



JYVÄSKYLÄN YLIOPISTO
UNIVERSITY OF JYVÄSKYLÄ

Konvoluutionaaliset neuroverkot maanpeiteluokittelussa ja puulajitunnistuksessa

Dosentti Ilkka Pölönen
Metsätieteen päivät / Taksattoriklubi
26.11.2018

JYU. Since 1863. | 26.11.2018 | 1

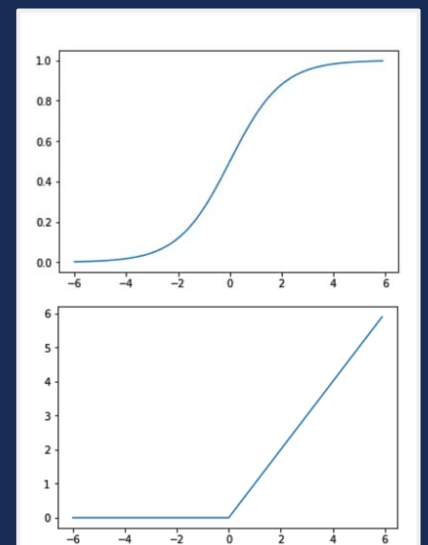
Neuroverkko

- Summaaja

$$f(x_k) = \sum_{j=1}^m w_{kj} x_j$$

- Aktivaatio

$$y_k = \phi(f(x_k) + b_k)$$

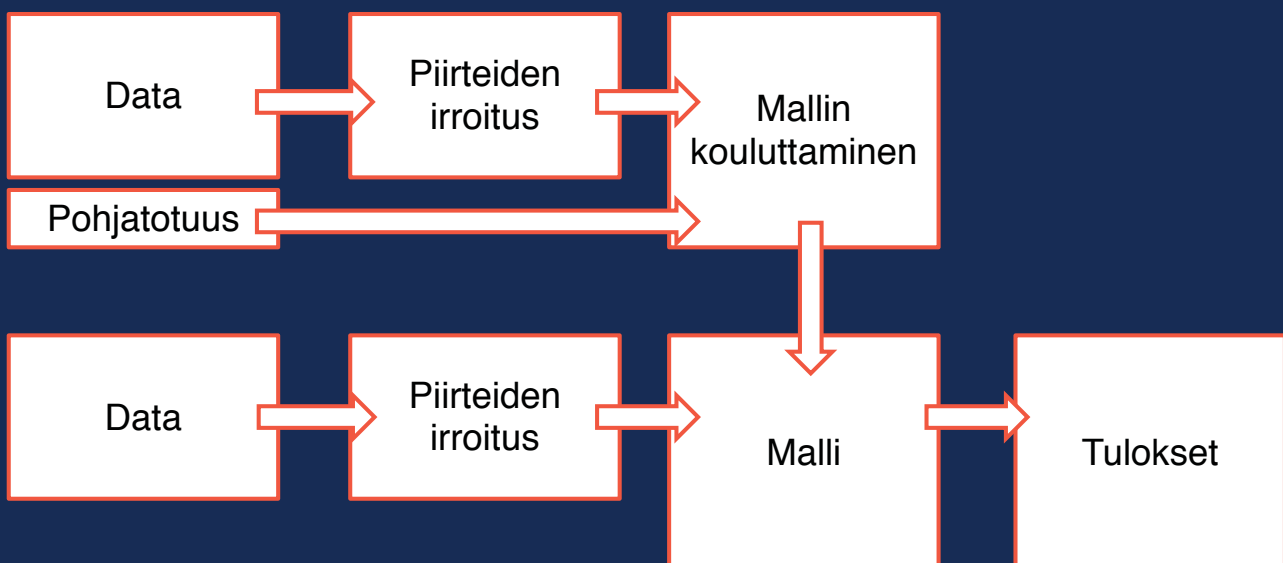


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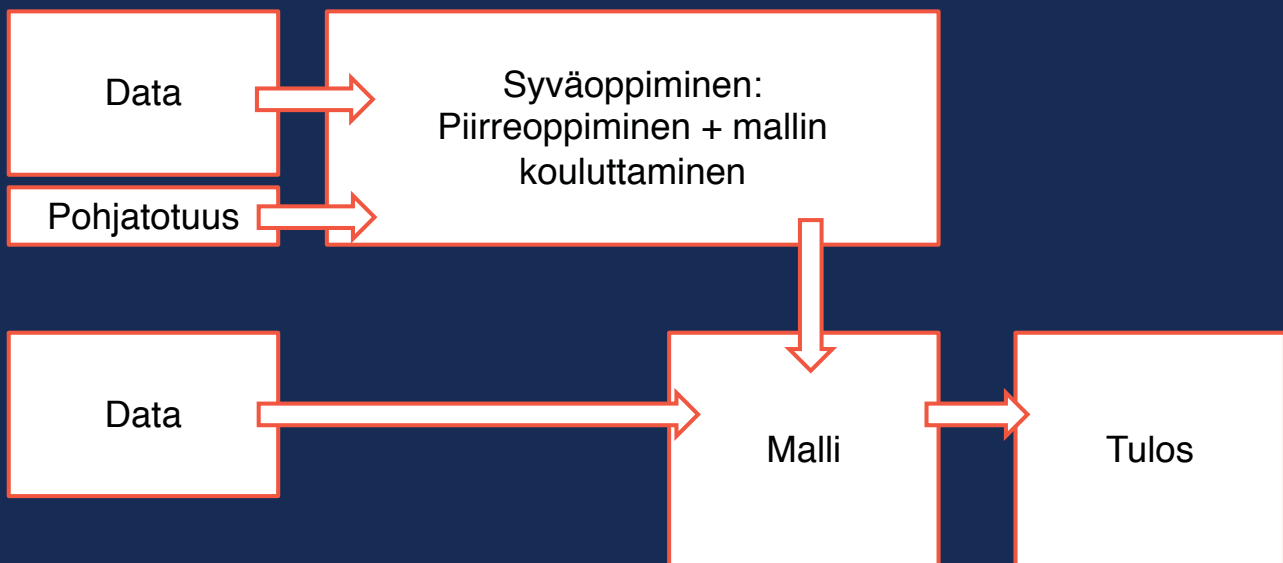
Monikerrosverkko

- $f(x_k) = \sum_{j=1}^m w_{kj} x_j$
- $g(x_k) = \sum_{j=1}^m w_{kj} x_j$
- $y_k = \phi(f(x_k) + b_k)$
- $\phi(g(\phi(f(x_k)))) = y_k$

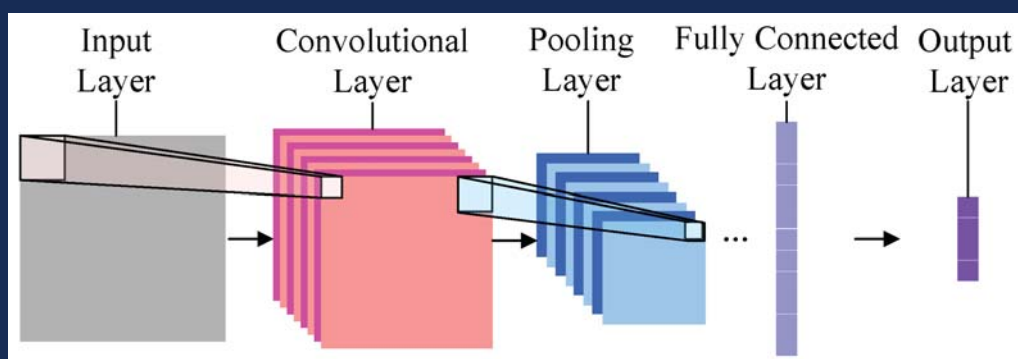
Ohjattu oppiminen



Syväoppiminen



Konvoluutionaalinen neuroverkko



?

$$\phi(g(\phi(f(x_k))))$$

2D konvoluutio

- $K = \begin{bmatrix} -1 & 0 & 1 \\ -2 & 0 & 2 \\ -1 & 0 & 1 \end{bmatrix}$

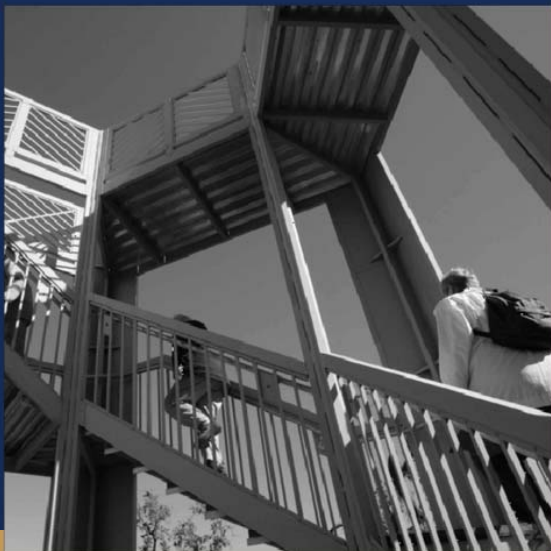
- F on kuva

- Konvoluutio:

$$[F * K](i, j) = \sum_{u, v} F(i - u, j - v)K(u, v)$$

Konvoluutio

- $K = \begin{bmatrix} -1 & 0 & 1 \\ -2 & 0 & 2 \\ -1 & 0 & 1 \end{bmatrix}$



Konvoluutio

$$\bullet K = \begin{bmatrix} -1 & -2 & -1 \\ 0 & 0 & 0 \\ 1 & 2 & 1 \end{bmatrix}$$

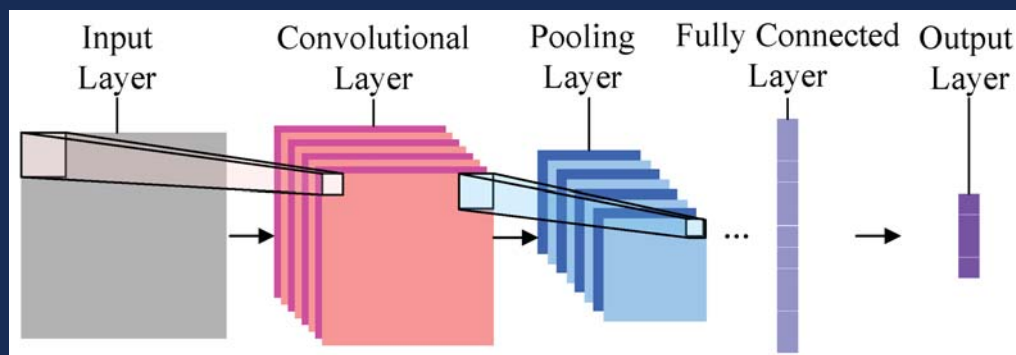


Konvoluutio

$$\bullet K = \begin{bmatrix} -1.2 & 0 & 0 \\ 0 & 0 & 0 \\ 0 & 0 & 0.8 \end{bmatrix}$$



Konvoluutionaalinen neuroverkko



K

$$\phi(g(\phi(f(x_k))))$$



Konvoluutionaalinen neuroverkko

Layer	Kernel / pool size or Activation	Output Shape	Parameters
Conv3D	(3,3,1) ReLU	(39, 39, 33, 64)	640
Conv3D	(3,3,3) ReLU	(37, 37, 31, 64)	110656
MaxPooling3D	(2,2,1)	(18, 18, 31, 64)	0
Conv3D	(3,3,3) ReLU	(16, 16, 29, 128)	221312
MaxPooling3D	(2,2,3)	(8, 8, 9, 128)	0
Conv3D	(3,3,3) ReLU	(6, 6, 7, 256)	884992
MaxPooling3D	(2,2,3)	(3, 3, 2, 256)	0
Flatten		(4608)	0
Dense	ReLU	(128)	589952
Dropout (0.25)		(128)	0
Dense	SoftMax	(3)	387
Total params:	1,807,939		
Trainable params:	1,807,939		
Non-trainable params:	0		

Table 1. Structure of our experimental CNN.



Konvoluutionaalinen neuroverkko

- Optimointi: Stochastic gradient decent
- Kustannusfunktio: Categorical cross entropy
 - / Laskee ristiin entropiaa luokkien välillä



TREE SPECIES IDENTIFICATION USING 3D SPECTRAL DATA AND 3D CONVOLUTIONAL NEURAL NETWORK

*Ilkka Pölönen¹, Leevi Annala¹,
Samuli Rahkonen¹, Olli
Nevalainen², Eija Honkavaara²,
Sakari Tuominen³, Niko Viljanen²,
Teemu Hakala²*

¹Faculty of Information Technology, University of Jyväskylä, P.O. Box 35, FI-40014 Jyväskylä, Finland

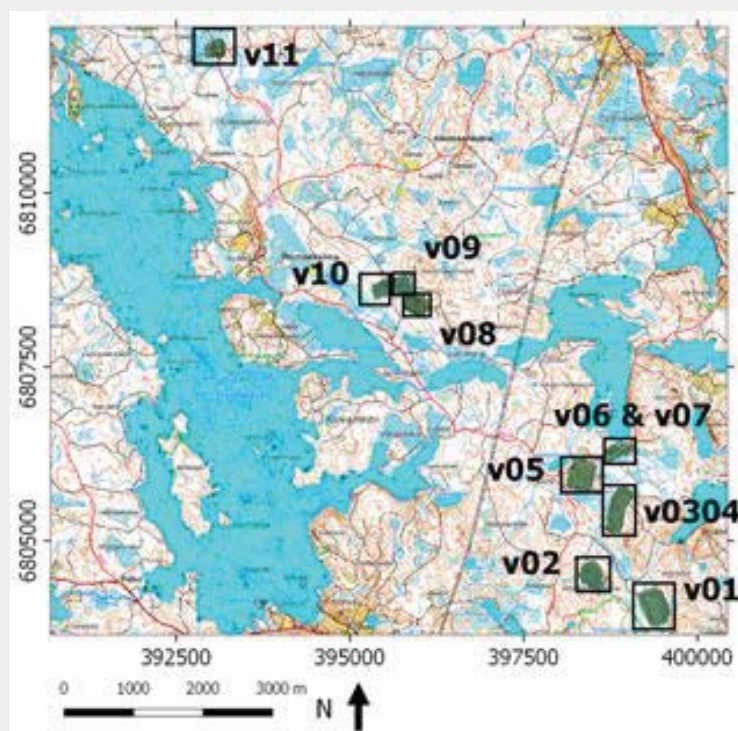
²Finnish Geospatial Research Institute, National Land Survey of Finland, Geodeetinrinne 2, 02430 Masala, Finland

³Natural Resources Institute Finland, PL 2 00791 Helsinki, Finland



Data

- Collected from Vesijako, 2015
- VTT-Proto-2012-b hyperspectral imager
- RGB -camera



Data

- Collected from Vesijako, 2015
- VTT-Proto-2012-b hyperspectral imager
- RGB -camera



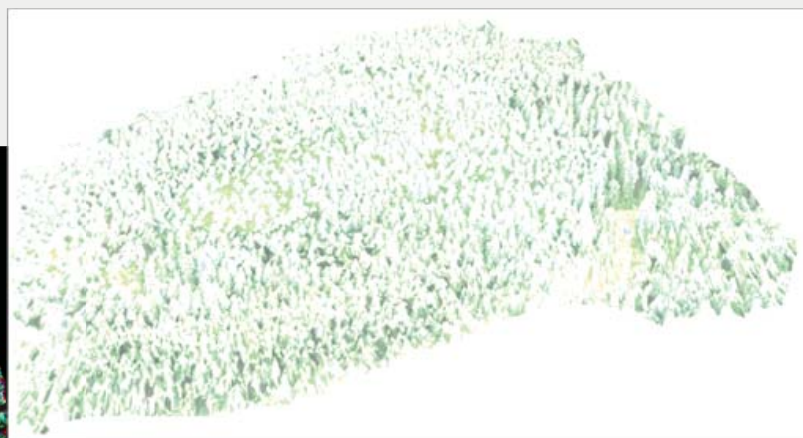
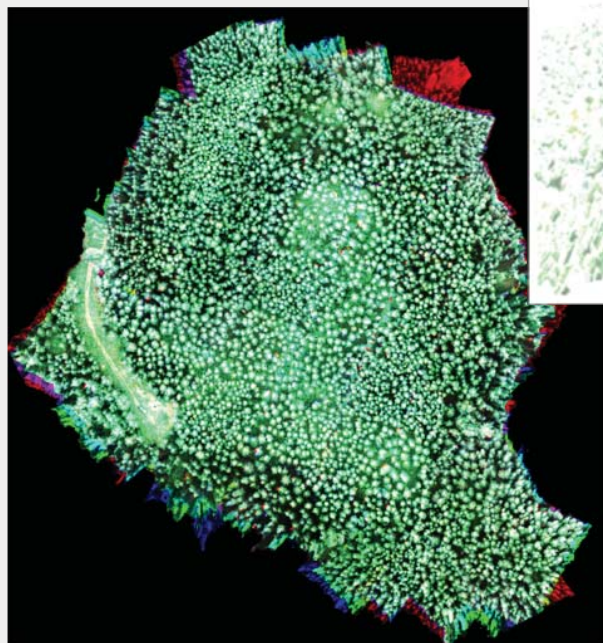


Training set

- 3D volume cube (41x41x34) pixels
 - / One treetop model
 - / 33 spectral channels
 - / 4x4 meter
- Approx. 1000 trees/class
- After augmentation 16555
 - / Simple rotation and flipping operations

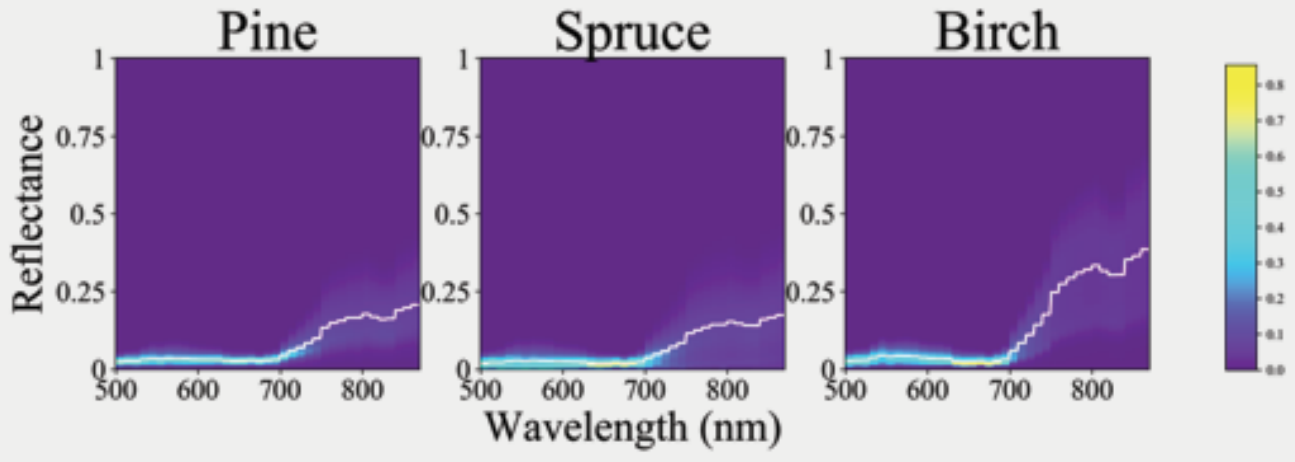


Data

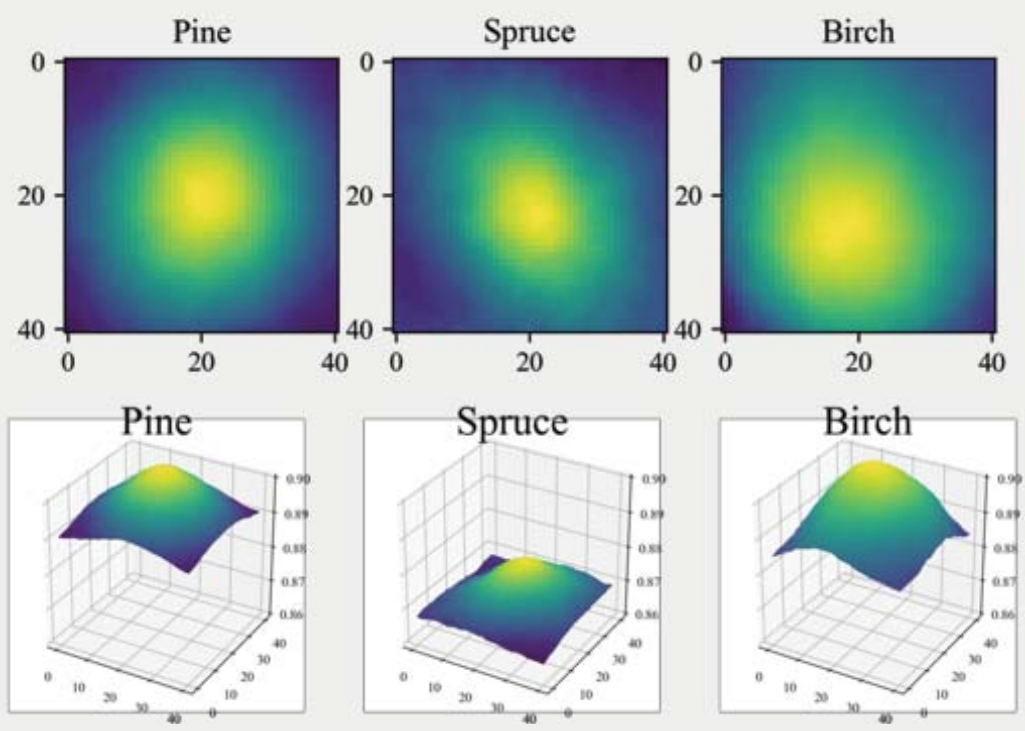




Spectral variance and mean between different tree species

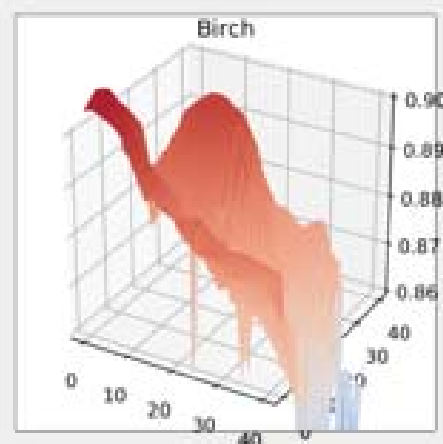
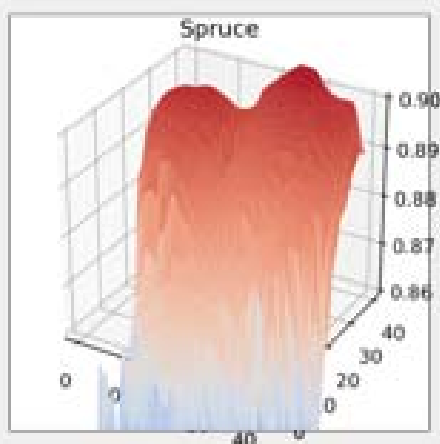
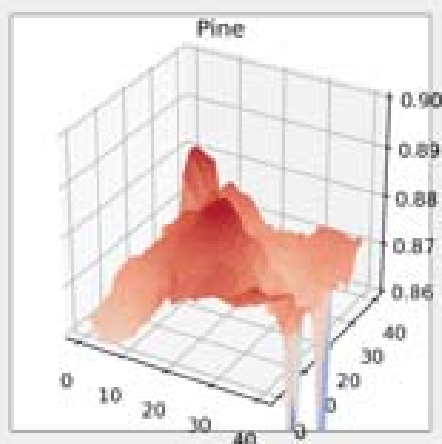


Average shapes of different treetops



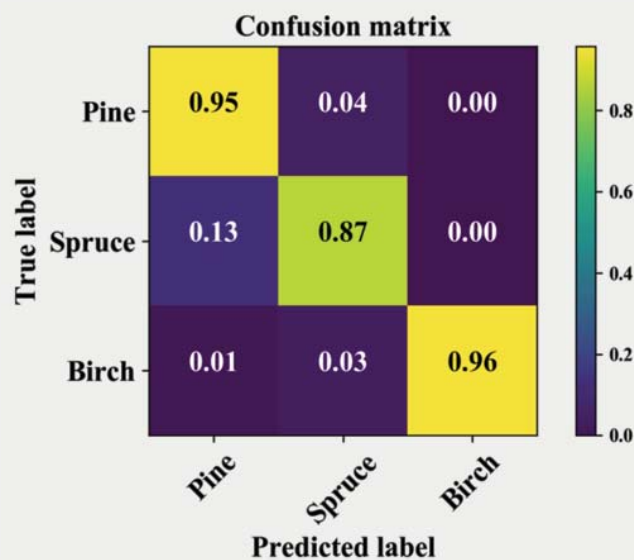
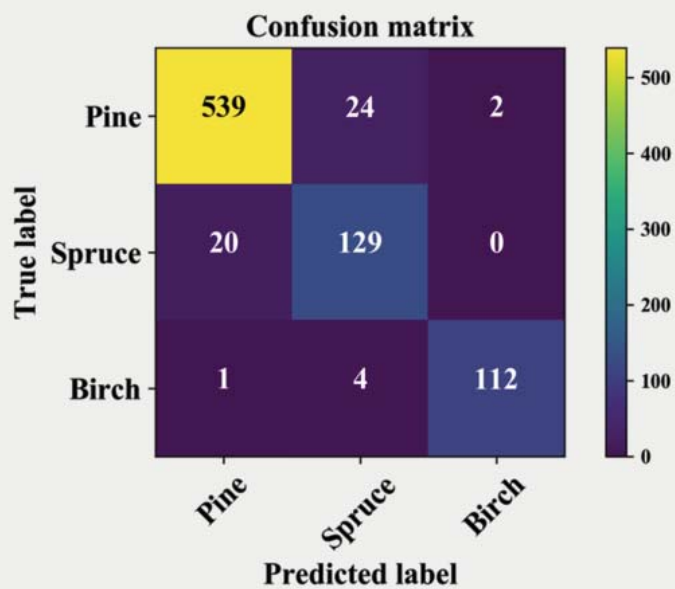


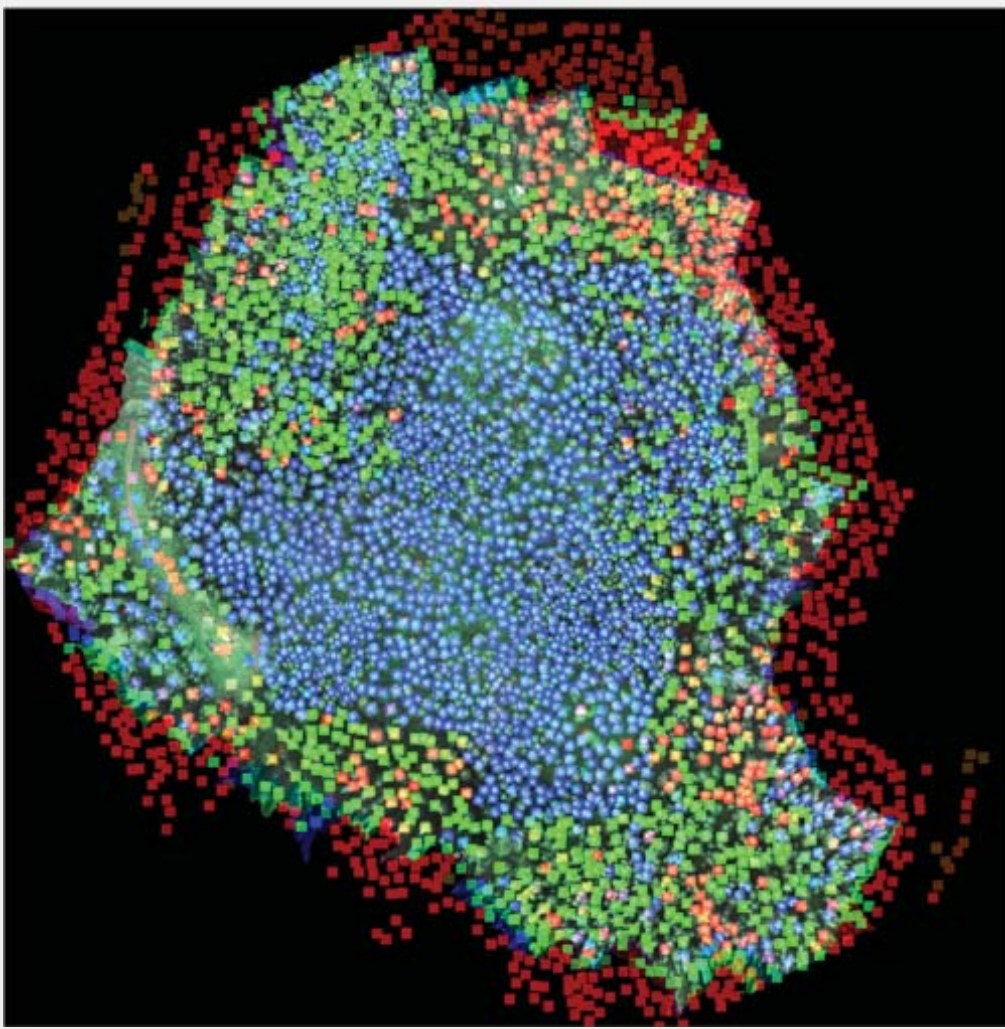
Random treetops from test data



Results

- Test set 831 samples



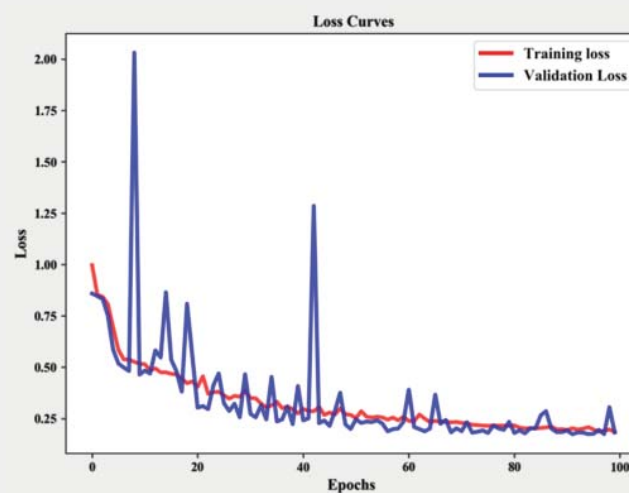
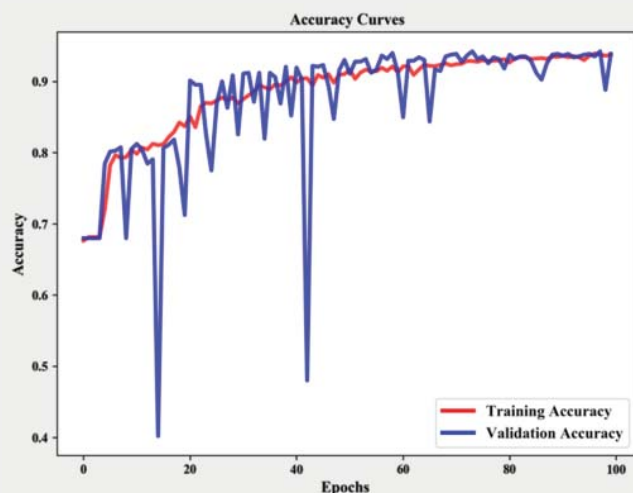


Riskit

- Ylisovittuminen
- Mustalaatikko



Accuracy and loss

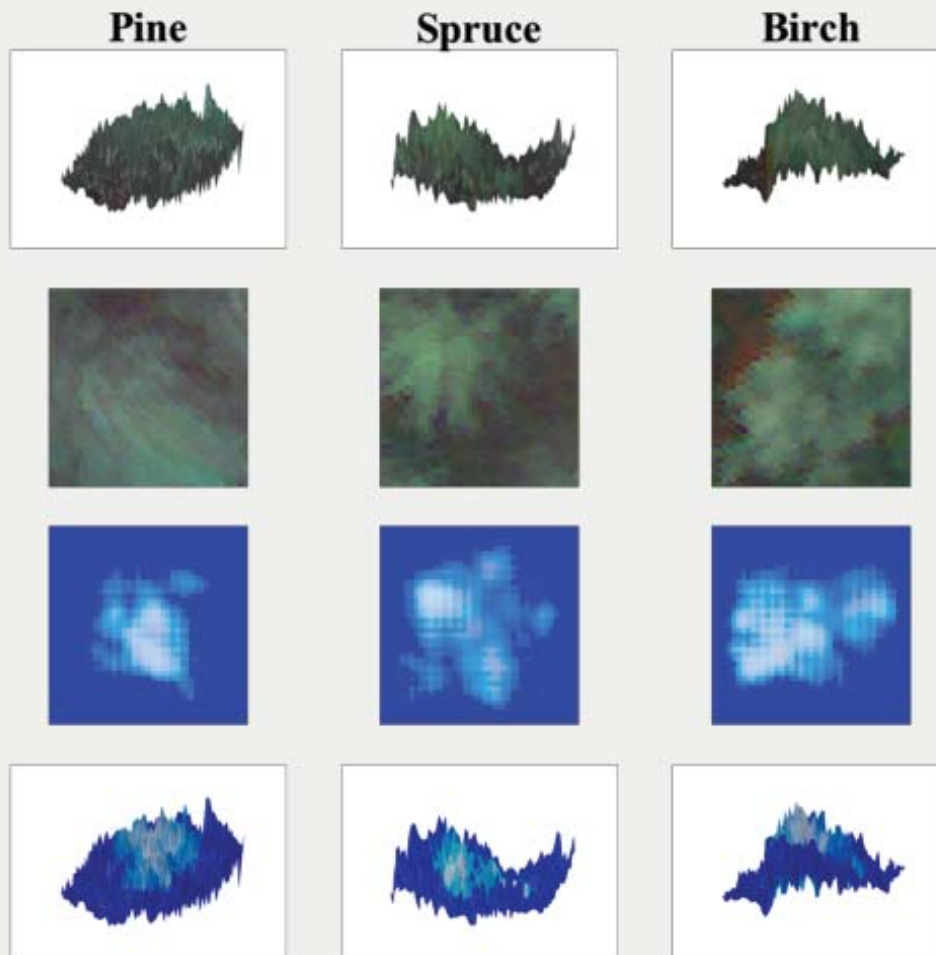
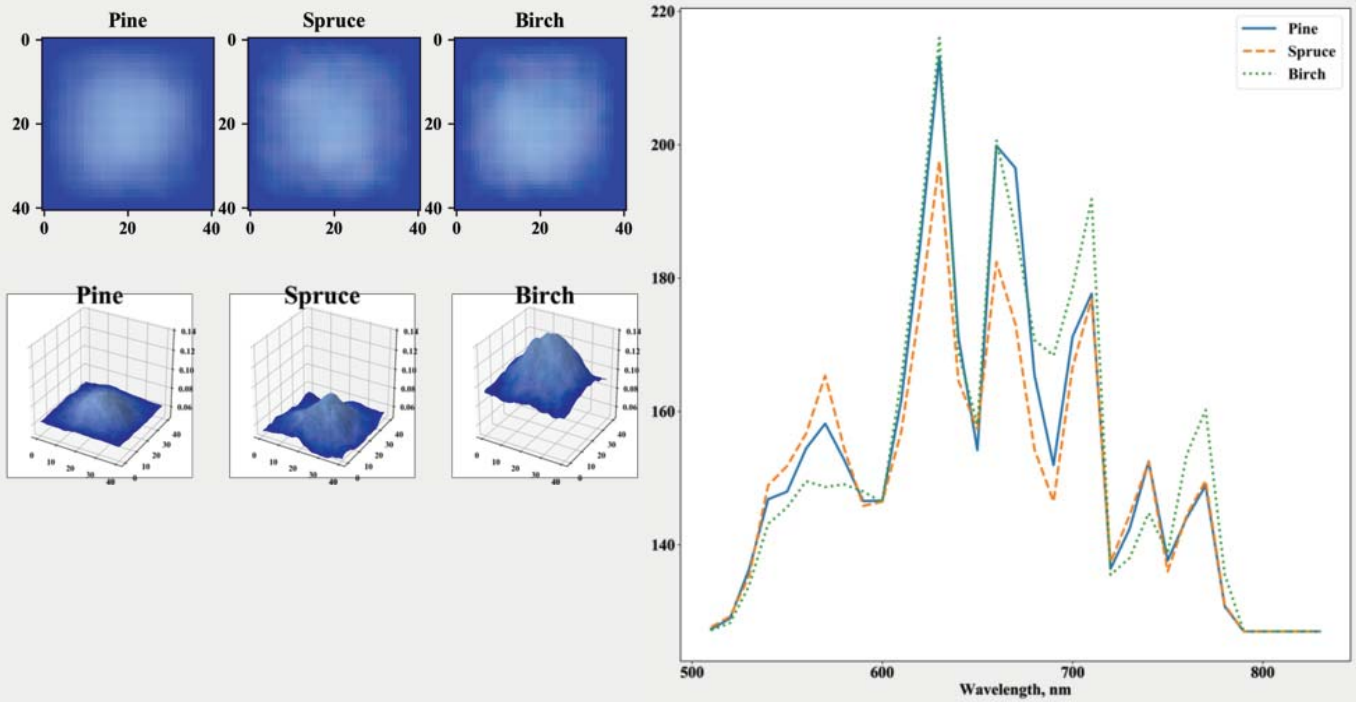


Saliency maps

- It is reasonable to ask, is the classification based on real feature of wanted object or something secondary such as ground type in tree species recognition.
- Calculate gradient over layers from output to input
- Higher values contributes most to classification results



Saliency maps





Land cover classification from multispectral data using convolutional autoencoder networks

Janne Mäyrä
Pro Gradu
2018
Jyväskylän yliopisto

Pian saatavilla:
jyx.jyu.fi



U-NET

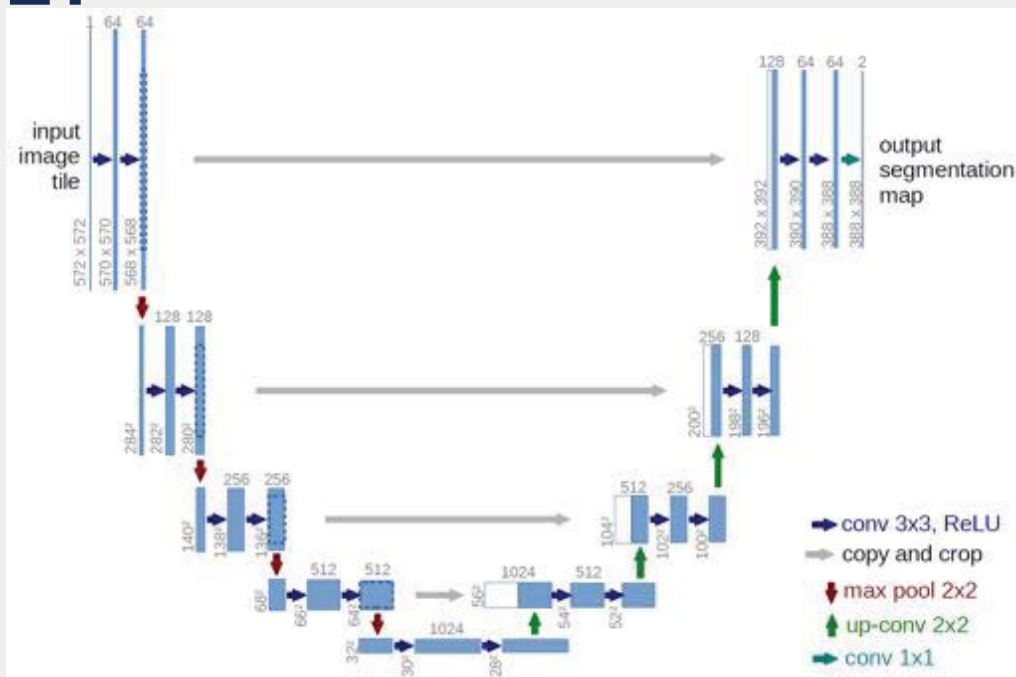


Figure 7. U-Net architecture (Ronneberger, Fischer, and Brox 2015)

