Random Forest and Deep Learning for Glacier Mapping

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Outline

Image classification

Random forest

From convolutional networks to fully-convolutional networks

Project description

Image classification

Image classification (in the context of remote sensing) or semantic image segmentation (in the context of machine learning/deep learning) is a problem of segmenting the whole digital image into semantically meaningful classes.

There are several types of features that help to classify objects in remotely sensed images:

- spectral
- textural
- shapes
- topological

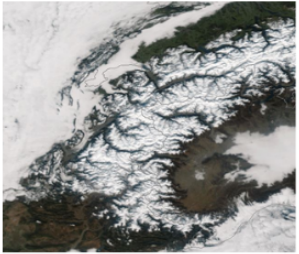




Image classification

In general, one can identify three approaches to address the classification problem:

- Pixel-to-pixel (the majority of the classification methods; can take into account only the spectral information)

$$\mathbf{y_{ij}} = f(\mathbf{x_{ij}}) + \epsilon \tag{1}$$

- Patch-to-pixel (textural analysis, convolutional neural networks, transformers)

$$\mathbf{y_{ij}} = f(\mathbf{X_{i:i+h,j:j+w}}) + \epsilon \tag{2}$$

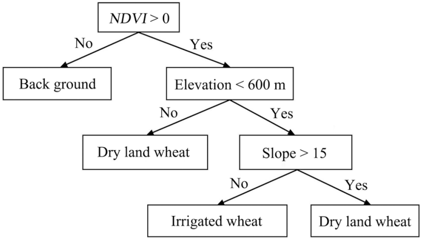
- Patch-to-patch (fully-convolutional neural networks, transformers)

$$\mathbf{Y_{i:i+h,j:j+w}} = f(\mathbf{X_{i:i+h,j:j+w}}) + \epsilon \tag{3}$$

Random forest

Random forest—an ensemble of decision trees trained to solve one problem.

Decision trees:



Source: Meng et al., 2014

- No-leaf nodes are splits (rules to build decision boundaries)
- Leaf nodes are decisions

- To make a split, compare how every feature threshold reduces 'impurity', e.g., Gini impurity
- $gini_{leaf} = 1 - p_0^2 - p_1^2$
- $gini_{split} = \frac{N_{yes}}{N_{yes}+N_{no}} gini_{yesleaf} + \frac{N_{no}}{N_{yes}+N_{no}} gini_{noleaf}$
- At each split, choose a threshold to minimize $gini_{split}$ in a greedy manner
- After every leaf is 'pure', assign labels to the leaves

Random forest

The output of a random forest model is the average prediction of the decision trees:

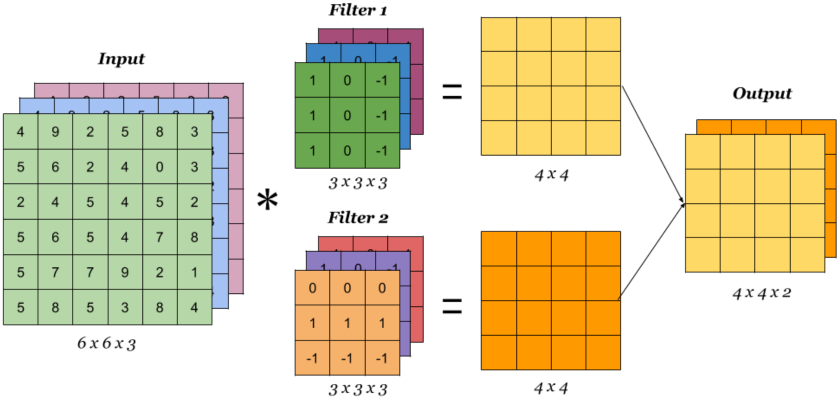
$$forest(\mathbf{x}) = \frac{1}{N_{trees}} \sum_i tree_i(\mathbf{x}). \tag{4}$$

But we do not want the decision trees to be correlated, so

- use data bootstrapping
- use feature bootstrapping at each split

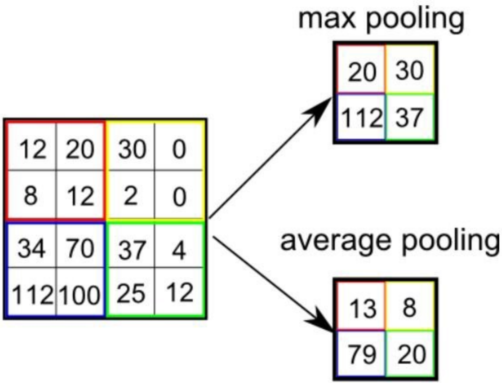
Fully-convolutional networks: convolutional layers

Let's first recall what convolutional neural networks are.



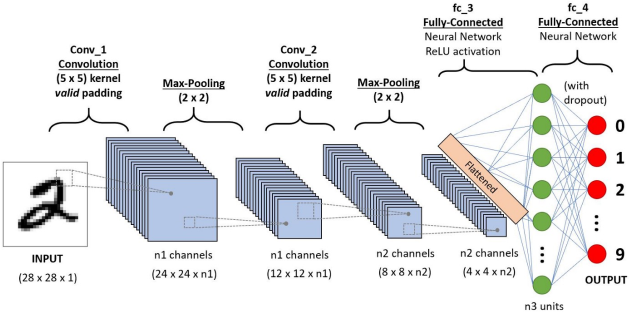
Source: `https://bit.ly/3eoHAJd`

Fully-convolutional networks: pooling/downsampling layers



Source: `https://bit.ly/3L0BHhL`

Fully-convolutional networks: typical convolutional network topologies

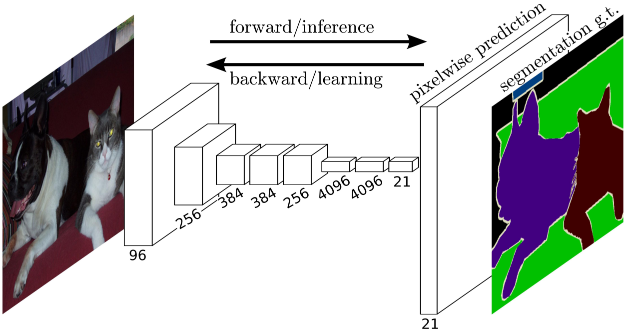


Source: `https://bit.ly/3wU3ryu`

- One inference to classify one pixel
- Computationally intensive
- Still can neglect some spatial correlations producing 'noisy' results

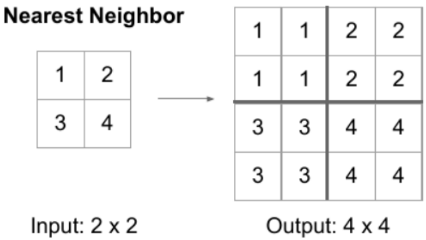
Fully-convolutional networks

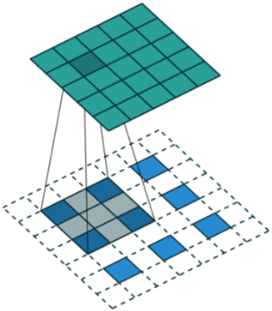
Can we do better? Yes!

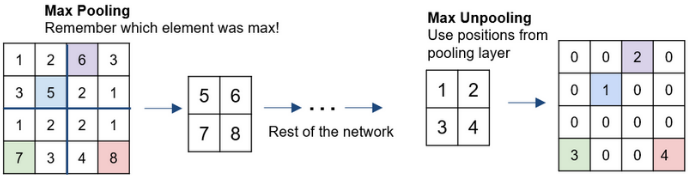


Source: Long et al., 2014

Fully-convolutional networks: upsampling layers

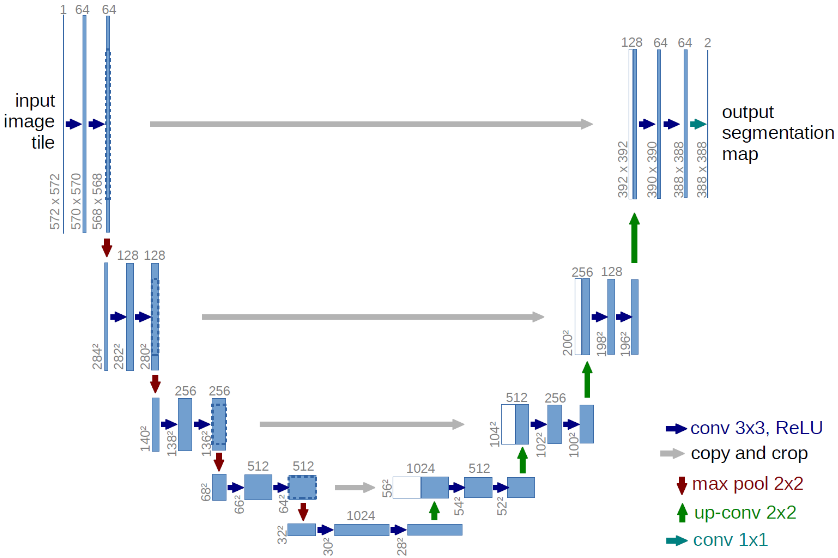






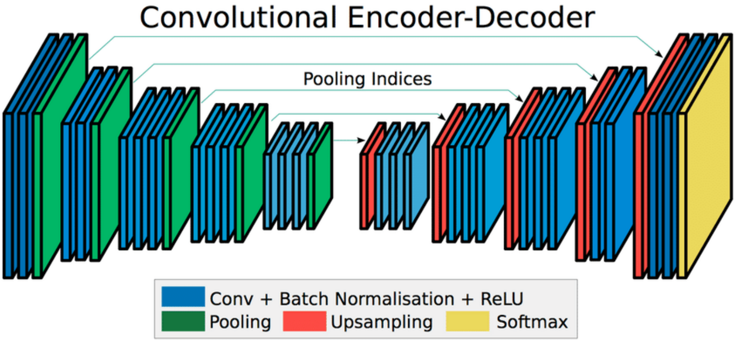
Source: `https://bit.ly/3RkuCL6`

Fully-convolutional networks: U-Net



Source: Ronneberger et al., 2015

Fully-convolutional networks: SegNet



Source: Badrinarayanan et al., 2015

Fully-convolutional networks: DeepLab

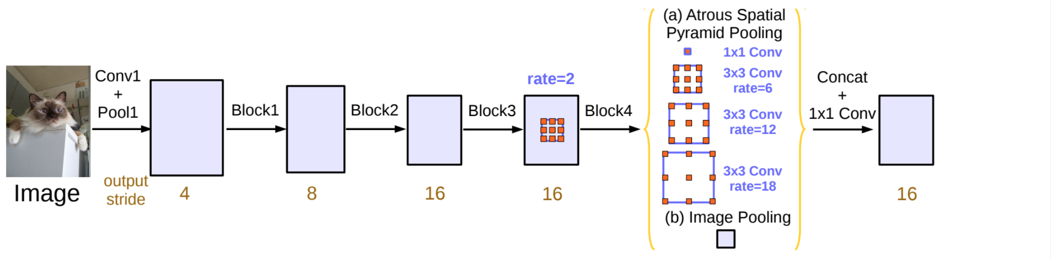
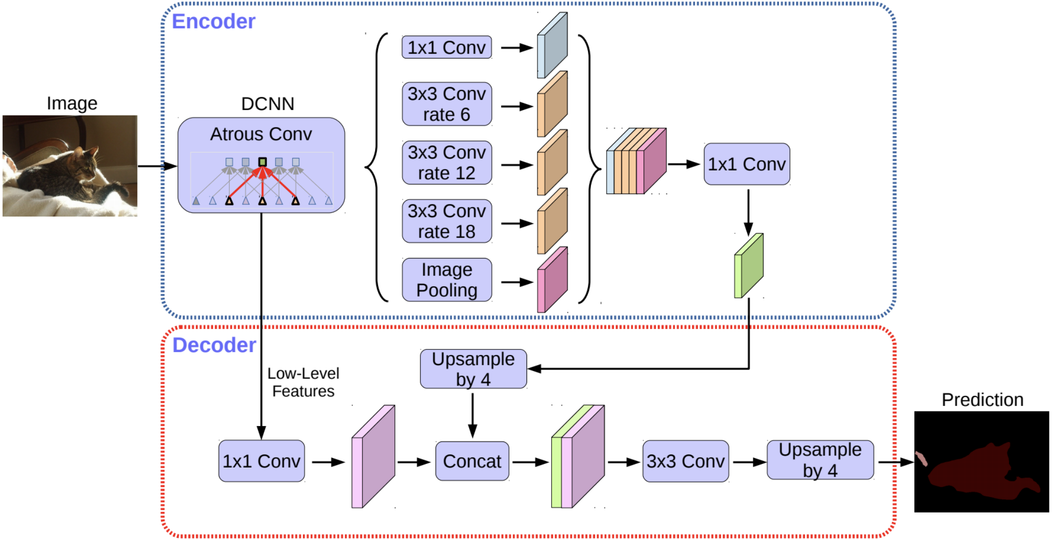


Figure 5. Parallel modules with atrous convolution (ASPP), augmented with image-level features.

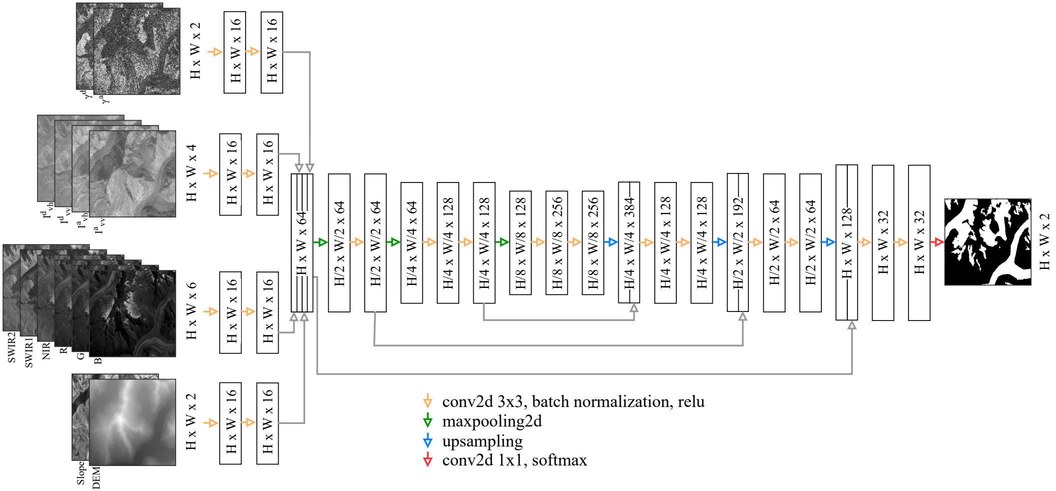
Source: Chen et al., 2017

Fully-convolutional networks: DeepLabV3+

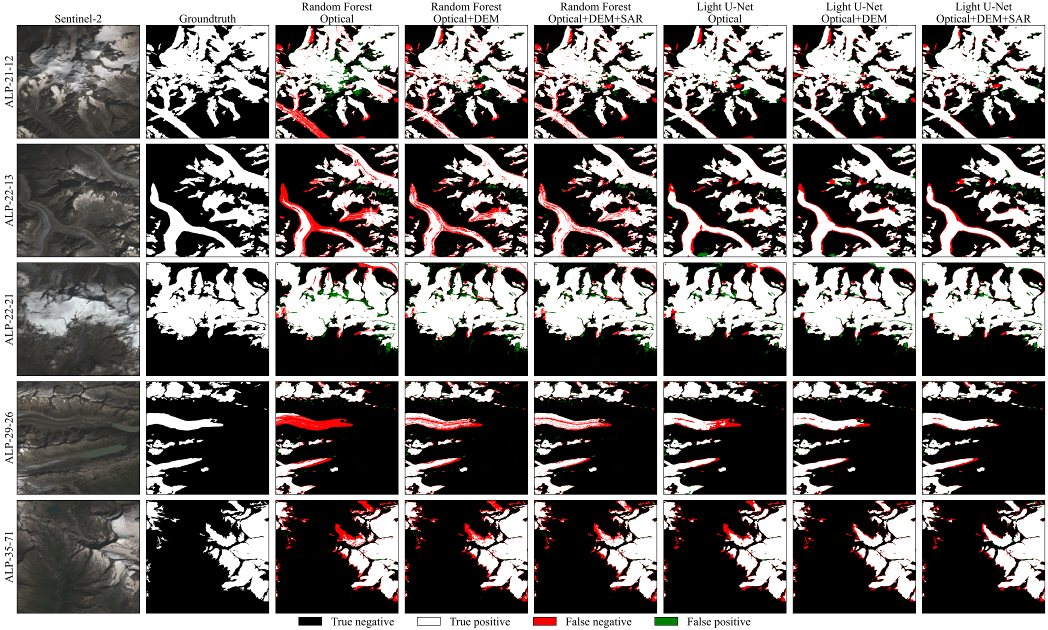


Source: Chen et al., 2018

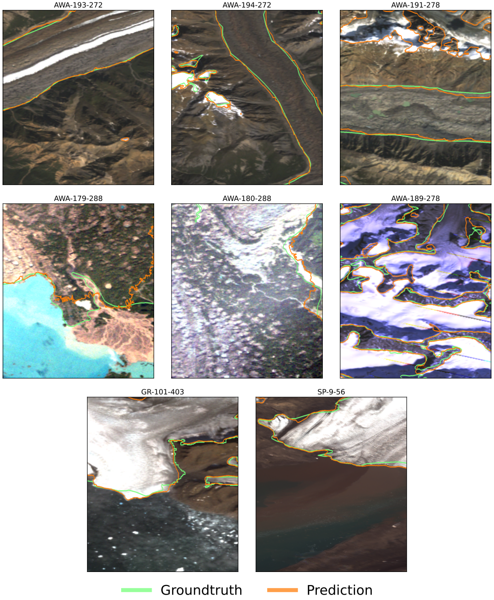
Case studies: glacier mapping in the Alps



Case studies: glacier mapping in the Alps



Case studies: multi-regional glacier mapping in the Arctic

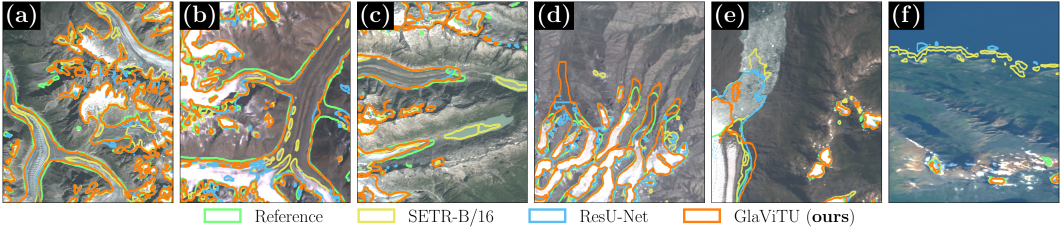


- In general, it nicely classifies debris-covered ice
- Surprisingly, it gives reasonable boundary estimates for vegetation-covered glaciers (but far from ideal)
- The model is robust to Landsat 5 artifacts at the scene boundaries
- Predictions for calving fronts are even better than groundtruth

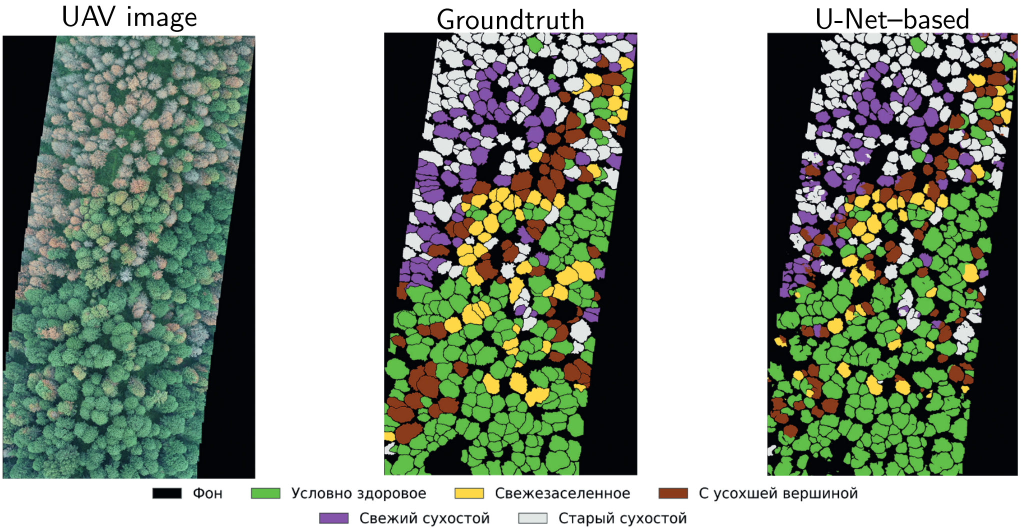
Case studies: multi-regional glacier mapping with CNN-transformer hybrids

- Recently, we proposed a hybrid CNN-transformer model (GlaViTU) for multi-regional glacier mapping
- It has fewer parameters compared to ResU-Net and SETR-B/16 but shows higher performance and generalizes better

Method	Params	IoU of different regions						IoU mean	IoU std.dev.
		ALP	HMA	LL	NZ	SA	SC		
SETR-B/16	102M	0.678	0.689	0.635	0.699	0.908	0.702	0.718	0.088
ResU-Net	33M	0.843	0.803	0.837	0.833	**0.955**	0.829	0.850	0.049
GlaViTU (**ours**)	**10M**	**0.844**	**0.812**	**0.864**	**0.855**	0.952	**0.866**	**0.866**	**0.043**



Case studies: mapping forests damaged by pests in Western Siberia



- Just to note that the methods can be relatively easily adapted for solving other problems

Project

In the project, we suggest going deeper with random forests and several deep learning models for glacier mapping in different world regions.

What we can offer for the beginning:

- A Jupyter notebook with the data preparation process
- A Jupyter notebook showing how to classify images with random forest
- A Jupyter notebook with fully-convolutional networks, from training to producing vector outputs
- Two pretrained models—U-Net, DeepLabV3+ (slightly modified)
- $\approx$ 200 GB dataset with optical imagery, SAR and DEM data that covers some of the Alps, Southern Andes, New Zealand and two areas in the Himalayas

Project: options

- Applying the pretrained models to other regions
- Tweaking the deep learning models
- Modifying the training routines
- Hyperparameter tuning for random forest
- Labelling snow cover and training multi-class classification models
- Exploring how different feature sets affect classification performance

  And more...

- Do not hesitate to suggest your ideas!

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Forskningsrådet

CloudFerro

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