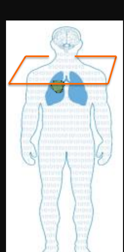
Deep learning with Medical Images

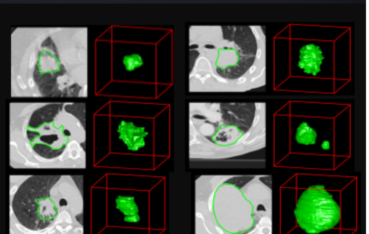
Chintan Parmar, PhD
Computational Imaging and Bioinformatics lab
DFCI-BWH-HMS

Outline

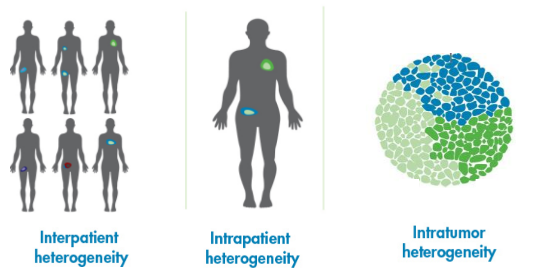
- Part 1: Discussion on deep learning applications with medical images (Radiomics)
- Part 2: Practical exercise

Tumors are different

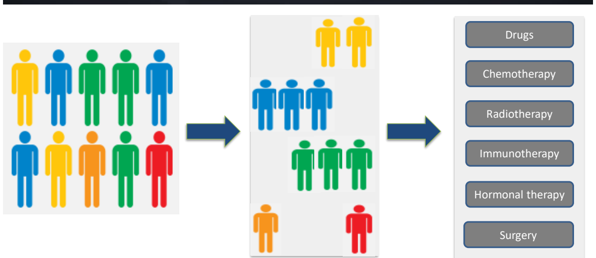




Heterogeneity in cancer



Precision Oncology



Use patient specific information

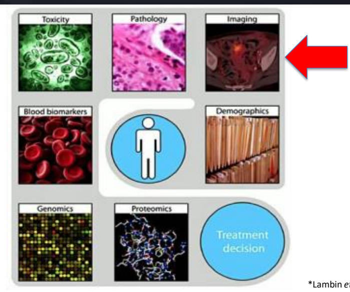
Patient subgroups

Treatment options

Different sources of patient specific information

*Lambin *et al.* Eur J Cancer 2012

Different sources of patient specific information



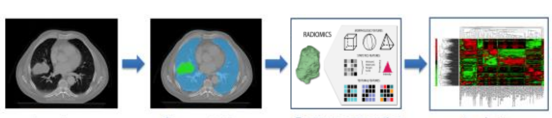
*Lambin *et al.* Eur J Cancer 2012

Medical imaging

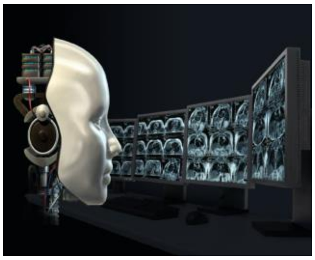
- Performed non-invasively
- Provides a complete picture of 3D phenotype
- Routinely performed in clinical practice
- Multiple times before, during and after treatment

Radiomics

Radiomics aims to provide a comprehensive quantification of the tumor phenotypic characteristics, including intra/inter tumor heterogeneity, in terms of medical imaging features.



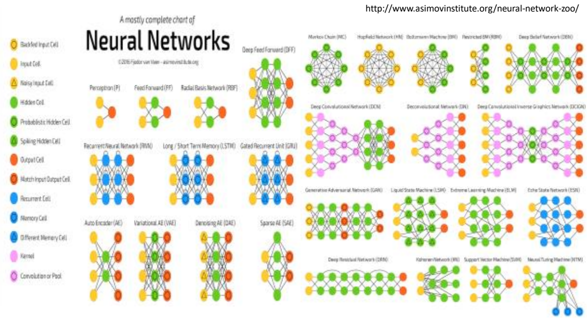
Machine learning for radiomics



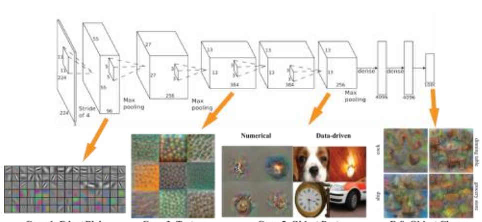
https://mse238blog.stanford.edu/2017/08/imunizr/ai-takes-on-radiology/

- Significant progress.
- Deep learning.
- Significant transformation of different fields like image recognition.

http://www.asimovinstitute.org/neural-network-zoo/



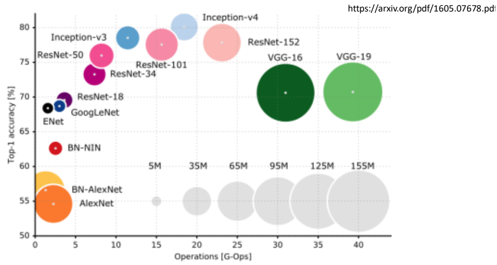
Deep Convolutional Neural network



http://vision03.csail.mit.edu/cnn_art/index.html

Popular architectures for image classification

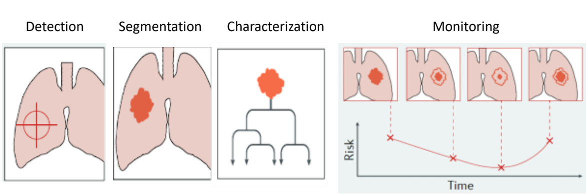
https://arxiv.org/pdf/1605.07678.pd



Deep learning for medical images

- Medical images are different from natural images.
- Volumetric (3D).
- Different acquisition techniques, data structures and storage.
- Appropriate design choices are required.
  - Application
  - Data

Medical image based DL application in Radiology



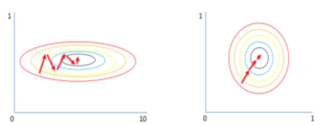
Design choices

- Normalization
- Input dimensions/ # of channels
- Transfer learning
- Architectures
- Regularization (Bias/variance)
- Train-Tune-Test strategies
- Performance metric

Normalization

https://www.jeremyjordan.me/batch-normalization/

- Input Normalization?
  - Scaling
  - Mean subtraction
  - Standardization (Z-score)



Gradient of larger parameter dominates the update

Both parameters can be updated in equal proportions

- Additional normalization steps for medical images
  - Isometric voxels?
  - MRI normalization
- Batch and/or layer normalization?

Input dimensions (# of channels)

- 2D, Single Channel
- 2D, Three Channels
  - Same 2D slice as three different channels
  - Three consecutive slices as three channels
  - Sagittal, Coronal and Axial slices as three channels
- 3D

Design choices

- Transfer learning
- Architectures
  - U-net, FCN etc. (detection/segmentation)
  - VGG, Resnet, Googlenet etc. (characterization)
  - Recurrent net (monitoring)
- Regularization (Bias/variance)
  - L1
  - L2
  - Dropouts
  - Batch/layer normalization
  - Augmentation

Design choices

- Train-Tune-Test strategies
  - Independent validation (test) data is important
- Performance metric
  - Accuracy, AUC, F-Score, Sensitivity-Specificity, Concordance index, RMS etc. (characterization/monitoring)
  - DICE, Hausdorff distance, Overlap fractions etc (segmentation/detection)

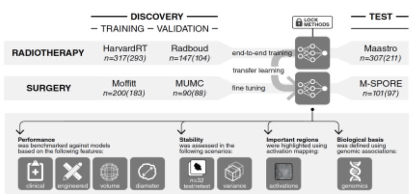
Examples

Example: 1

Characterization

Deep learning for automatic quantification of tumor phenotypes

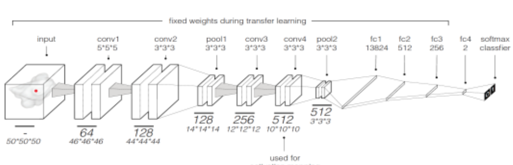
Ahmed Hosny, Chintan Parmar, Thibaud Coroller, Patrick Grossmann, Roman Zeleznik, Avnish Kumar, Johan Bussink, Robert J Gillies, Raymond Mak, Hugo JWL Aerts



Architecture

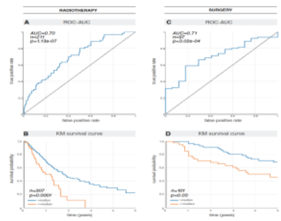
Deep learning for automatic quantification of tumor phenotypes

Ahmed Hosny, Chintan Parmar, Thibaud Coroller, Patrick Grossmann, Roman Zeleznik, Avnish Kumar, Johan Bussink, Robert J Gillies, Raymond Mak, Hugo JWL Aerts

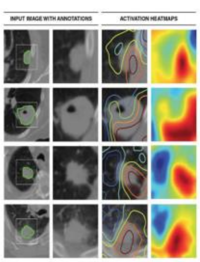


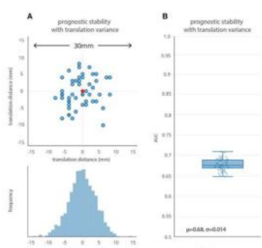
Performance

Deep learning for automatic quantification of tumor phenotypes
Ahmed Hosny, Chintan Parmar, Thibaud Coroller, Patrick Grossmann, Roman Zeleznik, Avnish Kumar, Johan Bussink, Robert J Gillies, Raymond Mak, Hugo JWL Aerts



Deep learning for automatic quantification of tumor phenotypes
Ahmed Hosny, Chintan Parmar, Thibaud Coroller, Patrick Grossmann, Roman Zeleznik, Avnish Kumar, Johan Bussink, Robert J Gillies, Raymond Mak, Hugo JWL Aerts



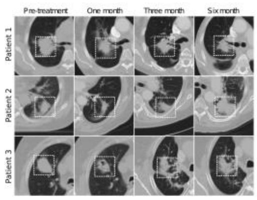


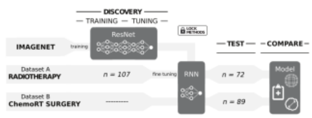
Example: 2

Monitoring

Deep learning based tracking of lung cancer treatment response using longitudinal imaging data

Yiwen Xu,, Ahmed Hosny, Thibaud Coroller, Roman Zeleznik, Chintan Parmar, Idalid Franko, Raymond Mak, Hugo JWL Aerts

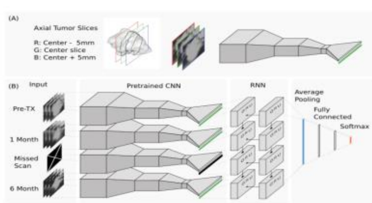




Architecture

Deep learning based tracking of lung cancer treatment response using longitudinal imaging data

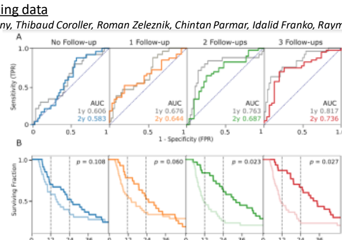
Yiwen Xu,, Ahmed Hosny, Thibaud Coroller, Roman Zeleznik, Chintan Parmar, Idalid Franko, Raymond Mak, Hugo JWL Aerts



Performance

Deep learning based tracking of lung cancer treatment response using longitudinal imaging data

Yiwen Xu,, Ahmed Hosny, Thibaud Coroller, Roman Zeleznik, Chintan Parmar, Idalid Franko, Raymond Mak, Hugo JWL Aerts

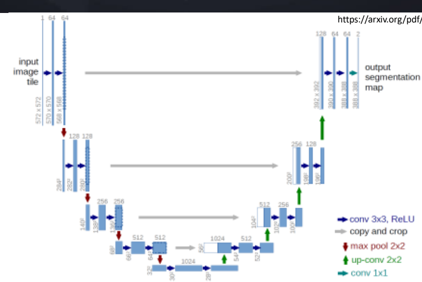


Example: 3

Detection/segmentation

https://arxiv.org/pdf/1505.04597.pdf

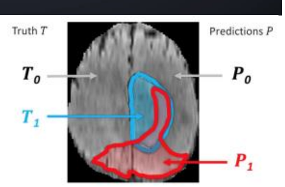
- U-net



Evaluation metric

- Dice Score

$$\mathrm{Dice}(P,T) = \frac{|P_1 \wedge T_1|}{(|P_1| + |T_1|)/2}$$



https://ieeexplore.ieee.org/stamp/stamp.jsp?tp=&arnumber=6975210

Thank you !