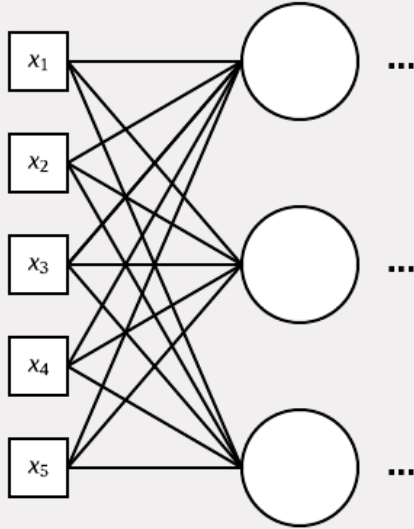


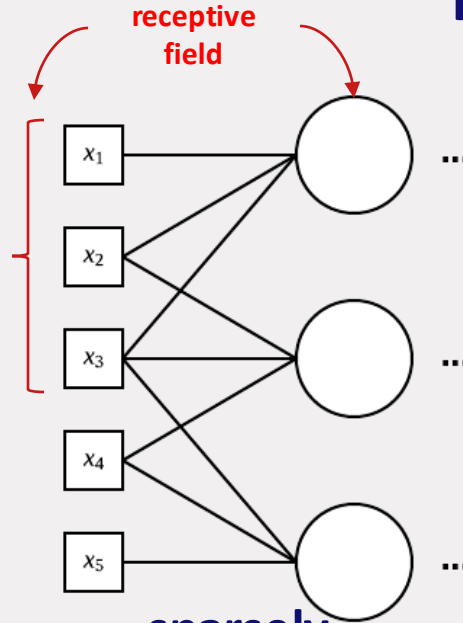
Deep Learning Frameworks and Applications (8DC00)

Cian Scannell

Previous lecture

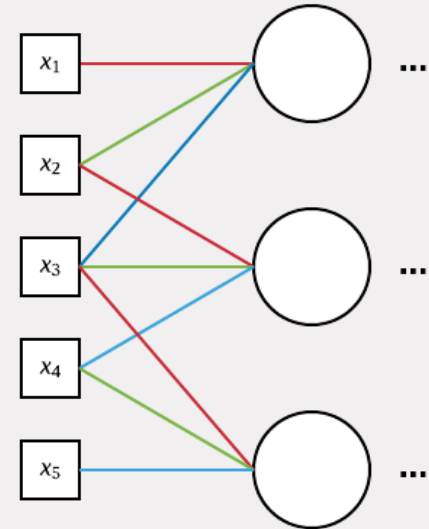


“regular” NN
15 weights



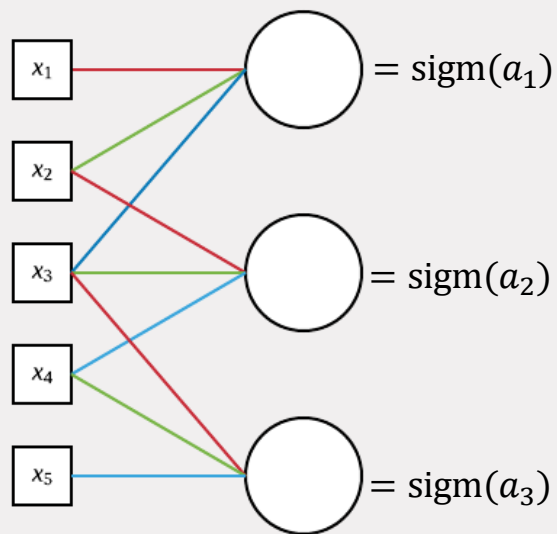
**sparsely
connected NN**
9 weights

Reducing # of weights



shared weights
3 weights

Previous lecture



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

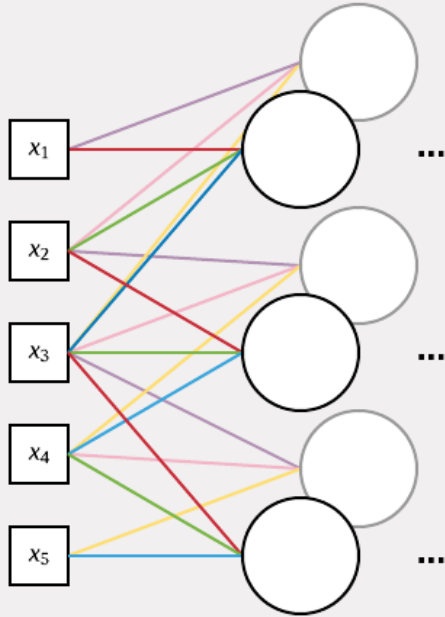
$$a_2 = x_2 w_1 + x_3 w_2 + x_4 w_3$$

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

$$\begin{bmatrix} a_1 & a_2 & a_3 \end{bmatrix} = \begin{bmatrix} x_1 & x_2 & x_3 & x_4 & x_5 \end{bmatrix} * \begin{bmatrix} w_1 & w_2 & w_3 \end{bmatrix}$$

convolution

Previous lecture



two sets shared weights
6 weights

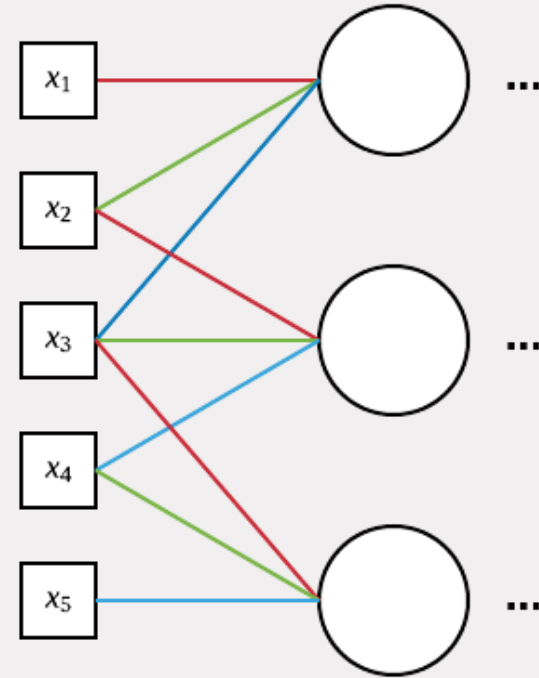
$$\begin{bmatrix} a_{1,1} & a_{1,2} & a_{1,3} \end{bmatrix} = \begin{bmatrix} x_1 & x_2 & x_3 & x_4 & x_5 \end{bmatrix} * \begin{bmatrix} w_{1,1} & w_{1,2} & w_{1,3} \end{bmatrix}$$

$$\begin{bmatrix} a_{2,1} & a_{2,2} & a_{2,3} \end{bmatrix} = \begin{bmatrix} x_1 & x_2 & x_3 & x_4 & x_5 \end{bmatrix} * \begin{bmatrix} w_{2,1} & w_{2,2} & w_{2,3} \end{bmatrix}$$

$\begin{bmatrix} w_{1,1} & w_{1,2} & w_{1,3} \end{bmatrix}$, and $\begin{bmatrix} w_{2,1} & w_{2,2} & w_{2,3} \end{bmatrix}$
are **convolution kernels**. They extract
features.

Previous lecture: properties of CNNs

- Sparse connectivity
- Weight sharing
- Parallel computations

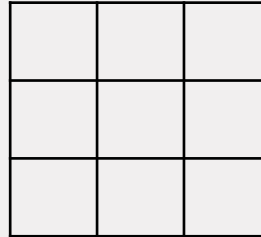


Previous lecture: Kernel size

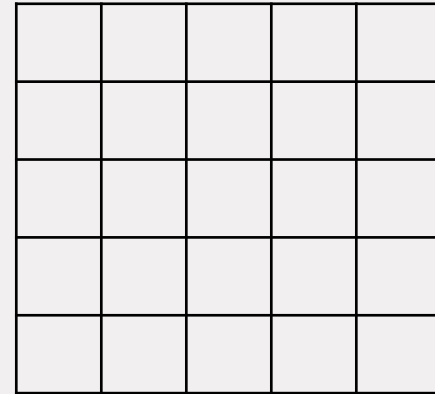
1 x 1



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 = 2×2

Addition to last lecture:

Stride = step size of the sliding window

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

Draw your number here

0123456789



Downsampled drawing: 3

First guess: 3

Second guess: 1

Layer visibility

Input layer

Show

Evolution layer 1

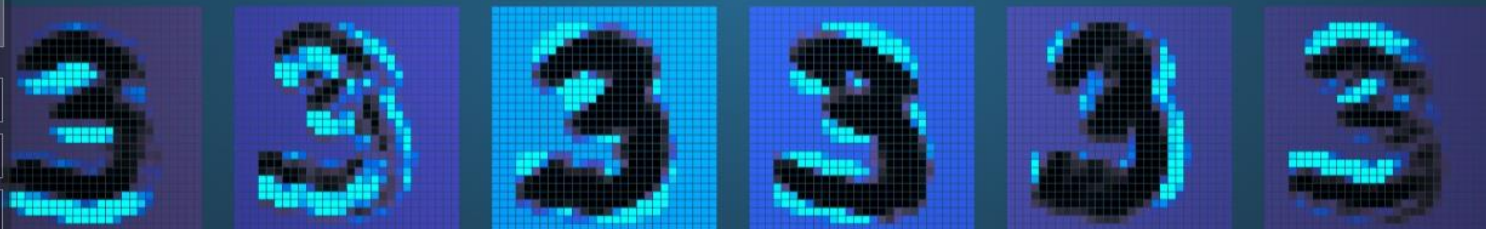
Show

Downsampling layer 1

Show

Evolution 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

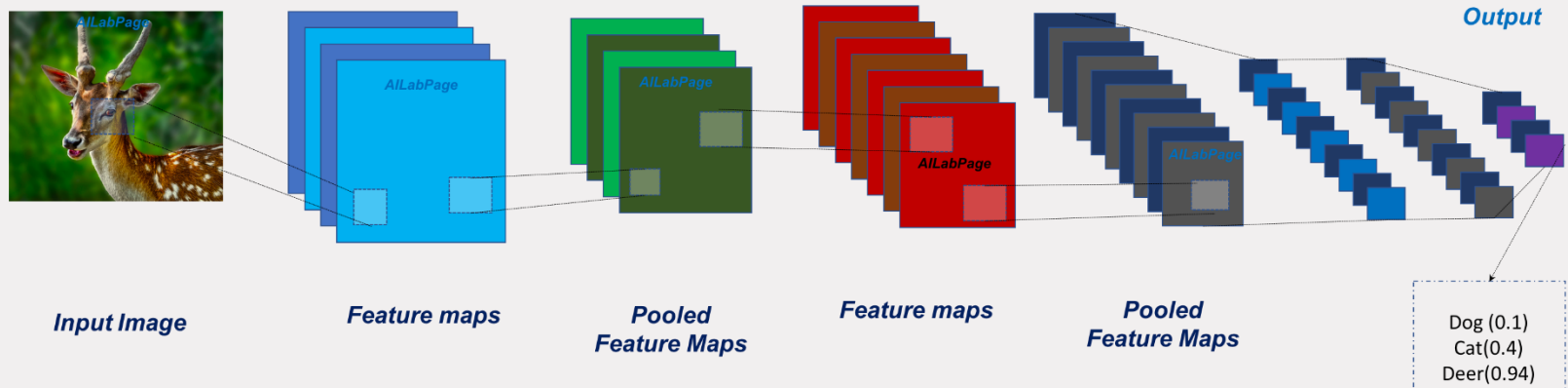
Through a process called 'backpropagation'. A good explanation can be found here:

<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)

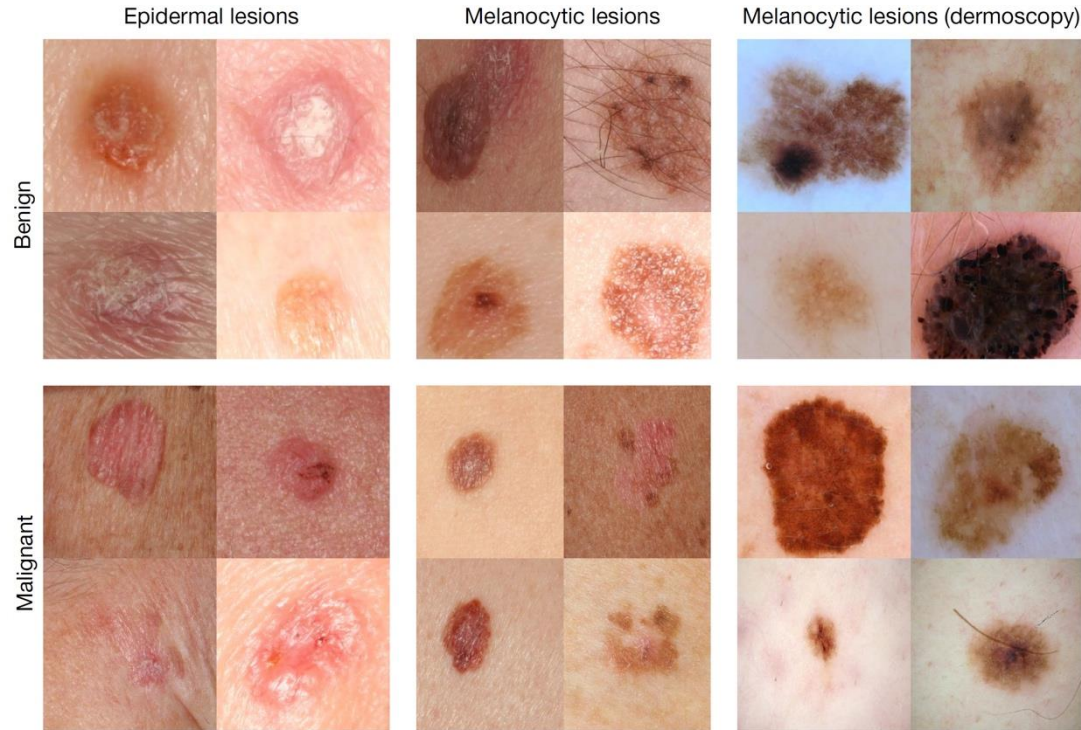
Learning outcomes

- 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

Classification

Two classes

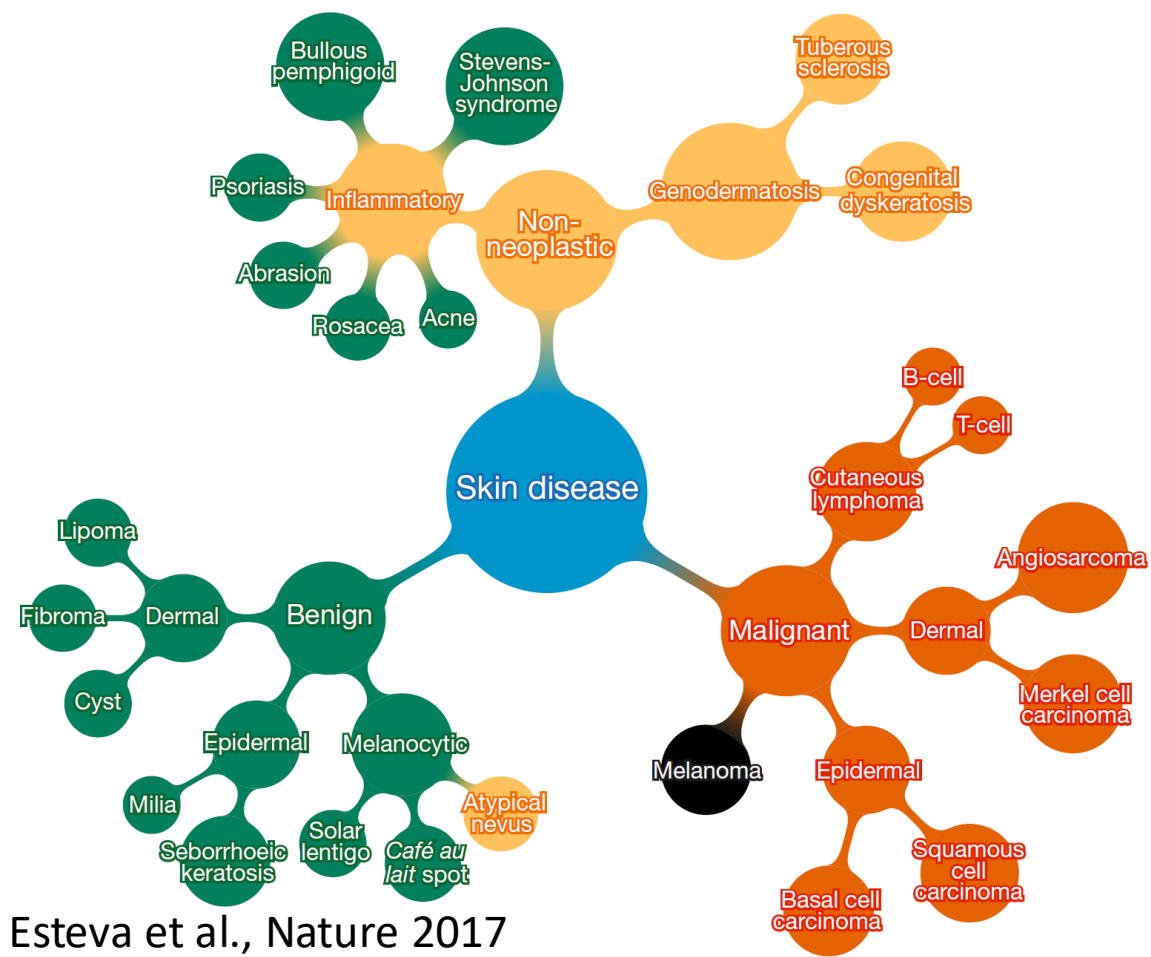
e.g. malignant lesions / other

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

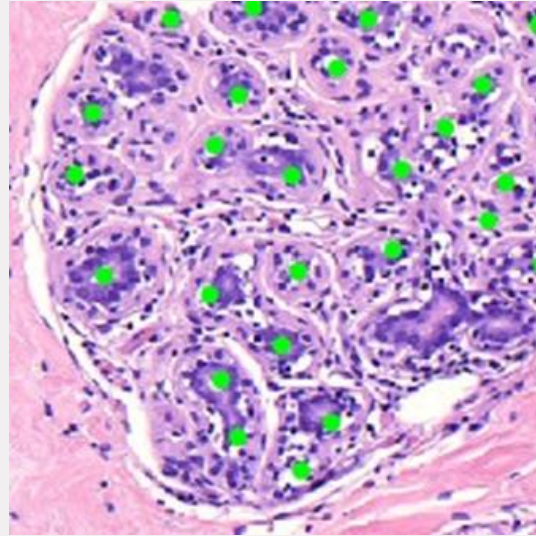
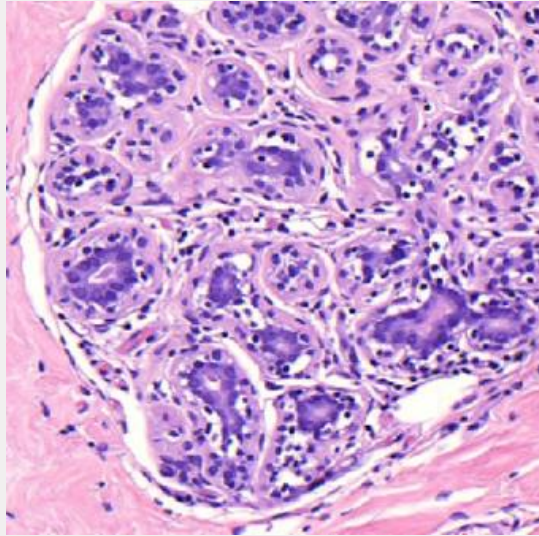
Multi-class

benign lesions / malignant lesions
/ non-neoplastic

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



Detection of Acini centers



Wetstein et al., SPIE-MI 2019

Regression

Retinal structures

- Arteriolar width
- Venular width
- Vessel Tortuosity

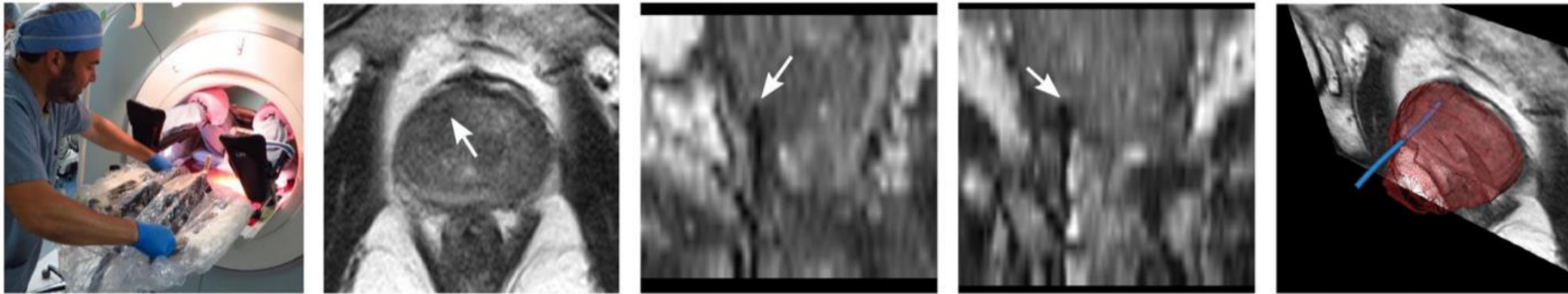
Heslinga et al., SPIE-MI 2019



Segmentation

- MRI-targeted prostate biopsy
- Needle segmentation

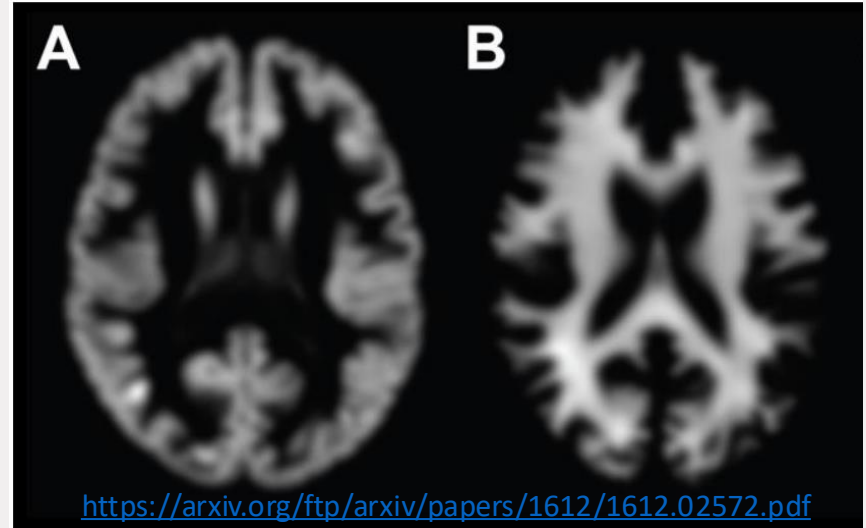
Mehrtash et al., IEEE Trans Med Imaging 2019



What should be the output of our CNN?



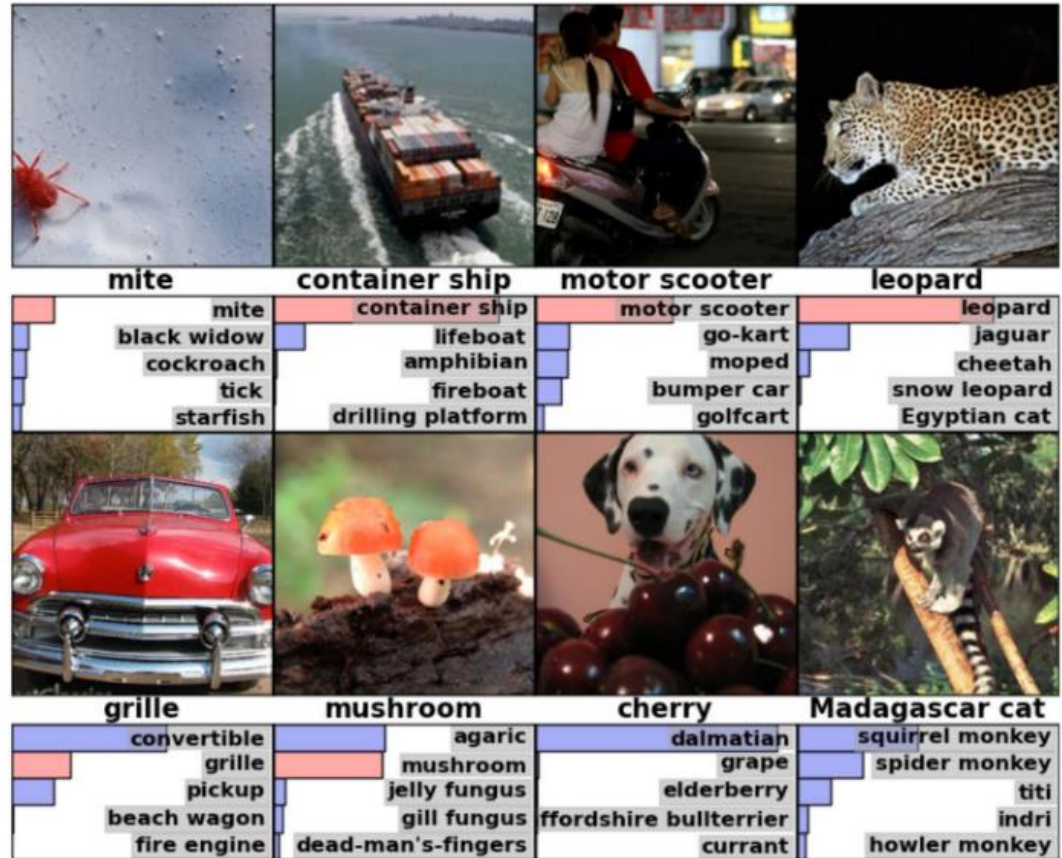
Retinopathy classification



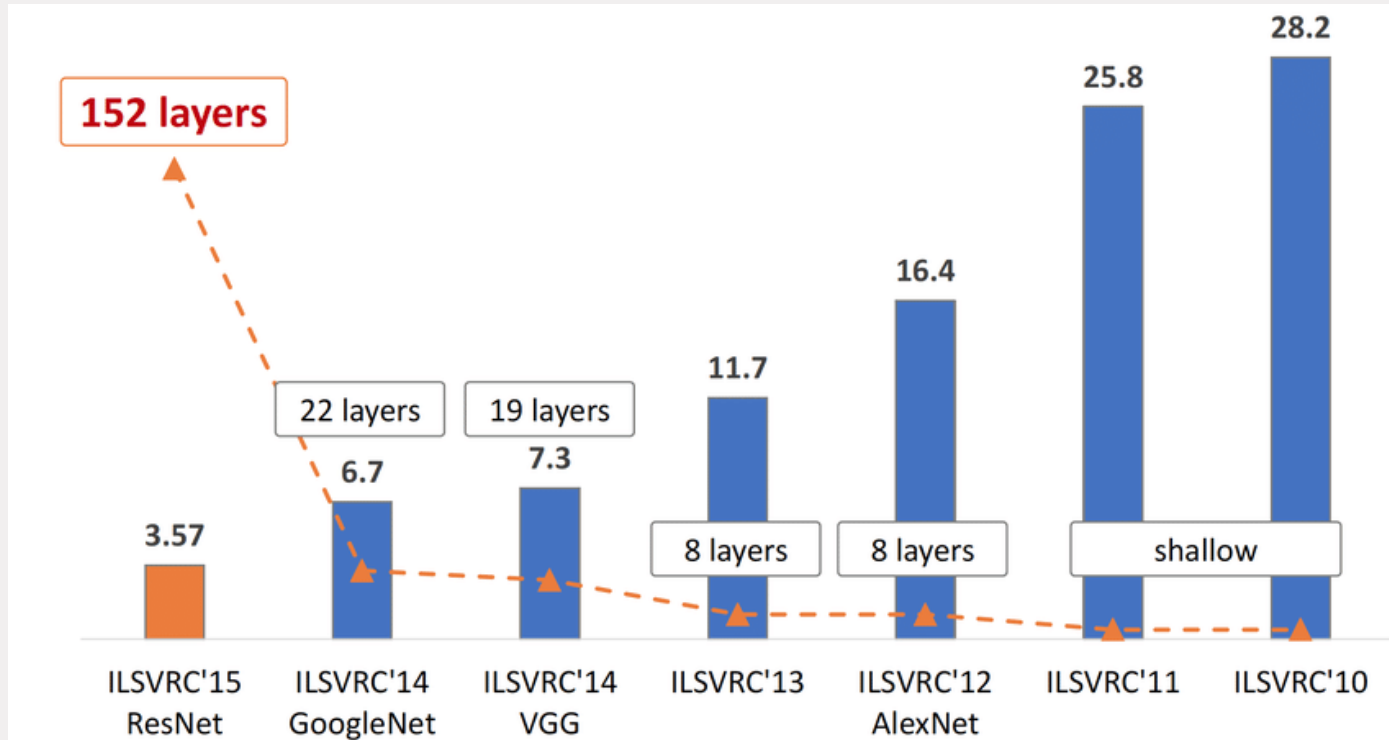
Brain age prediction

IMAGENET

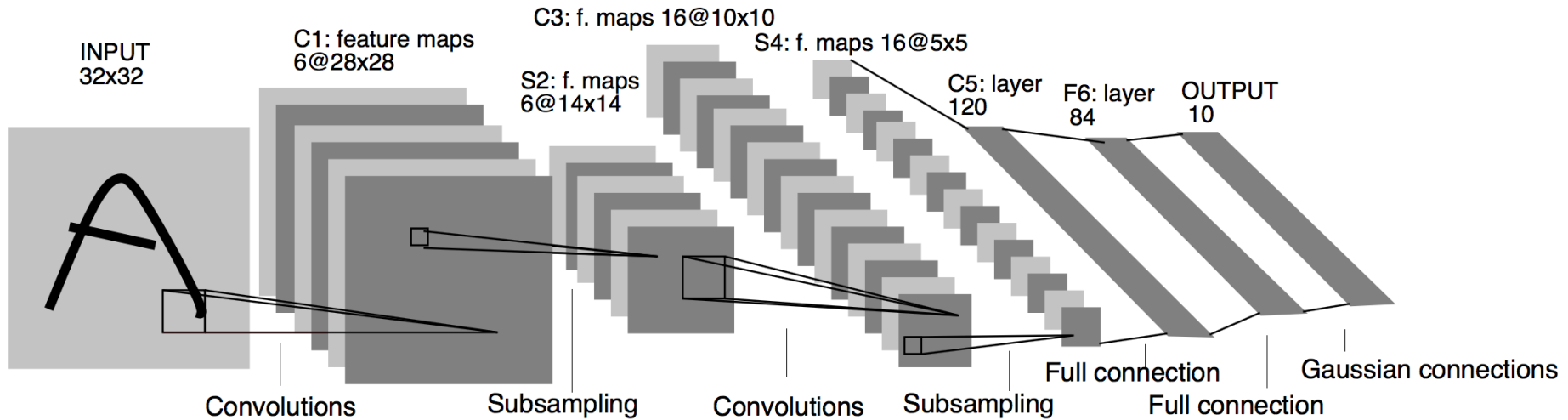
- 1,000 object classes (categories).
- Images:
 - 1.2 M train
 - 100k test.



Error rates ImageNet

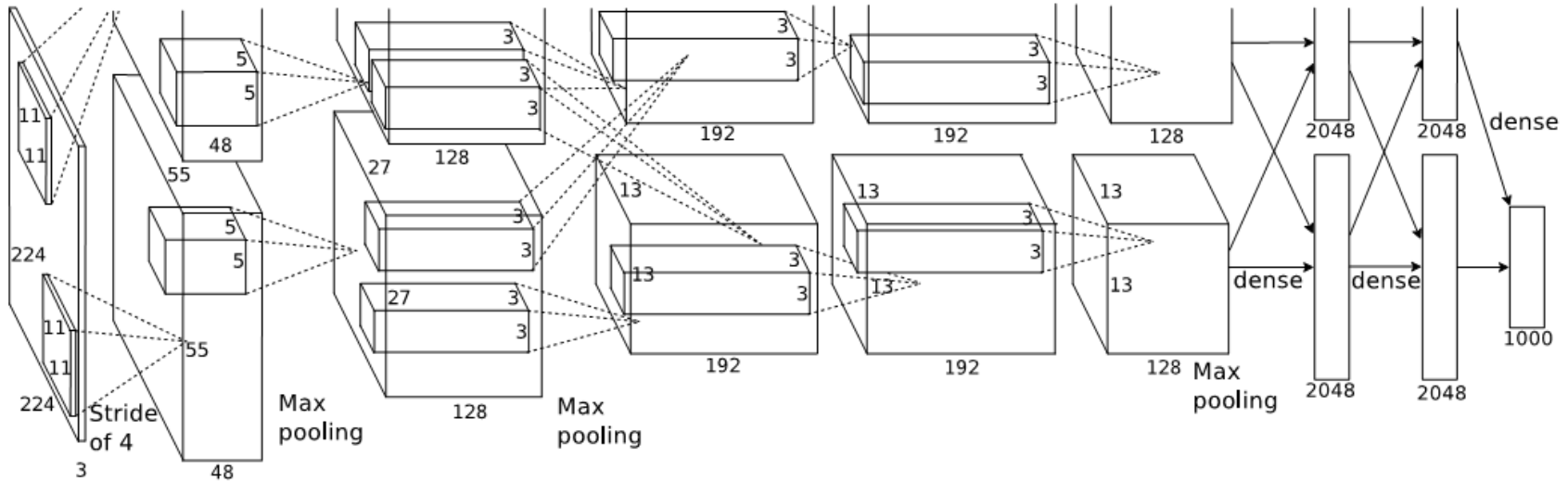


LeNet



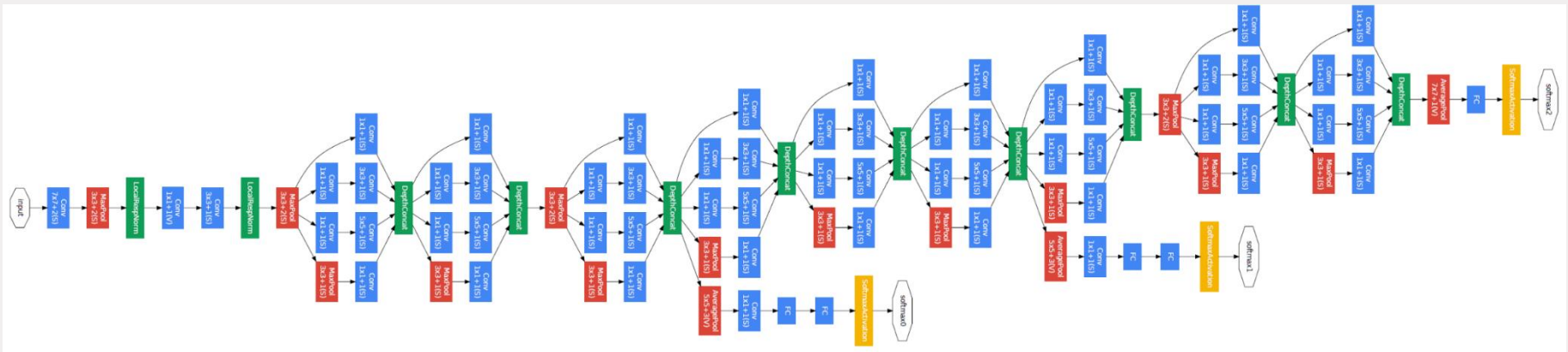
AlexNet

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



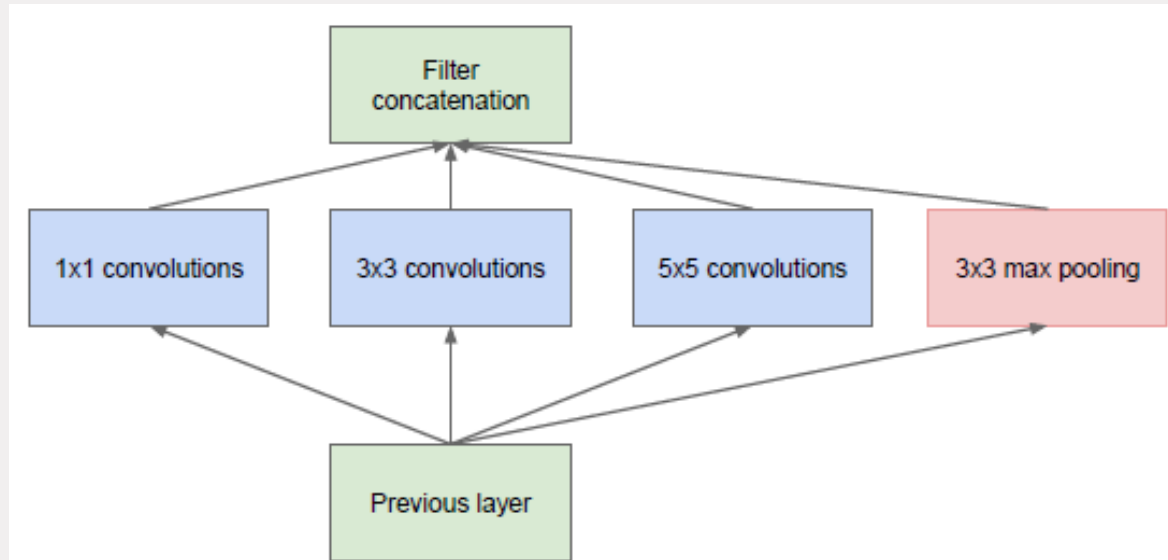
Inception v1 (GoogLeNet)

- Inception modules
- Auxiliary targets
- Global average pooling layer



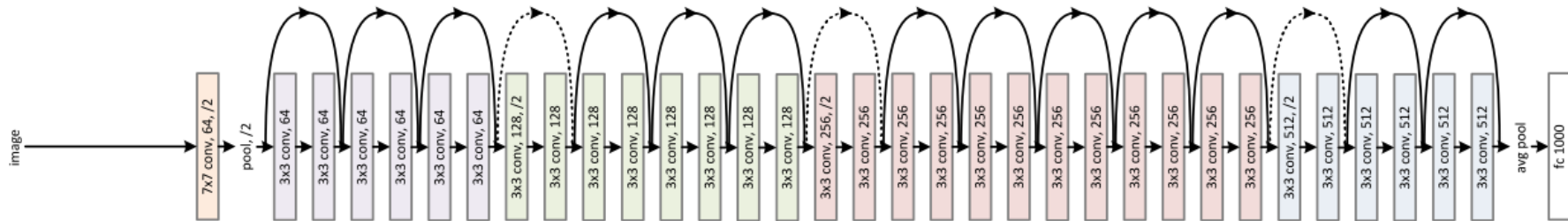
Inception module

- Multiple scales

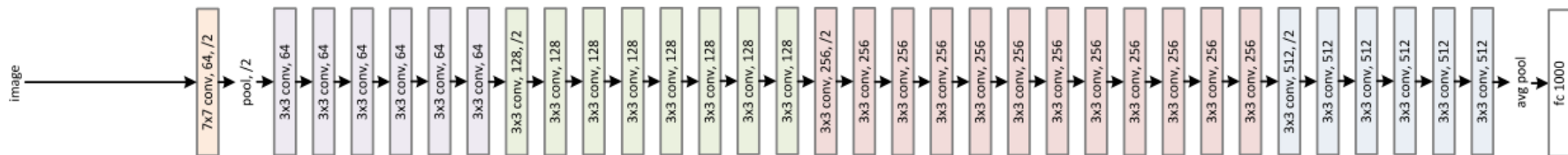


ResNet

34-layer residual

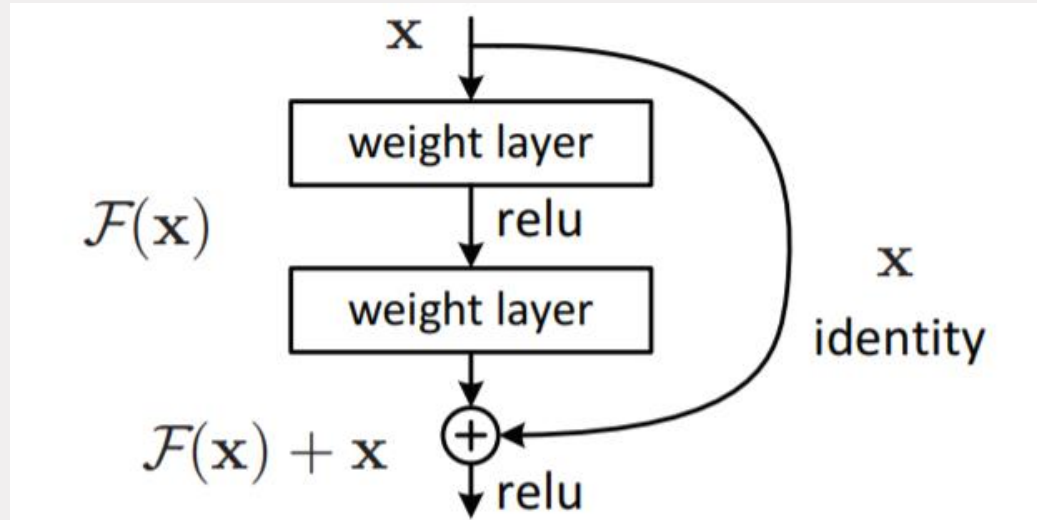


34-layer plain

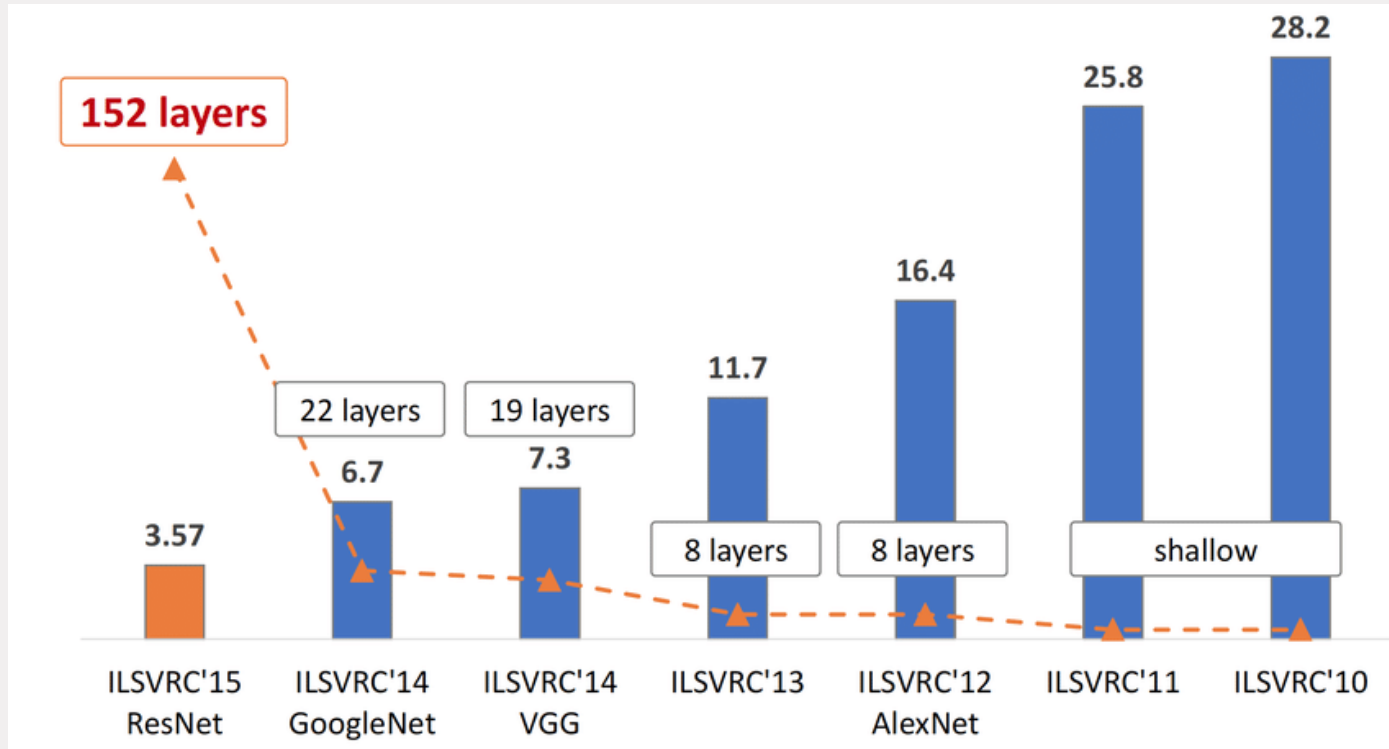


Residual block

Learn differences between input and output layer = residue

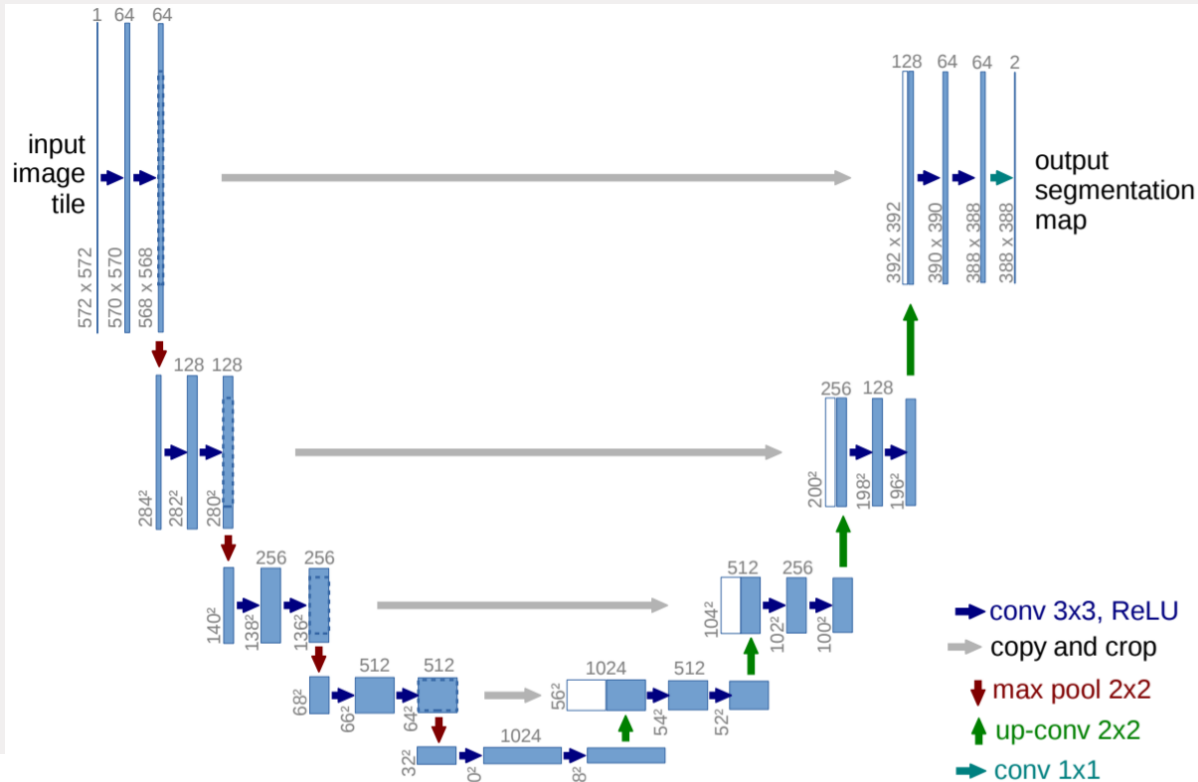


Error rates ImageNet (top 5 accuracy)



U-Net: Segmentation

Ronneberger et al., MICCAI 2015



Neural networks have been around

LEARNING INTERNAL REPRESENTATIONS BY ERROR PROPAGATION

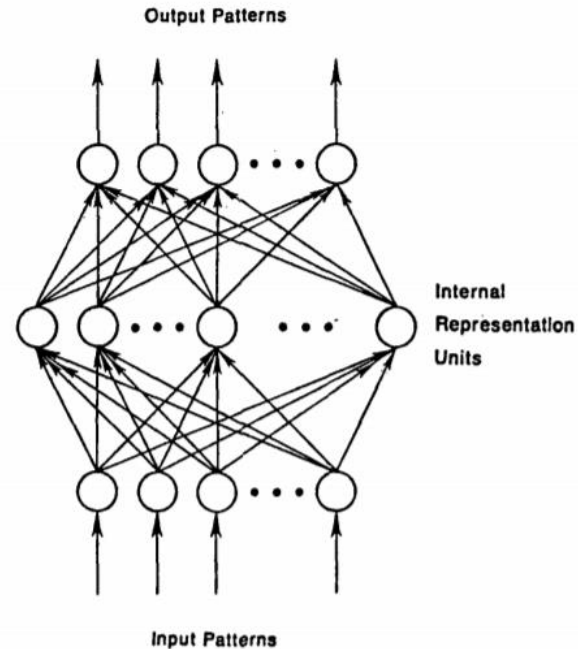
David E. Rumelhart, Geoffrey E. Hinton,
and Ronald J. Williams

September 1985

ICS Report 8506

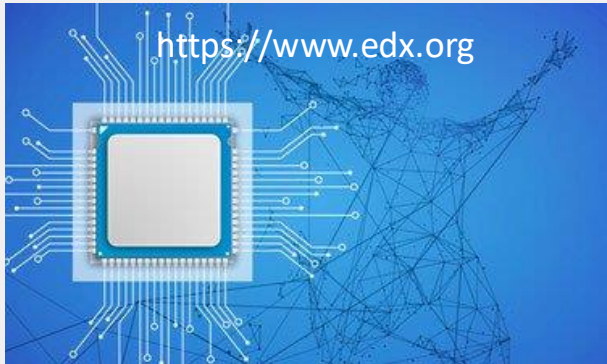


COGNITIVE
SCIENCE



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

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

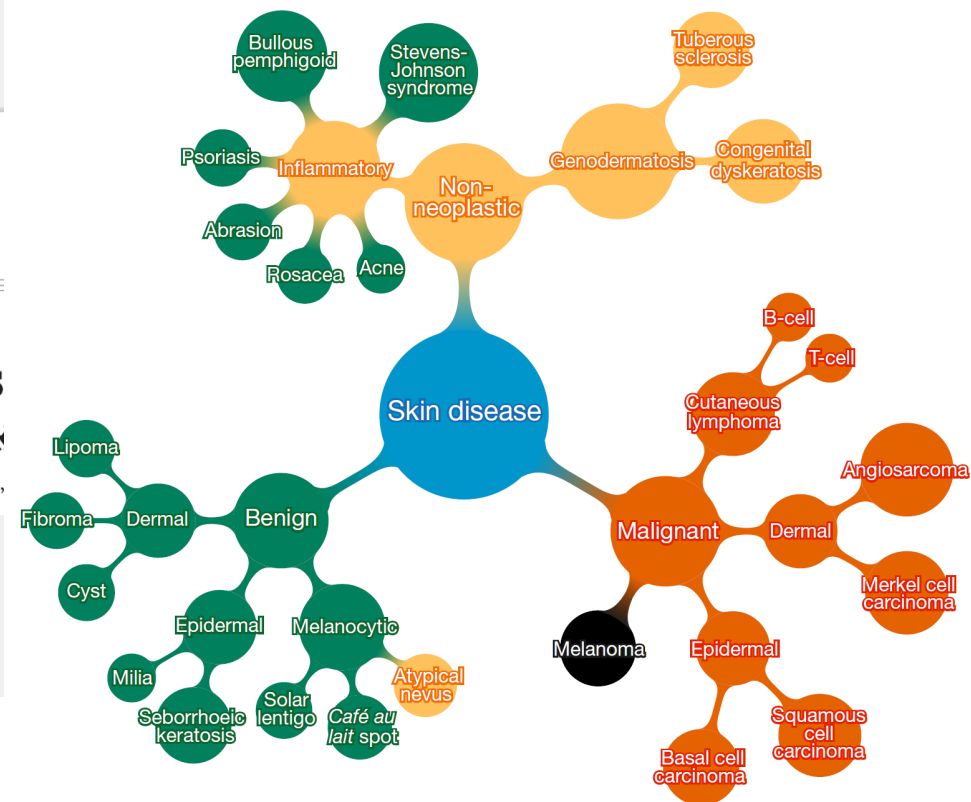
2,032 different diseases

3 classes

LETTER

Dermatologist-level class with deep neural network

Andre Esteva^{1*}, Brett Kuprel^{1*}, Roberto A. Novoa^{2,3}, Justin Ko²,

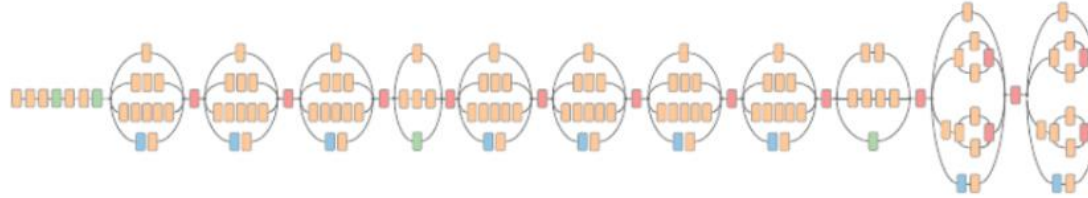


Inception v3

Skin lesion image

Deep convolutional neural network (Inception v3)

Training classes (757)



- Convolution
- AvgPool
- MaxPool
- Concat
- Dropout
- Fully connected
- Softmax

- Acral-lentiginous melanoma
- Amelanotic melanoma
- Lentigo melanoma
- ...
- Blue nevus
- Halo nevus
- Mongolian spot
- ...

Inference classes (varies by task)

92% malignant melanocytic lesion

8% benign melanocytic lesion

Dermatologist-level?

- 3 class classification → $72.1 \pm 0.9\%$ (mean \pm 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 Ko², Susan M. Swetter^{2,4}, Helen M. Blau⁵ & Sebastian Thrun⁶

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

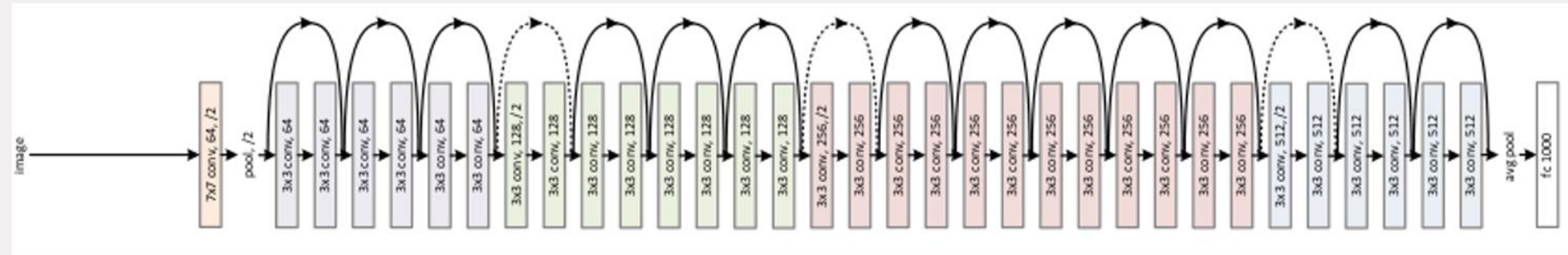
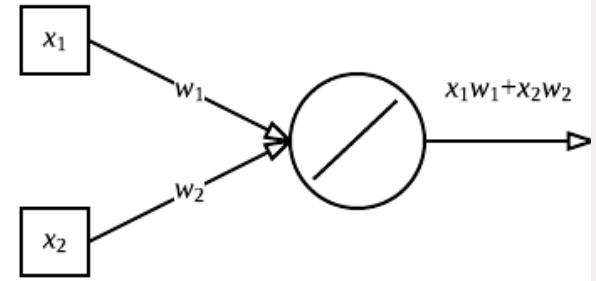
Biomarker	Description
Arteriolar width	Average width of arterioles within 0.5 to 1.0 disc diameters from the optic disc border
Venular width	Average width of venules
[...]	



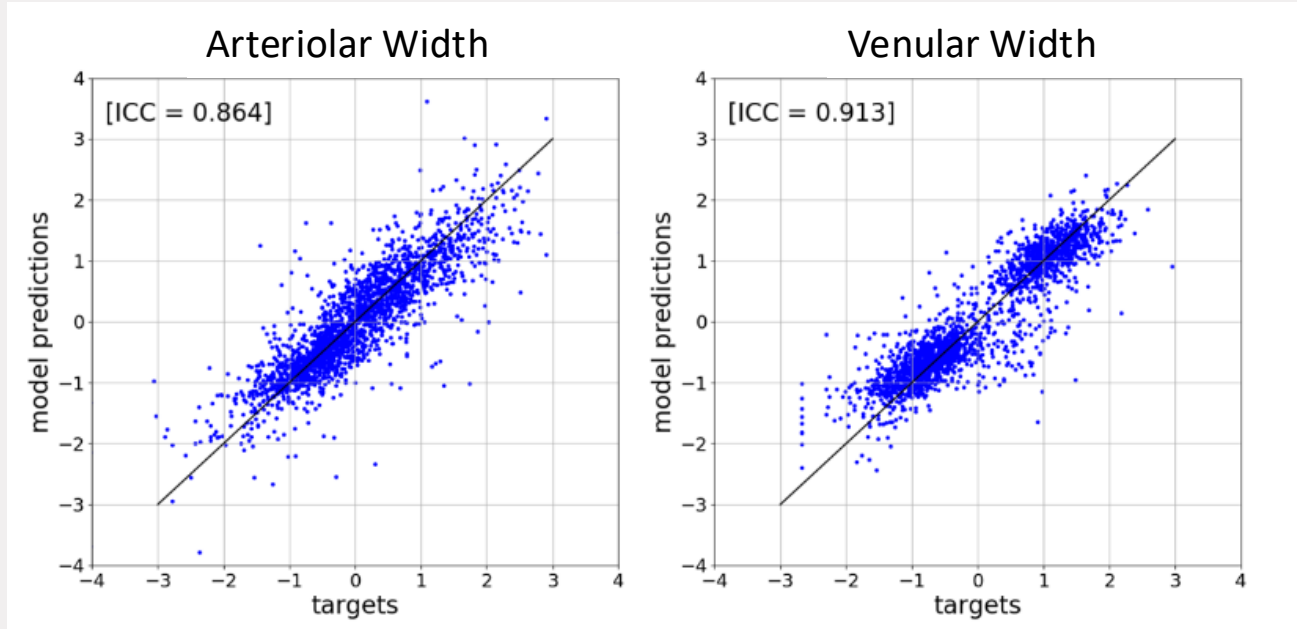
ResNet-50

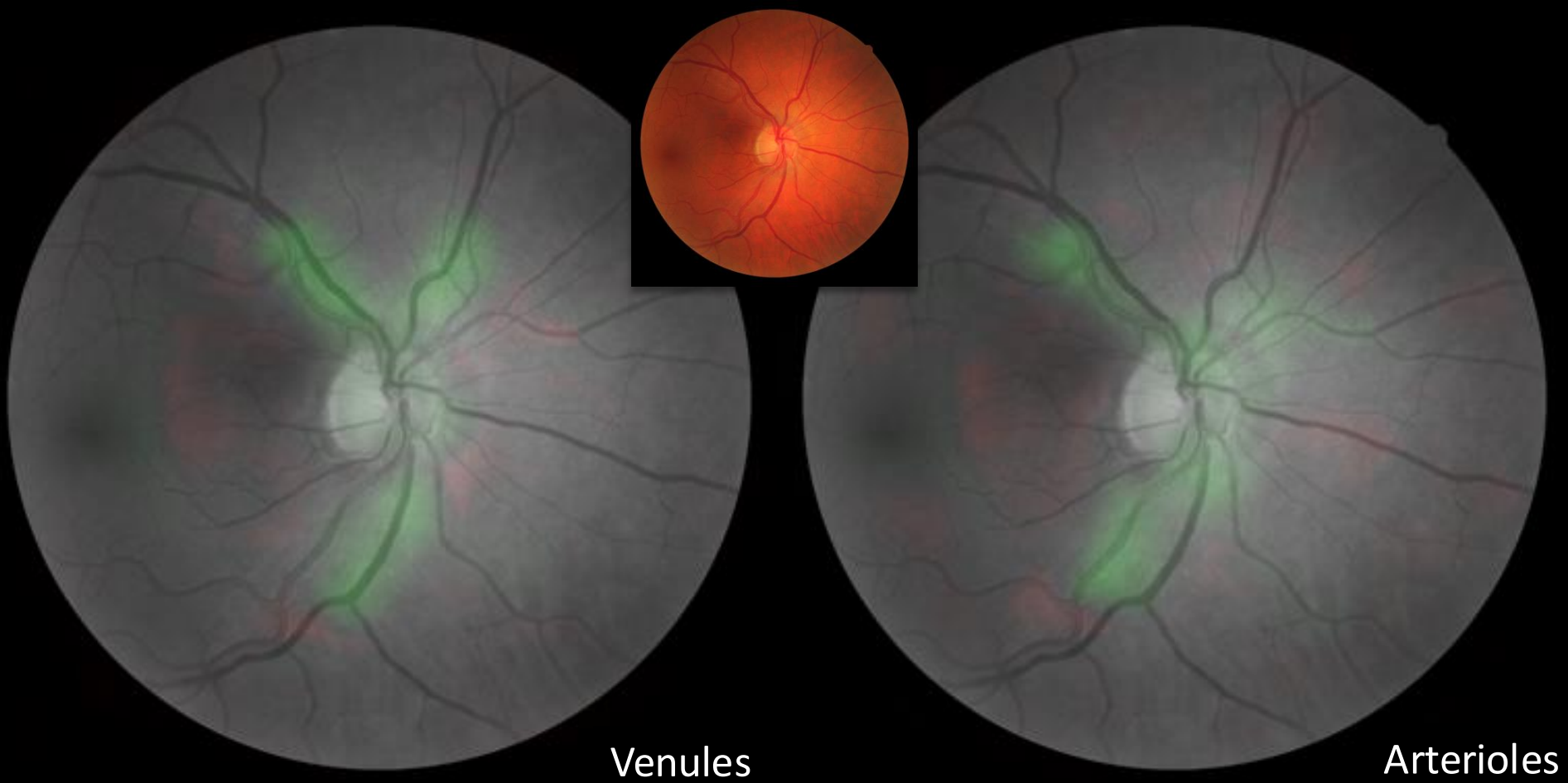
- Replace final layer
 - # of output nodes = # of biomarkers
- Regression problem!
 - No activation function in the final layer

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



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

Hao Dong ^{†1}, Guang Yang ^{‡2,3}, Fangde Liu ^{‡1}, Yuanhan Mo ¹, Yike Guo ^{‡1}

¹ Data Science Institute, Imperial College London, SW7 2AZ, London, UK

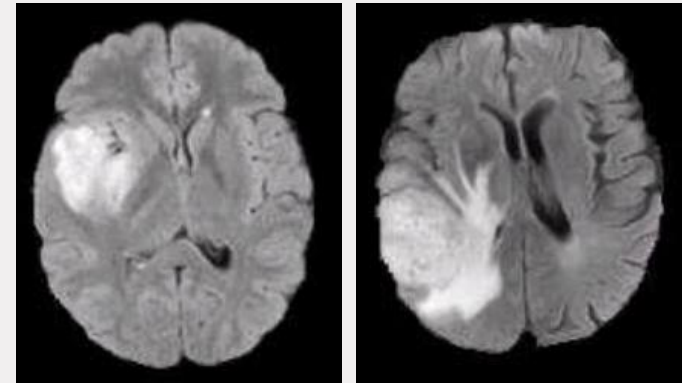
² Neurosciences Research Centre, Molecular and Clinical Sciences Institute,
St. George's, University of London, London SW17 0RE, UK

³ National Heart and Lung Institute, Imperial College London, SW7 2AZ, London, UK

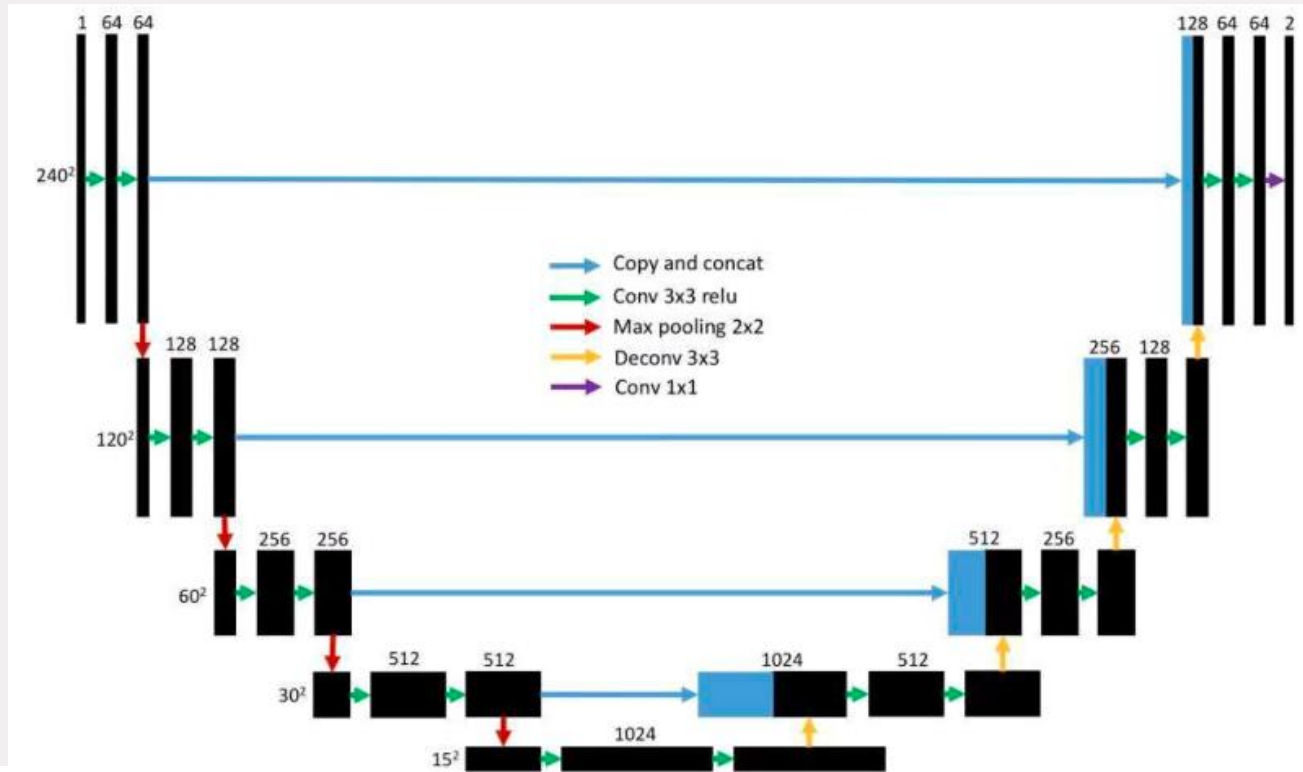
[†] Co-first authors contributed equally to this study.

[‡] Corresponding author.

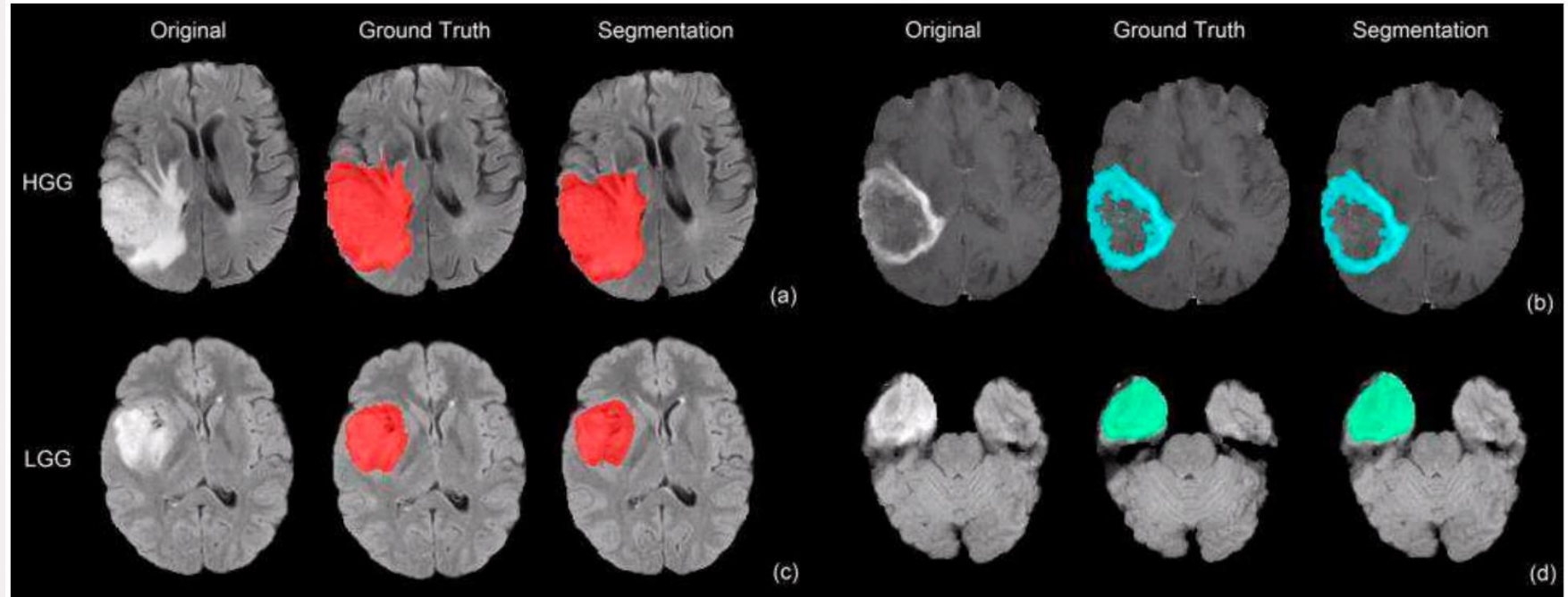
{hao.dong11, g.yang, fangde.liu, y.mo16, y.guo}@imperial.ac.uk



U-Net



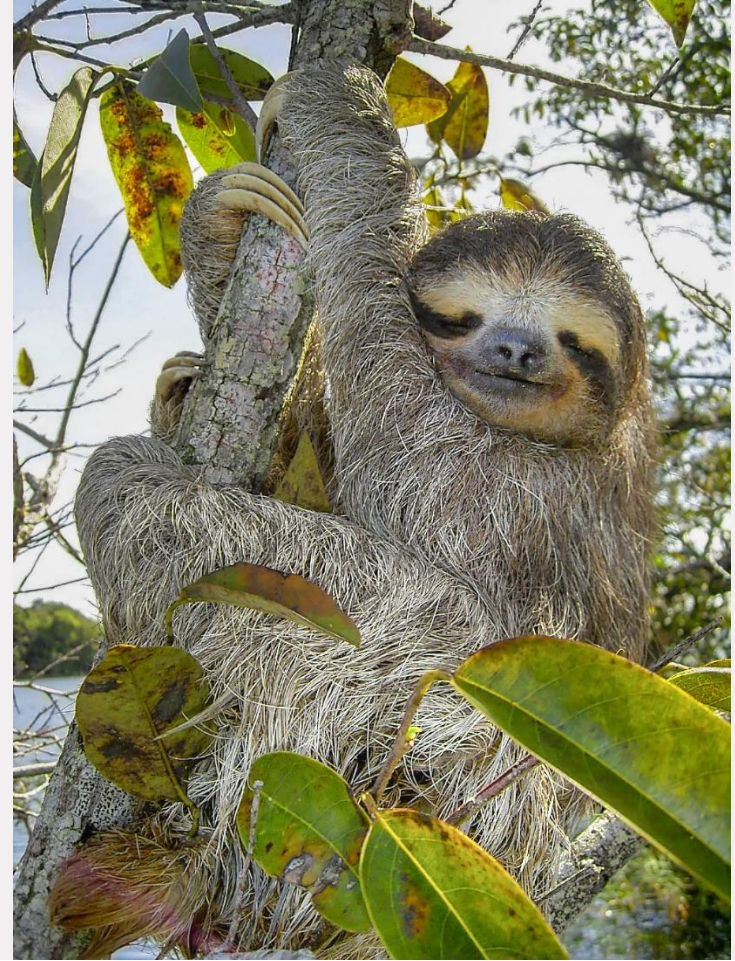
Segmentation results



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



Classify ImageNet classes with ResNet50

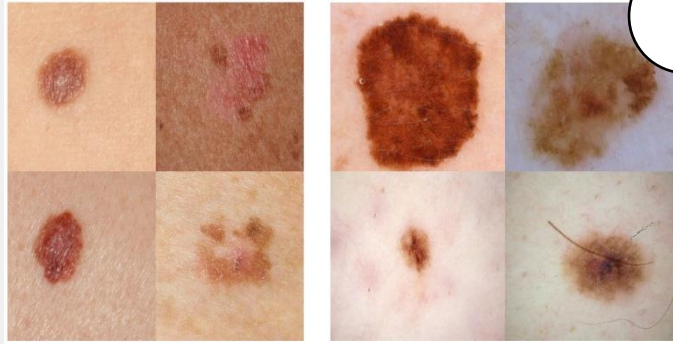
```
from keras.applications.resnet50 import ResNet50
from keras.preprocessing import image
from keras.applications.resnet50 import preprocess_input, decode_predictions
import numpy as np

model = ResNet50(weights='imagenet')

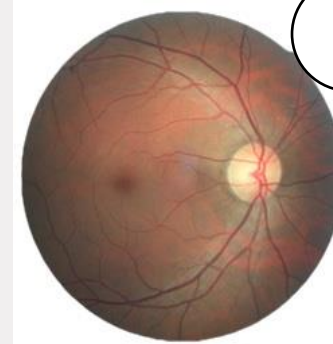
img_path = 'elephant.jpg'
img = image.load_img(img_path, target_size=(224, 224))
x = image.img_to_array(img)
x = np.expand_dims(x, axis=0)
x = preprocess_input(x)

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)]
```


Group exercise



1



2



3



4

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

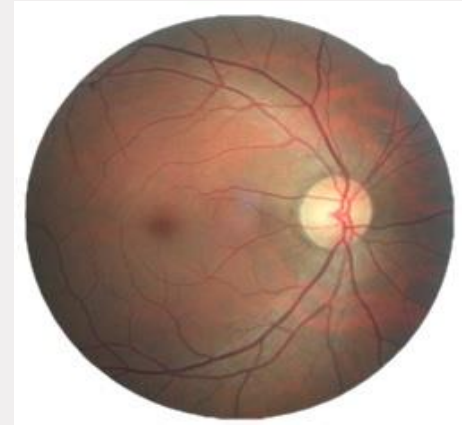
The Netherlands Cancer Institute (NKI) would like to develop an app that enables users to automatically assess skin lesions. The app should be deployable on any medium-end phone and all calculation should be done locally. The NKI has requested your group for general advice on the deep learning approach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



Esteva et al., Nature 2017

Problem 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 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 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>

Summary

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

