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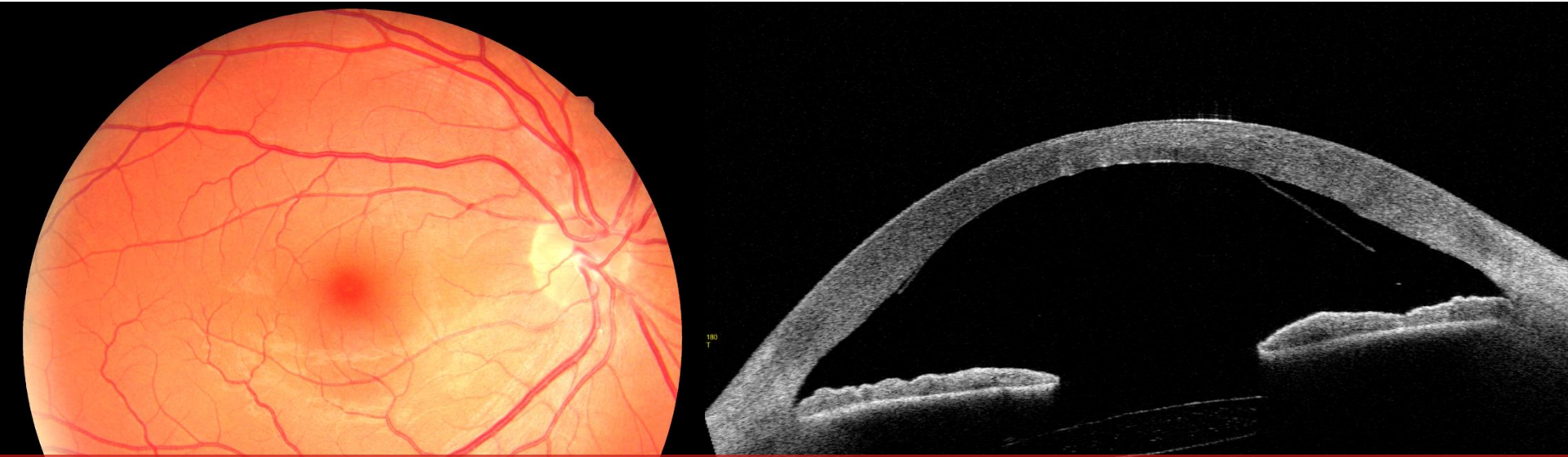
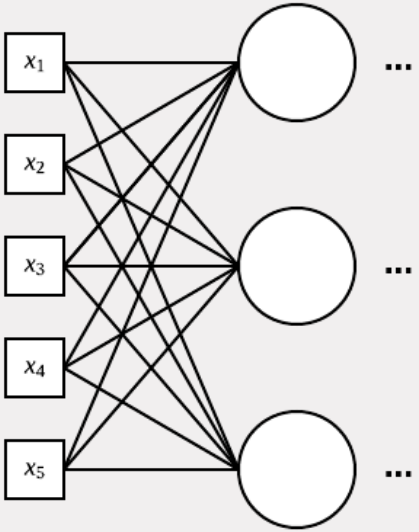


Deep Learning Frameworks and Applications (8DC00)

Friso G. Heslinga

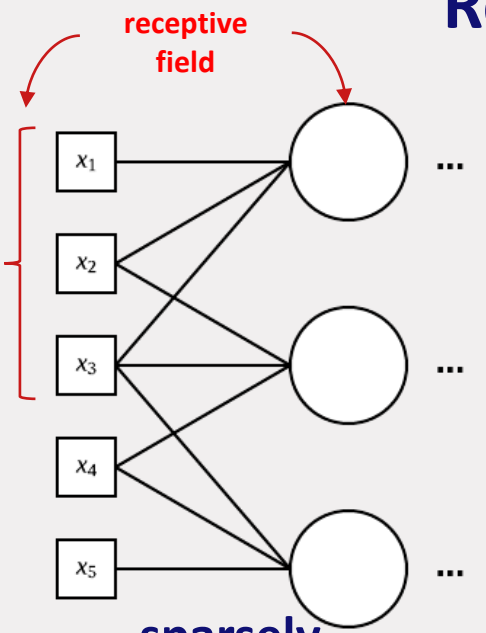
Previous lecture



“regular” NN

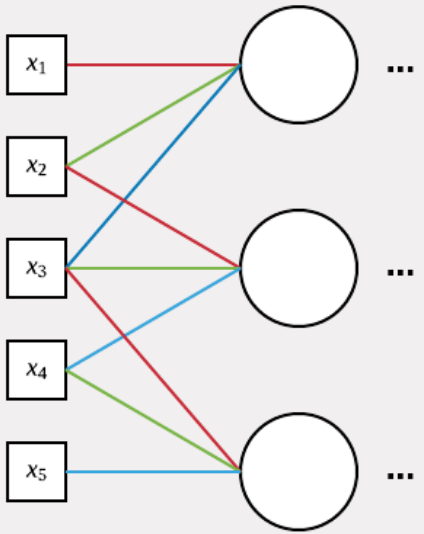
15 weights

Reducing # of weights



sparsely connected NN

9 weights



shared weights

3 weights

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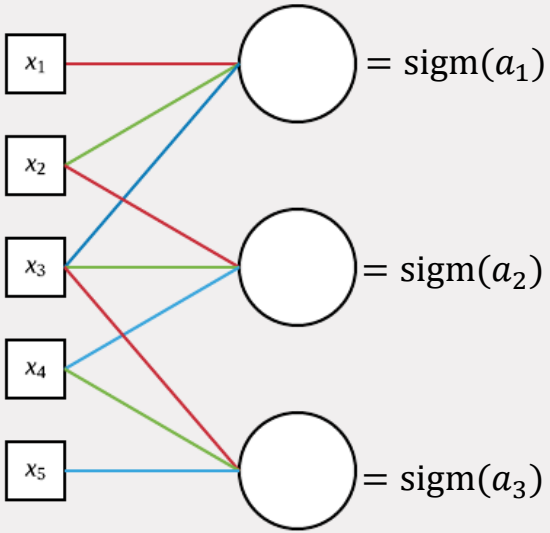
Previous lecture



$$a_1 = x_1 w_1 + x_2 w_2 + x_3 w_3$$

$$a_2 = x_2 w_1 + x_3 w_2 + x_4 w_3$$

$$a_3 = x_3 w_1 + x_4 w_2 + x_5 w_3$$

$$[a_1 \quad a_2 \quad a_3] = [x_1 \quad x_2 \quad x_3 \quad x_4 \quad x_5] * [w_1 \quad w_2 \quad w_3]$$

convolution

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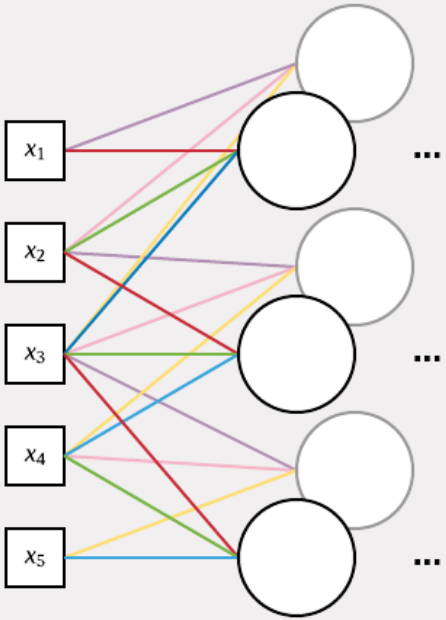
Previous lecture



two sets shared weights

6 weights

$$[a_{1,1} \quad a_{1,2} \quad a_{1,3}] = [x_1 \quad x_2 \quad x_3 \quad x_4 \quad x_5] * [w_{1,1} \quad w_{1,2} \quad w_{1,3}]$$

$$[a_{2,1} \quad a_{2,2} \quad a_{2,3}] = [x_1 \quad x_2 \quad x_3 \quad x_4 \quad x_5] * [w_{2,1} \quad w_{2,2} \quad w_{2,3}]$$

$[w_{1,1} \quad w_{1,2} \quad w_{1,3}]$, and $[w_{2,1} \quad w_{2,2} \quad w_{2,3}]$ are **convolution kernels**. They extract features.

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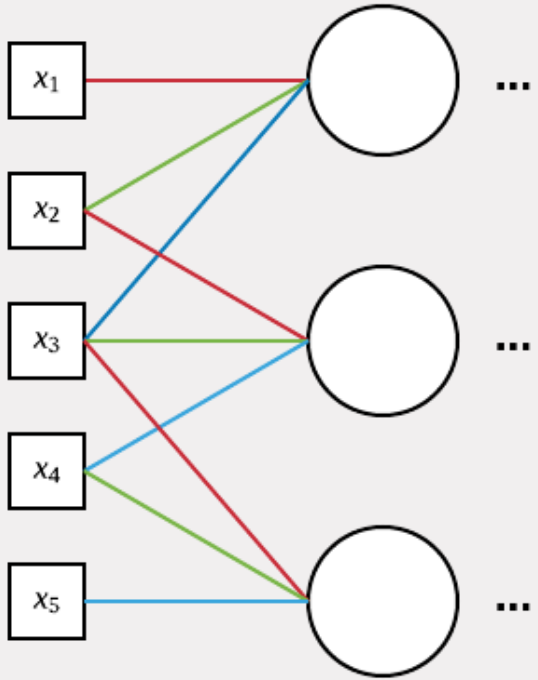
Previous lecture: properties of CNNs

- Sparse connectivity
- Weight sharing
- Parallel computations



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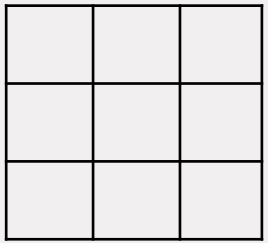
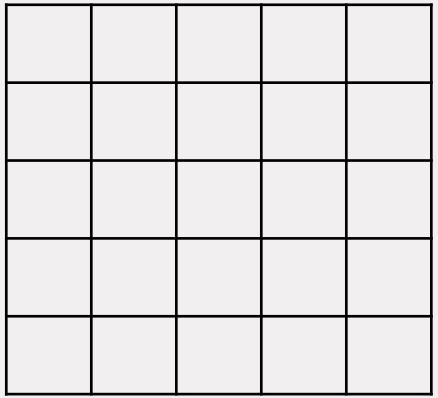
Previous lecture: Kernel size

1 x 1

3 x 3



5 x 5



- More weights → more information
- More computations / memory
- Receptive field

Previous lecture: Max-pooling

- Reduce size of feature space
- Maximum of features
- Typical kernel size = 2 x 2

Addition to last lecture:

Stride = step size of the sliding window

- Typically 1 for convolutions
- Typically equal to kernel size for pooling operations

aw your number here

Downsampled drawing: 3

First guess: 3

Second guess: 1

ver visibility

t layer	Show
volution layer 1	Show
nsampling layer 1	Show
volution layer 2	Show

Previous lecture: Training of CNNs

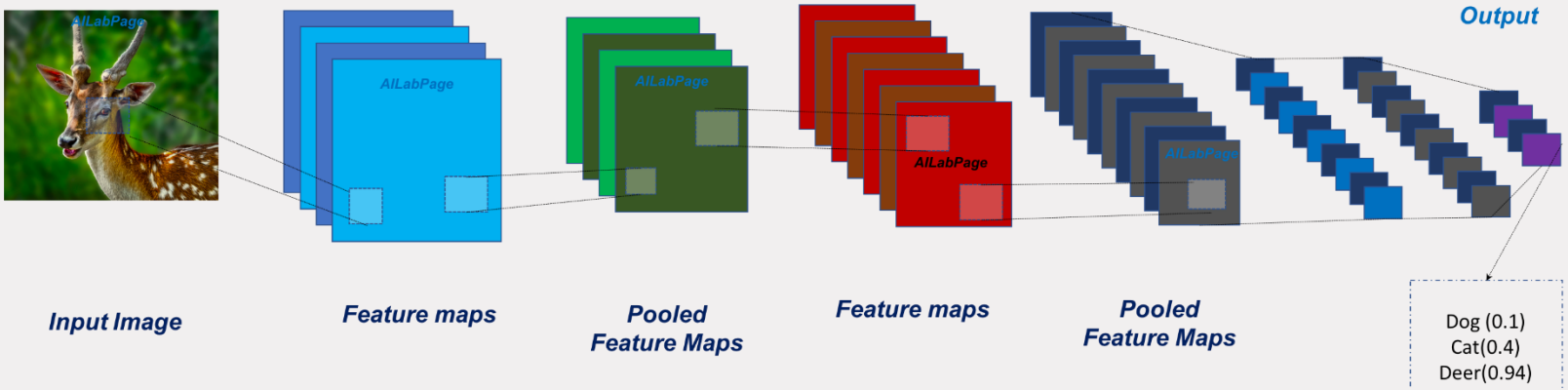
- Similar to training of ‘fully connected’ neural networks
- **Choose some (random) initial values for network weights**
- Optimize networks weights with respect to a loss function that describes difference between network output and label/annotation
- Update networks weights iteratively

Through a process called ‘backpropagation’. A good explanation can be found here: https://www.youtube.com/watch?v=i94OvYb6noo (5:10 - 28:00, not exam material)

- Keep track of model performance on train & validation set

Previous lecture

- Convolutional neural networks (CNN)



- By now: students can design a (simple) CNN

Image from: https://vinodsblog.com/

Challenges..

Disadvantage of designing yourself..?

- New implementation
- Design choices
- Time-consuming
- Debugging
- No reference performance
- Non-optimized model
- Train from scratch

Deep Learning Framework

Model architecture (from literature)

+

Framework (software packages)

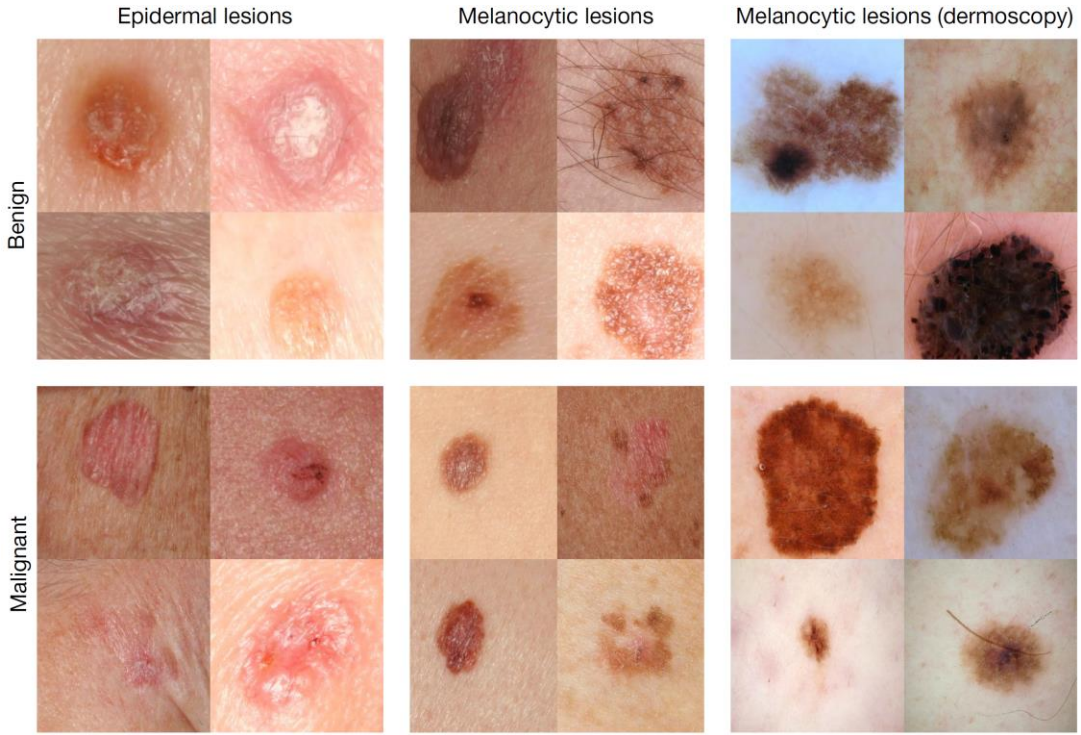
Learning outcomes

- Students will be able to name a few **deep learning models** and describe the **differences in model design**
- Students can motivate why they **would choose a deep learning model** for a specific research application
- Students can name **two key developments** that have enabled deep learning

Lecture outline

- Different applications → Different requirements
- Small exercise: “what should be the output?”
- History of deep learning models
- Examples of deep learning models & applications
- *Break (15 mins)*
- Examples of deep learning software
- Group exercise: *“choosing the right deep learning approach”*

Classification



Esteva et al., Nature 2017

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Classification

Two classes

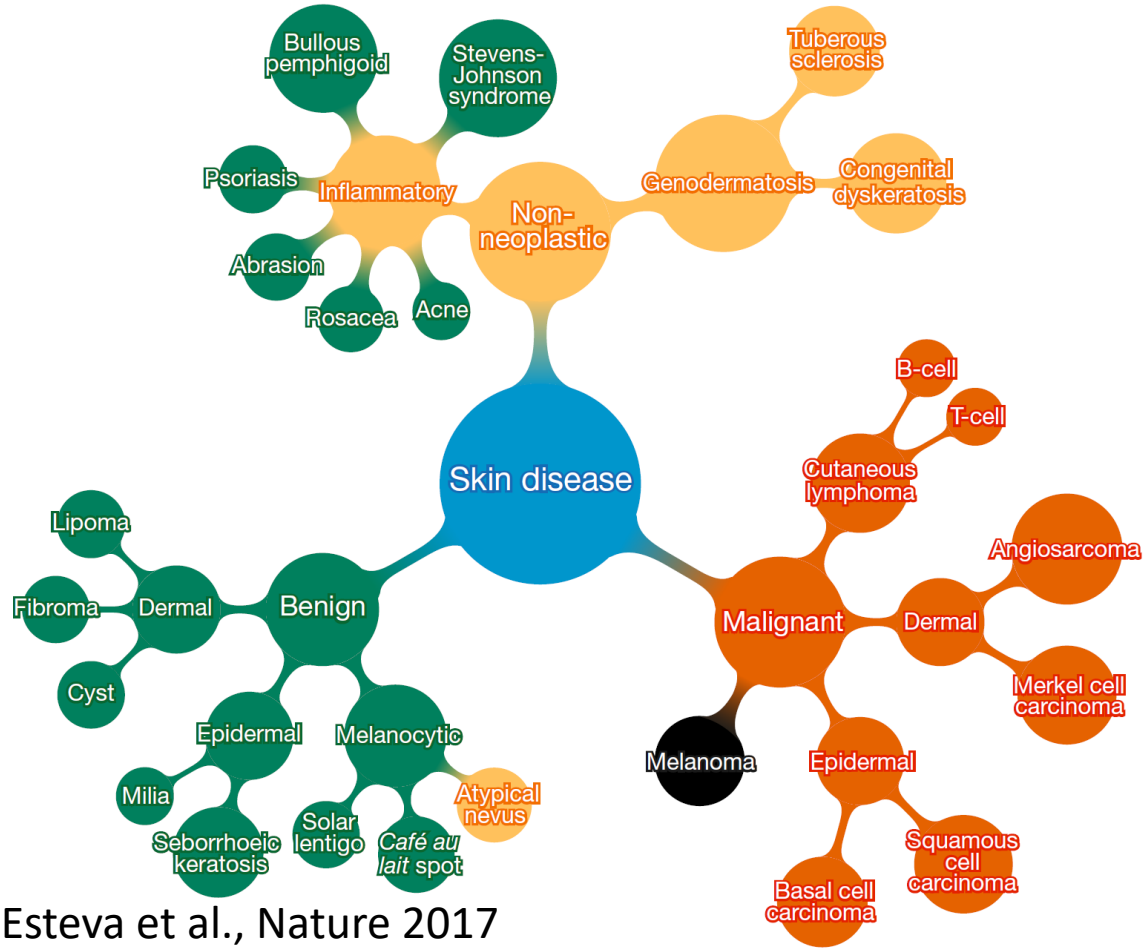
e.g. malignant lesions / other

$$\sigma(z) = \frac{1}{1 + e^{-z}}$$

Multi-class

benign lesions / malignant lesions / non-neoplastic

$$\sigma(\mathbf{z})_i = \frac{e^{z_i}}{\sum_j e^{z_j}}$$



Esteva et al., Nature 2017

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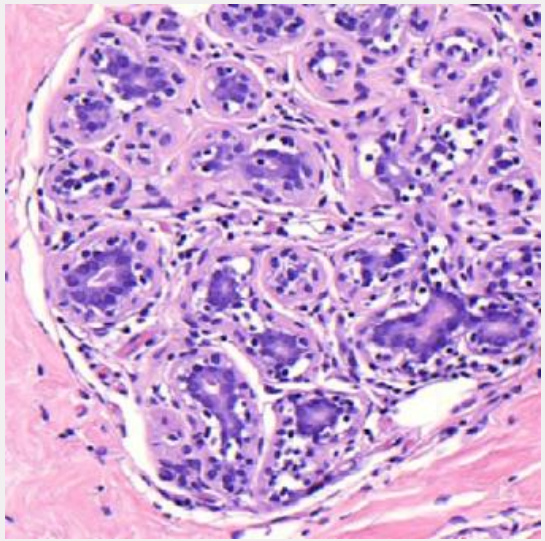
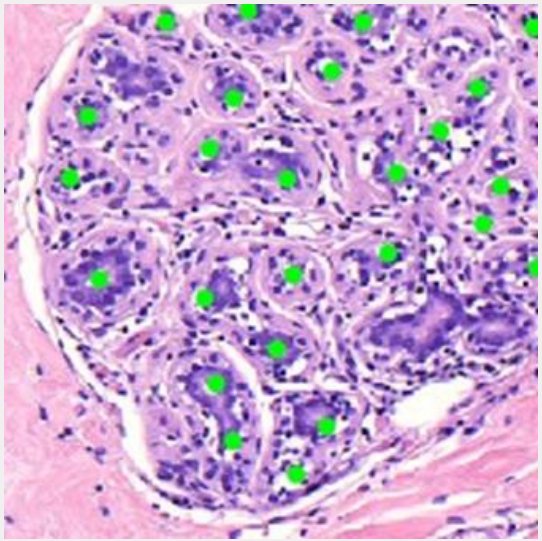
Detection of Acini centers





Wetstein et al., SPIE-MI 2019

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Regression

Retinal structures

- Arteriolar width
- Venular width
- Vessel Tortuosity

Heslinga et al., SPIE-MI 2019

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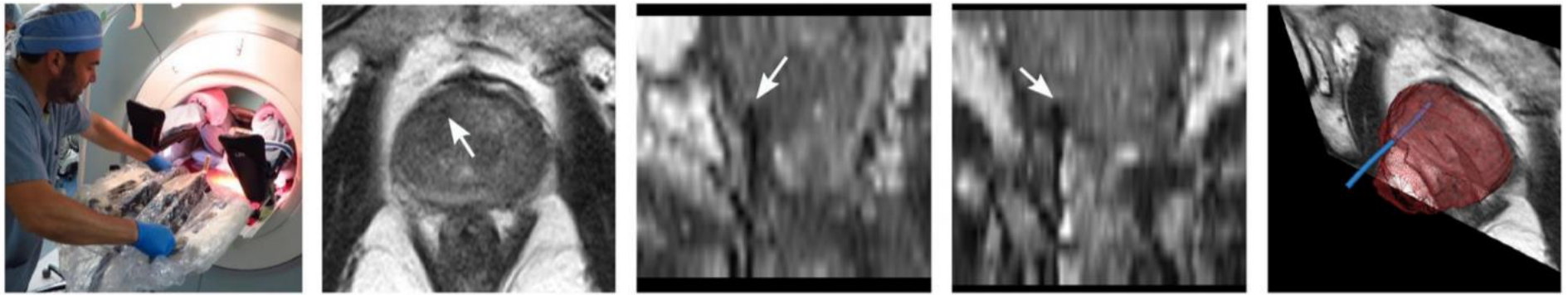
Segmentation

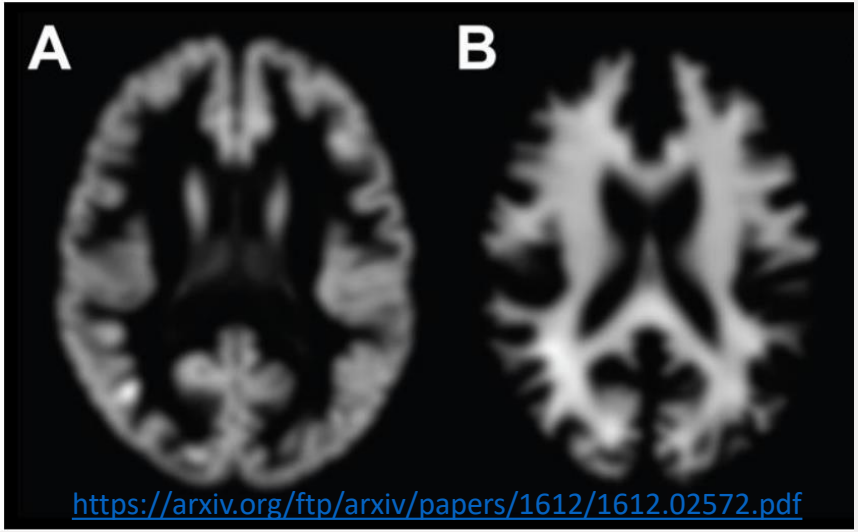
- MRI-targeted prostate biopsy
- Needle segmentation

Mehrtash et al., IEEE Trans Med Imaging 2019



What should be the output of our CNN?

Retinopathy classification



Brain age prediction

https://www.slideshare.net/xavigiro/image-classification-on-imagenet-d1l4-2017-upc-deep-learning-for-computer-vision/

IMAGENET

- 1,000 object classes (categories).
- Images:
  - 1.2 M train
  - 100k test.

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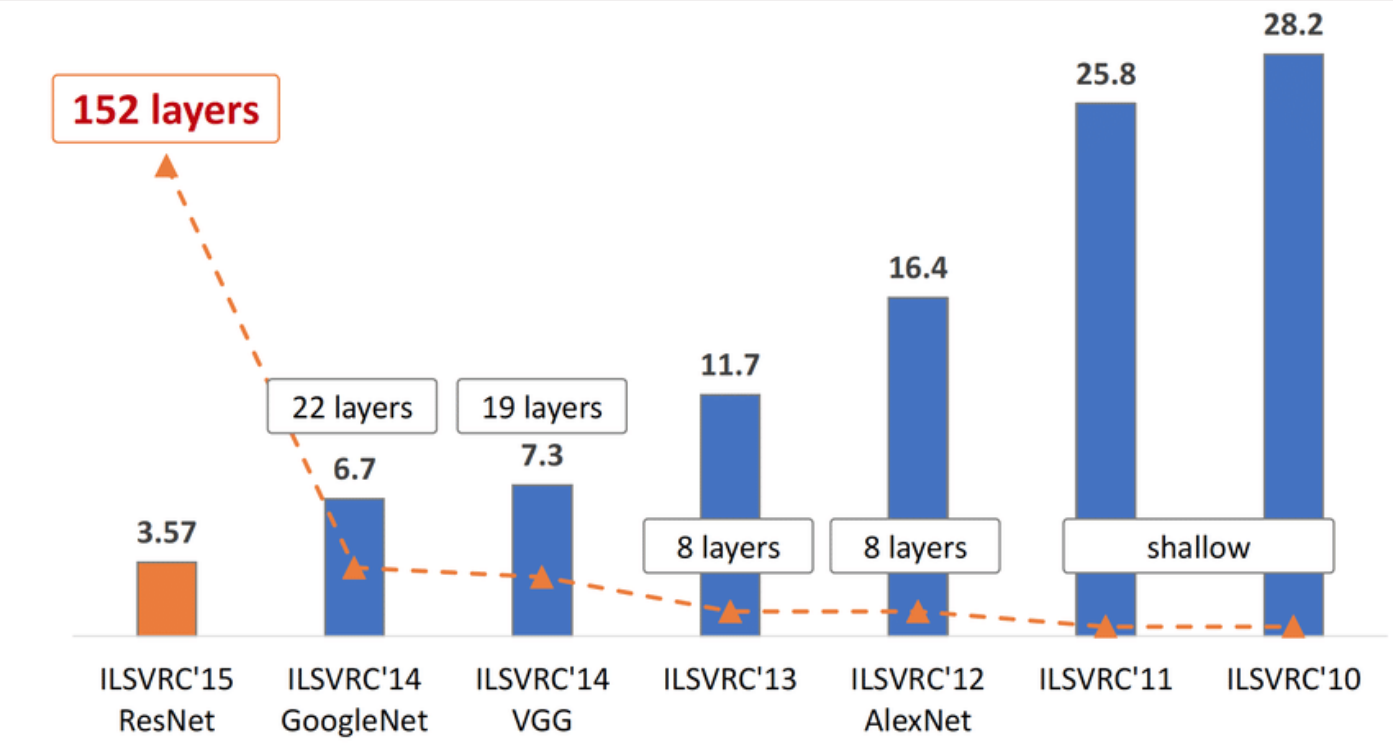
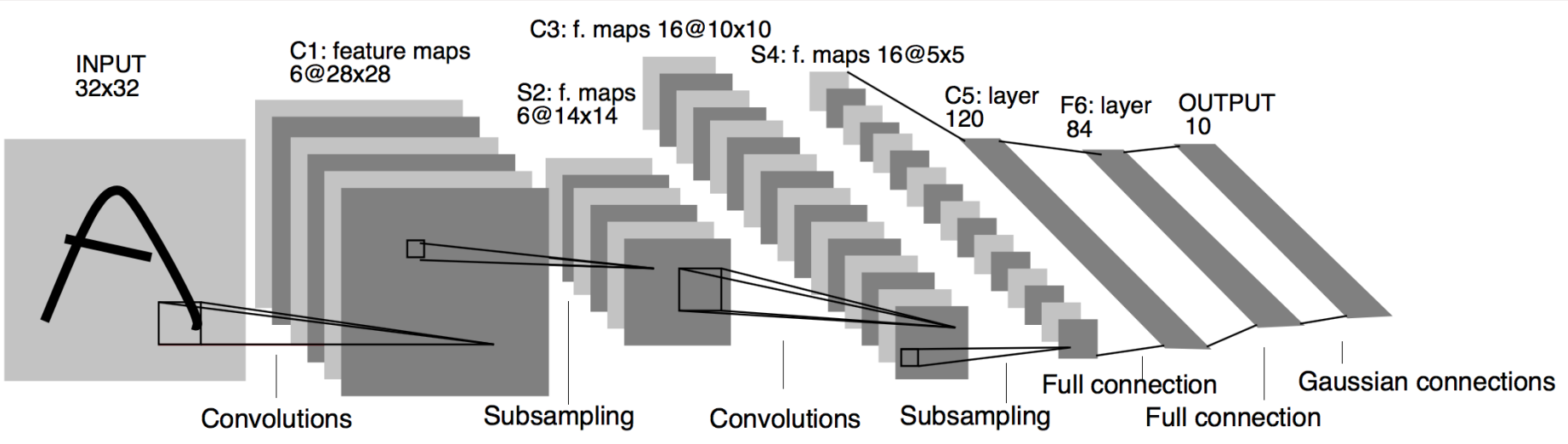
Error rates ImageNet



LeNet


INPUT
32x32
C1: feature maps
6@28x28
S2: f. maps
6@14x14
C3: f. maps 16@10x10
S4: f. maps 16@5x5
C5: layer
120
F6: layer
84
OUTPUT
10
Convolutions
Subsampling
Convolutions
Subsampling
Full connection
Full connection
Gaussian connections

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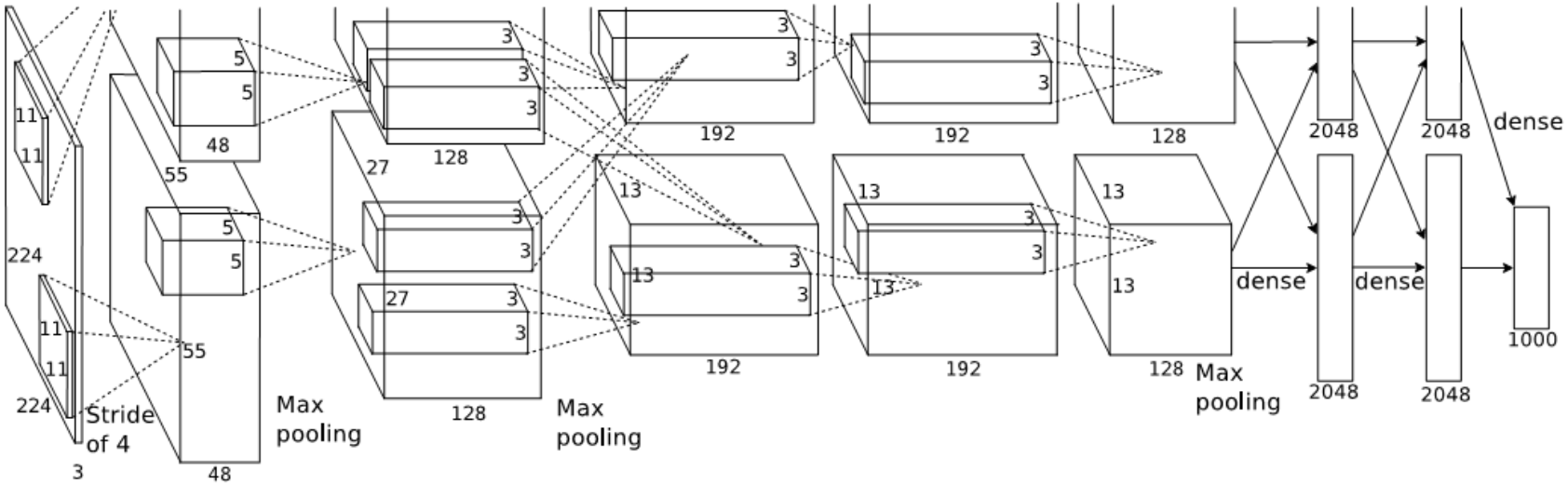
AlexNet

- ImageNet top-5 error from 26% to 15.3%



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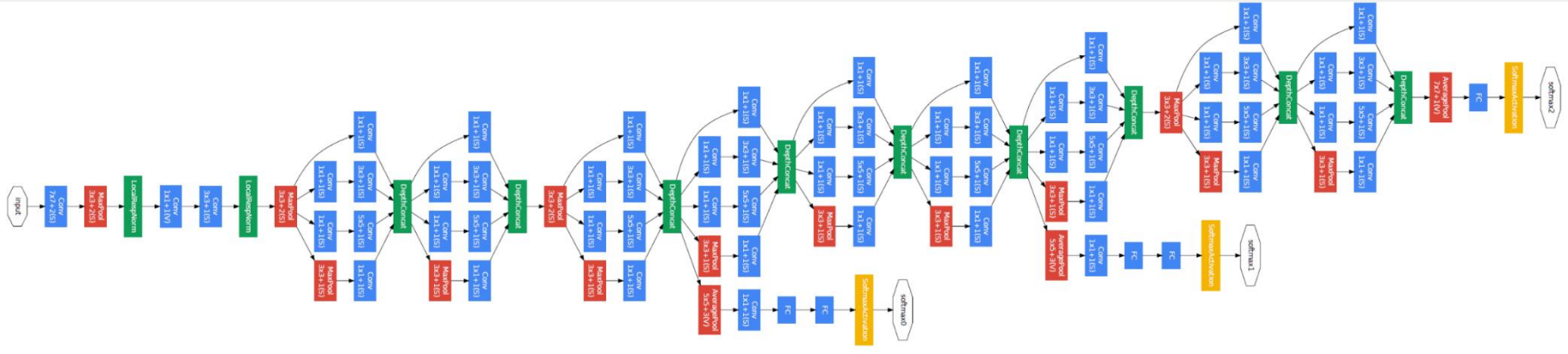
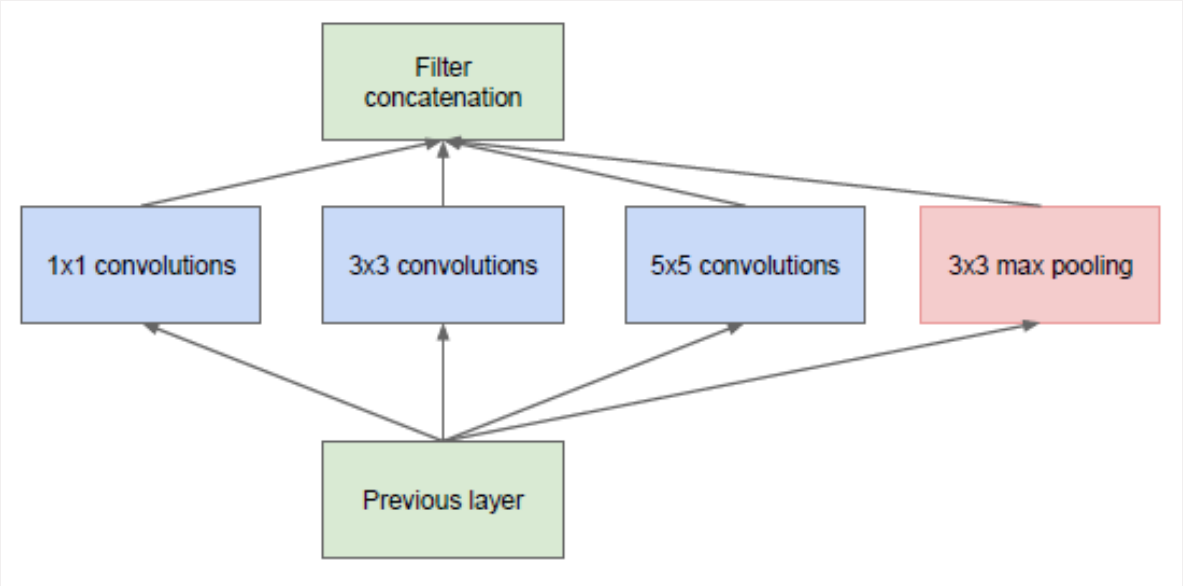
Inception v1 (GoogleNet)

- Inception modules
- Auxiliary targets
- Global average pooling layer

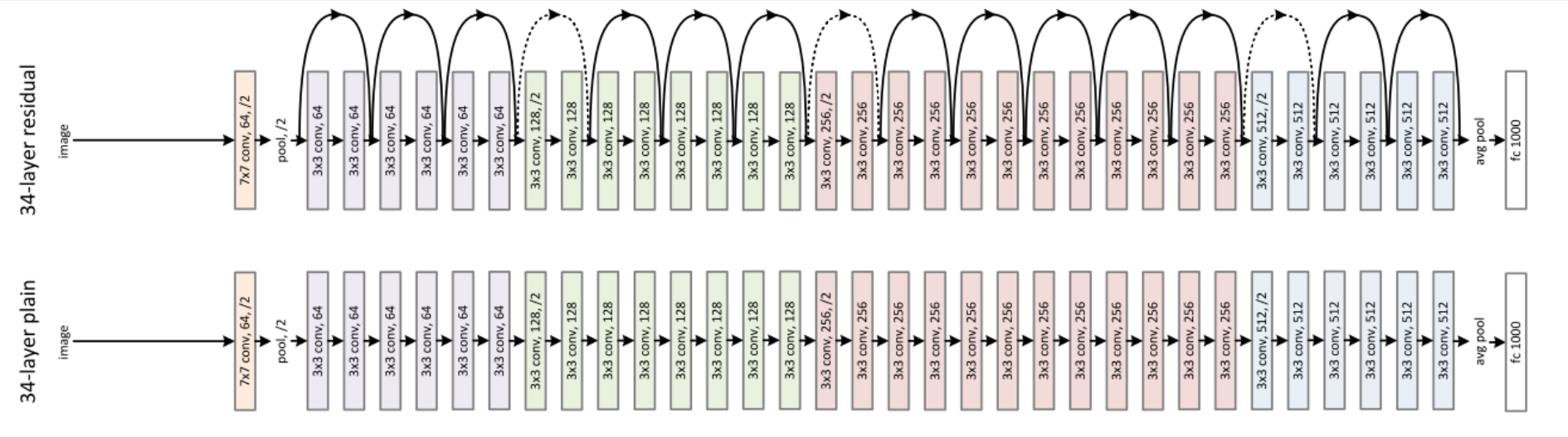


Inception module

- Multiple scales

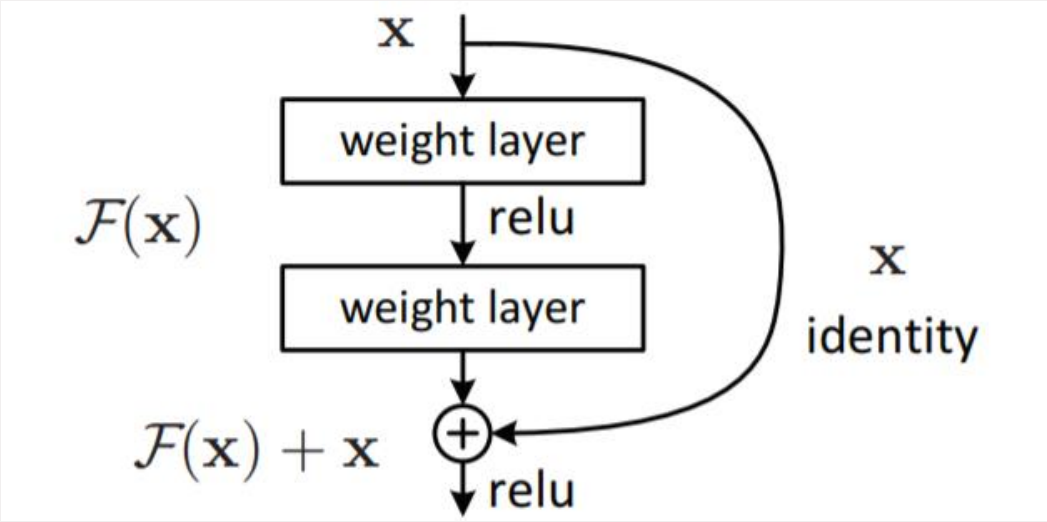


ResNet

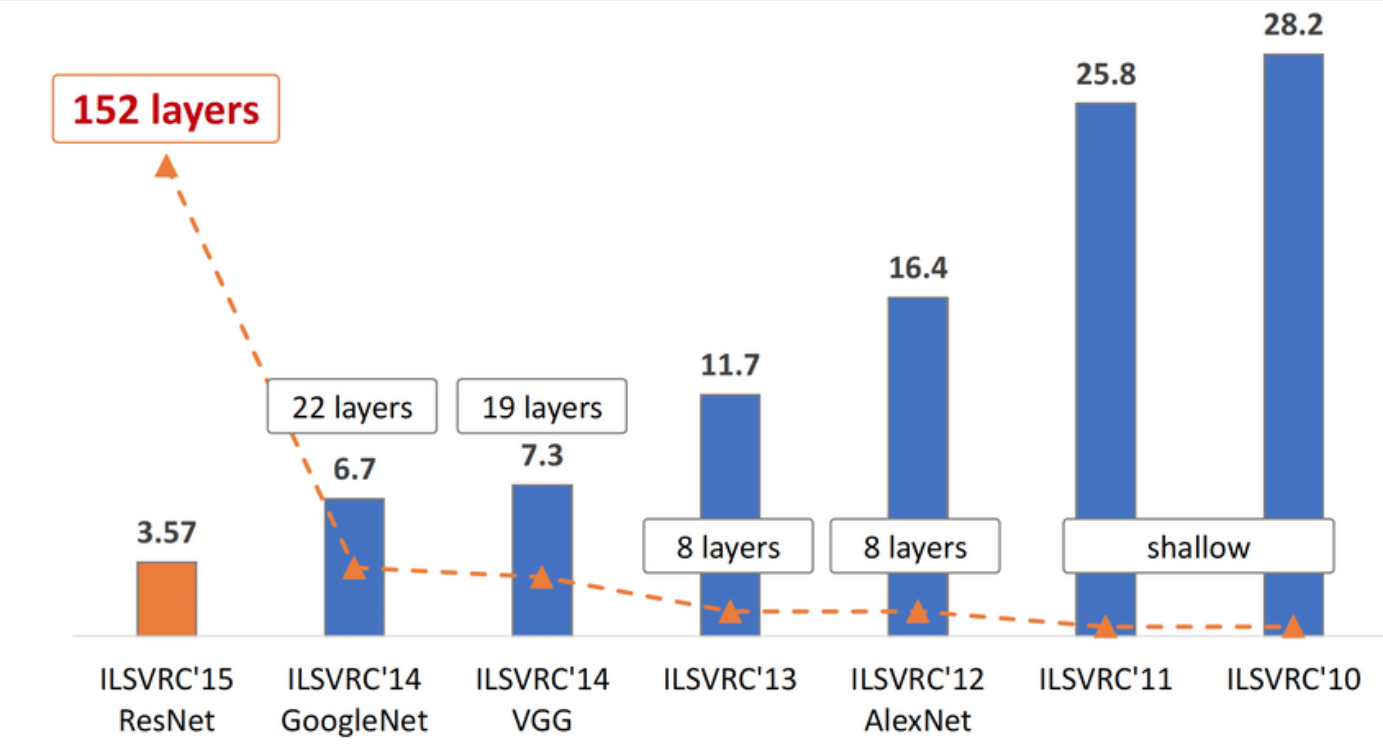

34-layer residual
image
7x7 conv, 64, /2
pool, /2
3x3 conv, 64
3x3 conv, 128
3x3 conv, 256
3x3 conv, 512
avg pool
fc 1000
34-layer plain
image
7x7 conv, 64, /2
pool, /2
3x3 conv, 64
3x3 conv, 128
3x3 conv, 256
3x3 conv, 512
avg pool
fc 1000

Residual block

Learn differences between input and output layer = residue

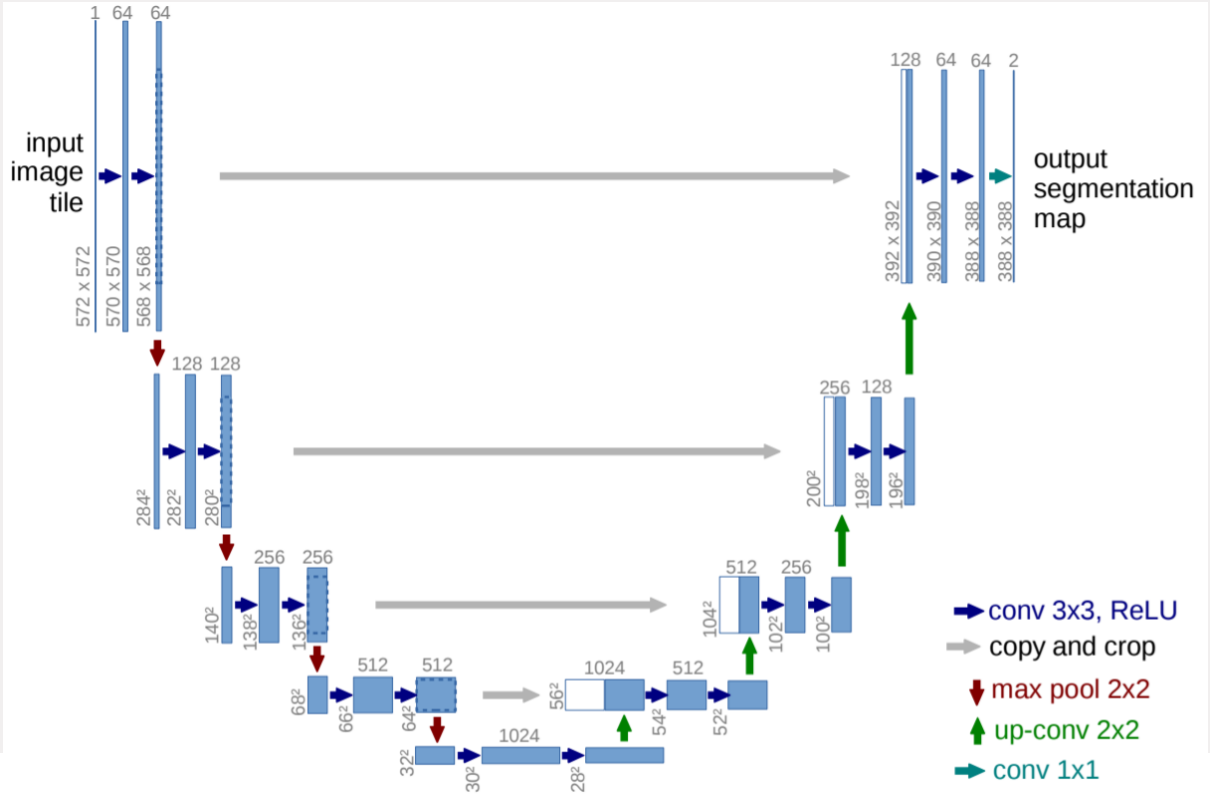


Error rates ImageNet (top 5 accuracy)



U-Net: Segmentation

Ronneberger et al., MICCAI 2015



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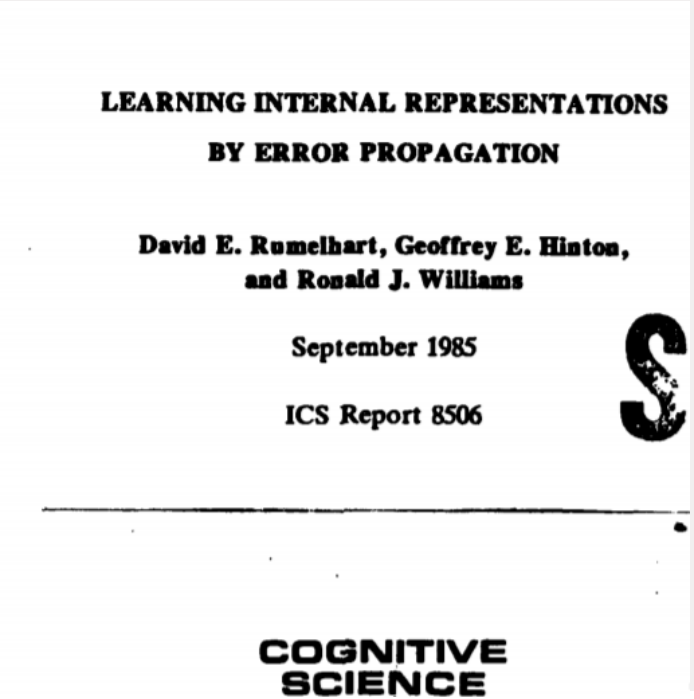
Neural networks have been around



LEARNING INTERNAL REPRESENTATIONS

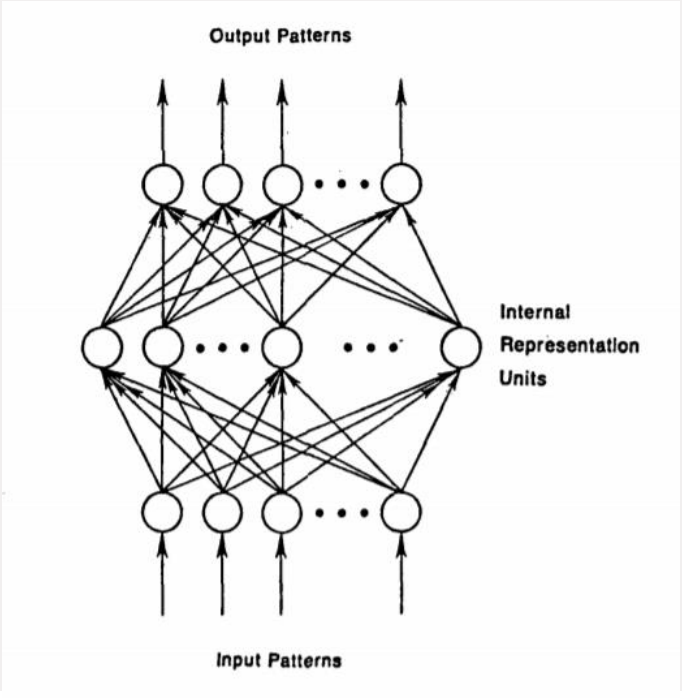
BY ERROR PROPAGATION

David E. Rumelhart, Geoffrey E. Hinton,
and Ronald J. Williams

September 1985

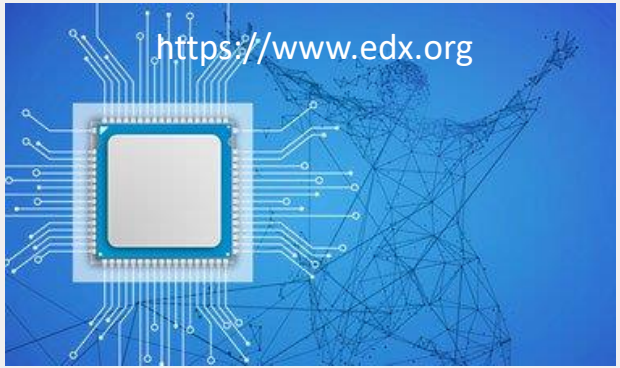
ICS Report 8506

COGNITIVE
SCIENCE



Deep learning enabled

Why did it take so long to develop these deep learning models?



- Hardware improvements
- Parallel computing (GPU)

- Digital data
- More (image) data

= also true for medical imaging

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Lecture outline

- Different applications → Different requirements
- Small exercise: “what should be the output?”
- History of deep learning models
- **Examples of deep learning models & applications**
- *Break (15 mins)*
- Examples of deep learning software
- Group exercise: *“choosing the right deep learning approach”*

Example 1: Skin lesion classification

129,450 clinical images

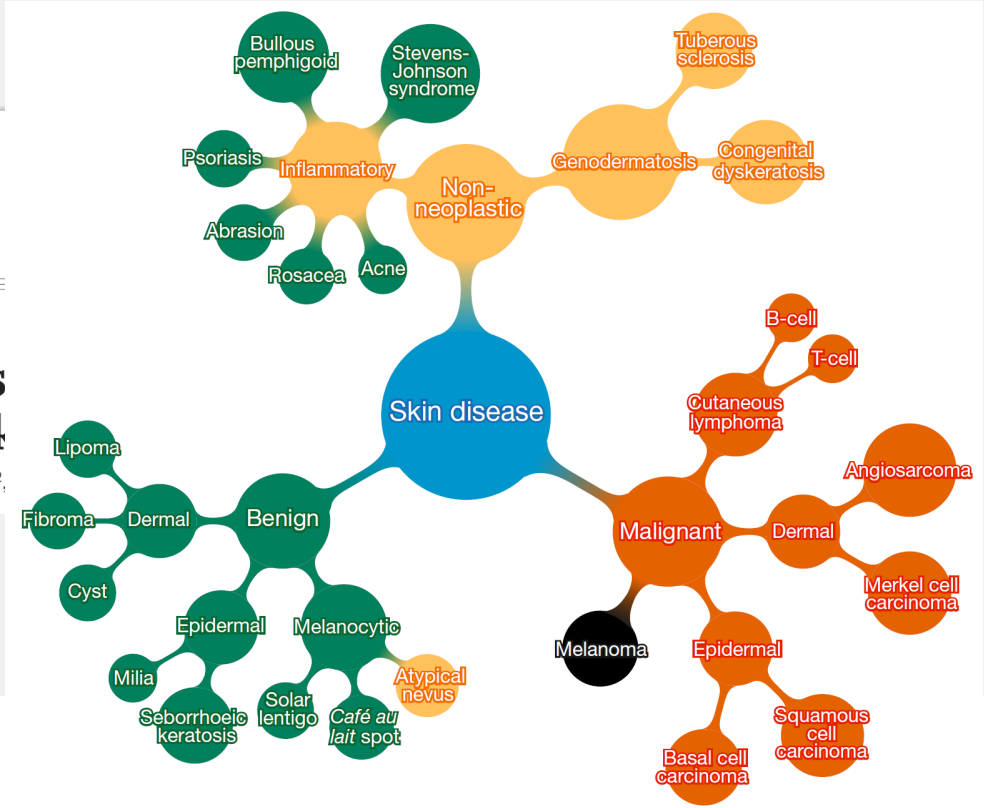
2,032 different diseases

3 classes

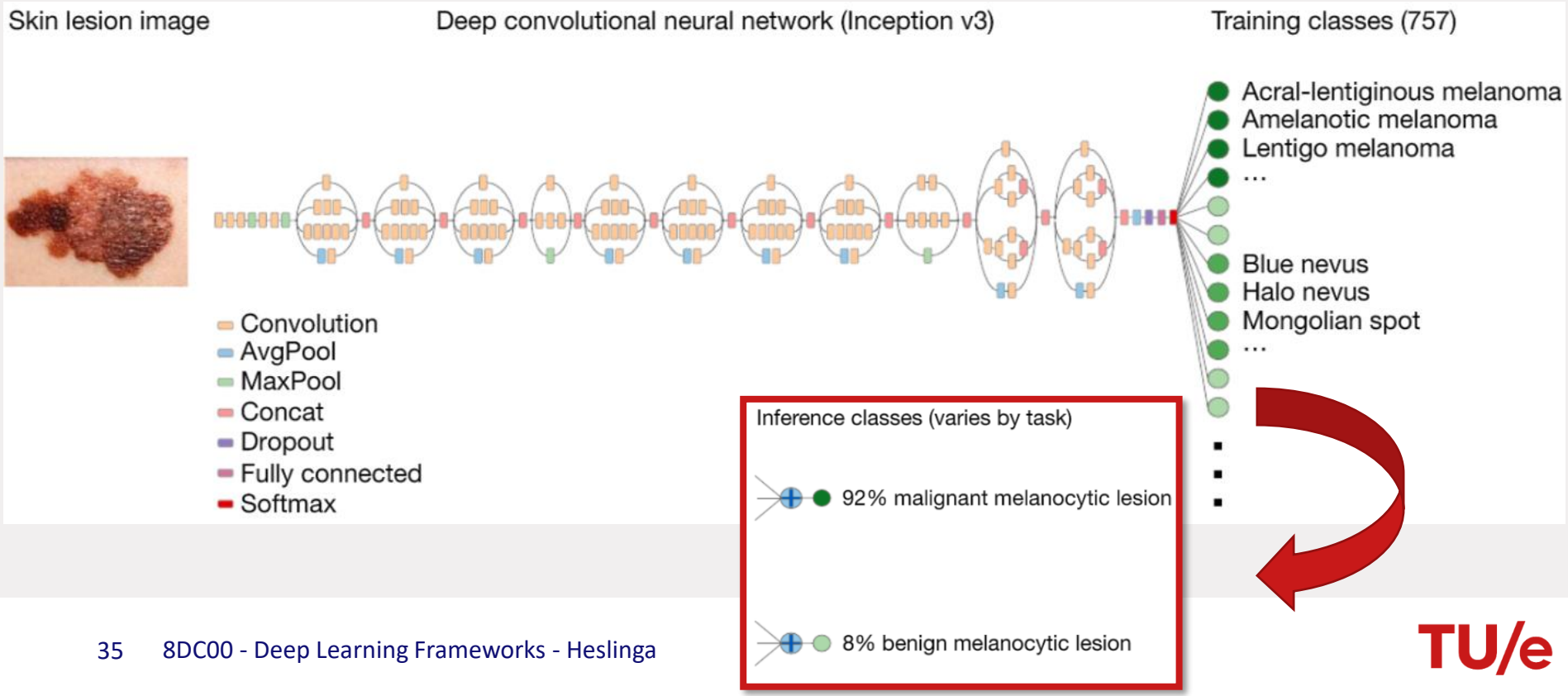
LETTER

Dermatologist-level class with deep neural network

Andre Esteva[1]*, Brett Kuprel[1]*, Roberto A. Novoa[2,3], Justin Ko[2],



Inception v3



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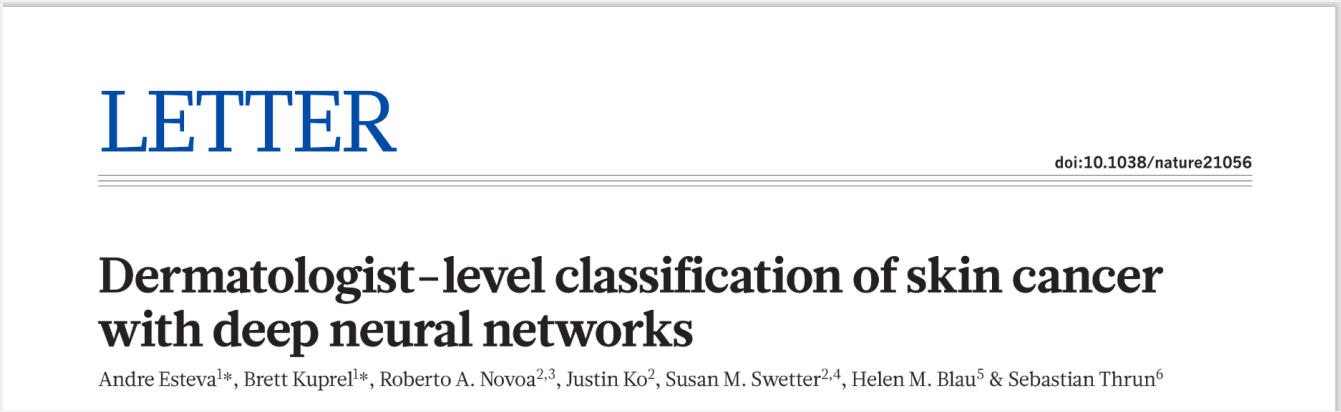
Dermatologist-level?

- 3 class classification → 72.1 ± 0.9% (mean ± s.d.) accuracy
- Two dermatologist → 65.56% and 66.0% accuracy
- But, only for 1 task!



LETTER

doi:10.1038/nature21056

Dermatologist-level classification of skin cancer with deep neural networks

Andre Esteva[1]*, Brett Kuprel[1]*, Roberto A. Novoa[2,3], Justin Ko[2], Susan M. Swetter[2,4], Helen M. Blau[5] & Sebastian Thrun[6]

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Example 2: Retinal vessel geometry approximation

- Color fundus images
- Vessel geometry related to systemic diseases (e.g. Type 2 Diabetes, hypertension)
- Approximate geometries measured with (slow) classic image analysis tools

Biomarker	Description
Arteriolar width	Average width of arterioles within 0.5 to 1.0 disc diameters from the optic disc border
Venular width	Average width of venules
[…]	

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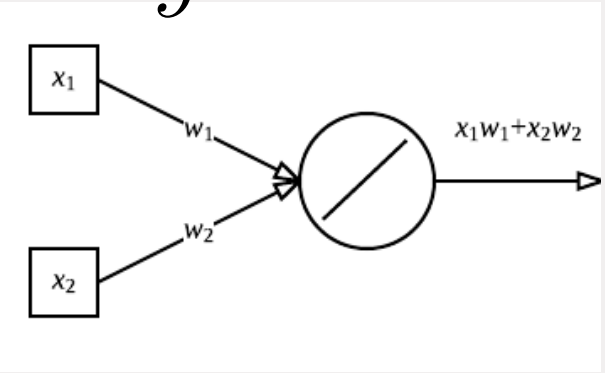
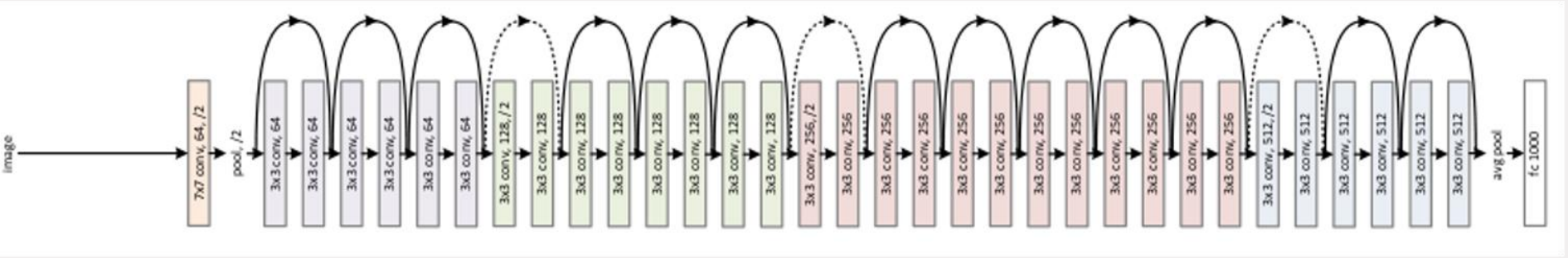
ResNet-50

$$\hat{y} = \theta^T \mathbf{x}$$

- Replace final layer
  - # of output nodes = # of biomarkers
- Regression problem!
  - No activation function in the final layer





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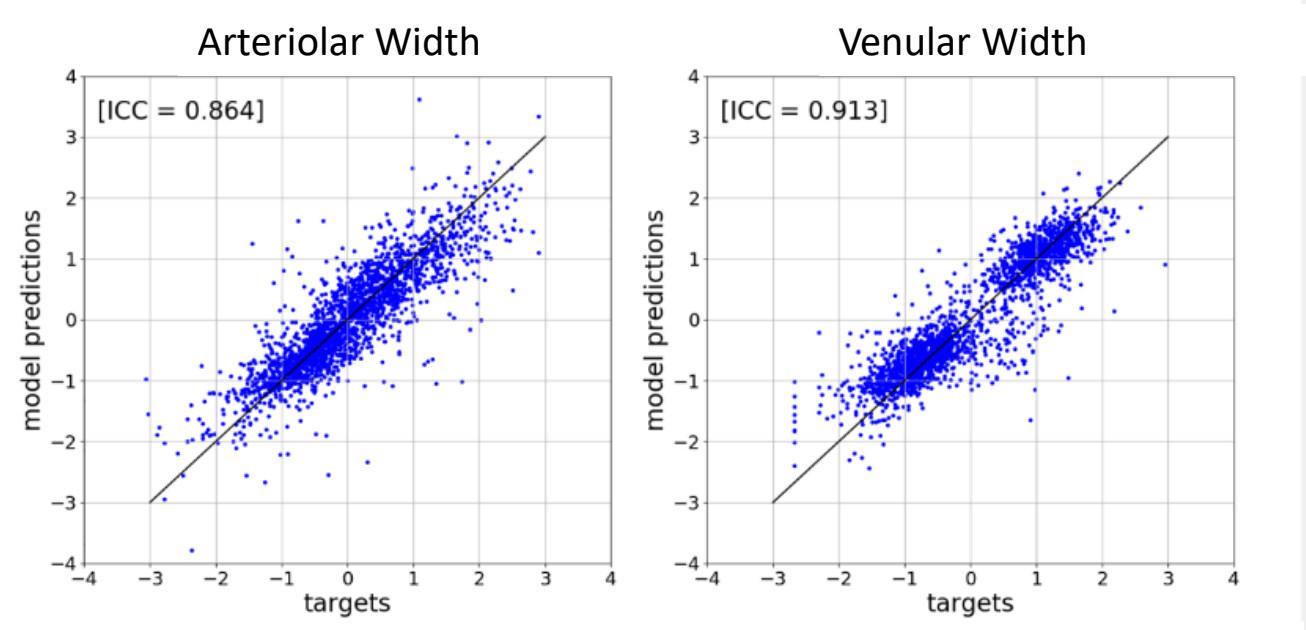
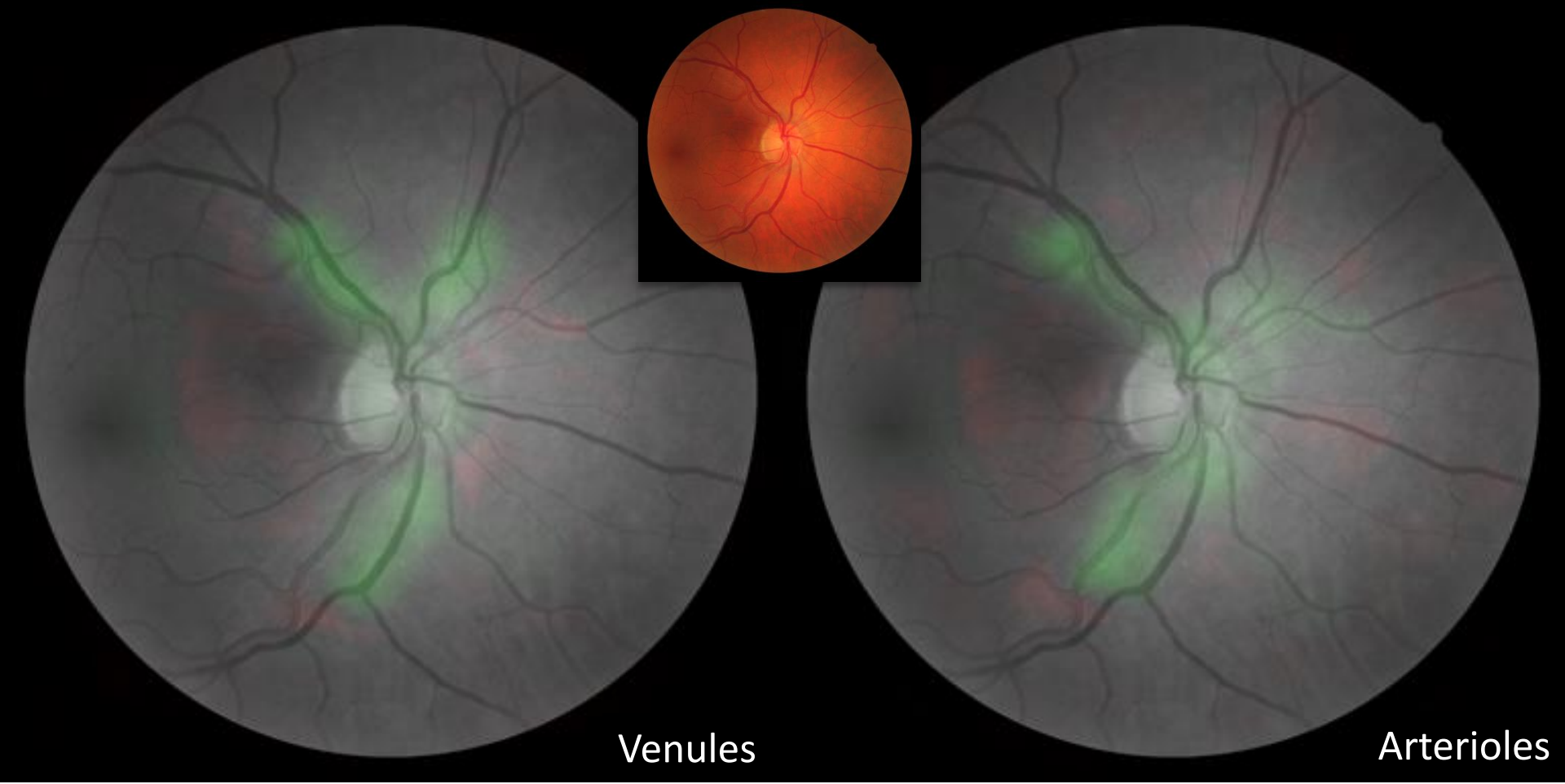
Results – Intra-Class Correlation




Venules
Arterioles

Example 3: Brain Tumor Segmentation

- MRI brain volumes (3D)
- FLAIR images
- Tumor segmentation

Automatic Brain Tumor Detection and Segmentation Using U-Net Based Fully Convolutional Networks

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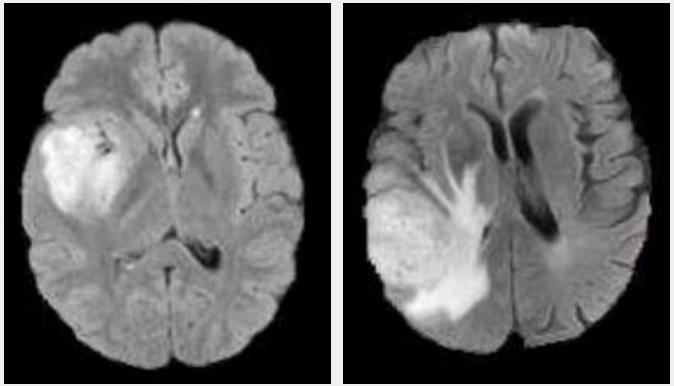
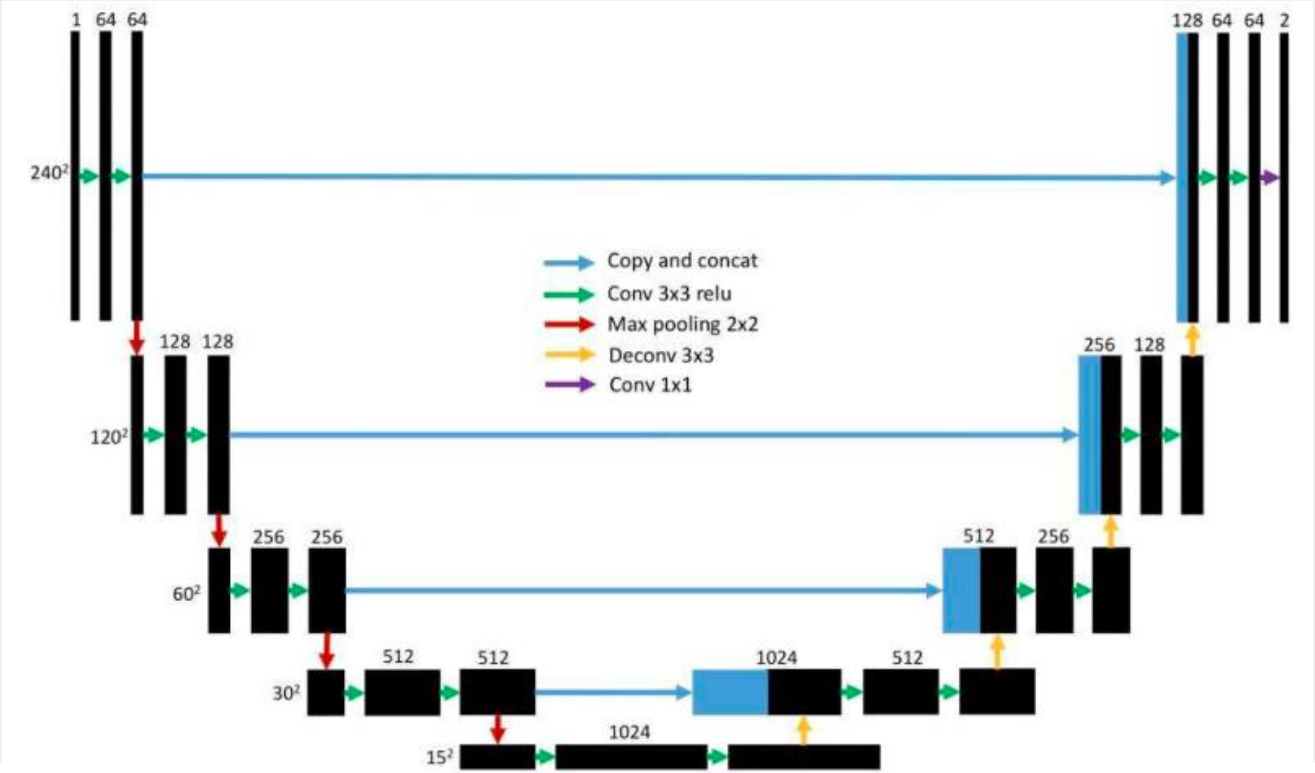
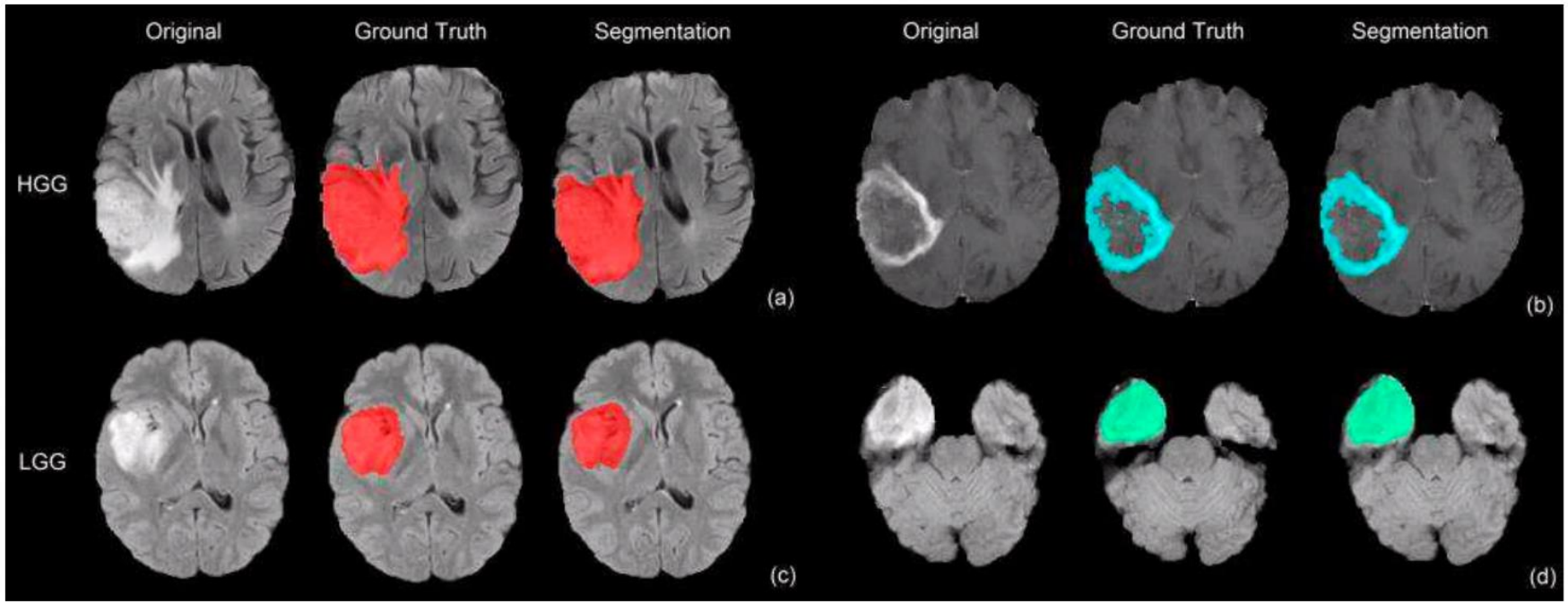


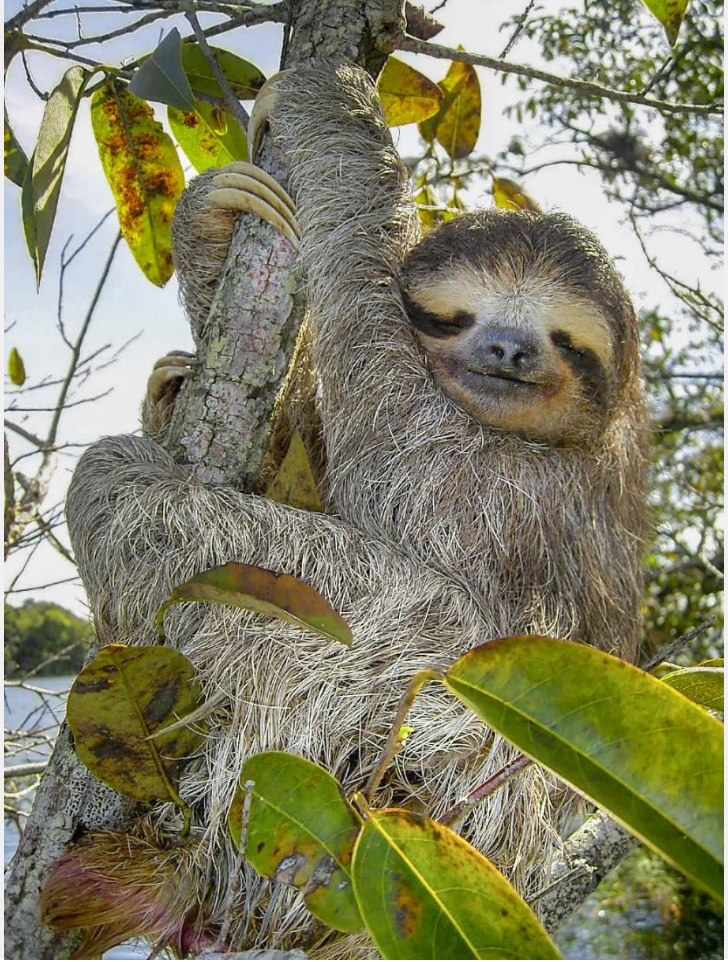
U-Net


1 64 64
128 64 64 2
240²
Copy and concat
Conv 3x3 relu
Max pooling 2x2
Deconv 3x3
Conv 1x1
128 128
256 128
120²
256 256
512 256
60²
512 512
1024 512
30²
1024
15²

Segmentation results



Break!



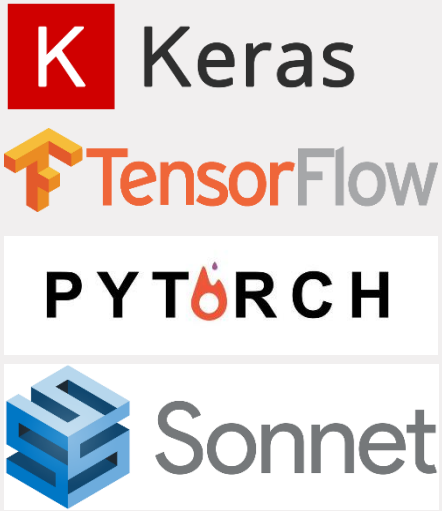
Brown-throated sloth (Panama)

https://en.wikipedia.org/wiki/Sloth

Deep learning frameworks

- Python / Matlab / R
- Tensorflow / PyTorch / Theano [RIP] / Deep learning toolbox for Matlab
- Keras / Sonnet

- Models on GitHub



Keras

https://keras.io/applications/

Classify ImageNet classes with ResNet50

```
from keras.applications.resnet50 import ResNet50
from keras.preprocessing import image
from keras.applications.resnet50 import preprocess_input, decode_predictions
import numpy as np

model = ResNet50(weights='imagenet')

img_path = 'elephant.jpg'
img = image.load_img(img_path, target_size=(224, 224))
x = image.img_to_array(img)
x = np.expand_dims(x, axis=0)
x = preprocess_input(x)

preds = model.predict(x)
# decode the results into a list of tuples (class, description, probability)
# (one such list for each sample in the batch)
print('Predicted:', decode_predictions(preds, top=3)[0])
# Predicted: [(u'n02504013', u'Indian_elephant', 0.82658225), (u'n01871265', u'tusker', 0.1122357),
              (u'n02504458', u'African_elephant', 0.061040461)]
```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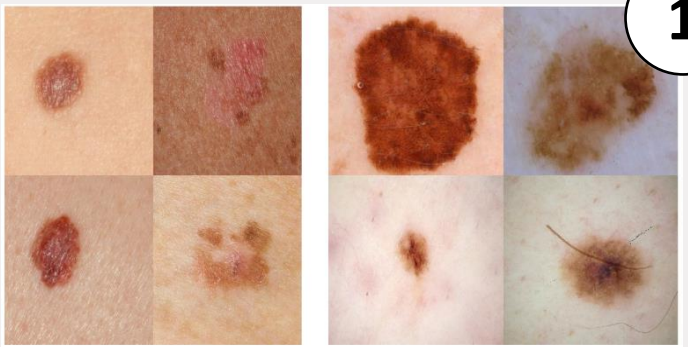
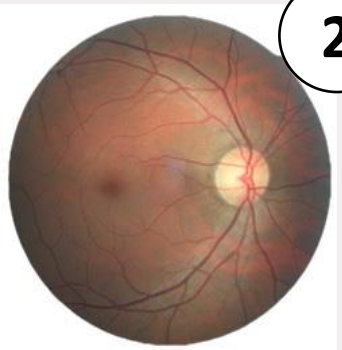
Group exercise

1



2



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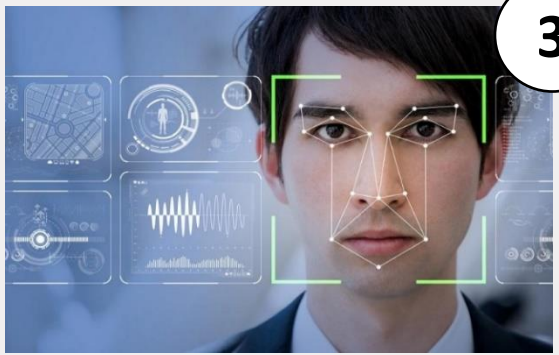

4

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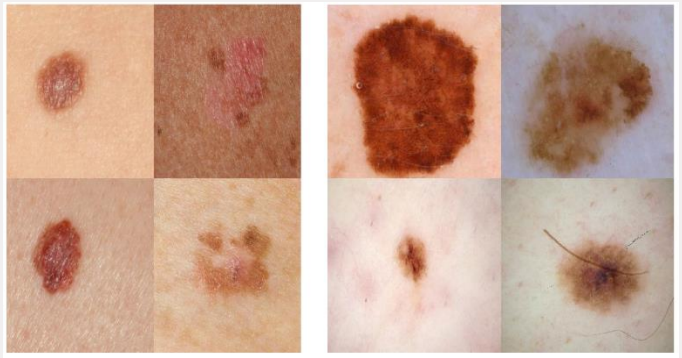
Group exercise

- Type of problem?
- Preprocessing steps?
- What kind of ‘labels’ do you need?
- What should the output look like?
- What should be the activation function in the final layer?
- What model do you choose?
- How do you evaluate performance?
- Other considerations?

Problem 1

The Netherlands Cancer Institute (NKI) would like to develop an app that enables users to automatically assess skin lesions. The app should be deployable on any medium-end phone and all calculation should be done locally. The NKI has requested your group for general advice on the deep learning approach they should take.



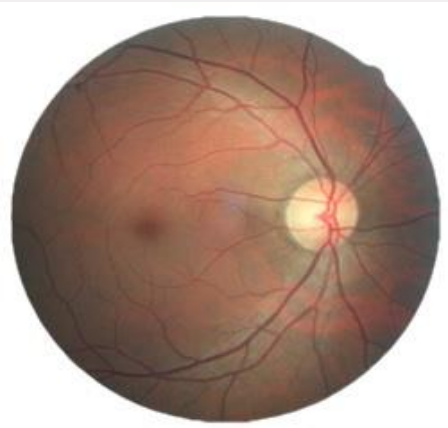
Esteva et al., Nature 2017

Problem 1

- Classification (2-class or multi-class)
- Small app → small model and reduced input sizes
- Normalization of image intensities (many different camera's)
- Output model (in case of 2 classes): e.g. chance of belonging to malignant class
- Activation function final layer CNN (in case of 2 classes): sigmoid
- Evaluate performance: e.g. classification accuracy

Problem 2

Your team is competing in an online challenge. The objective: classification of retinal fundus images in one of five stages of diabetic retinopathy. Class 0 = no retinopathy. Classes 1-4 correspond to increasing severity of retinopathy. What is your approach?



https://www.kaggle.com/c/diabetic-retinopathy-detection

Problem 2

- Classification (multi-class)
- Normalization of image intensities (many different camera's)
- Output model: e.g. chance of belonging to each class, and/or class with highest probability
- Activation function final layer CNN: softmax (not needed for exam)
- Evaluate performance: e.g. classification accuracy. One could take into account the extent of the error. Predicting class 0 while label is class 4 results in a bigger error than predicting class 3.
- To achieve high classification accuracy one could consider an ensemble of state-of-the art deep learning models

Problem 3

As part of a university project you are working on the development of an app that uses pictures of people's face to predict somebody's age. You can use the server of the university for the calculations.

https://www.freecodecamp.org/news/how-to-build-an-age-and-gender-multi-task-predictor-with-deep-learning-in-tensorflow-20c28a1bd447/

Problem 3

- Regression, as the output in continuous. However, classification (of binned age-groups) is also possible
- As preprocessing, one could crop the image to only the person's face. For this you could use user-input.
- Output model: predicted age, perhaps with boundaries (any number between 0 and 100)
- Activation function final layer CNN: none, since $\hat{y} = \theta^T \mathbf{x}$
- Evaluate performance: Euclidean distance between model predictions and actual age

Problem 4

A vascular surgeon performs endovascular surgery using x-ray angiography. She would like to continuously see the veins and arteries clearly distinguished from the background on the monitor next to her. How would you approach this?

https://blog.definitivehc.com

Problem 4

- Segmentation problem
- As preprocessing, one could reduce the number of frames
- Output model: image (mask) that shows locations of veins and vessels. It is possible to output multiple maps (one with background, one with veins and one with arteries.
- I could be approached as a pixel-wise classification problem. If so, the activation function of the final layer could be a sigmoid for veins vs background. Or a softmax for multiple classes.
- Evaluate performance: e.g. Dice
- Type of model: U-Net would be good starting point

Summary

- Different applications → different requirements
- History of deep learning models
- Deep learning enablers (computational power and data)
- Deep learning frameworks