Identify imaging biomarkers using Radiomics and Machine Learning from Multiparametric MRI

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Outlines

- The role of DWI in cancer care
- The application of radiomics and machine learning on Multiparametric MRI
  - Detection and Stratification of Prostate Cancer
  - Predicting pathologic response after preoperative chemoradiation therapy for locally advanced rectal cancer

The role of DWI in cancer care

DWI is sensitive to the arrangement, type, geometry, and permeability of cells at the micron scale due to its direct dependence of water diffusion on the tissue microstructural environment.

- Lesion Detection
- Lesion Characterization
  - Distinguish tumor from other entities such as inflammation, hemorrhage etc.
- Tumor Volume and Staging
- Treatment Response Evaluation

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Apparent Diffusion Coefficient

- The monoexponential ADC model is a commonly used model to describe water diffusion behavior.
- However, it lacks biological specificity since the ADC value depends on cell density, size, shape, permeability, subcellular architecture, extracellular matrix, and perfusion effects.
- Many different tissue structures could potentially lead to the same average water molecule displacement and the same DWI signal.
- Still the ADC model performs well for cancer detection and grading in various disease sites.

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Improving on ADC

- Account for diffusion anisotropy, fractional anisotropy
- Non monoexponential DWI signal attenuation, kurtosis adjusted diffusivity, biexponential model
- Compartment models
  - Two compartment model (The IntraVoxel Incoherent Motion)
  - Three compartment model (Vascular, Extracellular, and Restricted Diffusion for Cytometry in Tumours)

Multiparametric MRI + Radiomics + Machine Learning

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Detection and Stratification of Prostate Cancer

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Pca Detection and Aggressiveness

T2 ADC Ktrans

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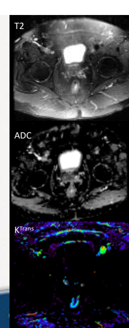
Multiparametric MRI Study

65 y/o AAM w/high risk prostate adenocarcinoma (T1c, GS 9=4+5, PSA 7.2)
There is evidence of bilateral seminal vesicle invasion, which is extensive on the right

	Right	Left
ADC ($\mu m^2/s$)	637.14	1400.43
K^{Trans} (min^{-1})	0.26	0



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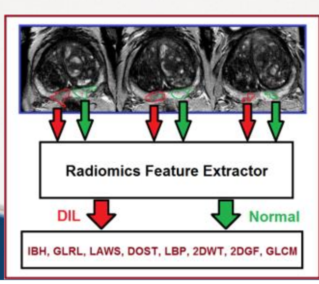
Studies using ADC to predict PCa Aggressiveness

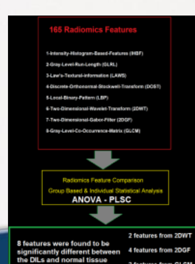
- ADC mean from a single slice
- ADC mean from the entire volume
- 10th percentile of the ADC computed from the entire lesion
- 10th percentile and ADC mean
- Various histogram-based ADC measures

Radiomics Features

- Radiomic data – 1st, 2nd and higher order statistics, extra quantitative features that result in the conversion of images into mineable data and used the data for diagnostic, prognostic, and predictive accuracy.
- First-order statistics describe the distribution of values of individual voxels without concern for spatial relationships.
- Second-order statistical descriptors generally are described as "texture" features; they describe statistical interrelationships between voxels with similar (or dissimilar) contrast values.

Texture Features

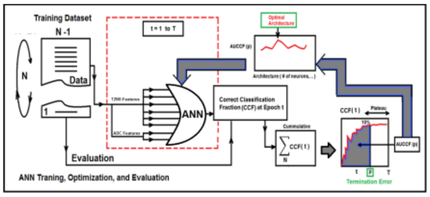




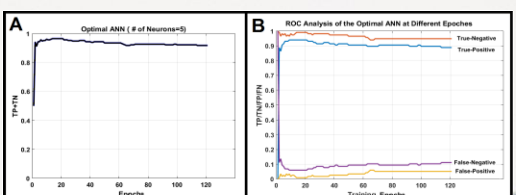
Artificial Neural Network (ANN)

Using the discriminant features set as input, an ANN was trained and optimized for detection of DILs and NTs.

ANN training, optimization and validation:
Leave-one-out method was used for training, optimization, and evaluation



ANN Training and Optimization



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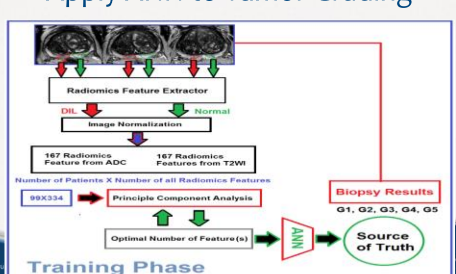
Apply ANN to Tumor Grading



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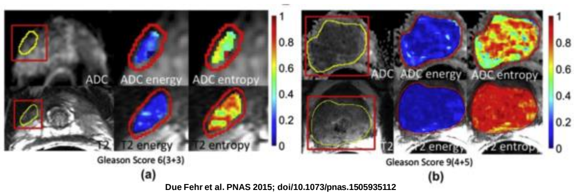
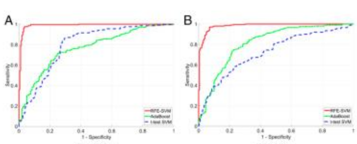
Texture Features in ADC and T2

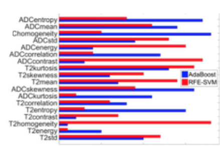
217 men, MR within 6months of prostatectomy,
Validated against whole-mount sections for histopathologic examination



Due Fehr et al. PNAS 2015; doi/10.1073/pnas.1505935112

ROC curves for for GS 3 + 4 vs. GS 4 + 3 occurring in (A) PZ and TZ and (B) PZ only.





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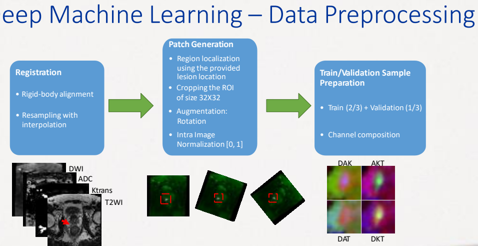
Deep Machine Learning – Data Preprocessing



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Convolutional Neural Network - Feature Visualization

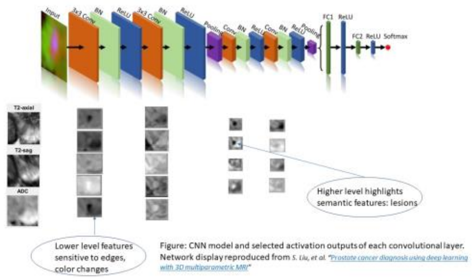
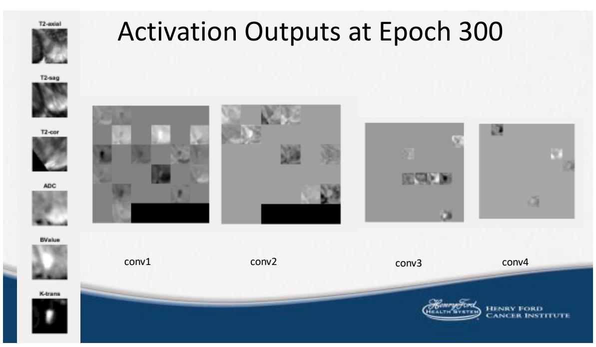
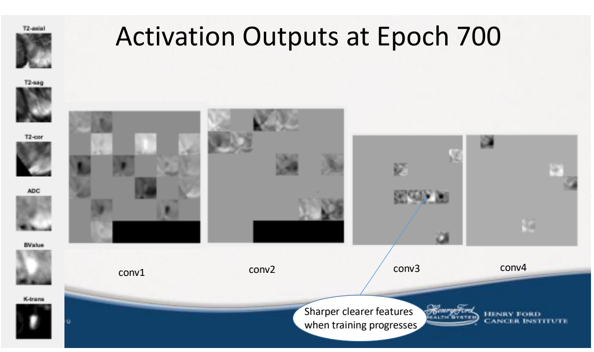


Figure: CNN model and selected activation outputs of each convolutional layer. Network display reproduced from *S. Liu, et al.* "[Prostate cancer diagnosis using deep learning with 3D multiparametric MRI]"

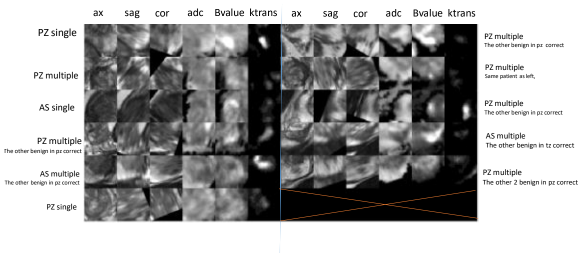
Activation Outputs at Epoch 300



Activation Outputs at Epoch 700



11 Malignant lesions (out of 239) classified as benign



Predicting pathologic response after preoperative chemoradiation therapy (CRT) for locally advanced rectal cancer

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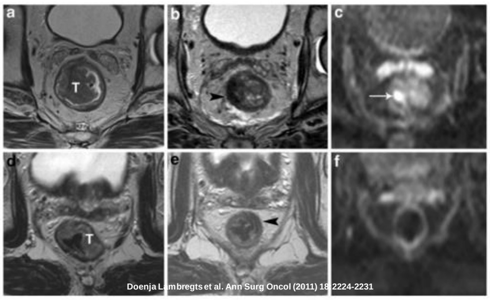
Selection of complete responders after chemoradiation for locally advanced rectal cancer

- Locally advanced rectal cancer (LARC), the standard-of-care treatment is preoperative concurrent chemoradiation treatment (CRT) followed by total mesorectal excision
- After CRT, approximately 15% to 27% of patients show a pathologic complete response
- 5-year follow-up were favorable for the nonsurgical group, with an overall and disease-free survival of 93% and 85%, respectively
- Noninvasive approaches to identify complete responders for an alternative surgical treatment such as sphincter-saving local excision.

Diffusion-Weighted MRI for Selection of Complete Responders

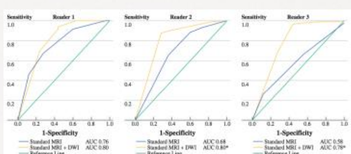


Doenja Lambregts et al. Ann Surg Oncol (2011) 18:2224-2231

Identification of a complete tumor response after CRT using T2 vs. T2+DWI

Residual Tumor vs. Fibrosis

- 120 consecutive patients who were treated for locally advanced rectal cancer
- Sensitivity for identification of a complete response improved by 16–52% for the three readers
- Substantial reduction in the number of equivocal scores (CL) and an improved interobserver agreement



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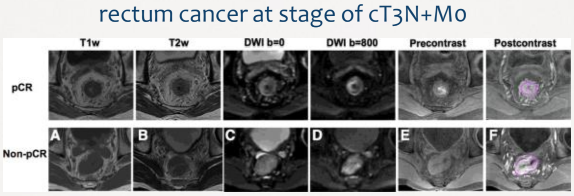
MultiParametric MRI of 2 male patients, with mid-rectum cancer at stage of cT3N+M0



All 48 patients received MR examinations 1 to 2 weeks before the chemoradiation and 1 week before surgery. A total of 103 quantitative imaging features were obtained for each patient.

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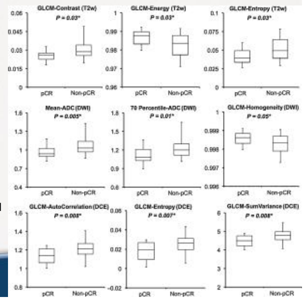
Ke Nie et al. Clin Cancer Res 2016;22:5256-5264

Differences between the pCR versus non-pCR groups

- None of the quantitative measures from anatomical T1, T2 images showed statistically significant differences
- The GR group had lower mean-ADC (0.91 ± 0.11) × 10^{-3} than those showing non-favorable responses (0.97 ± 0.09) × 10^{-3}
- The higher portions of the histogram percentiles (50%–80%) were lower in the pCR groups than in non-pCR
- All the texture measures from DCE-MRI showed statistically significant differences between GR and non-GR group



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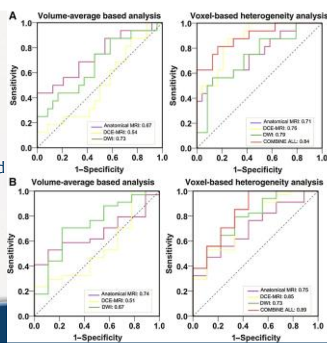
The ROC curves of selected individual parameters and combined feature sets in predicting pCR vs. non-pCR (A) and GR vs. non-GR (B)



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Conclusions

DWI is one of the most effective MR modality for cancer diagnosis and prognosis considering its sensitivity to tissue microstructure. However, diffusion dynamics is quite complicated and depends on many factors including cell density, size, shape, permeability, subcellular architecture, extracellular matrix, and perfusion effect.

The wealth of radiomics extracted from multiparametric MR images should be further explored to help tailoring the treatment into the era of personalized medicine.

Thank you!

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