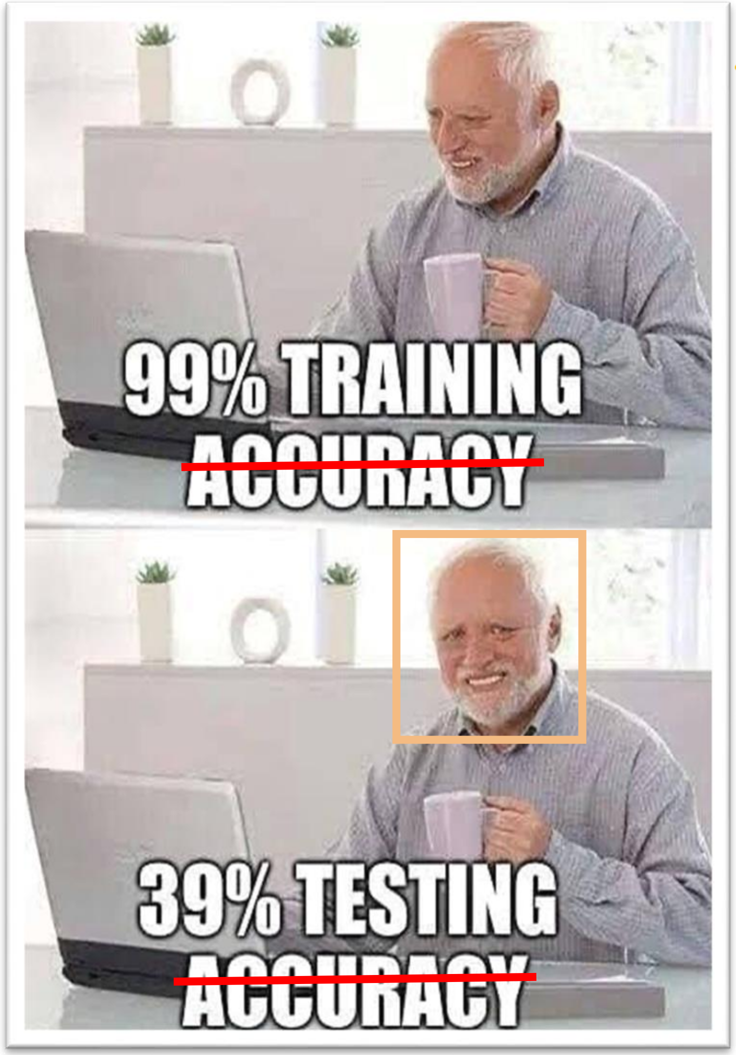


Test input image

Mask

Prediction

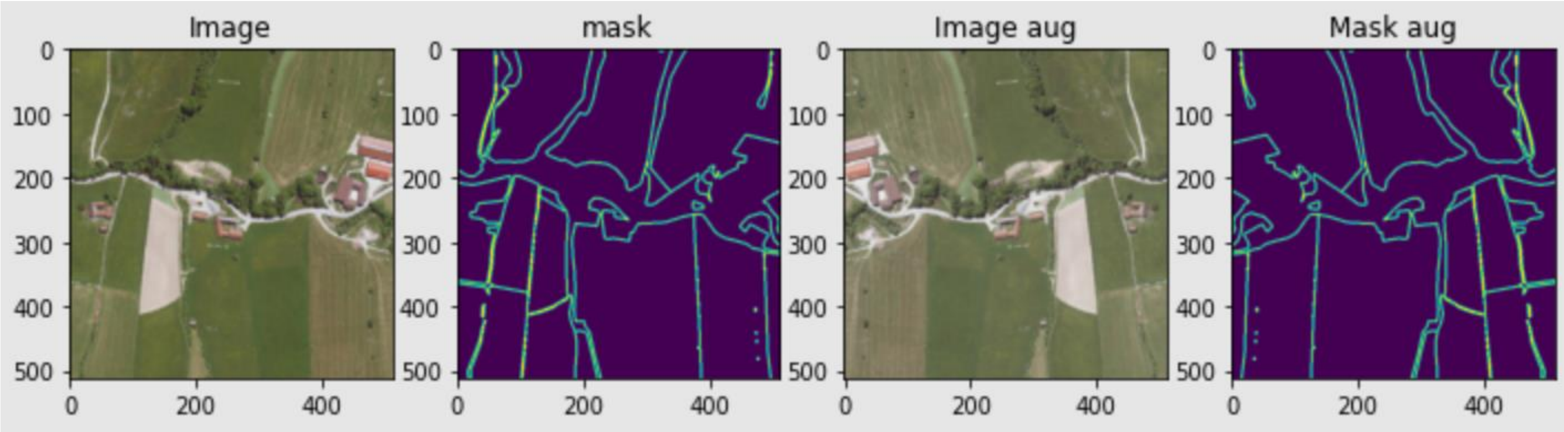
Lessons Learnt From Preliminary Results



Extremely **imbalanced data set** 0.027% boundary vs 99.973% interior pixels.

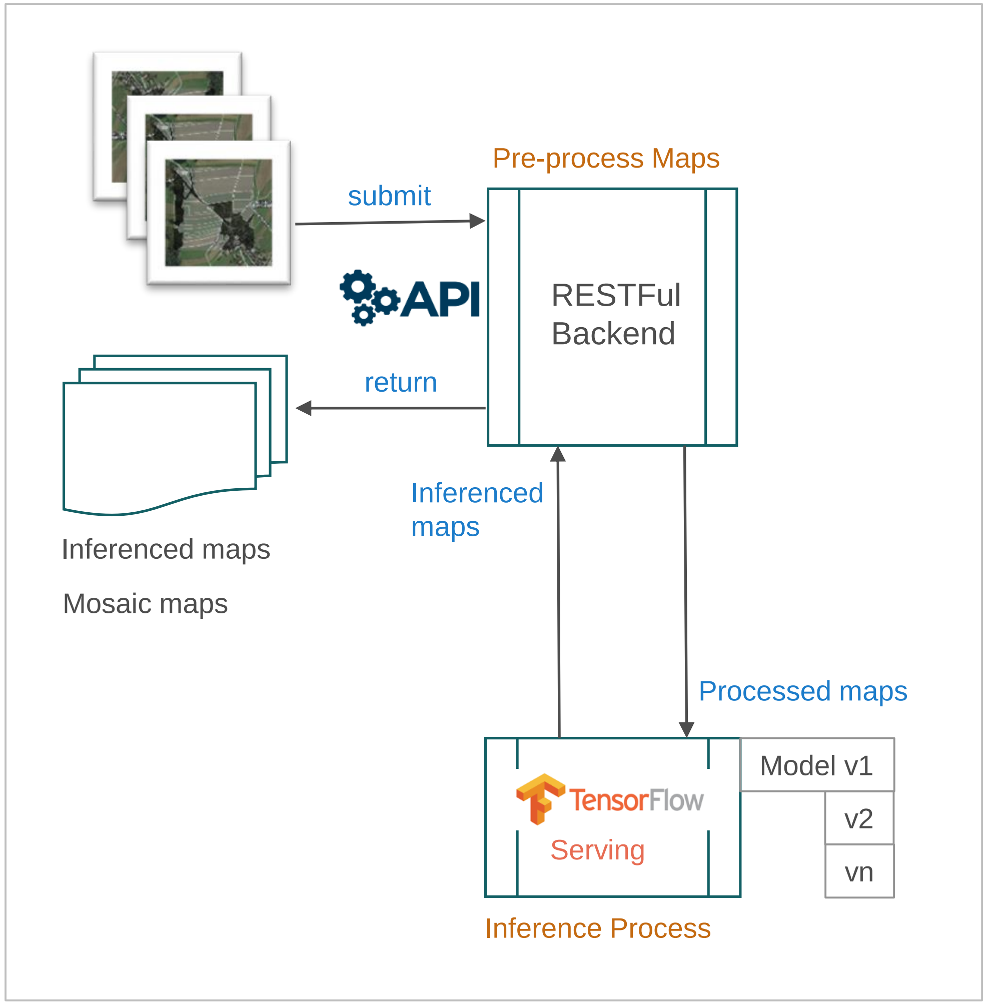
Techniques to deal with Imbalanced Classes in Machine Learning:

1. Oversampling: Adding more copies to the minority class.
2. Undersampling: Removing some observations of the majority class.
3. Filtering: Removing masks with less than X percentage of boundary pixels.
4. Removing exact and near duplicate using percentual hashing algorithm.
5. Image Augmentation: flip(H/V reflections), random brightness.



No random rotation & zoom in/out as they may break field symmetry.

Towards Real-time Service Mapping & Mosaic

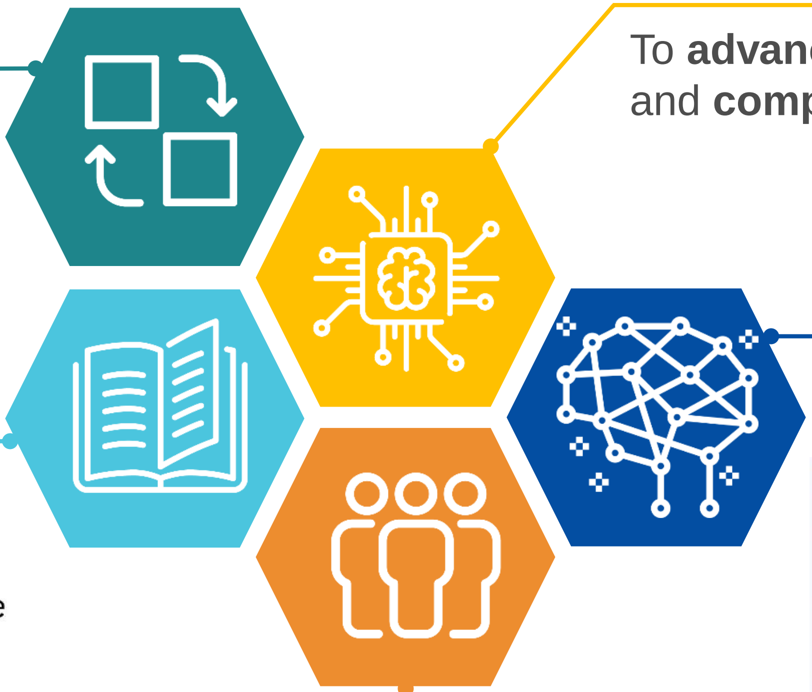


Example of inferenced maps

Next Steps

To **automate** the **delineation** of field boundary around the world, especially in under-served smallholder regions.

To **publish** the full **comparison** results, model weights and source code.



To **advance** and facilitate **research**, **development** and **comparison** for field boundary detection.

Can **Vision Transformers** outperform CNNs? [1,2,3]

To **foster** scientific **collaborations** in the community.

1. *Z.Liu, et al., (2021),* Swin Transformer: Hierarchical Vision Transformer using Shifted Windows, *IEEE Xplore*.
2. *M.Pu, et al., (2022)*, EDTER: Edge Detection with Transformer, *Accepted by CVPR2022.*
3. *Z. Dong, et al.,(2022),* Computer vision to recognize construction waste compositions: A novel boundary-aware transformer (BAT) model, *Journal of Environmental Management.*

Thank you

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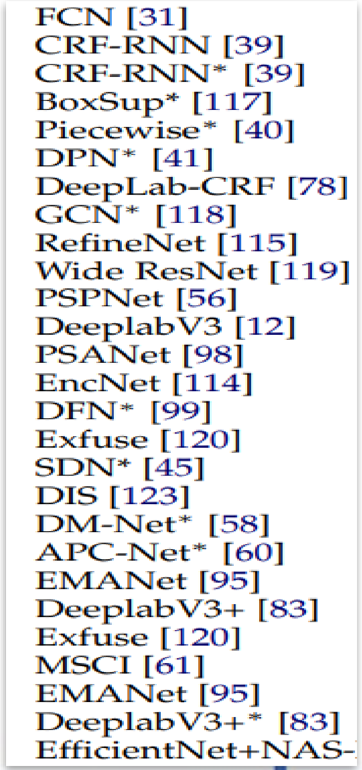
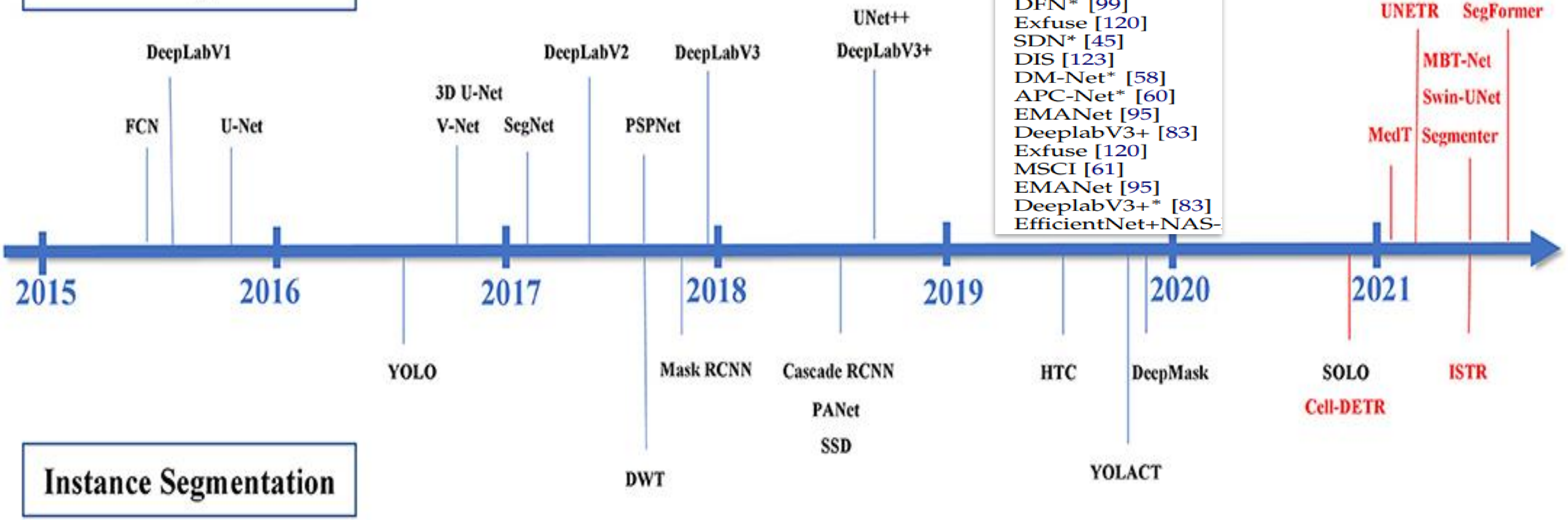
Only Some Deep Learning Architectures



FCN [31]
CRF-RNN [39]
CRF-RNN* [39]
BoxSup* [117]
Piecewise* [40]
DPN* [41]
DeepLab-CRF [78]
GCN* [118]
RefineNet [115]
Wide ResNet [119]
PSPNet [56]
DeeplabV3 [12]
PSANet [98]
EncNet [114]
DFN* [99]
Exfuse [120]
SDN* [45]
DIS [123]
DM-Net* [58]
APC-Net* [60]
EMANet [95]
DeeplabV3+ [83]
Exfuse [120]
MSCI [61]
EMANet [95]
DeeplabV3+* [83]
EfficientNet+NAS-

Transformer-based methods



Source: ResearchGate, DOI:10.3389/fmedt.2021.767836