# An overview of deep learning in medical imaging focusing on MRI

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# Machine learning in image

- objects in an image are segmented by use of a segmentation technique (thresholding, edge-based segmentation, and an active contour model)
- features (contrast, circularity, and size) are extracted from the segmentation part by use of a feature extractor
- the extracted features as input of an ML model(inear or SVM), model is trained with sets of input features and known class labels. The prediction is performed for determination(cancer,or non-cancer)

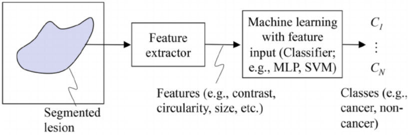
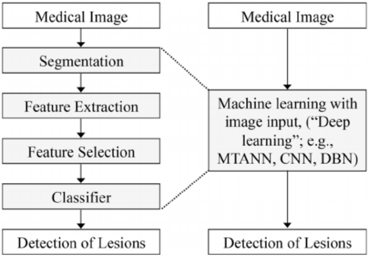



Fig1: A Standard Machine Learning process

# Deep Learning

Actually what we use in Deep Learning is something called ANN, but computers learn useful representations and features automatically.



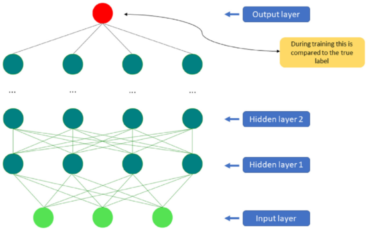




Fig2: A simple DNN Model

# CNN + Deep learning

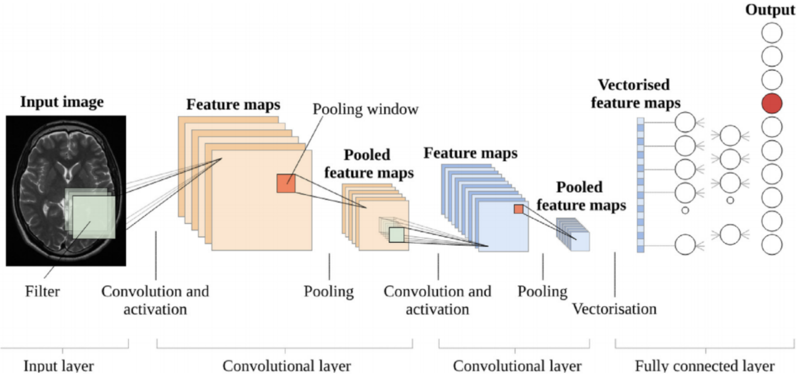



Fig3. A typical CNN, courtesy of author

# Convolution example shown in 2D using 3*3 filter

input image:

| | | | | |
|---|---|---|---|---|
| 1 | 1 | 1 | 0 | 0 |
| 0 | 1 | 1 | 1 | 0 |
| 0 | 0 | 1 | 1 | 1 |
| 0 | 0 | 1 | 1 | 0 |
| 0 | 1 | 1 | 0 | 0 |

filter/kernel:

| | | |
|---|---|---|
| 1 | 0 | 1 |
| 0 | 1 | 0 |
| 1 | 0 | 1 |

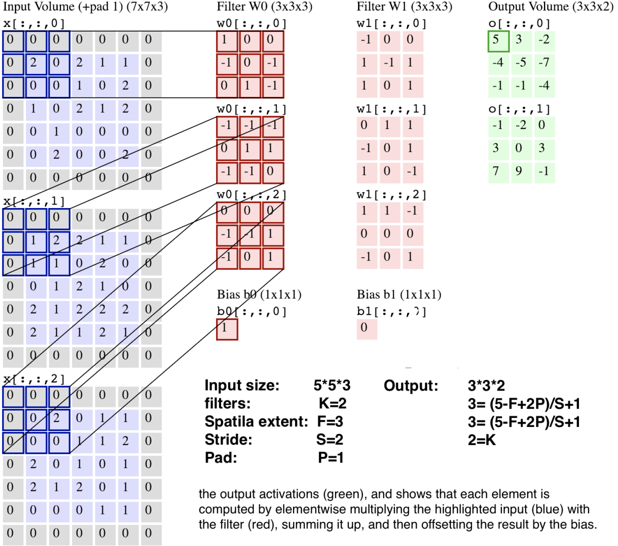
Operation:

| | | | | |
|---|---|---|---|---|
| 1 | 1x1 | 1x0 | 0x1 | 0 |
| 0 | 1x0 | 1x1 | 1x0 | 0 |
| 0 | 0x1 | 1x0 | 1x1 | 1 |
| 0 | 0 | 1 | 1 | 0 |
| 0 | 1 | 1 | 0 | 0 |

feature map:

| | | |
|---|---|---|
| 4 | 3 | 4 |
| 2 | 4 | 3 |
| 2 | 3 | 4 |

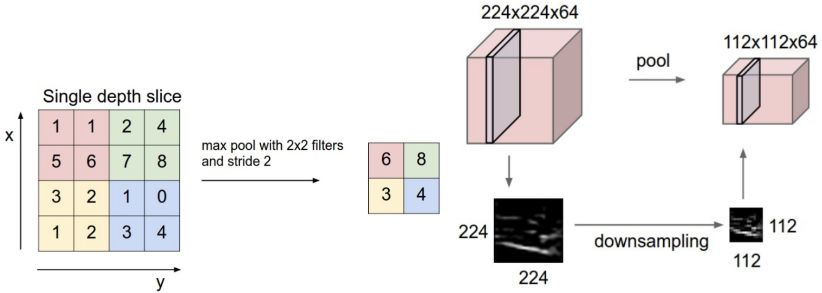
# Convolution example shown in 3D using 3*3*3 filters




| | | | |
|---|---|---|---|
| **Input size:** | **5*5*3** | **Output:** | **3*3*2** |
| **filters:** | **K=2** | | **3= (5-F+2P)/S+1** |
| **Spatila extent:** | **F=3** | | **3= (5-F+2P)/S+1** |
| **Stride:** | **S=2** | | **2=K** |
| **Pad:** | **P=1** | | |

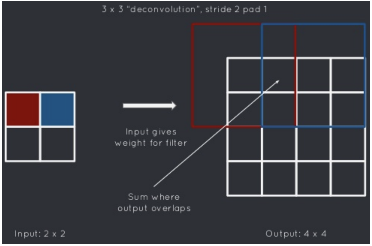
the output activations (green), and shows that each element is computed by elementwise multiplying the highlighted input (blue) with the filter (red), summing it up, and then offsetting the result by the bias.

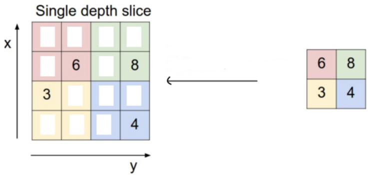
# Max-Pooling example shown in 2D/3D using filters size 2



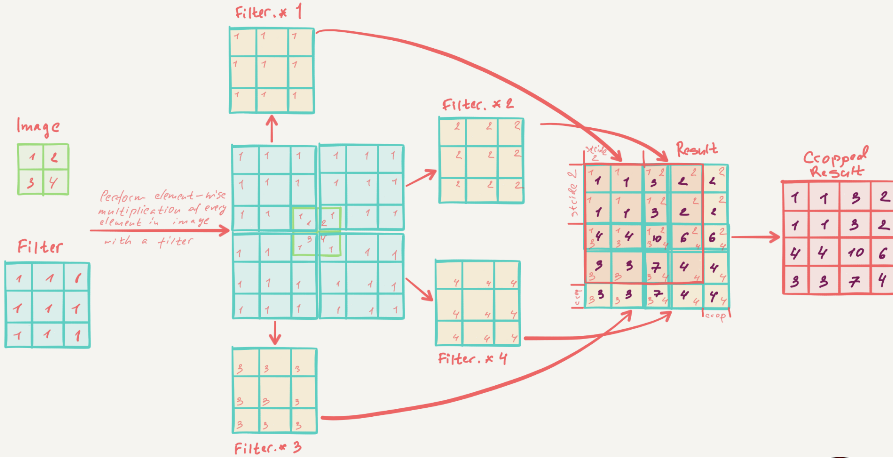
# Deconvolution example

- Reversed Max-pooling for upsampling.
- Directly using a convolution can be termed as transposed convolution. Switch variables: recording the locations of maxima



# Deconvolution example



# Deep Learning in MRI

## Some CNN architectures

- AlexNet
  2012, winning 2012 ILSVRC competition
- VGG
  2014, using small filter and training up to 19 layers
- GoogLeNet
  2014, contains multiple inception modules,won the 2014 ILSVRC competition.
- GANs
  2014, a generative adversarial network consists of two neural networks pitted against each other
- U-net
  2015, for segmentation in 2D, skip connections that concatenates features from the downsampling to the upsampling paths.
- ResNet
  2016, skip connections make it simply copy the activations from layer to layer, A 152 layer deep, won 2015 ILSVRC competition
- DenseNet
  2016, Builds on ResNet, but concatenated activations together,well-suited for smaller data sets
- V-net
  2016, 3D version of U-net with convolutions and skip connection as in ResNet

# AlexNet(ImageNet): Classical Deep CNN

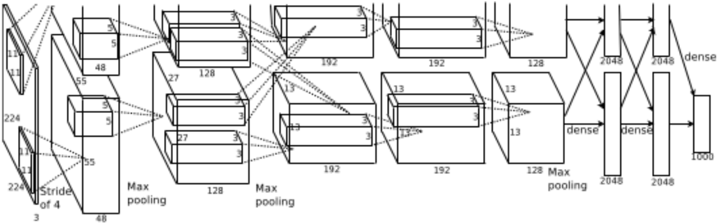
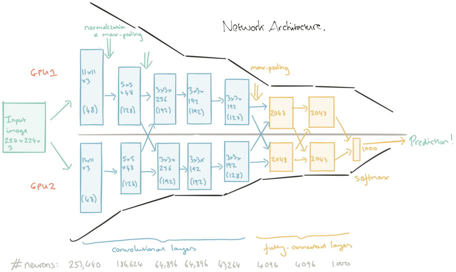



Fig4: AlexNet Architecture

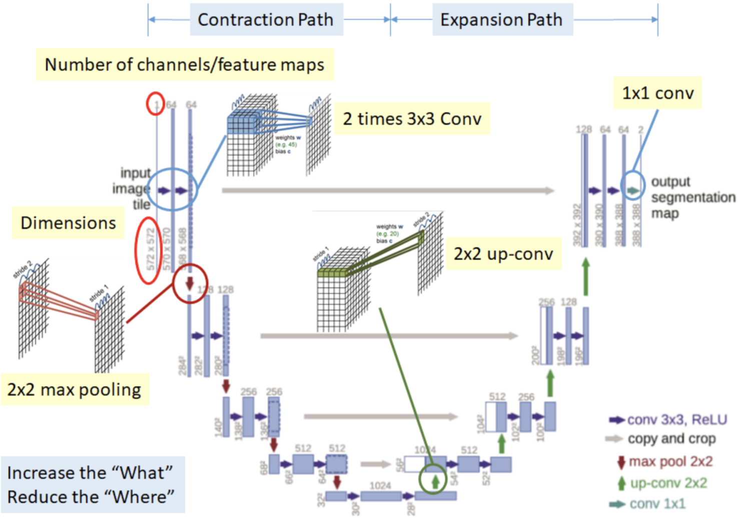
- Network training is split across 2 GPUs.
- 8 learned layers = 5 Conv +3 FC
- Activation function: ReLU($f(x) = max(0, x)$), more fast than Sigmoid.

# AlexNet(ImageNet): Classical Deep CNN



- Since Since the architecture has 60 million parameters, overfitting was a major problem..
- Approch 1: Data augmentation. Enlarging the datset without affectting label.
- Approch 2: Dropout. tackle overfitting was the dropout technique, such as randomly removing units from the hidden layer

# UNet: Famous Fully Convolutional Networks



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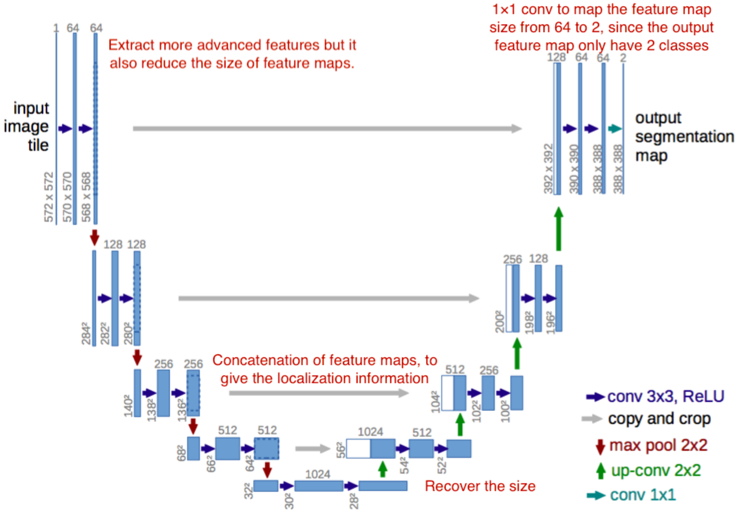

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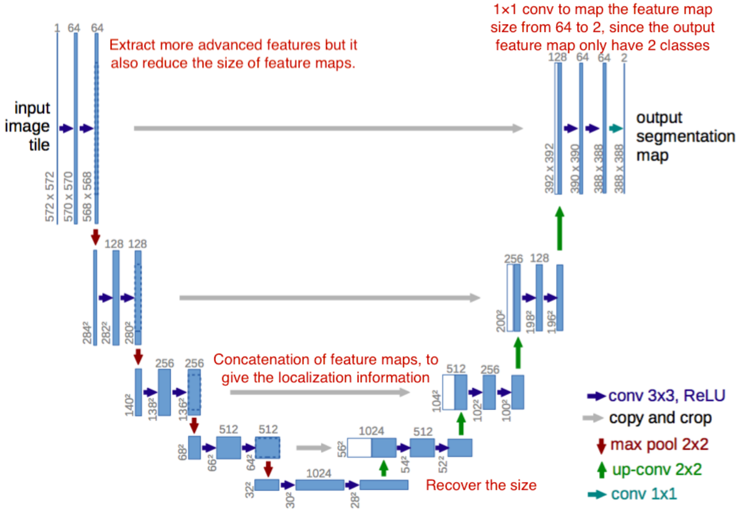

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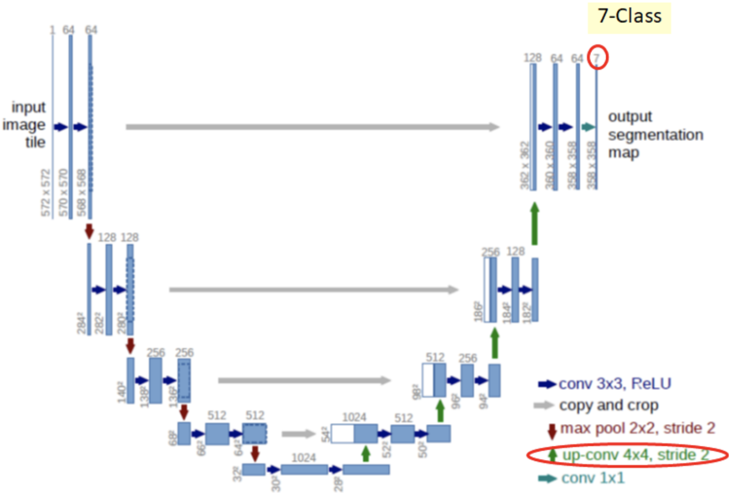


- Deep learning in the MR signal processing has been applied at each step of entire workflow, from image acquisition (in complex-valued k-space) and image reconstruction,to image restoration (e.g. denoising) and image registration.

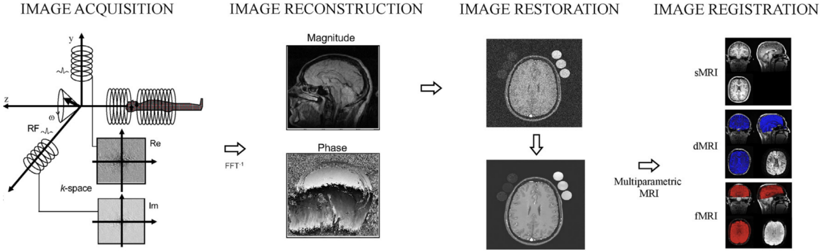



Fig: Deep Learning in MRI

# Deep ADMM-Net for Fast MRI: Reconstruction pioneer

For reconstructing good quality cardiac MR images with better accuracy and speed.

- Deep ADMM-Net:under-sampled k-space data, propose a novel deep architecture, dubbed ADMM-Net, inspired by the ADMM iterative procedures for optimizing a general CS-MRI model.(pioneered by Yang et al.at NIPS 2016 and Wang et al.)

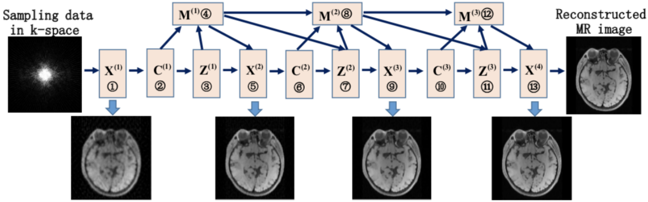



Fig5: Deep ADMM

# Deep ADMM-Net for Fast MRI

Illustration of four types of graph nodes (i.e., layers in network) and their data flows in stage n. The solid arrow indicates the data flow in forward pass and dashed arrow indicates the backward pass when computing gradients in backpropagation.

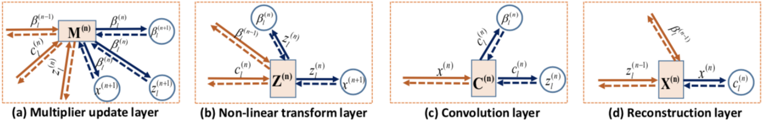



Fig6: 4 graph nodes of Deep ADMM

# Deep cascade of concatenated CNN: using data augmentation

- Dynamic MRI reconstruction, making use of data augmentation, both rigid and elastic deformations, to increase the variation of the examples seen by the network and reduce overfitting.

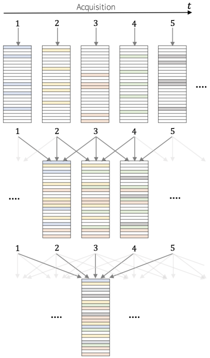



Fig7

# Image restoration: denoising

- Methods in the past: Bayesian Markov random field models, higher-order singular value decomposition,independent component analysis.
- Recently deep learning approches: Data set augmentaion: generated images by GANs
- Denoising Autoencoder Network. This network consists of a convolutional neural network of increasing filter size, followed by a deconvolutional neural network of decreasing filter size. It takes a noisy image as the input and returns the denoised image

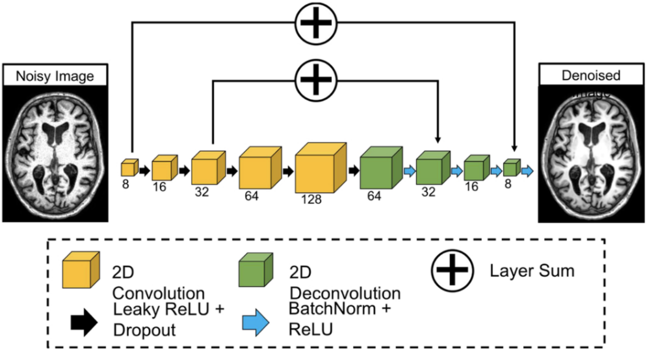



Fig9: Denoising Autoencoder

# Image restoration: detecion

- Deep learning is applied to MR artifact detection: poor quality spectra in MRSI; detection and removal of ghosting artifacts in MR spectroscopy; and automated reference-free detection of patient motion artifacts in MRI
- Motion artifact detection(3D Convs):
  Per-patch basis of input size $H * W * D$ voxels.
  The respective conv kernel sizes $M * L * B$

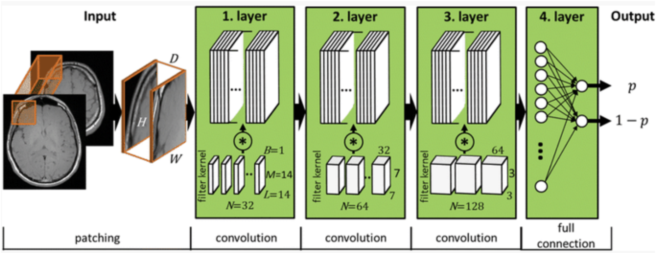
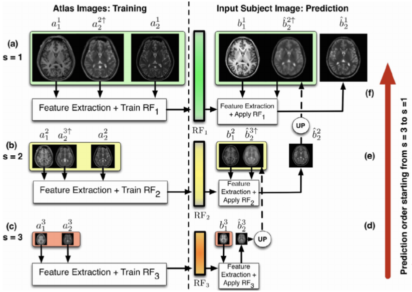



Fig10: automated detection in MRI

# Image synthesis

- Derived new parametric images or new tissue contrast from a collection of MRI
- A supervised random forest image synthesis approach that learns a nonlinear regression to predict.
- The left portion shows the training for all scales, 3 RF with feature maps. The feature extraction step extracts different features at each level The trained RF at each level are then applied to input subject image, starting from s3 to s1.



# Image synthesis

- Image synthesis using deep learning techniques, synthesis MR to CT using unpaired data, especially generative adversarial networks
- Synthetic data generation can increase the training data set with desired characteristics (e.g., tumor size, location, etc.) without the need of labor-intensive manual annotation.
- Training GAN for tumor segmentation with (a) real and (b) synthetic image-label pairs.

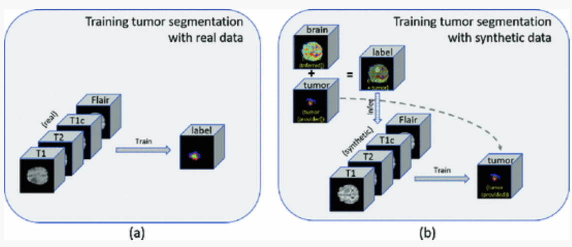



Fig12: generate synthetic abnormal MRI images with brain tumors by training a GAN, (a) real and (b) synthetic image-label pairs.

# Image registration

- Deep learning approch: deformable image; model-to-image; unsupervised learning model for deformable, pair-wise image ...

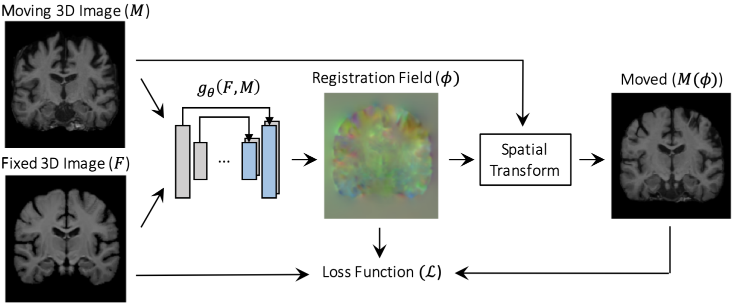
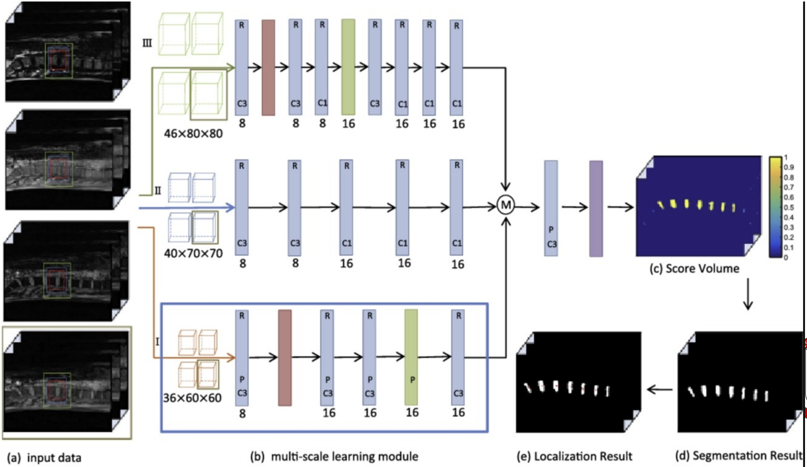



Fig13: Taking two 3D volumes images as input, to be registered by CNN, loss function compares spatial transform(M) and F and enforces smoothness of Moved(M).

# Image segmentation

- From 1985 using statistical pattern recognition to segment, today deep learning in segmentation:



# Diagnosis and prediction Apps

Some deep learning applications for Brain, Kidney, Prostate, Spine

- Functional connectomes:
  Transfer learning approach to enhance deep neural network classification of brain functional connectomes
- Cyst segmentation:An
  artificial multi-observer deep neural network for fully automated segmentation of polycystic kidneys
- Cancer (PCa):
  Deep CNN and a non-deep learning using feature detection were used to distinguish pathologically confirmed PCa patients from prostate benign conditions patients with prostatitis or prostate MR images
- Intervertebral disc localization:
  3D multi-scale fully connected CNNs with random modality voxel dropout learning for intervertebral disc localization and segmentation from multi-modality MR images

# content-based image retrieval-CBIR

- To help radiologists in the decision-making process, provide medical cases similar to a given image.

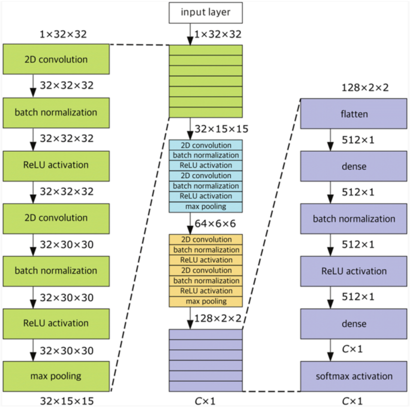



Fig15: CNN comprised of 27 sequential layers

# Conclusions

- Deep learning in the MR signal processing has been applied at each step of entire workflow, from image acquisition (in complex-valued k-space) and image reconstruction,to image restoration (e.g. denoising) and image registration.

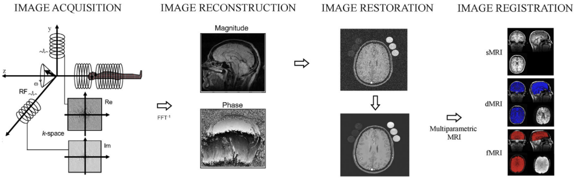



Fig16: Deep Learning in MRI

- It is clear that deep neural networks are very useful when one is tasked with producing accurate decisions based on complicated data sets.
But they come with some significant challenges and limitations

# Challenges and limitations

1. Some models are get good experiemntal result and parameters value, but lack of mathematical and theoretical underpinnings, and the resulting difficulty in deciding exactly what it is that makes one model better than another
2. Another One quickly meet challenges associated to memory and compute consumption when using CNNs with higher-dimensional image data, such 3D Convlotional NN
3. How to trust predictions based on feature you can understand? As deep neural networks relies on complicated interconnected hierarchical representations of the training data to produce its predictions, interpreting these predictions becomes very difficult.
4. The big problem : data access,privacy issues, data protection, heavy work for artificial labeled, and more.

# future perspectives

Even though there are many challenges, the methods produce results that are too valuable to discard. As machine learning researchers and practitioners gain more experience, it will become easier to classify problems.

1. transfer learning, augmenting training dataset, blockchain as data share platform... for data access,privacy issues
2. More cooperation and self-study for mathematical and theoretical underpinnings.

Beyond the researchers of machine learning, we believe that the attention in the medical community can also be uesful and make high-impact in our research.

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