

# A “Gentle” Intro to Deep Learning in Medical Imaging

## A Magnetic Resonance Journal Club (MRJC) Discussion

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# Outline

1 MRJC Intro

2 Overview

3 Introduction

4 Materials & Methods

5 Results

6 Discussion

# MRJC Introduction

Welcome!

- Aims: stimulate discussion of emerging MRI technologies, clinical and scientific applications, basic concepts, and its history
- When?: last Tuesday of each month (Feb 25th; March 31st; April 28th; etc.)
- Time: 11am - 12pm
- Where: 3113 (except Feb 25th: A3-131)
- Expectations:
  - ▶ no prior knowledge: just be curious!
  - ▶ ask anything, do not be afraid of looking silly
  - ▶ please try to read and understand the paper before attending (but not required)

# Today's Journal Article

## A gentle introduction to deep learning in medical image processing

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<https://doi.org/10.1016/j.zemedi.2018.12.003>

(note: I also heavily borrowed from Zubarev, V. (2019) Machine Learning for Everyone. ([https://vas3k.com/blog/machine\\_learning/](https://vas3k.com/blog/machine_learning/)) and Lundervold, AS. (2019) An overview of deep learning in medical imaging focusing on MRI. Z Med Phys **29** 102–127)

# Overview

- Introduction
- Materials and Methods:
  - ▶ Machine Learning and Pattern Recognition
  - ▶ Neural Networks
  - ▶ Network Training
  - ▶ Deep Learning
  - ▶ Important Architectures in Deep Learning
  - ▶ Advanced Deep Learning Concepts
- Results
  - ▶ Image Detection and Recognition
  - ▶ Image Segmentation
  - ▶ Image Registration
  - ▶ Computer Aided Diagnosis
  - ▶ Physical Simulation
  - ▶ Image Reconstruction
- Discussion

# Introduction

- Deep Learning has had a huge impact in recent years:

## Examples

- speech recognition
  - image recognition
  - AI that beat humans in GO and ATARI games
  - art & music
- 
- What can it do for medical imaging?



# Introduction

This paper's main aims are to:

- summarize relevant theory of deep learning
- connect to traditional concepts in pattern recognition and machine learning
- give applications to medical imaging processing and analysis
- explore weaknesses
- outline potential remedies

# Machine Learning and Pattern Recognition

## Example

Jill wants to buy a car. She observes that new cars cost \$40,000, a one year old car costs \$35,000, and a two year old car costs \$30,000. Jill realizes that for each year, the price goes down by \$5,000. In machine learning terms, Jill just invented linear regression.

- Problem is, the world is more complex than simple linear regressions. There are many factors and relationships, which are hard to analyze
- It would be nice if a machine could find the hidden patterns for us

# Machine Learning and Pattern Recognition

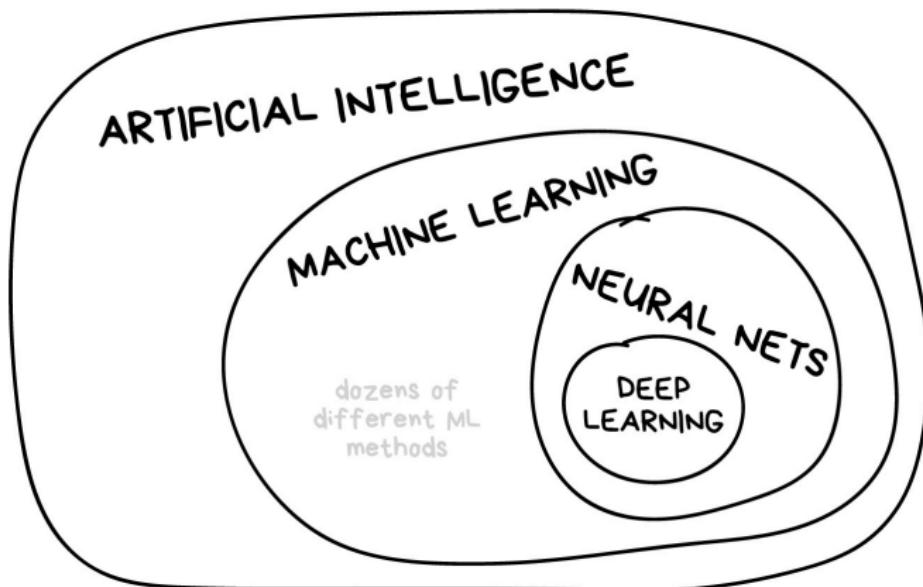
## Definition

**Machine Learning:** “algorithms [that] build a mathematical model based on sample data, known as “training data”, in order to make predictions or decisions without being explicitly programmed to perform the task”

- Training phase
  - ▶ need training data
- Types of training:
  - ▶ supervised (task driven)
  - ▶ unsupervised (data driven)
  - ▶ reinforcement (algorithm learn to react to environment)
- Testing phase
  - ▶ different data from training data

# Neural Networks and Deep Learning

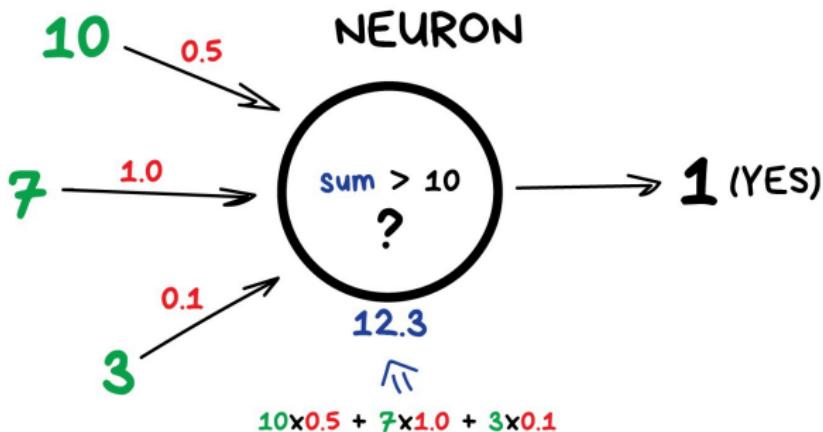
- Deep Learning is a modern method of building, training, and using neural networks, which is itself a type of machine learning



Zubarev, V. (2019). Machine Learning for Everyone. ([https://vas3k.com/blog/machine\\_learning/](https://vas3k.com/blog/machine_learning/))

# Neural Nets

- **Neural network:** nodes (neuron) and connections (axons)
- **Neuron:** function that takes inputs and gives one output
- **Axons:** connect neurons, and can have *weights*

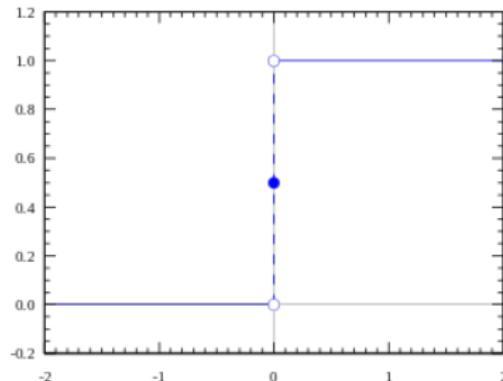


Zubarev, V. (2019). Machine Learning for Everyone. ([https://vas3k.com/blog/machine\\_learning/](https://vas3k.com/blog/machine_learning/))

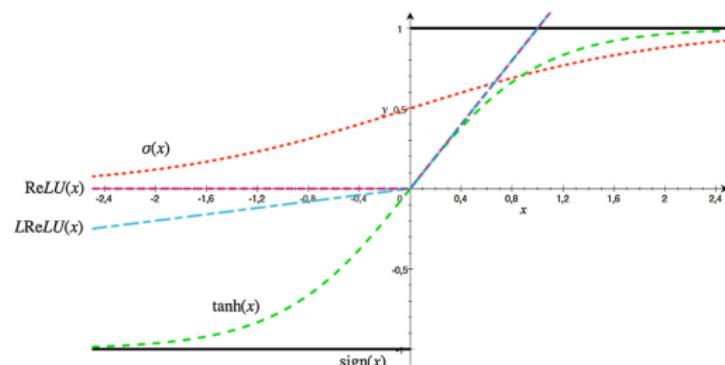
- **Activation Function:** how neuron decides to fire or not

# Activation Functions

- Binary function, such as a step function

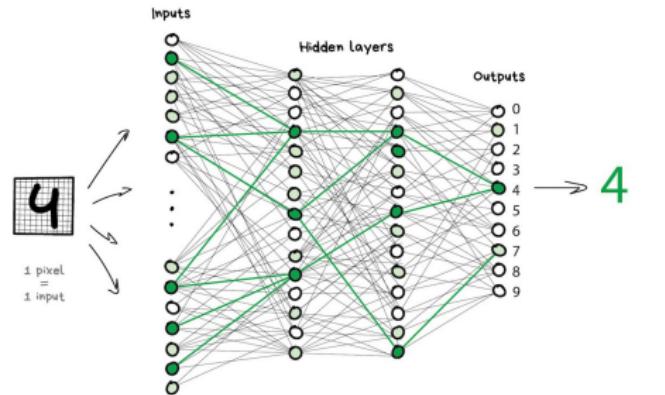


- Intermediate (analog) activation



# Neural Nets

- Rules:
  - ▶ Neurons are linked by layers, not randomly
  - ▶ Not linked within layer
  - ▶ One direction
- How to train:
  - ① random weights assigned
  - ② show drawing of 4
  - ③ check if result is '4'
  - ④ backpropagate and adjust weights based on error
  - ⑤ function used to compute error known as *loss function*
  - ⑥ hundreds of thousands of such cycles of 'infer-check-punish'



Zubarev, V. (2019). Machine Learning for Everyone.

([https://vas3k.com/blog/machine\\_learning/](https://vas3k.com/blog/machine_learning/))

# Recap of Terms

## Definitions

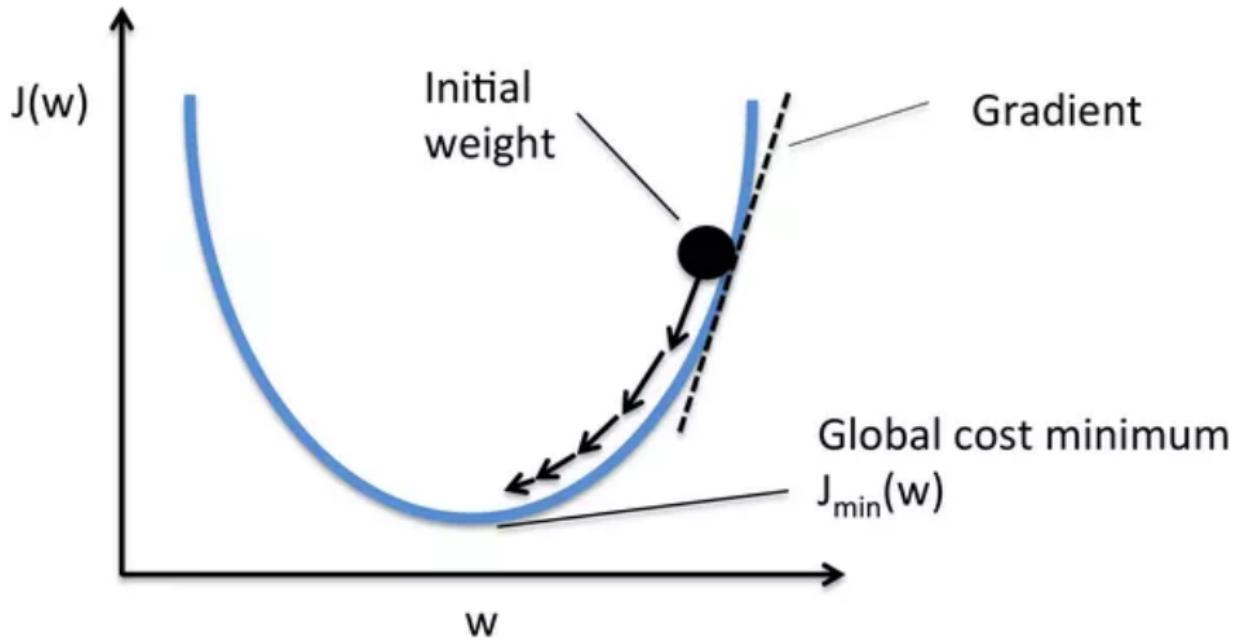
**Error:** calculated as the difference between the actual output and the predicted output

**Loss Function:** function that is used to compute this error. Different loss functions will give different errors for the same prediction

**Back Propagation:** current error is typically propagated backwards to a previous layer, where it is used to modify the weights and bias in such a way that the error is minimized

Weights are modified using a function called **Optimization Function.**

**Gradient Descent:** optimization algorithm used to minimize some function by iteratively moving in the direction of steepest descent as defined by the negative of the gradient.

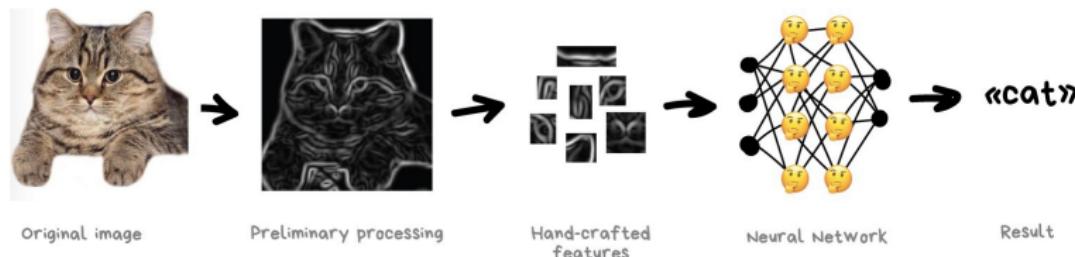


Agrawal, A (2017). Loss Functions and Optimization Algorithms. Demystified.

(<https://medium.com/data-science-group-iitr/loss-functions-and-optimization-algorithms-demystified-bb92daff331c>)

# Deep Learning

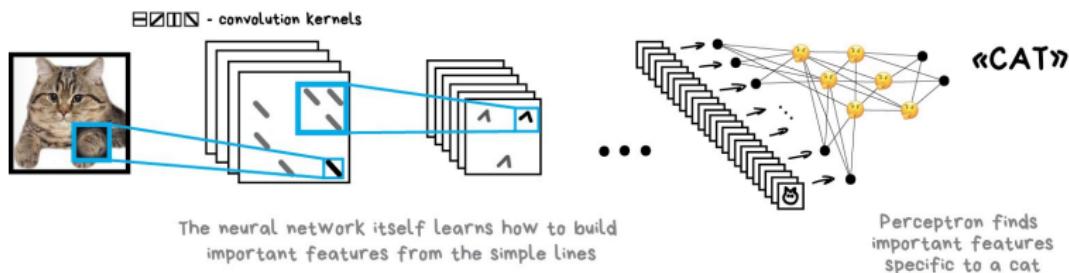
- Neural networks with a large number of layers require large computational power
- Deep Learning: new methods of training that could handle bigger networks, including:
  - ▶ New activation functions, such as ReLU and LReLU
  - ▶ Specialized Layers, such as convolution layer and pooling layer
- ‘Hand-Crafting’ no longer required



Zubarev, V. (2019). Machine Learning for Everyone. ([https://vas3k.com/blog/machine\\_learning/](https://vas3k.com/blog/machine_learning/))

# Convolutional Neural Network

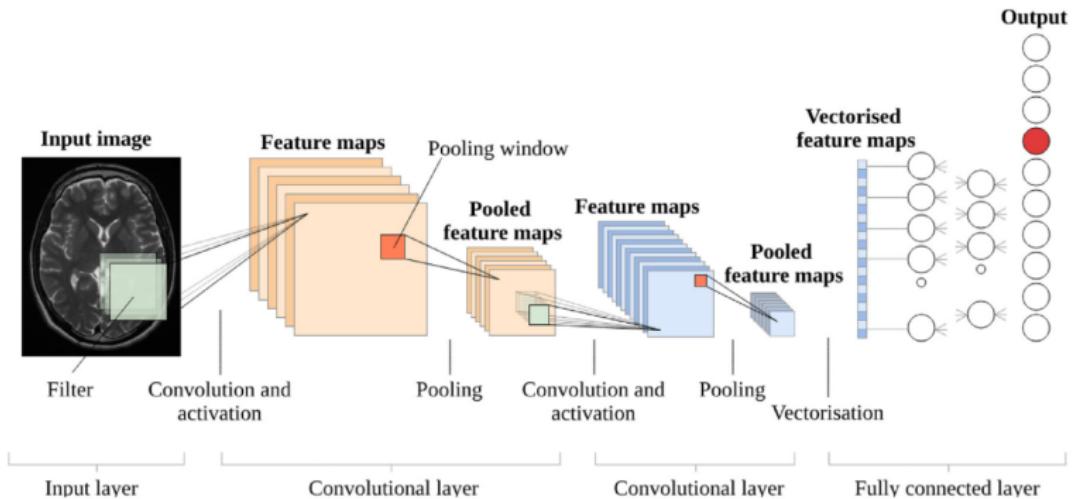
- Breaks input down to simpler units or kernels
- Very few connections between layers
- Able to form highly efficient representation of input data, well-suited for image-oriented tasks (MRI, for e.g.)
- Example: divide the whole image into 8x8 pixel blocks and assign to each a type of dominant line, either vertical bar, horizontal bar, or diagonal bars



## CONVOLUTIONAL NEURAL NETWORK (CNN)

Zubarev, V. (2019). Machine Learning for Everyone. ([https://vas3k.com/blog/machine\\_learning/](https://vas3k.com/blog/machine_learning/))

# Convolutional Neural Network in MRI



Lundervold, A. (2018). An Overview of Deep Learning in Medical Imaging Focusing on MRI. Z Med Phys 29 102-127

- Pooling operations take small grid regions as input and produce single number for each region

# Deep Learning Caveats

- **Exploding Gradient:** when loss increases too quickly after beginning.  
Typically because the learning rate has been set too high
- **Vanishing Gradient:** when loss increases too slowly after beginning.  
Typically because the learning rate has been set too low
- **Over-Fitting:** so closely fitted to the training set that it is difficult to generalize and make predictions for new data
- **Validation Set:** independent data; provides an unbiased evaluation of a model fit on the training dataset while tuning the model's hyperparameters. Stop training when the error on the validation dataset increases (typically)
- Be careful not to introduce bias, such as confounding factors (two different scanners for two different groups)
- Perform multiple training runs with different initialization techniques

# Important Architectures in Deep Learning

- Autoencoders
- Generative Adversarial Networks (GANs)
- Google's Inception Network
- Ronnenberger's U-Net
- ResNets
- Variational Networks
- Recurrent Neural Networks

# Advanced Deep Learning Concepts

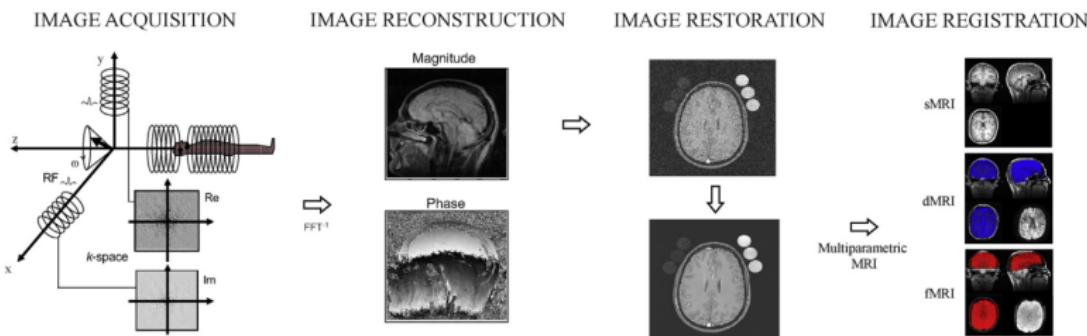
- **Data Augmentation:** common sources of variation are explicitly added to training samples; used to improve number of infrequent observations
- **Precision Learning:** include known operators / a priori knowledge
- **Adversarial Examples:** try to find a small perturbation that tricks the network
- **Deep Reinforcement Learning:** refers to goal-oriented algorithms, which learn how to attain a complex objective (goal) or how to maximize along a particular dimension over many steps; for example, they can maximize the points won in a game over many moves.

# MRI Applications

- Data Acquisition & Image Reconstruction

- ▶ ex: reconstructing good quality cardiac MR images from highly undersampled complex-valued k-space data by learning spatio-temporal dependencies <sup>1</sup>
- ▶ ex: real-time (200 ms per section) image reconstruction, outperforming conventional parallel imaging and compressed sensing reconstruction <sup>2</sup>

- Image Restoration and Registration



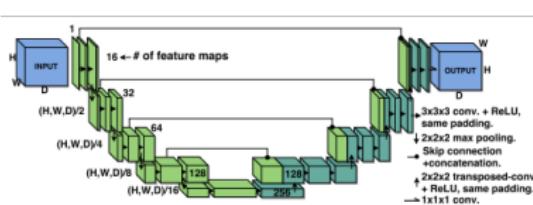
Lundervold, A. (2018). An Overview of Deep Learning in Medical Imaging Focusing on MRI. *Z Med Phys* **29** 102-127

<sup>1</sup> Qin C, Hajnal JV, Rueckert D, Schlemper J, Caballero J, Price AN. Convolutional recurrent neural networks for dynamic MR image reconstruction. *IEEE Trans Med Imaging* 2018.

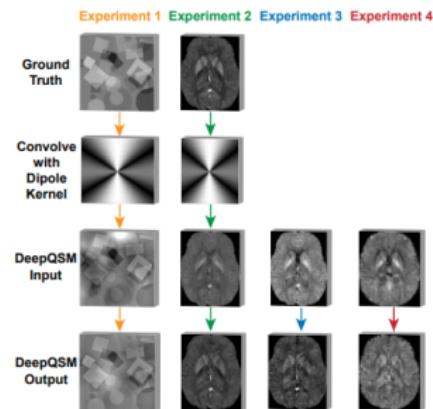
<sup>2</sup> Chen F, Taviani V, Malkiel I, Cheng JY, Tamir JI, Shaikh J, et al. Variable-density single-shot fast Spin-Echo MRI with deep learning reconstruction by using variational networks. *Radiology* 2018;180445.

# Applications

- Super-resolution
  - ▶ 7T images from 3T scanner <sup>3</sup>
- Quantitative Parameters
  - ▶ Quantitative Susceptibility Mapping (field-to-source inversion) <sup>4</sup>



**Fig. 2.** The DeepQSM architecture consists of a contracting and expanding part. The contracting part is made up of a series of convolutions with a ReLU activation function followed by a pooling layer. The expanding part consists of transposed convolutions to undo the spatial reduction caused by the pooling operations and convolutions with ReLUs similar to those of the contracting part. Convolutions used a stride of 1x1x1, transposed convolutions a stride of 2x2x2, pooling a stride of 2x2x2. The input given to the image must have spatial dimensions that yield a positive integer when divided by 16. DeepQSM will output a volume with identical dimensions to the input.



Rasmussen, KGB (2018). DeepQSM-using deep learning to solve the dipole inversion for MRI susceptibility mapping. Biorxiv

## • ▶ MR Fingerprinting

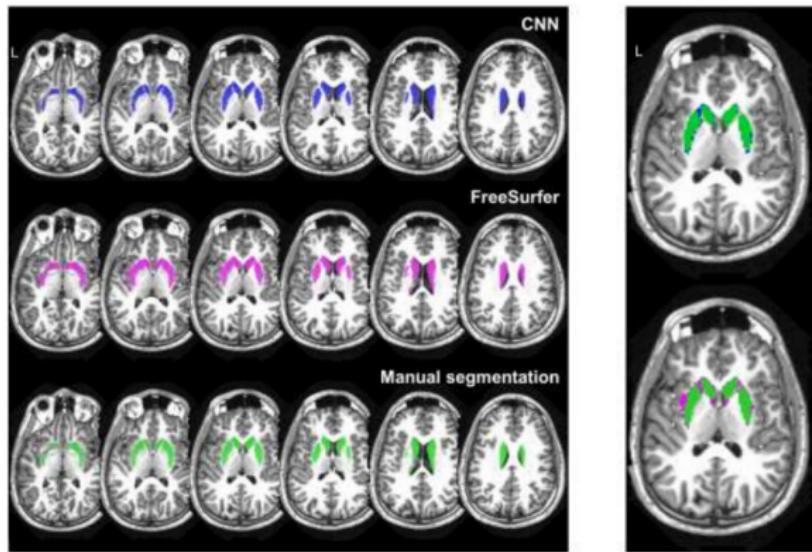
<sup>3</sup>Bahrami K, Shi F, Rekik I, Gao Y, Shen D. 7T-guided super-resolution of 3T MRI. Med Phys 2017;44:1661–77.

<sup>4</sup>Rasmussen KGB, Kristensen MJ, Blendal RG, Ostergaard LR, Plocharski M, O'Brien K, et al. DeepQSM-using deep learning to solve the dipole inversion for MRI susceptibility mapping. Biorxiv 2018:278036.

# Applications

- Image Segmentation

- ▶ has become the biggest target for deep learning approaches in medical imaging



Choi H, Jin KH. (2016) Fast and robust segmentation of the striatum. J Neurosci Methods; 274:146–53.

- ▶ Image Detection and Recognition
- ▶ Computer-Aided Diagnosis
- ▶ Physical Simulation

# Discussion

## Challenges and Limitations

- DL is extremely data hungry: training set, validation set, test set

A short list of medical imaging data sets and repositories.

Name	Summary	Link
OpenNeuro	An open platform for sharing neuroimaging data under the public domain license. Contains brain images from 168 studies (4,718 participants) with various imaging modalities and acquisition protocols.	<a href="https://openneuro.org">https://openneuro.org</a> <sup>a</sup>
UK Biobank	Health data from half a million participants. Contains MRI images from 15,000 participants, aiming to reach 100,000.	<a href="http://www.ukbiobank.ac.uk/">http://www.ukbiobank.ac.uk/</a>
TCIA	The cancer imaging archive hosts a large archive of medical images of cancer accessible for public download. Currently contains images from 14,355 patients across 77 collections.	<a href="http://www.cancerimagingarchive.net">http://www.cancerimagingarchive.net</a>
ABIDE	The autism brain imaging data exchange. Contains 1114 datasets from 521 individuals with Autism Spectrum Disorder and 593 controls.	<a href="http://fcon_1000.projects.nitrc.org/indi/abide">http://fcon_1000.projects.nitrc.org/indi/abide</a>
ADNI	The Alzheimer's disease neuroimaging initiative. Contains image data from almost 2000 participants (controls, early MCI, MCI, late MCI, AD)	<a href="http://adni.loni.usc.edu/">http://adni.loni.usc.edu/</a>

<sup>a</sup> Data can be downloaded from the AWS S3 Bucket <https://registry.opendata.aws/openneuro>.

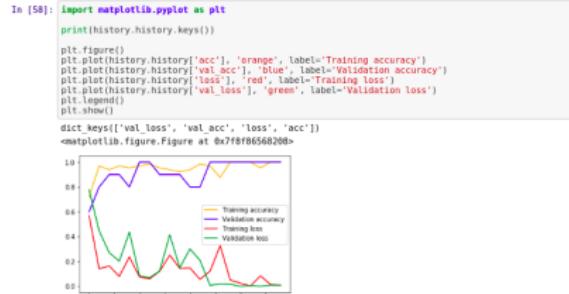
Lundervold, A. (2018). An Overview of Deep Learning in Medical Imaging Focusing on MRI. Z Med Phys 29 102-127

- Memory and compute consumption when using CNNs with higher-dimensional image data
- “Black Box”: how can you trust predictions based on features you cannot understand? One solution: compute uncertainty using *Bayesian Deep Learning*

# Discussion

## How to get started?

- Select a problem you find interesting based on openly available data, a method described in a preprint (<http://arxiv.org>), and an implementation uploaded to GitHub (<https://github.com>)
- Jupyter Notebook Tutorials ex:  
[https://github.com/kbreininger/tutorial-dlframework/blob/master/tutorial\\_dl.ipynb](https://github.com/kbreininger/tutorial-dlframework/blob/master/tutorial_dl.ipynb)
- BCCHRI workshop?



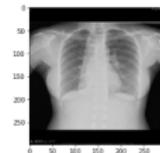
```
In [55]: import numpy as np
from keras.preprocessing import image

img_path1 = '/home/username/data/Open_I_abd_vs_CXRs/TRAIN/chest1.png' #change to location of chest x-ray
img_path2 = '/home/username/data/Open_I_abd_vs_CXRs/TRAIN/abd2.png' #change to location of abd x-ray
img = image.load_img(img_path1, target_size=(img_width, img_height))
img2 = image.load_img(img_path2, target_size=(img_width, img_height))
plt.imshow(img)
plt.show()

img = image.img_to_array(img)
x = np.expand_dims(img, axis=0) * 1./255
score = model.predict(x)
print('Predicted:', score, 'Chest X-ray' if score < 0.5 else 'Abd X-ray')

plt.imshow(img2)
plt.show()

img = image.img_to_array(img2)
x = np.expand_dims(img, axis=0) * 1./255
score2 = model.predict(x)
print('Predicted:', score2, 'Chest X-ray' if score2 < 0.5 else 'Abd X-ray')
```



[https://github.com/paras42>Hello\\_World\\_Deep\\_Learning/blob/master/HelloWorldDeepLearning.ipynb](https://github.com/paras42>Hello_World_Deep_Learning/blob/master/HelloWorldDeepLearning.ipynb)