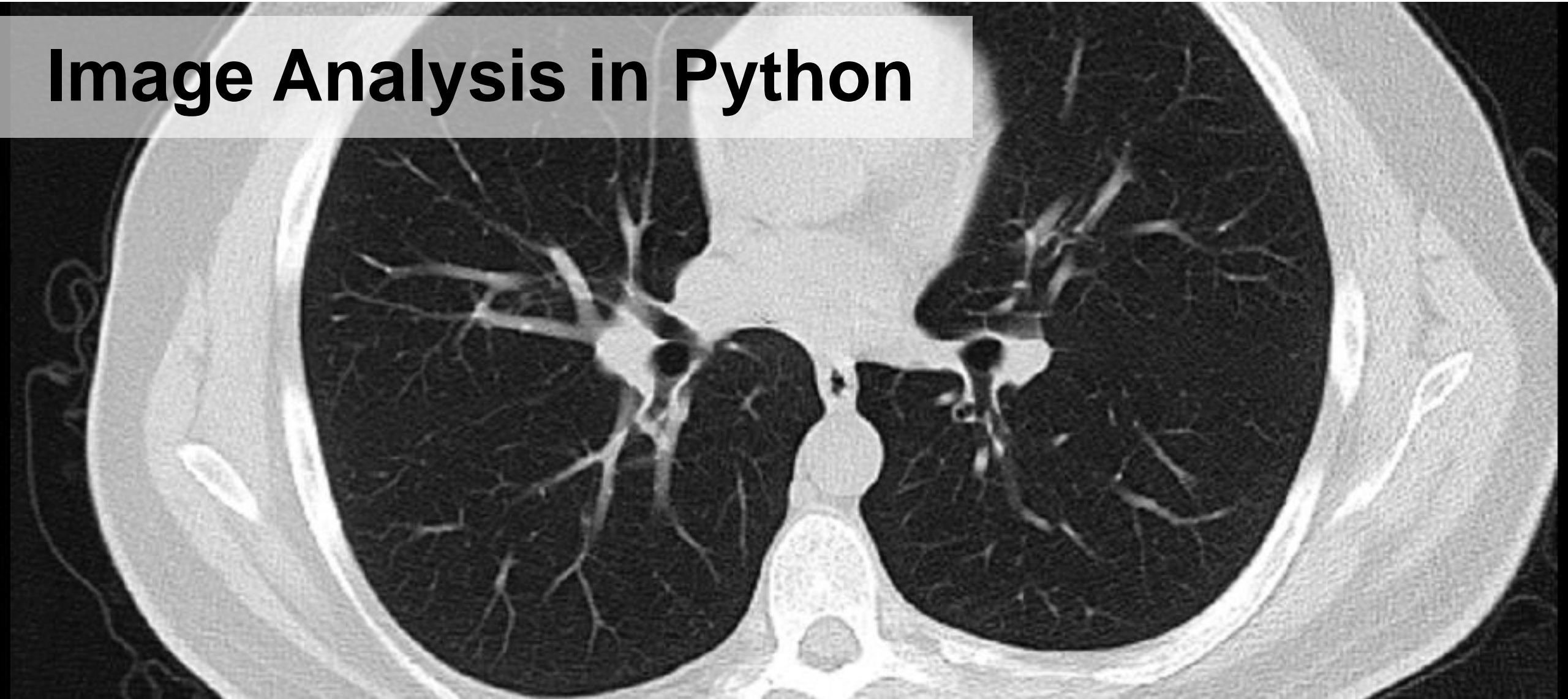
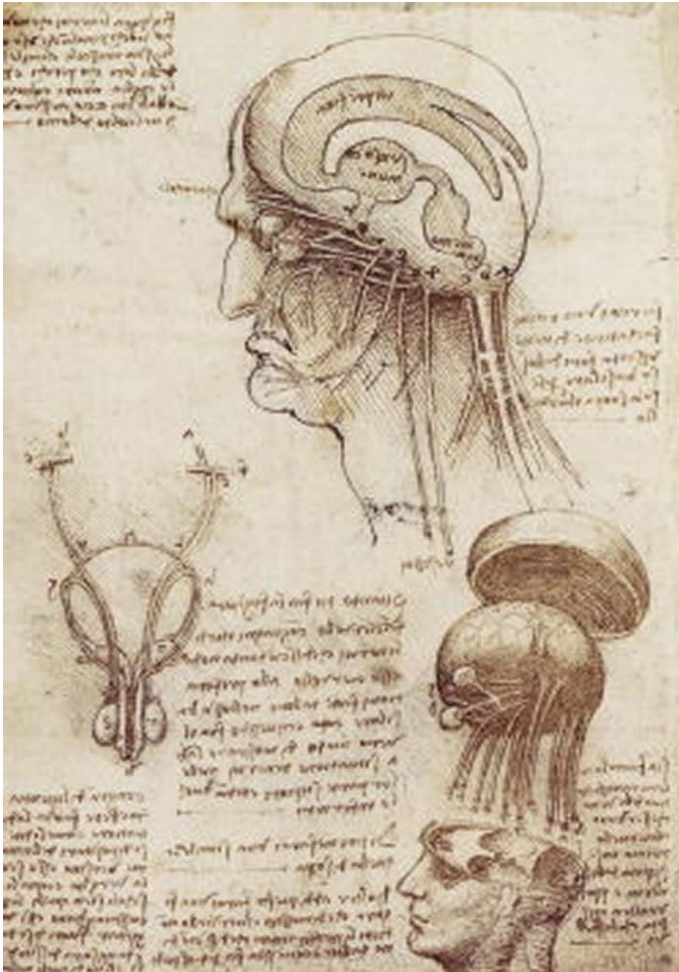




Image Analysis in Python



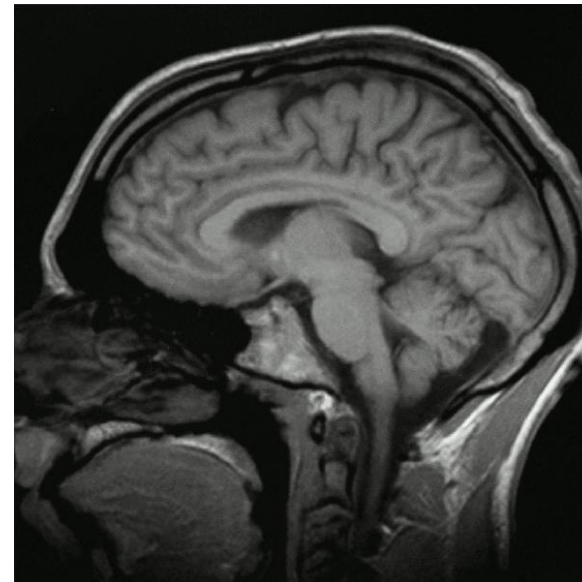
Medical imaging



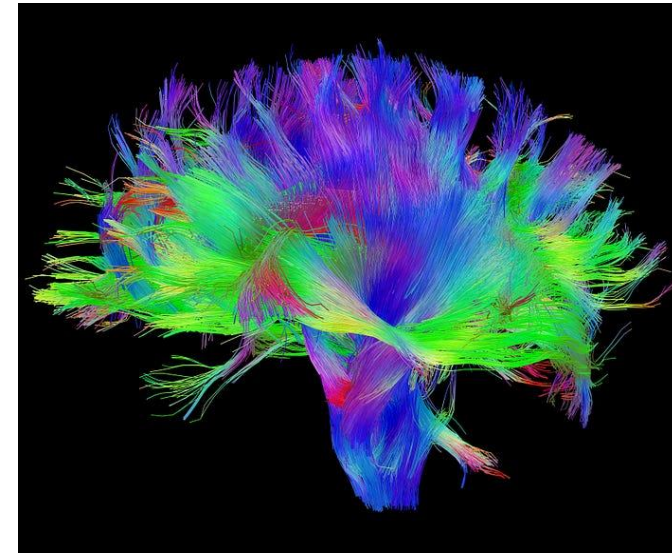
da Vinci drawing (1500)



Pneumoencephalography
(1917)



MRI (1970s - present)

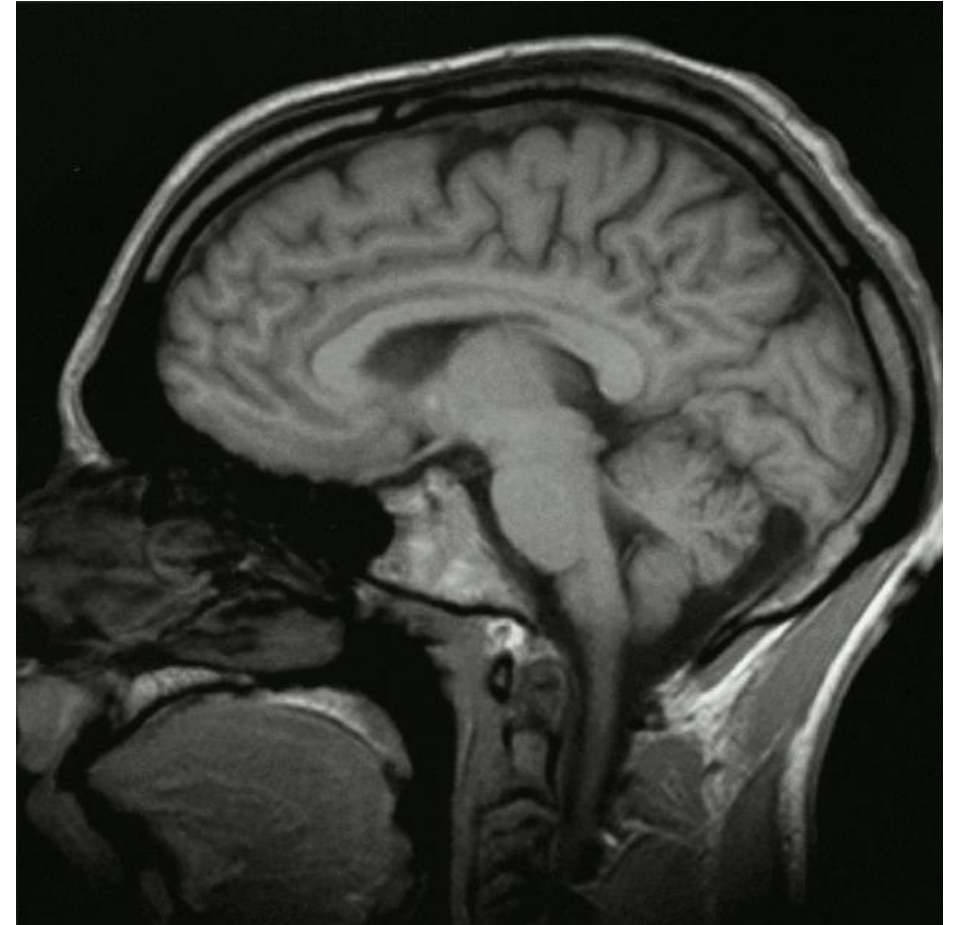


Human connectome
project (ongoing)

Medical image analysis

Medical image data is now more **complex** and **abundant**:

- 3D image stacks contain multiple slices
- Subtle differences in morphology may be clinically relevant
- Metadata must also be taken into consideration



AI vs. machine learning vs. deep learning

	AI	Machine learning	Deep learning
Optimal data volumes	Varying data volumes	Thousands of data points	Big data: millions of data points
Outputs	Anything from predictions to recommendations to decision-making	Numerical value, like a classification or score	Anything from numerical values to free-form elements, like free text and sound
How it works	Machines are programmed to mimic human activity with human-like accuracy	Uses various types of automated algorithms that learn to model functions and predict future actions from data	Uses neural networks that pass data through many processing layers to interpret data features and relationships
How it's managed	Algorithms require human oversight in order to function properly	Algorithms are directed by data analysts to examine specific variables in data sets	Algorithms are largely self-directed on data analysis once they're put into production

Machine learning in healthcare

- Self-learning algorithm adapts to new data
 - Relatively fast to implement
 - Open source
 - Can be used to help with a SPECIFIC TASK (predict outcomes, detect anomalies, analyse images)
-
- Performance depends on the quality of the training data
 - Initial time investment may be higher than other methods

Objectives

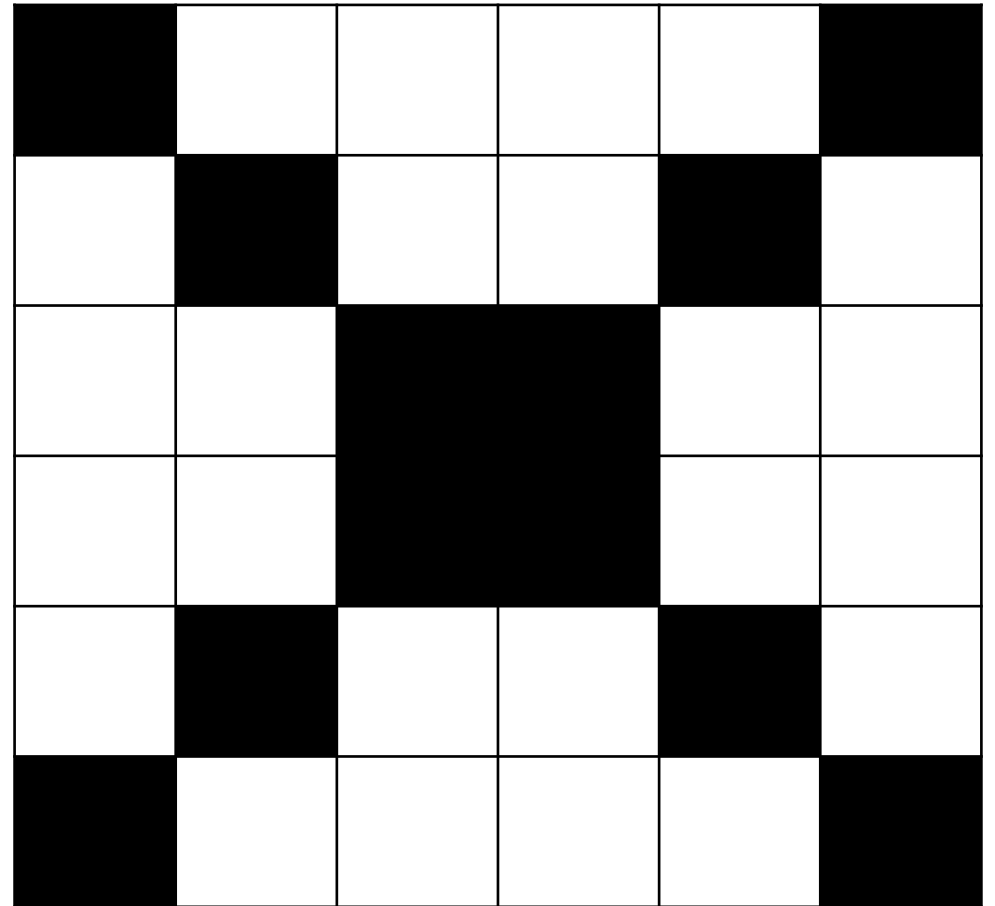
- Understand how computers read medical image data
- Learn strategies for loading data
- Understand the benefits of exploratory data analysis
- Learn how to prepare data for further analysis
- Compare supervised and unsupervised machine learning techniques
- Perform a machine learning analysis task

Objectives

- Understand how computers read medical image data
- Learn strategies for loading data
- Understand the benefits of exploratory data analysis
- Learn how to prepare data for further analysis
- Compare supervised and unsupervised machine learning techniques
- Perform a machine learning analysis task

How does the computer “see” an image?

- A single point in the image is called a pixel (picture element)
- A single cube in a 3D image is called a voxel (volume element)



How does the computer “see” an image?

- A single point in the image is called a pixel (picture element)
- A single cube in a 3D image is called a voxel (volume element)
- Each pixel has a numerical value
- 0 indicates no colour
- The maximum number of shades is controlled by the “bit depth”

1	0	0	0	0	1
0	1	0	0	1	0
0	0	1	1	0	0
0	0	1	1	0	0
0	1	0	0	1	0
1	0	0	0	0	1

How does the computer “see” an image?

- A 2-bit image has $2^1 - 1 = 1$ colour (black)

1	0	0	0	0	1
0	1	0	0	1	0
0	0	1	1	0	0
0	0	1	1	0	0
0	1	0	0	1	0
1	0	0	0	0	1

How does the computer “see” an image?

- A 2-bit image has $2^1 - 1 = 1$ colour (black)
- An 8-bit image has $2^8 - 1 = 255$ shades of a colour (255 + black)

90	0	0	0	0	30
0	90	0	0	50	0
0	0	90	70	0	0
0	0	70	90	0	0
0	50	0	0	90	0
30	0	0	0	0	90

How does the computer “see” an image?

- A 2-bit image has $2^1 - 1 = 1$ colour (black)
- An 8-bit image has $2^8 - 1 = 255$ shades of a colour (255 + black)
- A colour image represents red, green, and blue (RGB) in separate channels

1	0	0	0	0	1
0	1	0	0	1	0
0	0	1	1	0	0
0	0	1	1	0	0
0	1	0	0	1	0
1	0	0	0	0	1

Red

1	0	0	0	0	1
0	1	0	0	1	0
0	0	1	1	0	0
0	0	1	1	0	0
0	1	0	0	1	0
1	0	0	0	0	1

Blue

0	0	0	0	0	0
0	0	0	0	0	0
0	0	0	0	0	0
0	0	0	0	0	0
0	0	0	0	0	0
0	0	0	0	0	0

Green

COMBINED

1	0	0	0	0	1
0	1	0	0	1	0
0	0	1	1	0	0
0	0	1	1	0	0
0	1	0	0	1	0
1	0	0	0	0	1

How does the computer “see” what is important to us?

- The computer reads a table of numbers
- YOU have the clinical knowledge of what’s relevant
- Remember: Garbage in, garbage out!
- Consider: The signal to noise ratio (SNR)
- You define signal vs. noise
- This affects downstream analysis

1	0	0	0	0	1
0	1	0	0	1	0
0	0	1	1	0	0
0	0	1	1	0	0
0	1	0	0	1	0
1	0	0	0	0	1

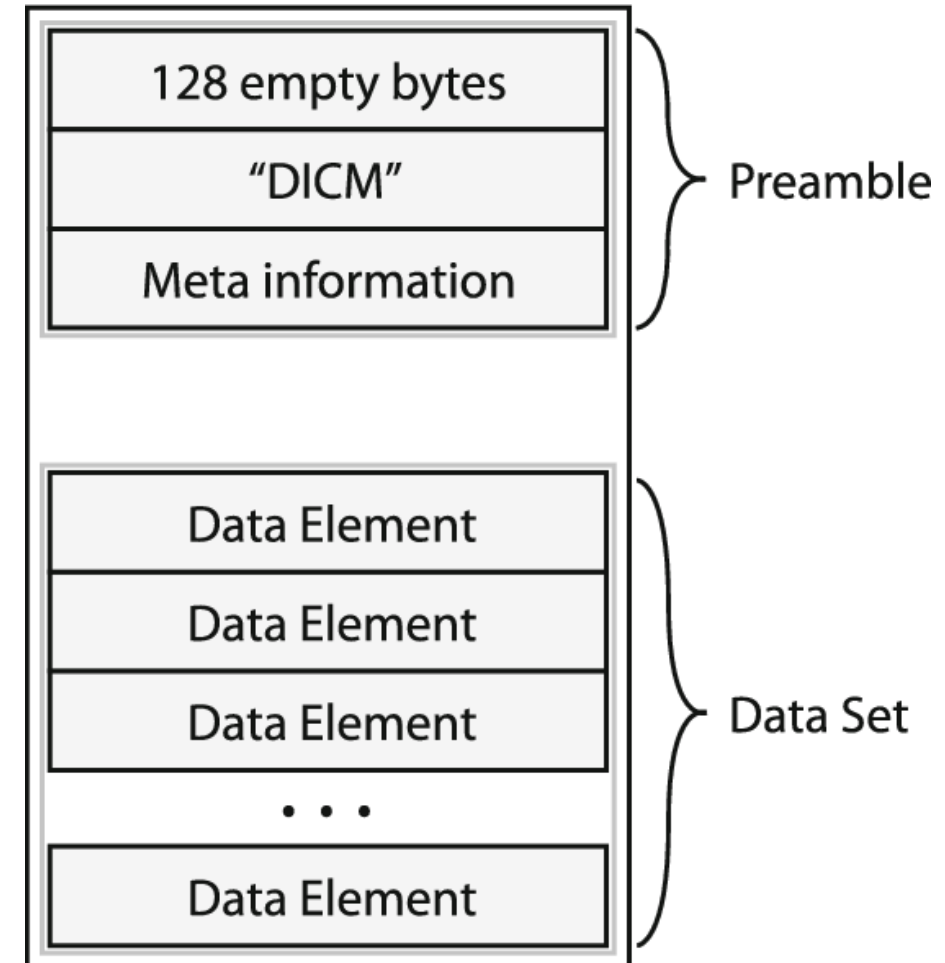
Objectives

- Understand how computers read medical image data
- **Learn strategies for loading data**
- Understand the benefits of exploratory data analysis
- Learn how to prepare data for further analysis
- Compare supervised and unsupervised machine learning techniques
- Perform a machine learning analysis task

Loading data

Medical images come in many different file types:

- **DICOM (.dcm)** – the gold standard!
- Works with JPEG, TIFF, GIF, and PNG
- Contains header with metadata and image combined into single file
- You may also encounter **ANALYZE** (.hdr + .img), **NIFTI** (.nifti) and **NII** (.nii) formats
- Header and image stored separately
- NIFTI also contains orientation information



Loading data



scikit-image
image processing in python



imageio

- Many packages available for loading data
- We'll use sk-image and imageio
- Load data as numerical tables (NumPy)
- Can be plotted with packages like matplotlib
- Can load both single images and 3D stacks



NumPy

matplotlib

Objectives

- Understand how computers read medical image data
- Learn strategies for loading data
- **Understand the benefits of exploratory data analysis**
- Learn how to prepare data for further analysis
- Compare supervised and unsupervised machine learning techniques
- Perform a machine learning analysis task (segmentation)

Exploratory data analysis

Once we have our data, we can explore key qualities:

- Number of images
- Image dimensions
- Patient metadata

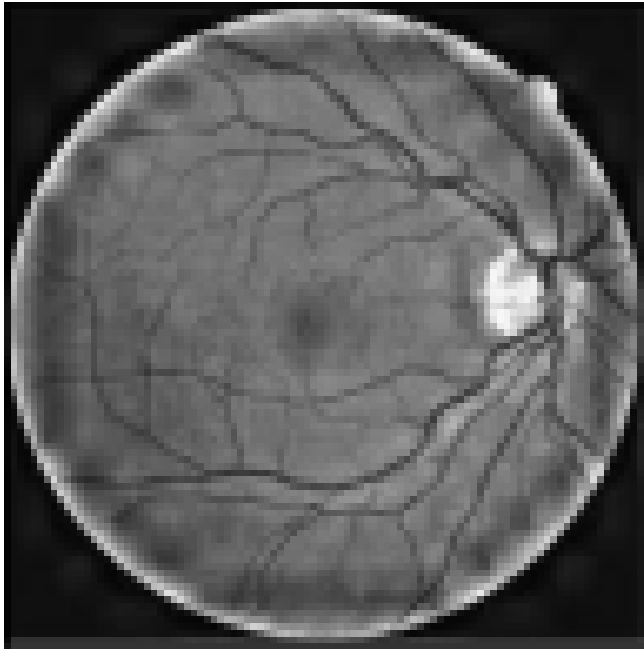
We can also inspect the images to ask key questions:

- Is there any obviously corrupted data?
- Are there any steps we could take to enhance the SNR?
- This informs pre-processing of data

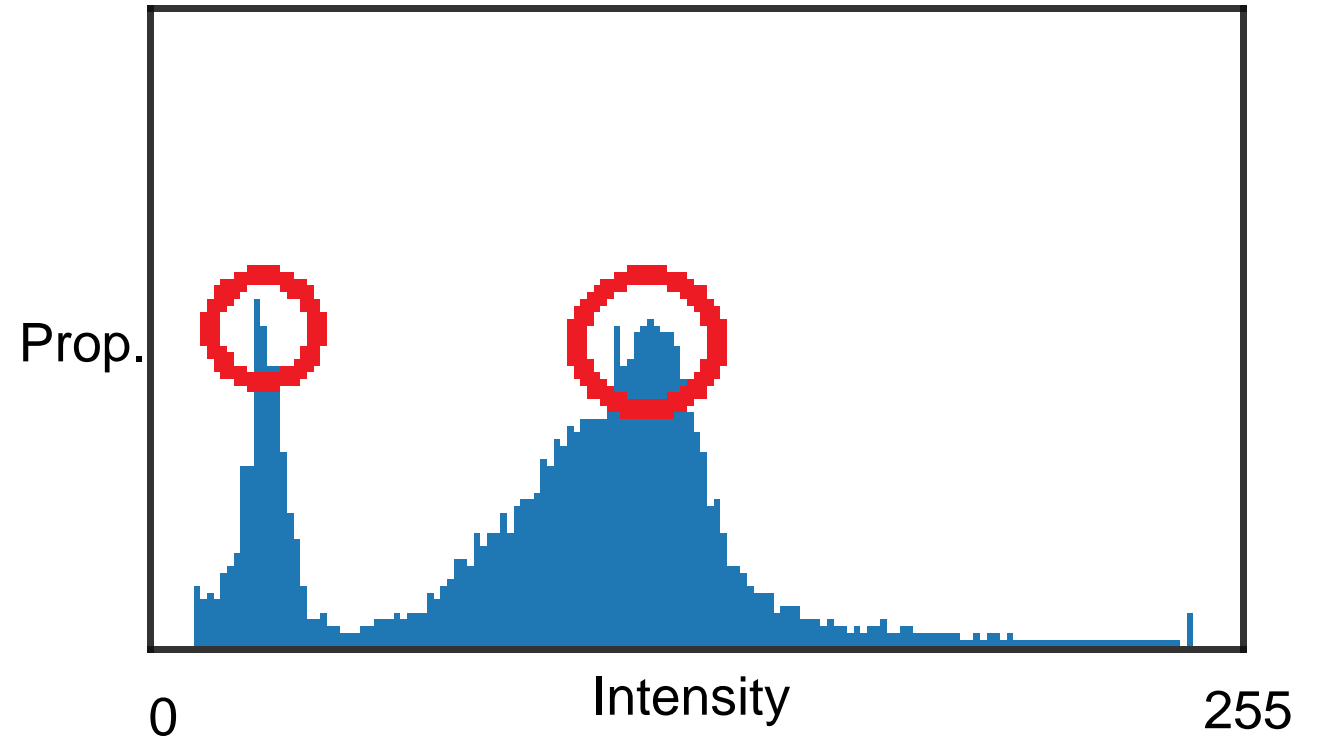
Pixelwise intensity histogram

Plot the proportion of pixels in the image at each level of grey.

Original Noisy Image



Histogram



Objectives

- Understand how computers read medical image data
- Learn strategies for loading data
- Understand the benefits of exploratory data analysis
- **Learn how to prepare data for further analysis**
- Compare supervised and unsupervised machine learning techniques
- Perform a machine learning analysis task (segmentation)

Data preparation

- Masking
- Thresholding
- Filtering
- Simple feature detection

Masking

Remove unnecessary pixels using a binary mask.



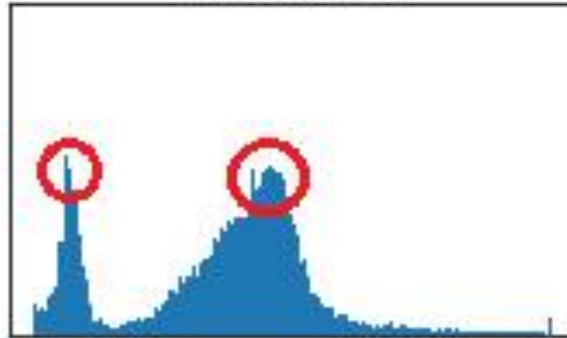
Thresholding

Manually filter noise by setting a limit on pixel intensity

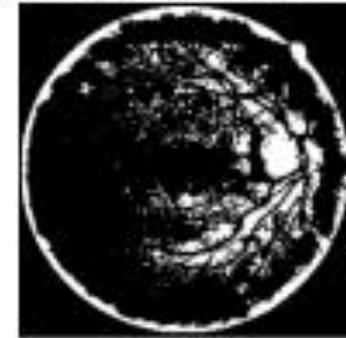
Original Noisy Image



Histogram



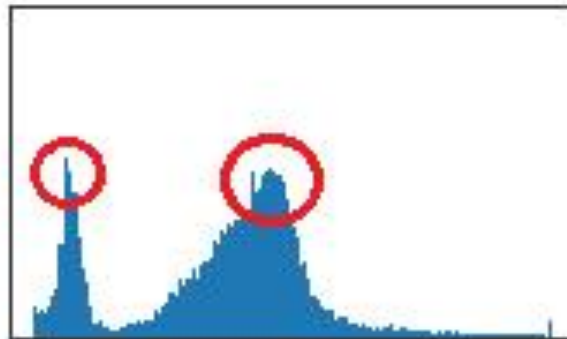
Global Thresholding ($v=127$)



Original Noisy Image



Histogram

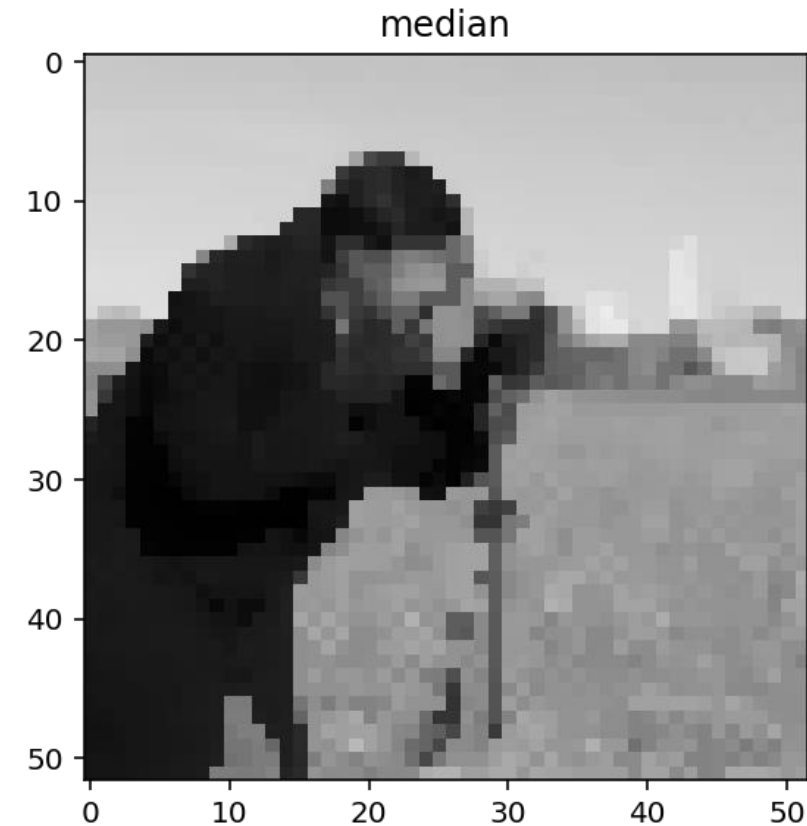
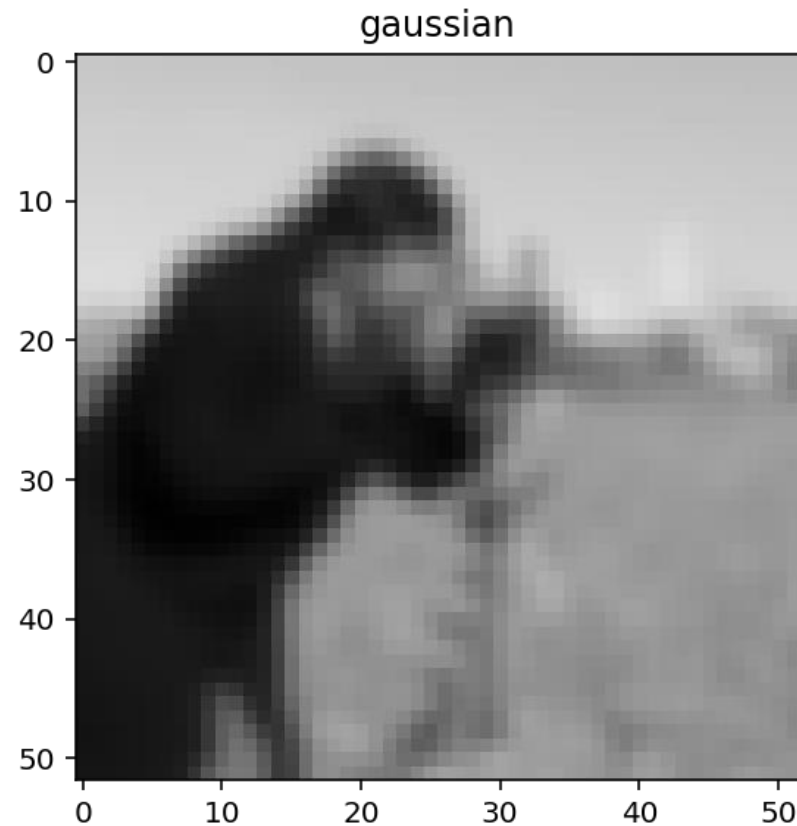
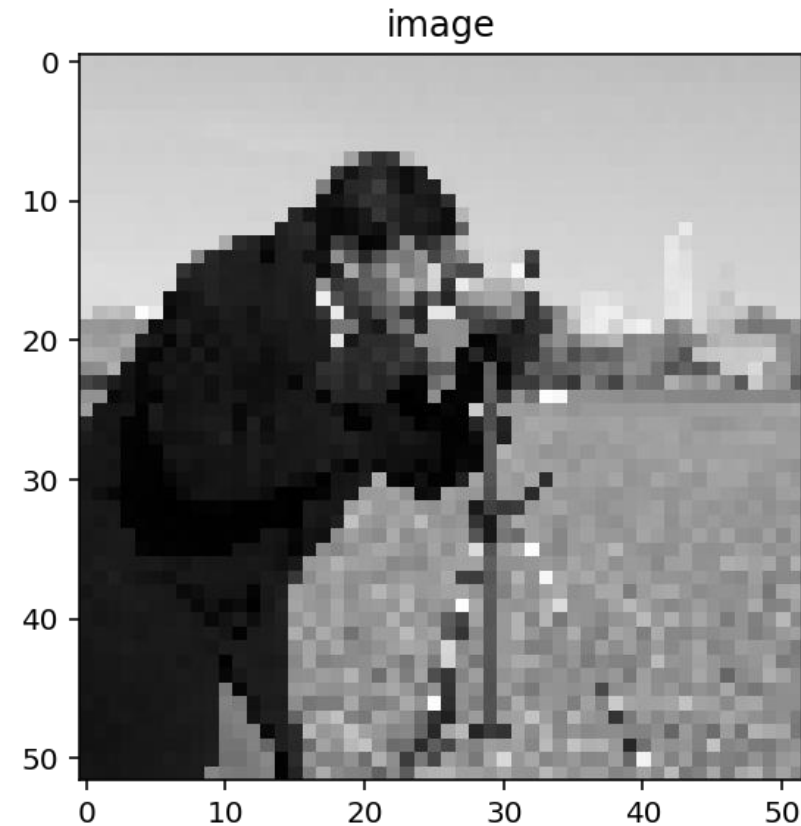


Otsu's Thresholding



Filtering

Remove noise by blurring the image e.g. Gaussian smoothing, median filter.



Feature detection

Detect features e.g. edges using common filters.

Roberts Edge Detection



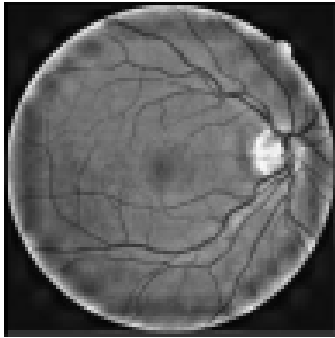
Sobel Edge Detection



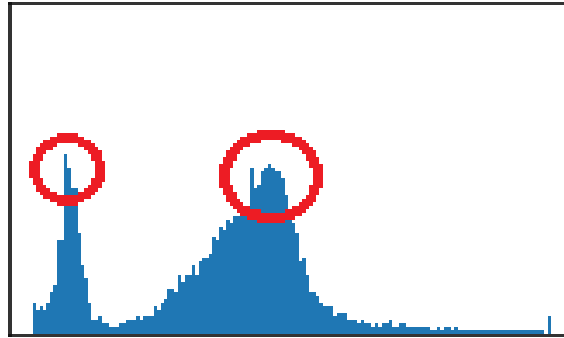
Filtering

Remove noise by blurring the image e.g. Gaussian smoothing.

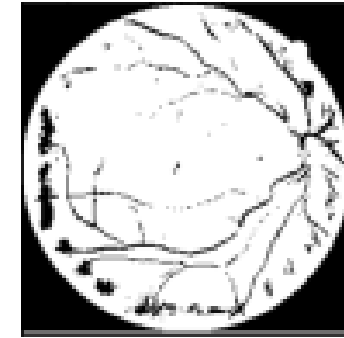
Original Noisy Image



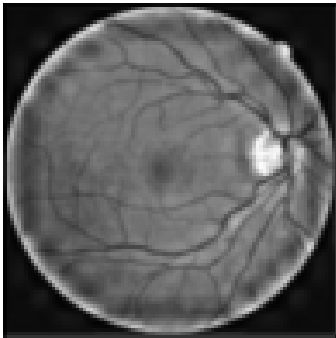
Histogram



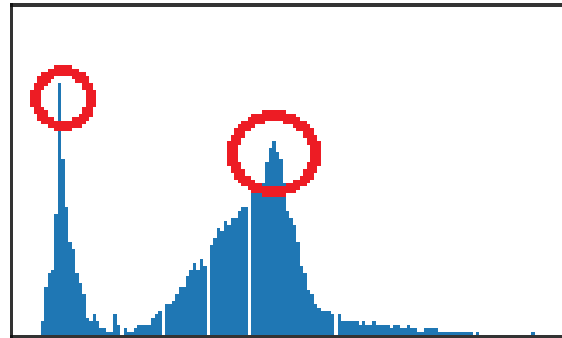
Otsu's Thresholding



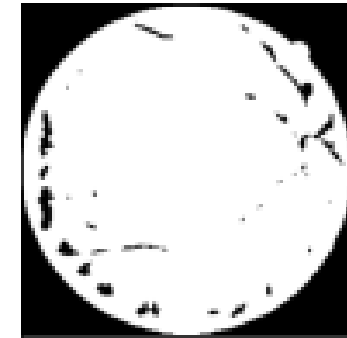
Gaussian filtered Image



Histogram



Otsu's Thresholding



Demo: Image manipulation in Python

+

Create

🏠

Home

🏆

Competitions

📁

Datasets

🔗

Models

🔗

Code

💬

Discussions

🔍

Search

Sign In

Register

SHASHANK S · UPDATED 16 DAYS AGO

▲

11

New Notebook

📄

Download (7 MB)

⋮

Skin Cancer Dataset

Skin Cancer Dataset: Categorized Images for Malignant and Benign Classes

Data Card

Code (2)

Discussion (0)

Suggestions (0)

Break

Objectives

- Understand how computers read medical image data
- Learn strategies for loading data
- Understand the benefits of exploratory data analysis
- Learn how to prepare data for further analysis
- **Compare supervised and unsupervised machine learning techniques**
- Perform a machine learning analysis task

Unsupervised machine learning

Create an algorithm to discover patterns in unlabelled data without human input.

Dataset

MRI brain
scans

Train model

Output
transformed
images

Classify data
de novo

You may want to **perform image registration**, clustering, pattern recognition, anomaly detection, or create an atlas.

Image registration

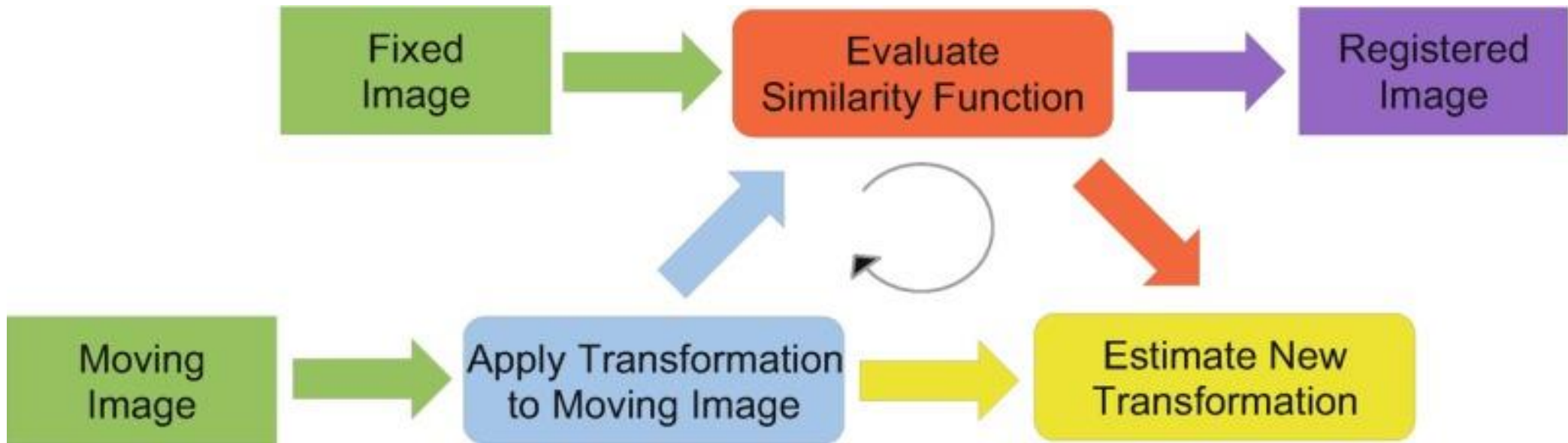
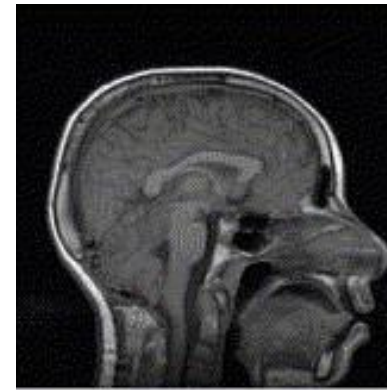
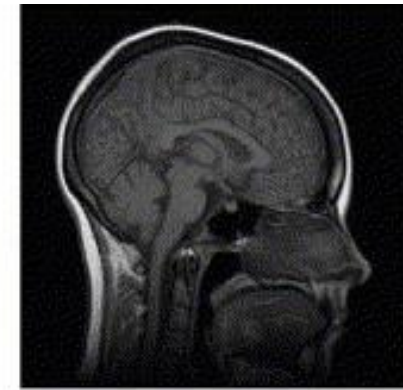


Image registration

- Find the optimal translation to align one image to another
- Deform the image to minimise differences in intensity without introducing artefacts
- Orientation of imaging data is key



(a) source



(b) target



(c) registered source



(d) before registration



(e) after registration

Image registration

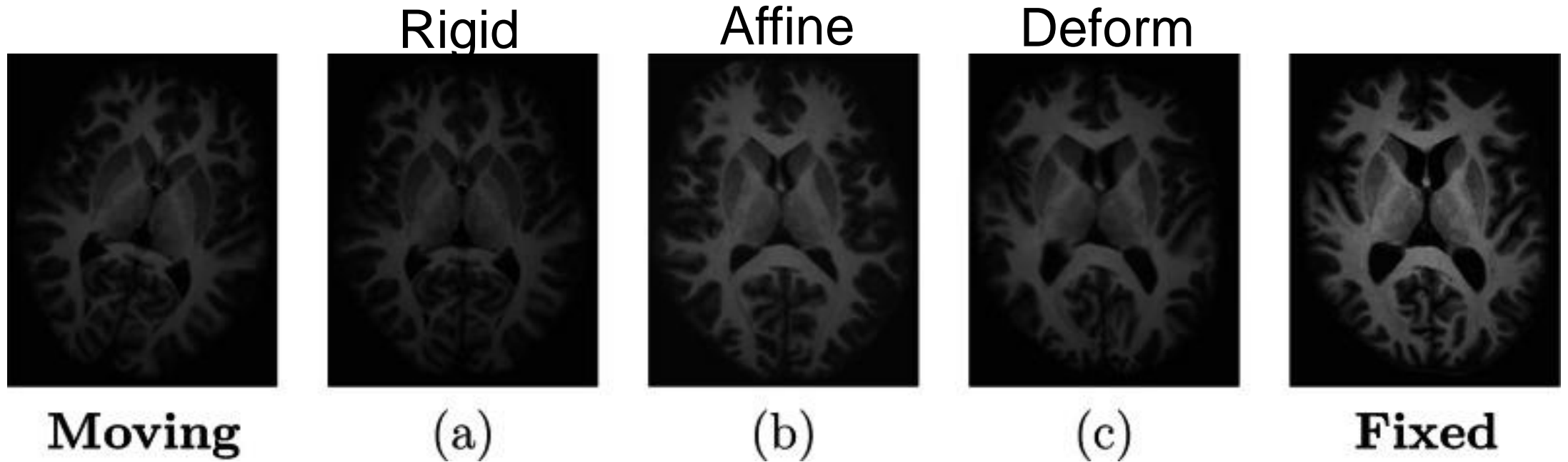
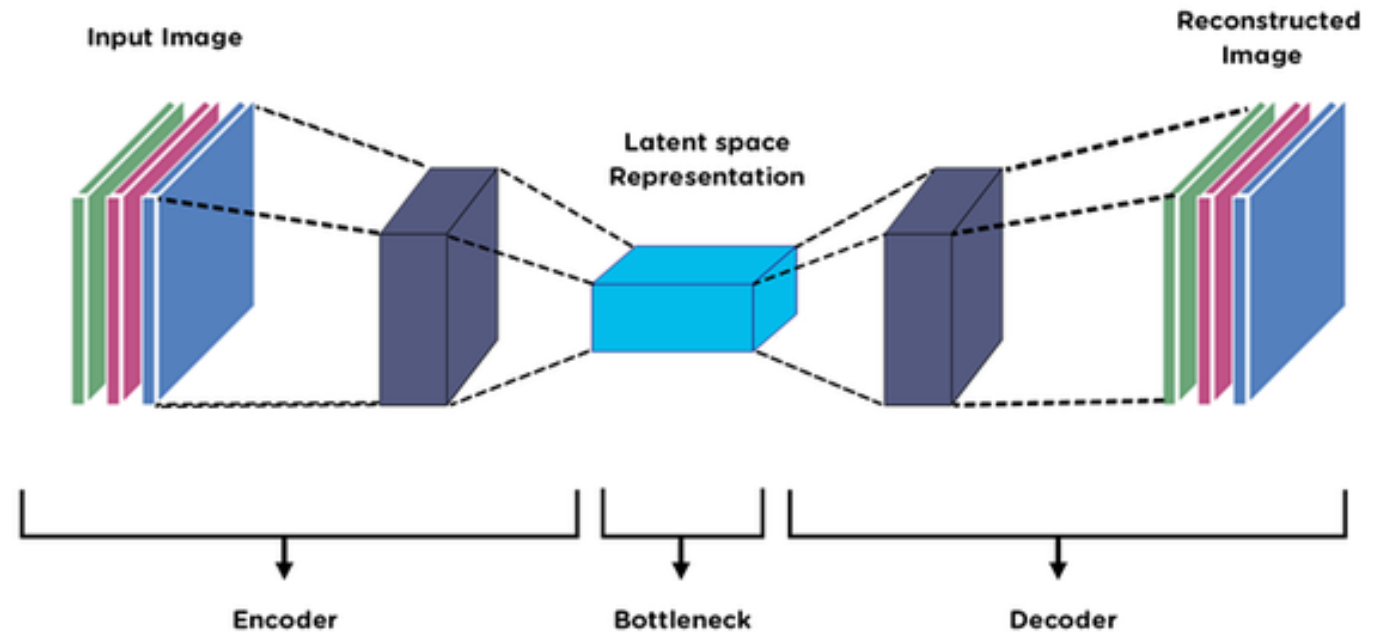


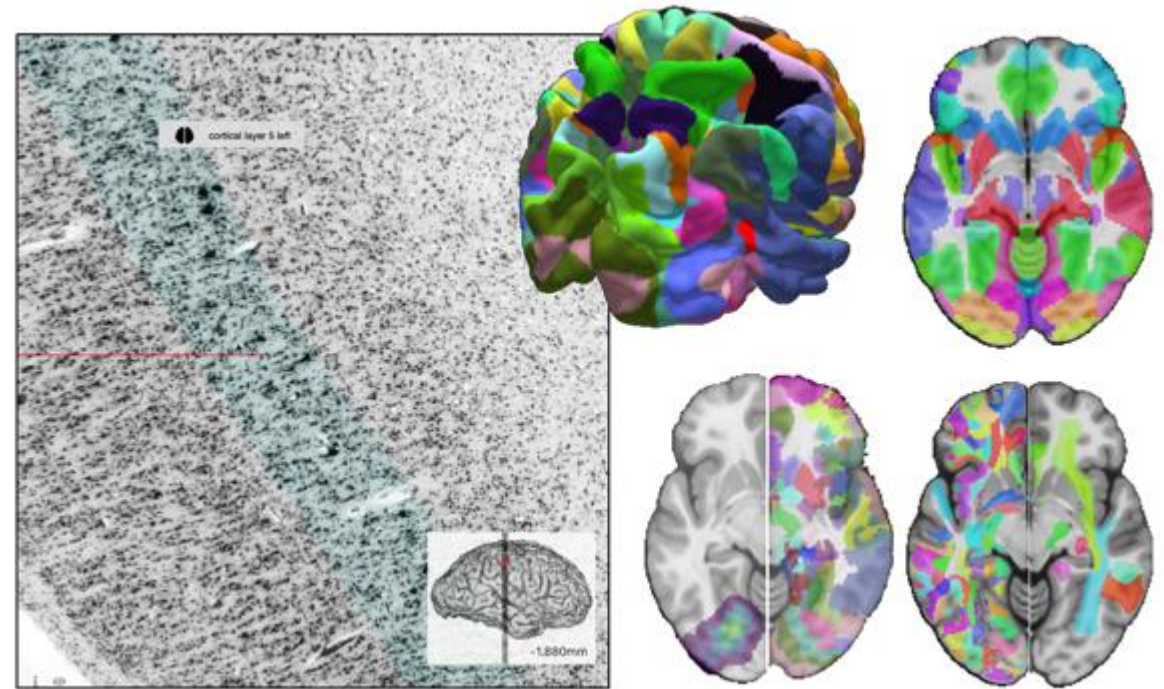
Image registration

- Optimised via loss function (e.g. sum of square differences, mutual information)
- Often uses autoencoders which are trained to reconstruct input data and output the result



Applications

- Compare morphometric data from multiple patients
- Create or align data to an atlas e.g. Human Brain Project →
- Label transfer from existing sources



Supervised machine learning

Use a labelled dataset to train algorithms to make predictions.



- Labels = disease state, health history / outcome
- Many models to choose from, some pre-trained
- Predict which label describes the new data

NB. Labels must be balanced!

Supervised machine learning

Use a labelled dataset to train algorithms to make predictions.

What?

Classification

How much?

Regression

There!

Detection

Not there!

Segmentation

You may want to use **convolutional neural networks (CNNs)**, linear regression, decision trees, random forest, or support vector machines (SVM).

Why CNNs?

Motivation and purpose

[Evol Intell.](#) 2022; 15(1): 1–22.

Published online 2021 Jan 3. doi: [10.1007/s12065-020-00540-3](https://doi.org/10.1007/s12065-020-00540-3)

PMCID: PMC7778711

PMID: [33425040](https://pubmed.ncbi.nlm.nih.gov/33425040/)

Convolutional neural networks in medical image understanding: a survey

[D. R. Sarvamangala](#)¹ and [Raghavendra V. Kulkarni](#)²

CNNs have contributed significantly in the areas of image understanding. CNN-based approaches are placed in the **leader board of the many image understanding challenges**, such as Medical Image Computing and Computer Assisted Intervention (MICCAI) biomedical challenge, Brain Tumor segmentation (BRATS) Multimodal Brain Tumor Segmentation challenge [48], Imagenet classification challenge, challenges of International Conference on Pattern Recognition (ICPR) [31] and Ischemic Stroke Lesion Segmentation (ISLES) challenge [32]. CNN has become a powerful choice as a technique for medical image understanding. Researchers have successfully applied CNNs for many medical image understanding applications like **detection of tumors** and their classification into **benign and malignant** [52], detection of **skin lesions** [50], detection of optical coherence tomography images [39], detection of **colon cancer** [71], **blood cancer**, anomalies of **the heart** [40], **breast** [36], chest, eye etc. Also CNN-based models like CheXNet [56, 58], used for classifying 14 different ailments of the chest **achieved better results compared to the average performance of human experts.**

Convolutional Neural Networks (CNNs)

Consist of 3 major types of layers:

- Convolutional
- Pooling
- Fully connected

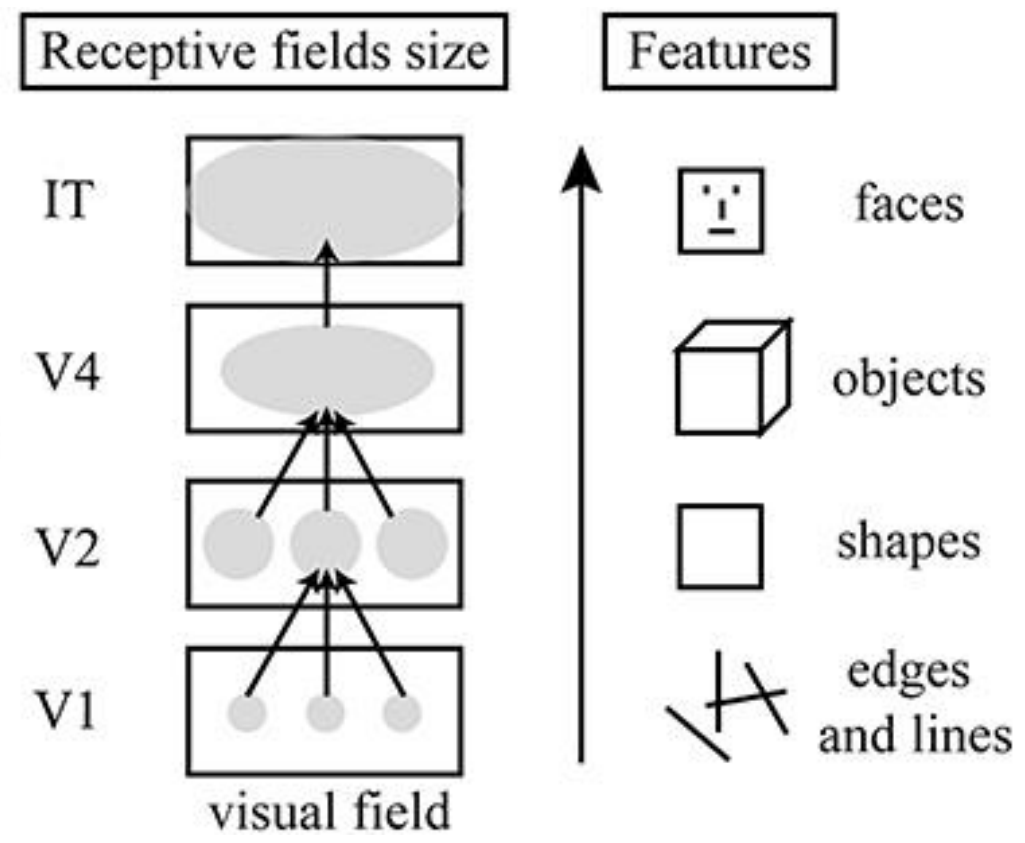
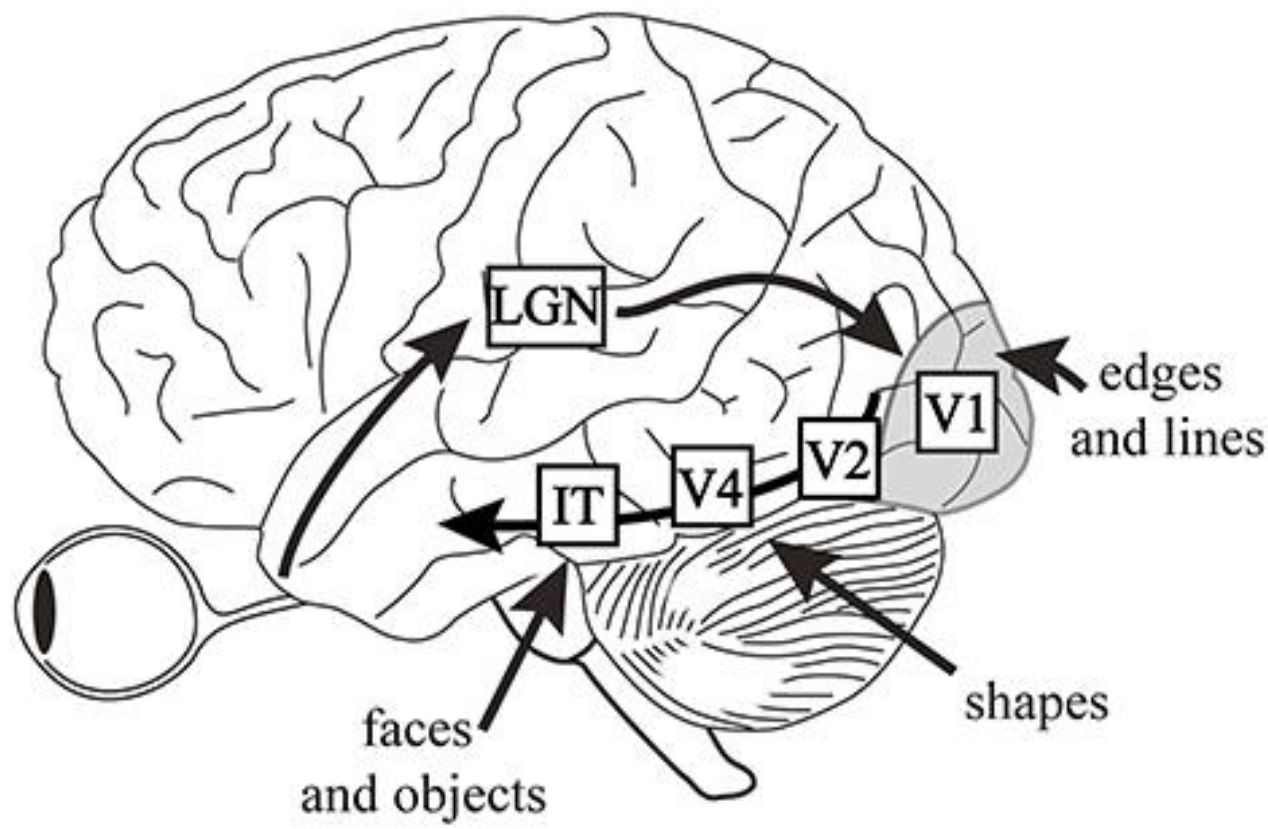
output



input

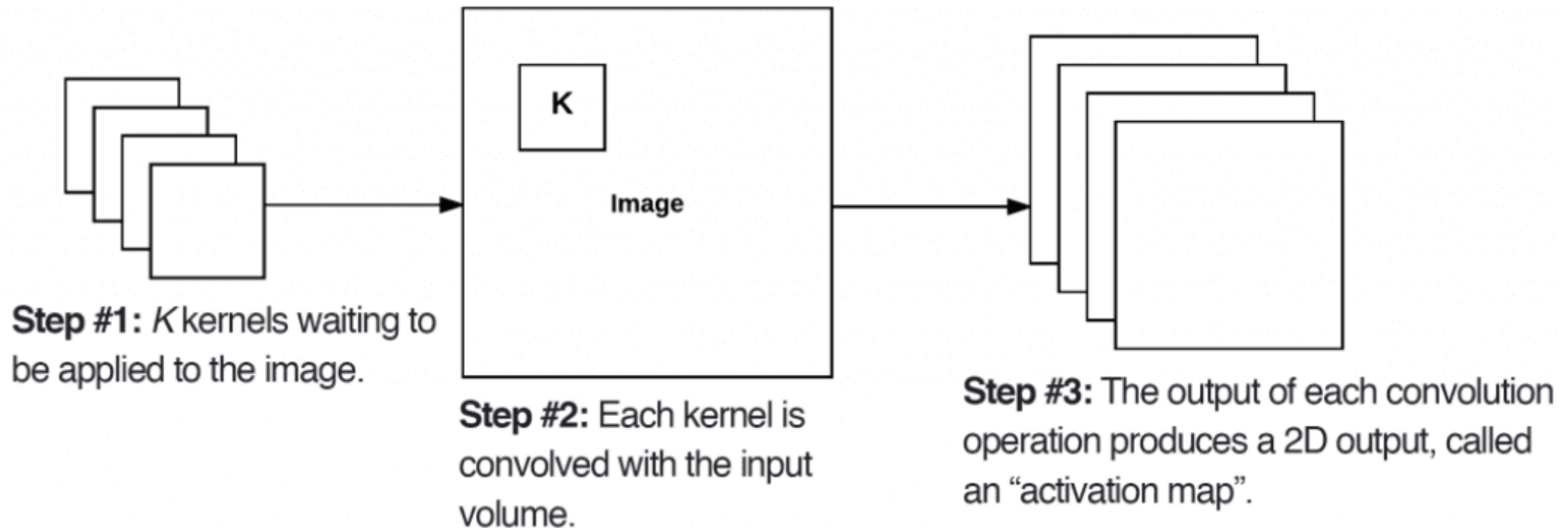


CNNs vs. the visual system



Convolutional layers

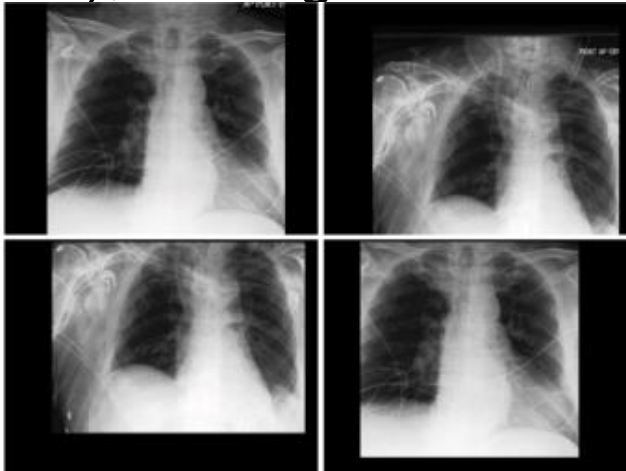
Apply a function (e.g. edge detection) to regions of the image to create a feature map.



Pooling layers

Downsample the feature map to improve performance.

- Dimensionality reduction reduces downstream computation time
- Translation-invariance: shifting the image does not affect performance of the CNN.
- The deeper the network (more conv and pool layers), the higher the invariance



Max Pooling

29	15	28	184
0	100	70	38
12	12	7	2
12	12	45	6

2 x 2
pool size

100	184
12	45

Average Pooling

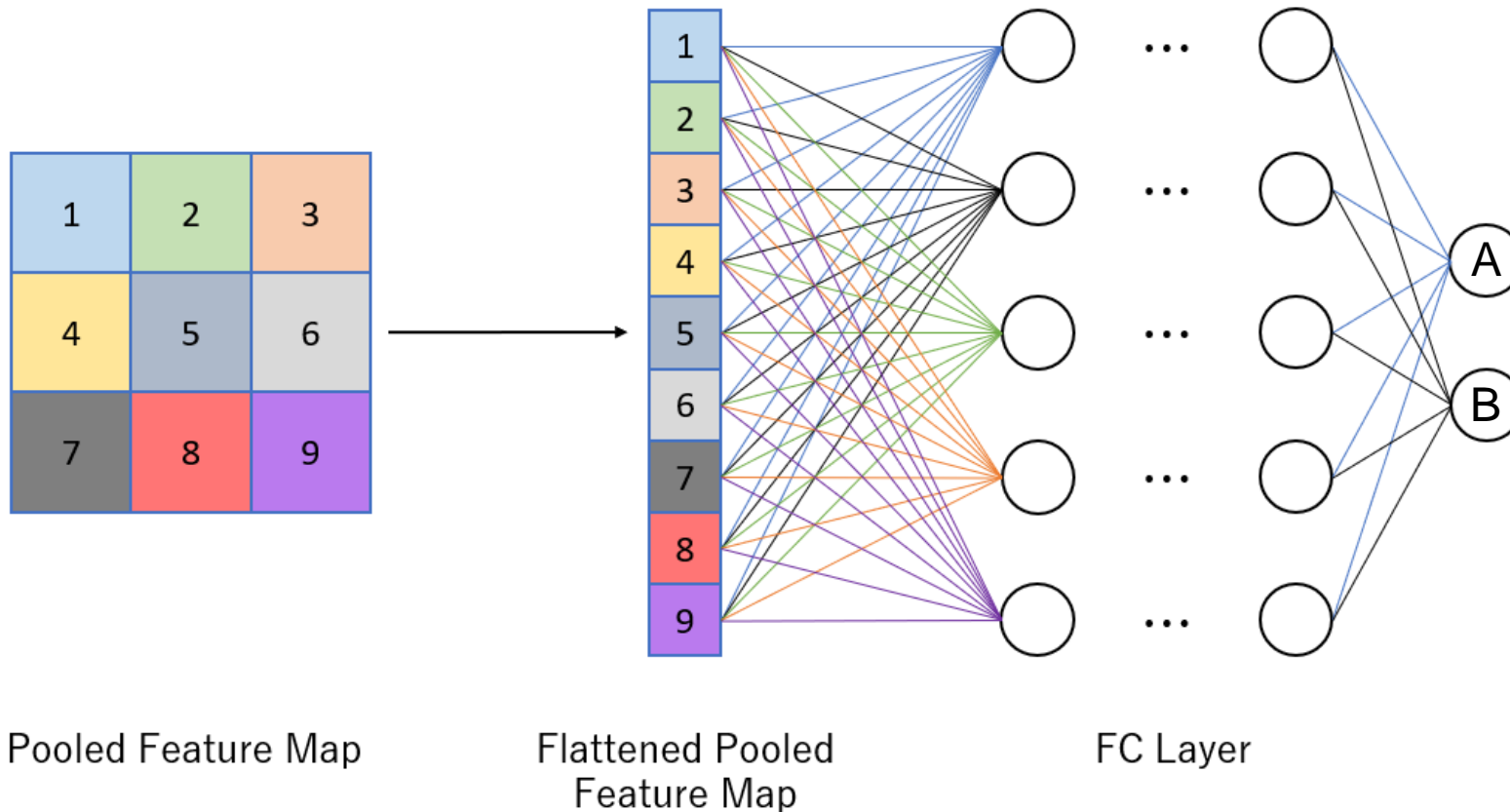
31	15	28	184
0	100	70	38
12	12	7	2
12	12	45	6

2 x 2
pool size

36	80
12	15

Fully connected layers

Flatten the layers, assess weights, and predict result.



Input

-249	-91	-37
250	-134	101
27	61	-153



ReLU

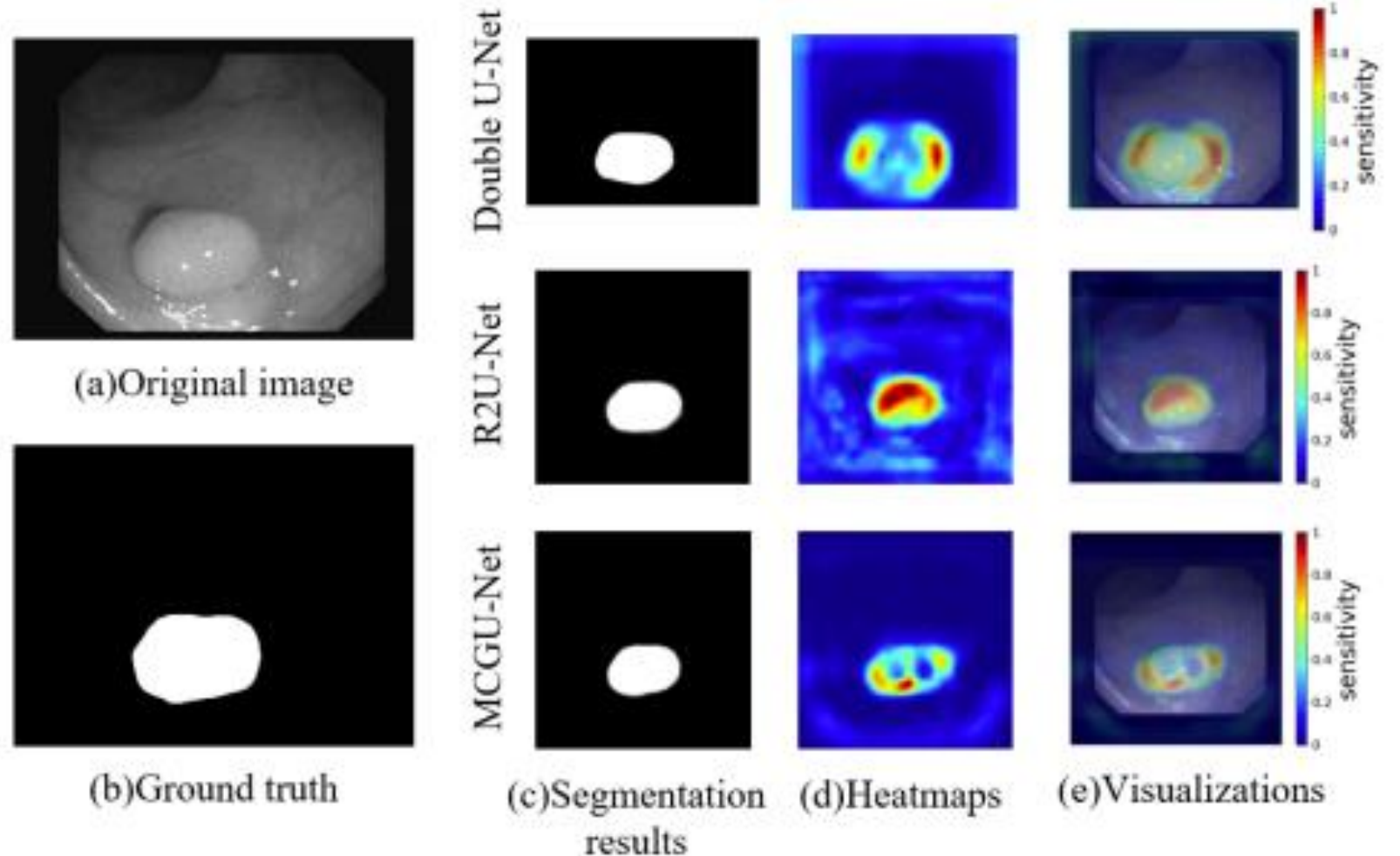
0	0	0
250	0	101
27	61	0

Class Activation Mapping (CAM)

“... can determine the contribution of input features to the result of the classification task and visualize these contributions as heatmaps.”

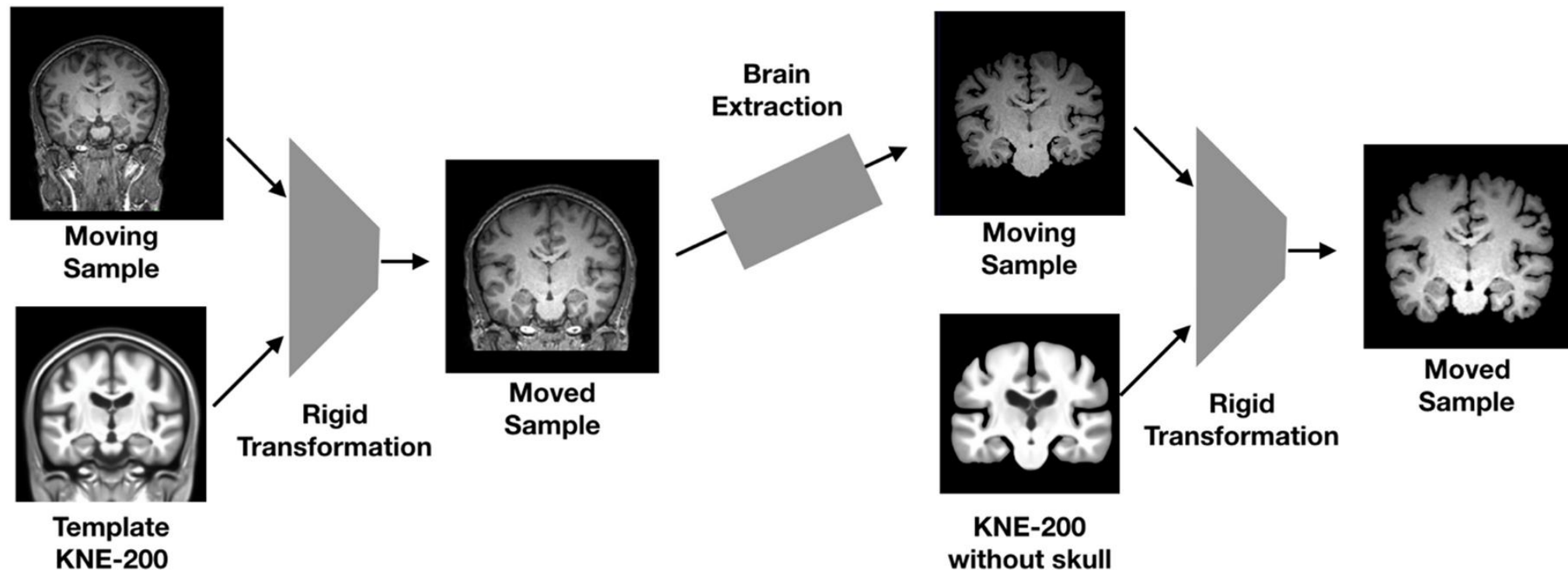
Xiao et al, 2021.

‘A visualization method based on the Grad-CAM for medical image segmentation model’



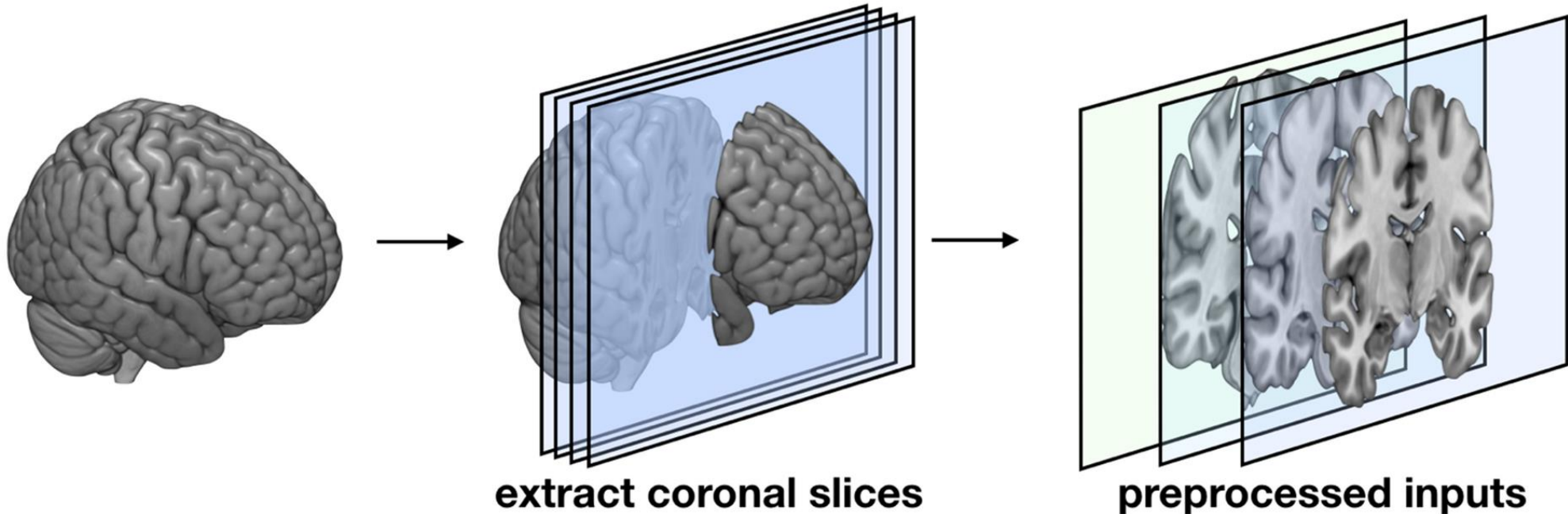
Combining learning methods: Alzheimer's example – Bae et al, 2020

Step 1: Image registration (unsupervised).



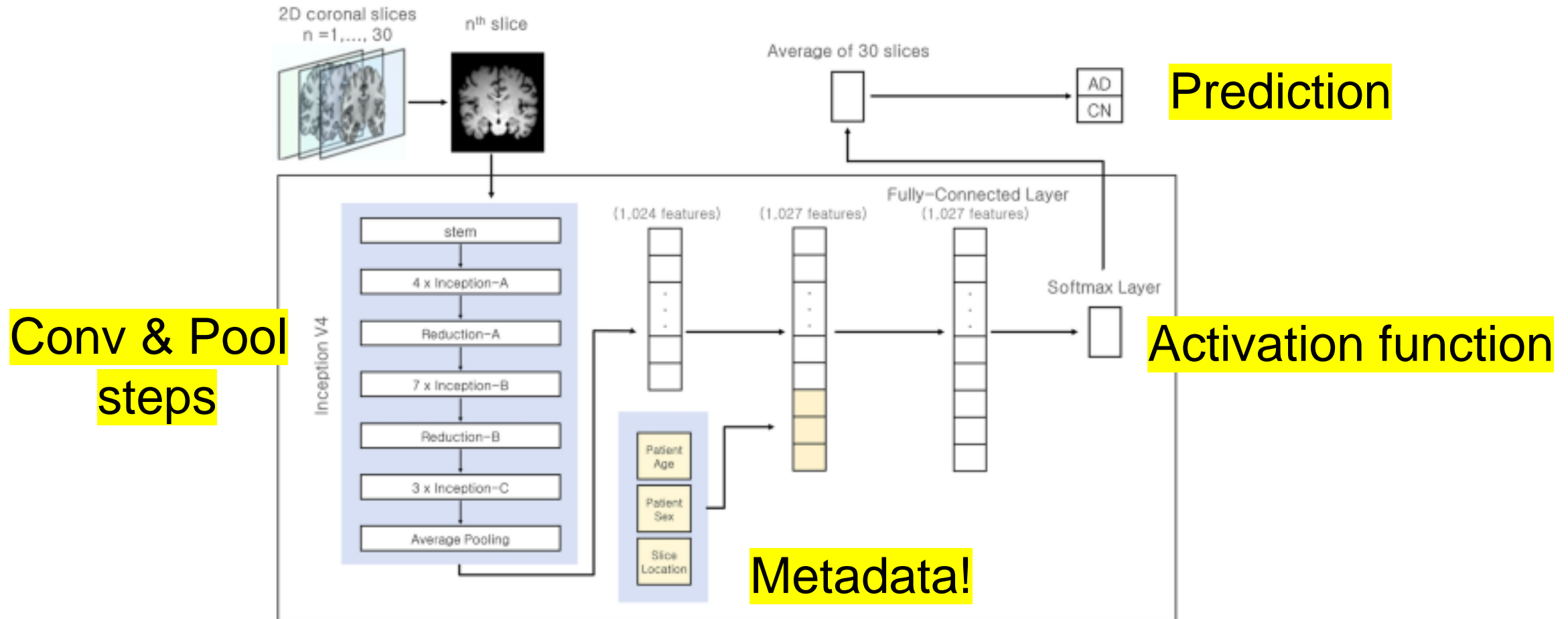
Combining learning methods: Alzheimer's example

Step 1: Image registration (unsupervised).



Alzheimer's example

Step 2: CNN on registered slices (supervised).



Alzheimer's example

Result: Classification of new patient data as either AD or non-AD with a mean processing time of **24s**.

Article | [Open access](#) | Published: 17 December 2020

Identification of Alzheimer's disease using a convolutional neural network model based on T1-weighted magnetic resonance imaging

[Jong Bin Bae](#), [Subin Lee](#), [Wonmo Jung](#), [Sejin Park](#), [Weonjin Kim](#), [Hyunwoo Oh](#), [Ji Won Han](#), [Grace Eun Kim](#), [Jun Sung Kim](#), [Jae Hyoung Kim](#) & [Ki Woong Kim](#) 

[Scientific Reports](#) **10**, Article number: 22252 (2020) | [Cite this article](#)

20k Accesses | **83** Citations | **11** Altmetric | [Metrics](#)

Objectives

- Understand how computers read medical image data
- Learn strategies for loading data
- Understand the benefits of exploratory data analysis
- Learn how to prepare data for further analysis
- Compare supervised and unsupervised machine learning techniques
- Perform a machine learning analysis task

Demo: Machine learning with imaging data

Summary

- Learned how computers read medical image data
- Learned strategies for loading data
- Explored the benefits of exploratory data analysis
- Learned how to prepare data for further analysis
- Compared supervised and unsupervised machine learning techniques
- Performed a machine learning analysis task

Thanks for listening! 😊

rachel.s.williams@ucl.ac.uk

- Title slide image: By Ptrump16 - Own work, CC BY-SA 4.0, <https://commons.wikimedia.org/w/index.php?curid=114999332>

Activation functions

Transform the output and send it on to the pooling layer.

- Most commonly used function is the rectified linear activation function (ReLU)
- Only keeps positive values, any negatives set to zero
- Not strictly its own layer – always assumed to follow a conv layer
- However, good to specify as there are other activation functions used in edge cases

Input			ReLU		
-249	-91	-37	0	0	0
250	-134	101	250	0	101
27	61	-153	27	61	0