BAINES IMAGING

ARTIFICIAL INTELLIGENCE IN LUNG CANCER: USING RADIOMICS TO PREDICT TUMOR RECURRENCE

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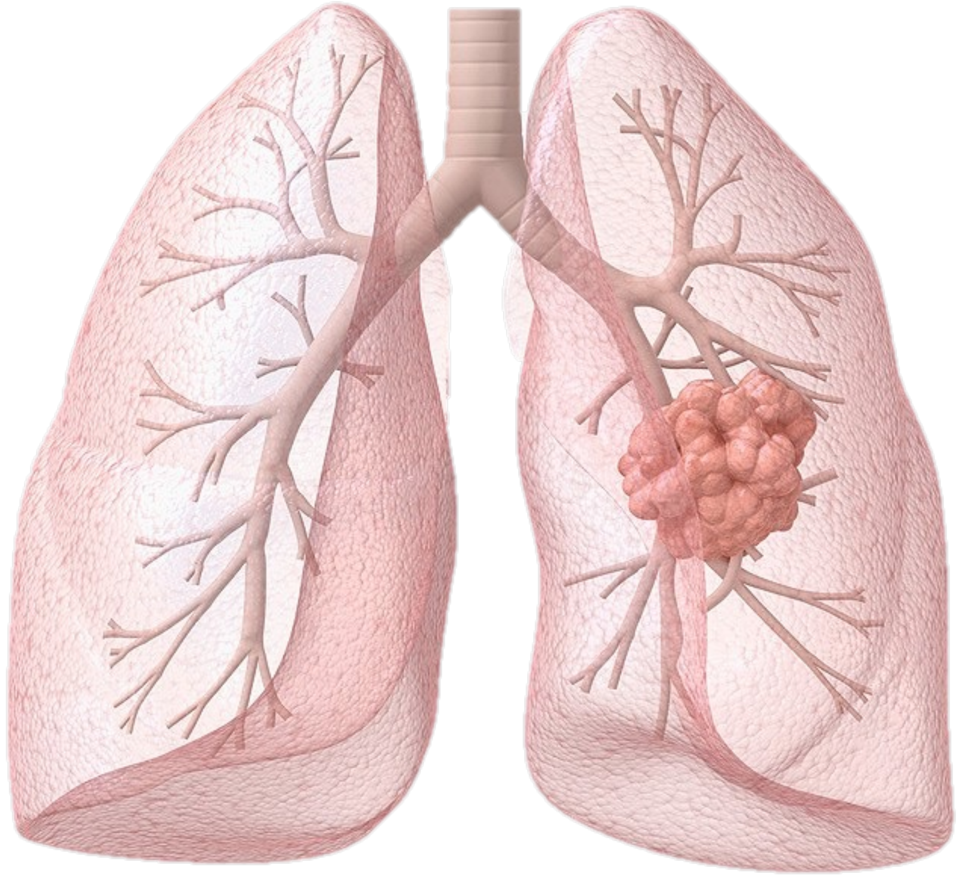
Western

Non-Small Cell Lung Cancer

- Survival rates remain quite poor despite advances in diagnosis and treatment.
- 5-year survival rates:
  - Stage I: 55-75%
  - Stage II: 40-50%
  - Stage III: 5-35%
  - Stage IV: <5%



Lang-Lazdunski, L. et al. Eur Resp Soc. (2013) 382-404.
SEER Stat Fact Sheets: Lung and Bronchus Cancer.

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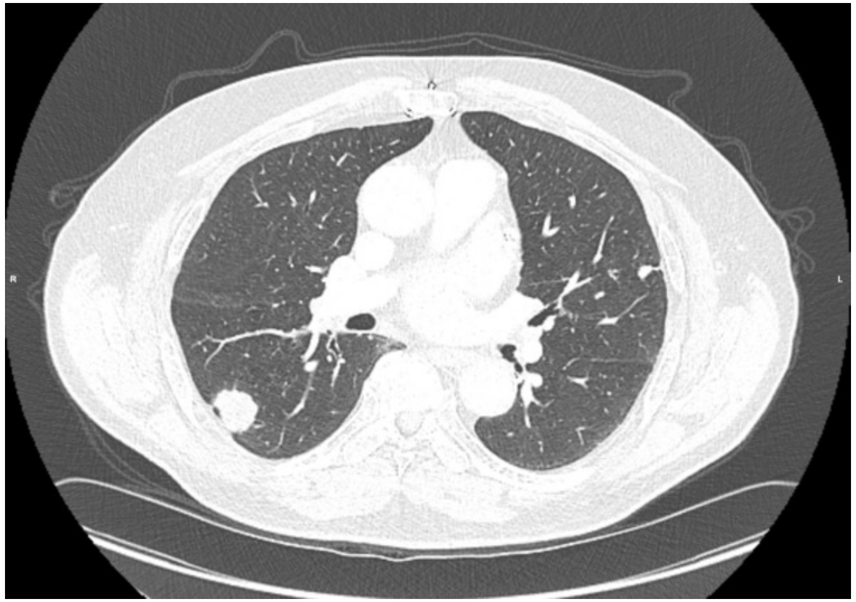
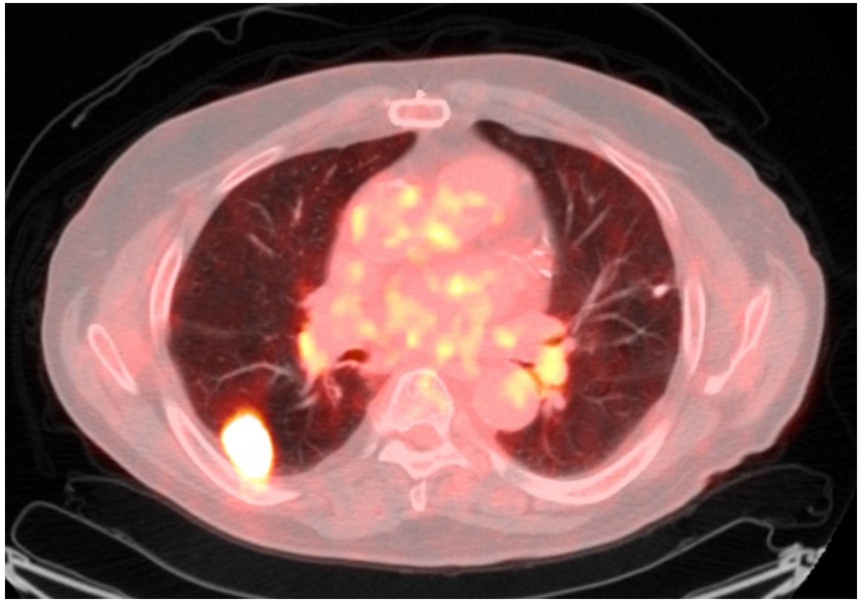
The Role of Imaging

Computed Tomography (CT)



Positron Emission Tomography (PET)



The Role of Imaging

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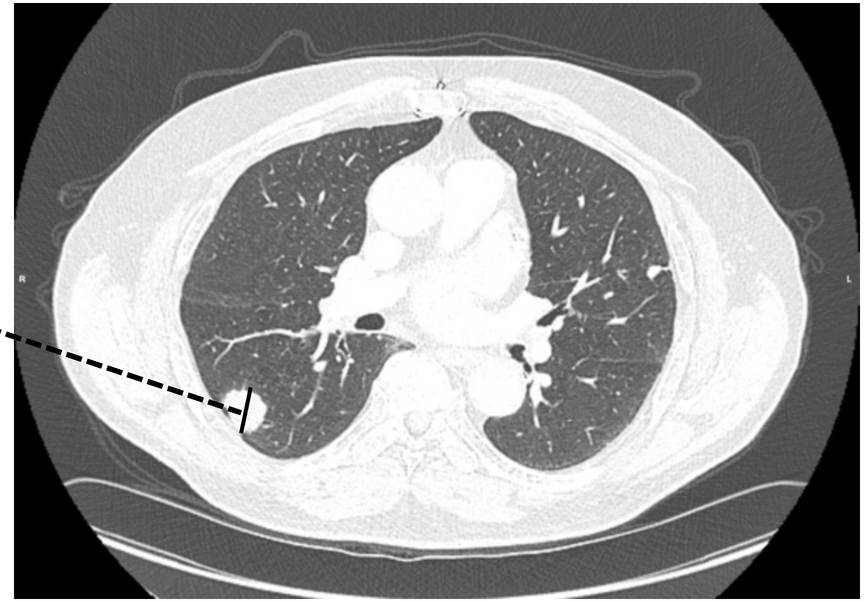
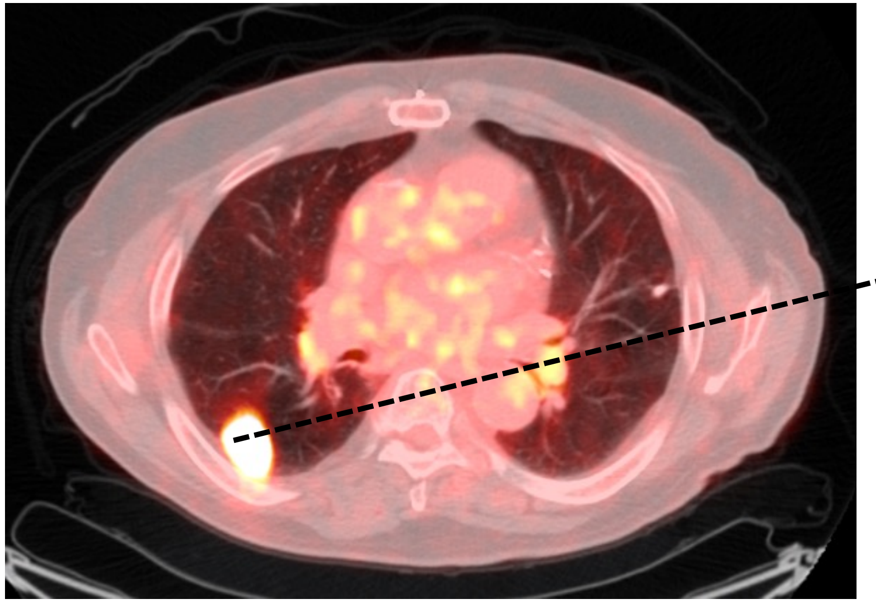


3 cm

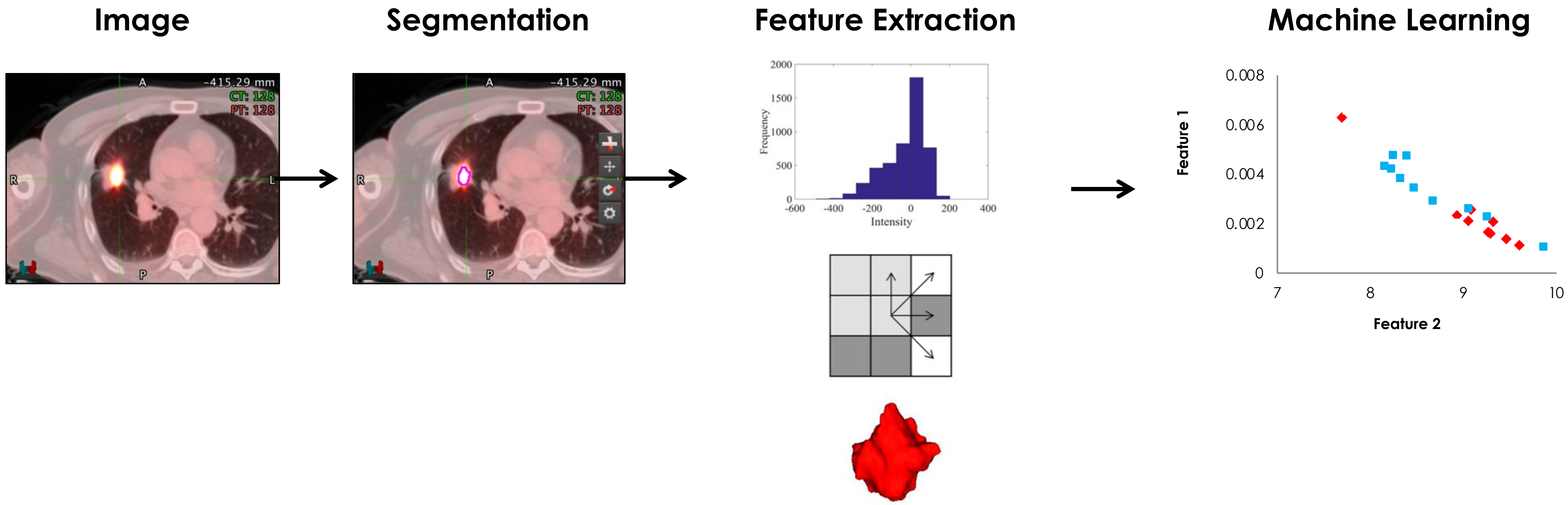
Positron Emission Tomography (PET)



SUVmax = 9

Radiomics

- Radiomics aims to extract more complex quantitative information (e.g., texture) from standard medical images.



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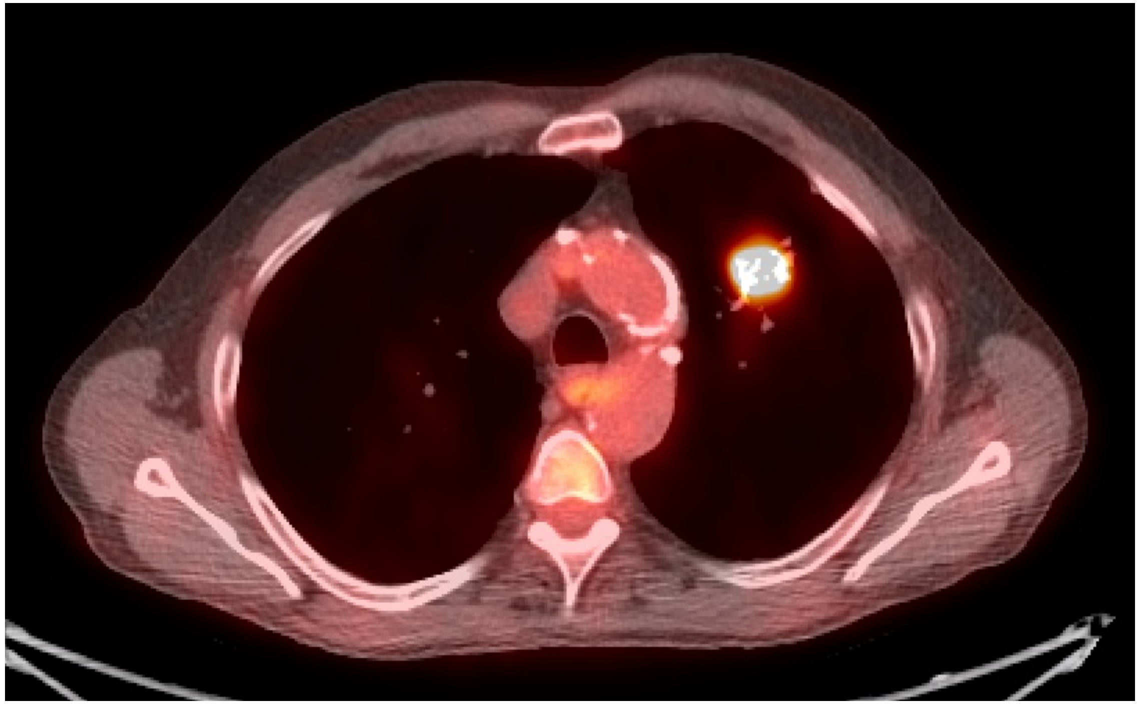
Positron Emission Tomography (PET)

- SUVmax has been shown to predict a higher risk of recurrence or death in NSCLC.



Travis WD, et al. J of Thor Onc. (2011) 6:244-285.
Kadota K, et al. J of Thor Onc. (2015) 10:806-814.
Lee et al., European Radiology (2017) 27:1912–1921.

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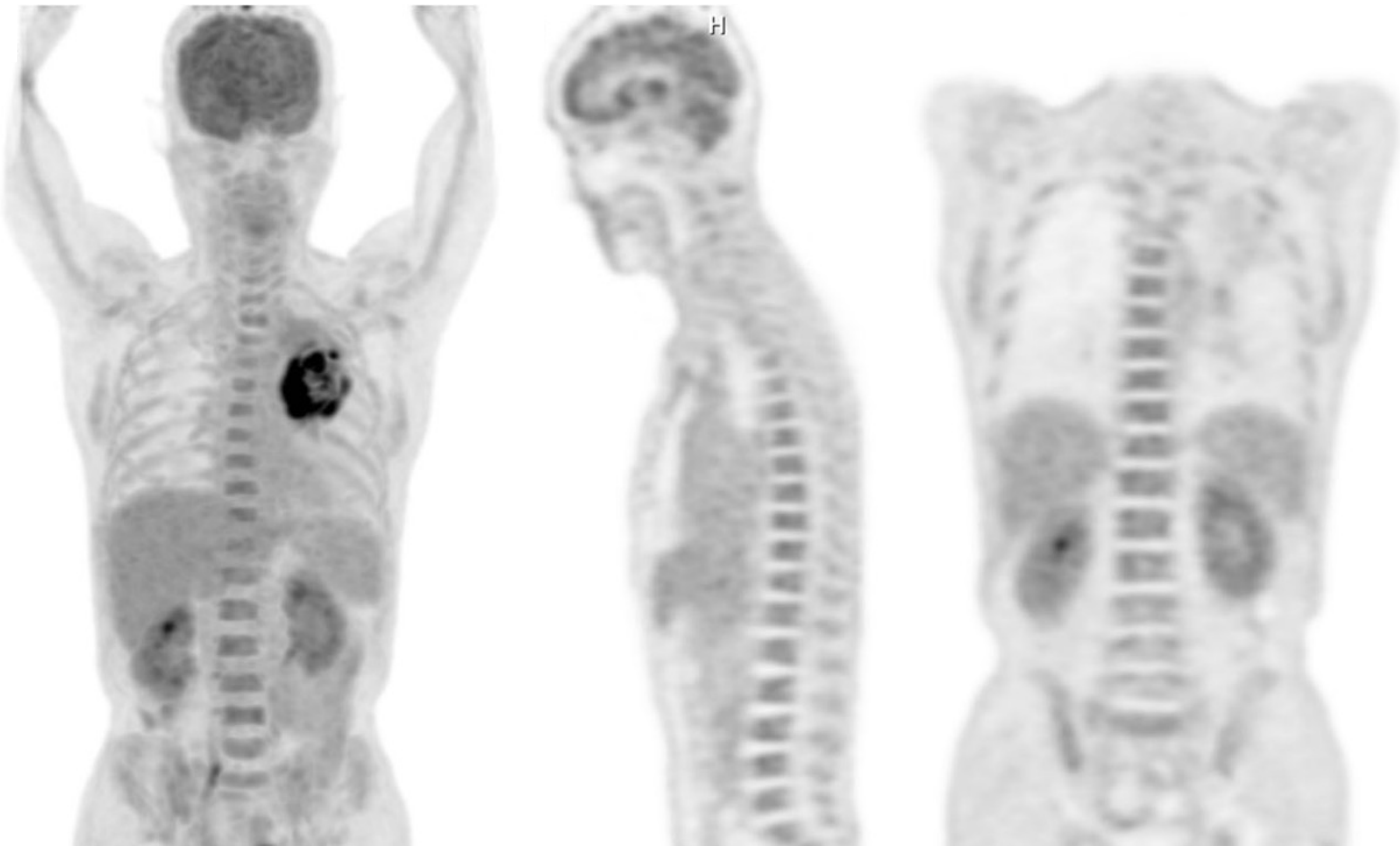
Positron Emission Tomography (PET)

- Tumour invasion from the main tumour mass.
- Dissemination of disease throughout the body.



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Kadota K, et al. J of Thor Onc. (2015) 10:806-814.
Lee et al., European Radiology (2017) 27:1912–1921.

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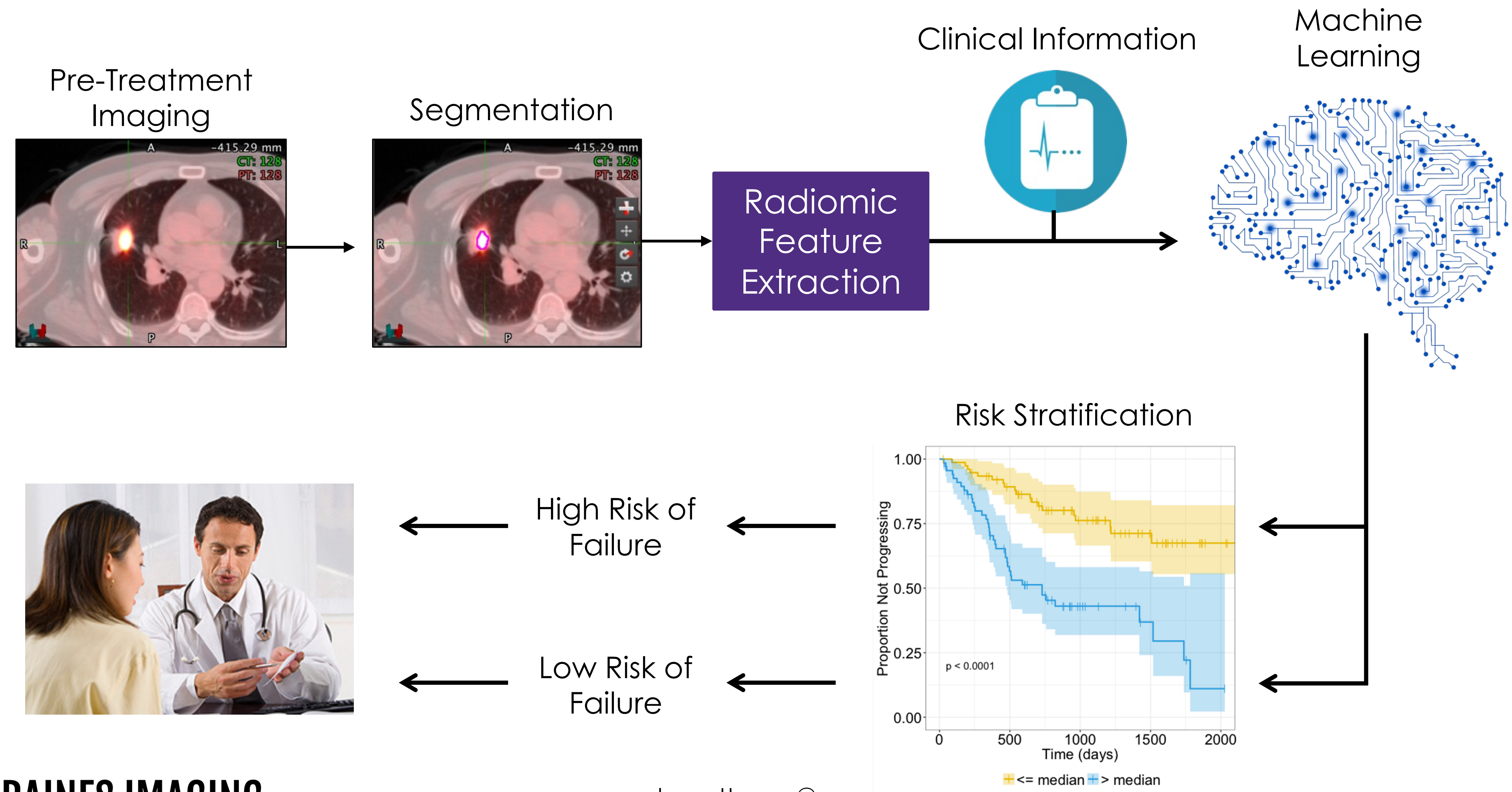
Objective

To develop a software system integrating PET imaging and non-imaging biomarkers to improve lung cancer prognosis and risk stratification.

Computer-Aided Risk Stratification



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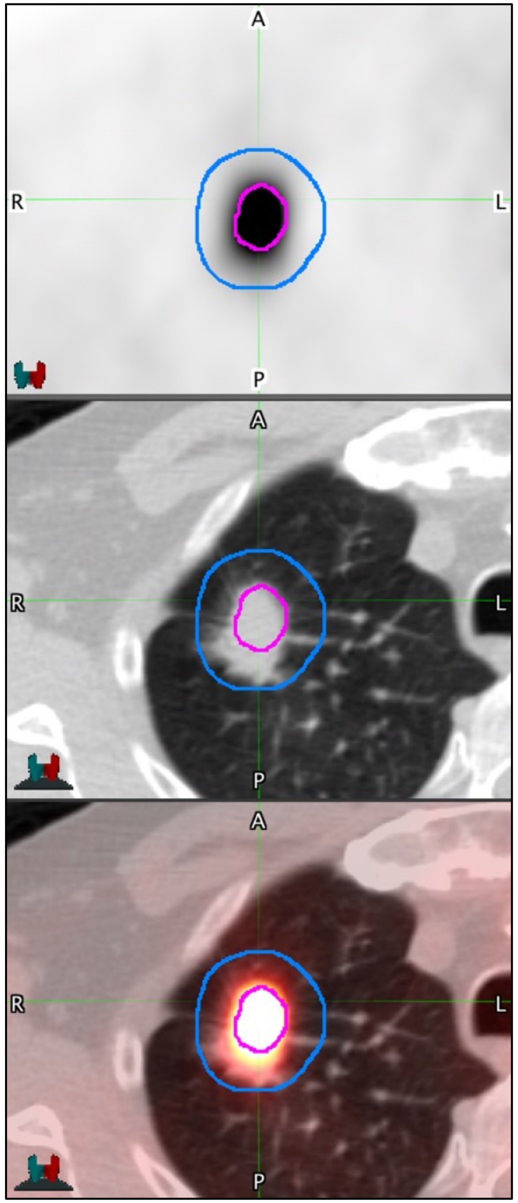
Materials

- **Training Cohort (n = 145):**
  - Selected from two local medical centers.
  - All patients had pre-operative PET/CT performed prior to surgery.
    - Feature selection and model development

- **Testing Cohort (n = 146):**
  - Selected from three local medical centers.
  - Underwent PET/CT imaging prior to definitive treatment as part of observational biomarker study.
    - Model evaluation

Segmentation: Tumour

- The **metabolic tumour volume (MTV)** was segmented on the PET image.
- A 3-dimensional **penumbra** region was also generated surrounding the MTV to sample surrounding uptake.
- Three regions were evaluated:
  - MTV only
  - Penumbra only (excluding the MTV)
  - MTV plus penumbra



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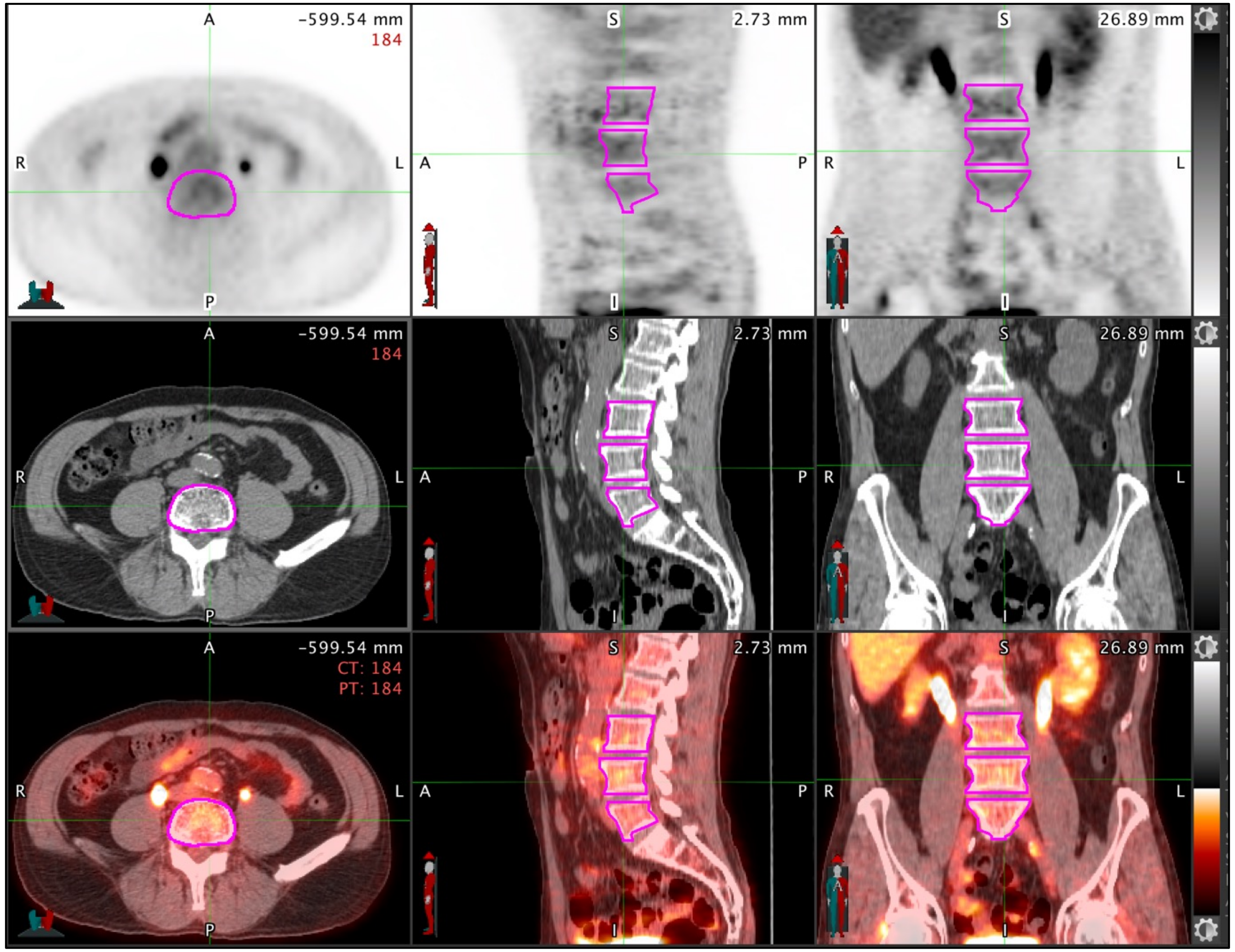
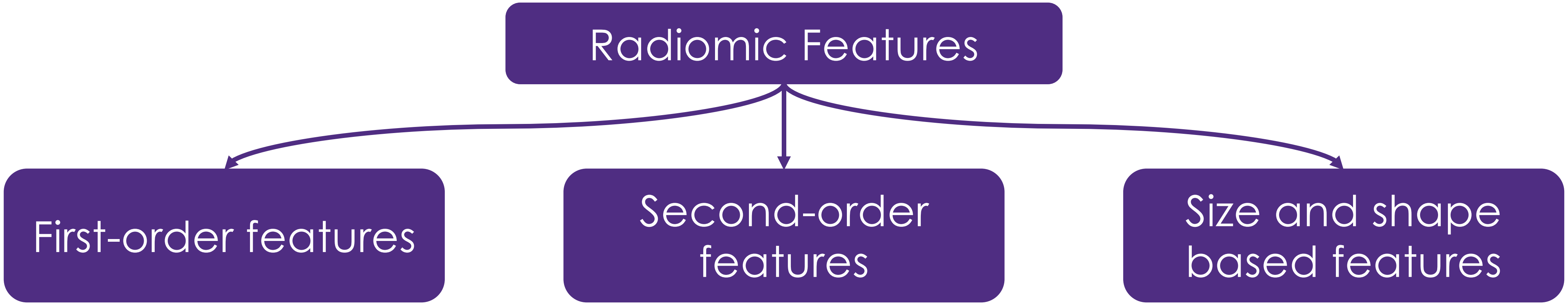
Methods: Bone Marrow Segmentation



MIM (MIM Software Inc., Cleveland, OH).

Mattonen, et al. Radiology: 293(2), 451-459, 2019.

Radiomic Feature Extraction



- A total of **668 radiomics features** were extracted from the volumes of interest.

Echegaray, S., et al. (2017) J Digit Imaging, 1-12 .
GitHub: riipl/3d_qifp

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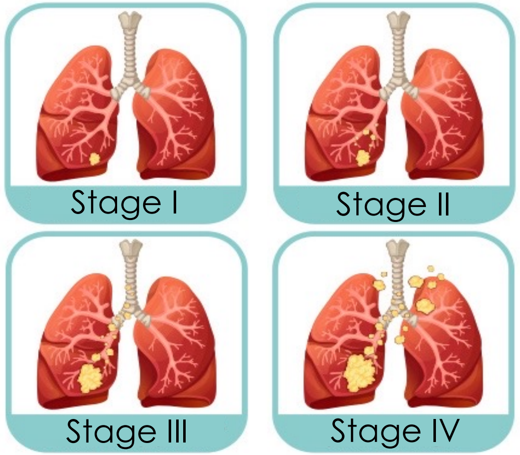
Methods: Model Training

- Top predictive features were selected using randomizations of 4-fold cross-validation of LASSO Cox regression.



Clinical

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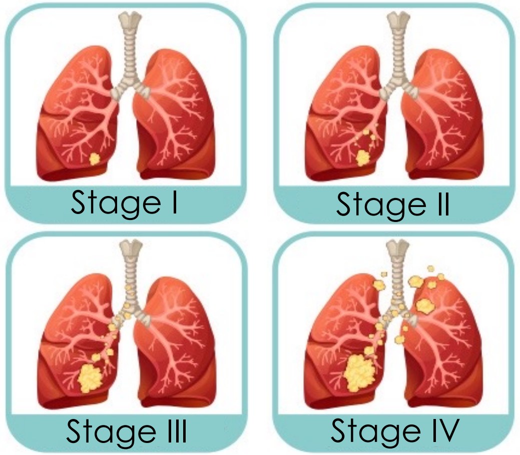

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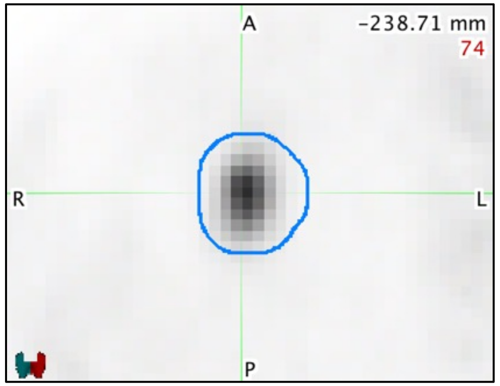

Clinical

Tumour Plus Penumbra

Methods: Model Training

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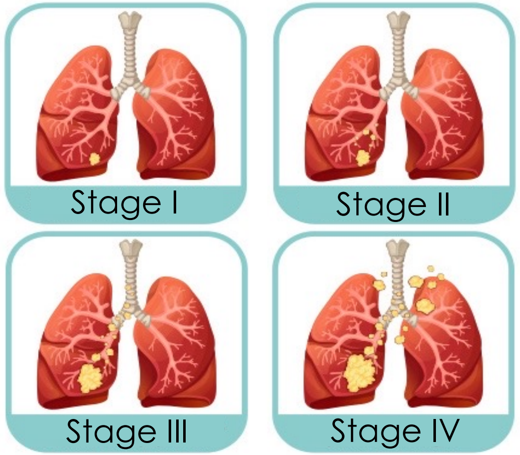
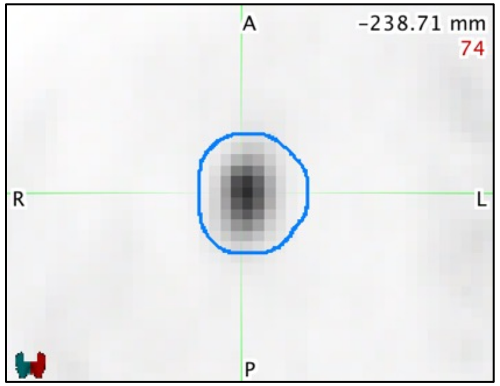
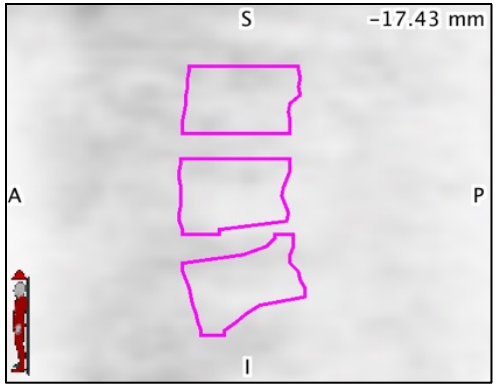


Clinical



Tumour Plus Penumbra



Bone Marrow

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Results: Multivariate Model Clinical + Tumour + Bone Marrow

Feature Type	Feature	HR [95% CI]	p-value
Clinical	**Stage**	**1.98 [1.45-2.70]**	**p<0.001***
Blood	WBC (1000/uL)	0.99 [0.88-1.11]	p=0.81
	Hemoglobin (g/dL)	0.99 [0.82-1.20]	p=0.93
	Platelets (1000/uL)	1.00 [1.00-1.01]	p=0.93
Tumor	MTV Plus Penumbra GLCM Energy (MAD)	0.69 [0.40-1.19]	p=0.18
	Penumbra GLCM Entropy (IQR)	1.35 [0.97-1.86]	p=0.07
	Penumbra GLCM Cluster Shade (Max)	1.17 [0.84-1.63]	p=0.36
Bone Marrow	**GLCM Sum Mean (Skewness)**	**0.52 [0.32-0.84]**	**p=0.008***
	GLCM Cluster Tendency (Skewness)	**1.62 [1.02-2.59]**	**p=0.04***

Mattonen, et al. Radiology, 2019.

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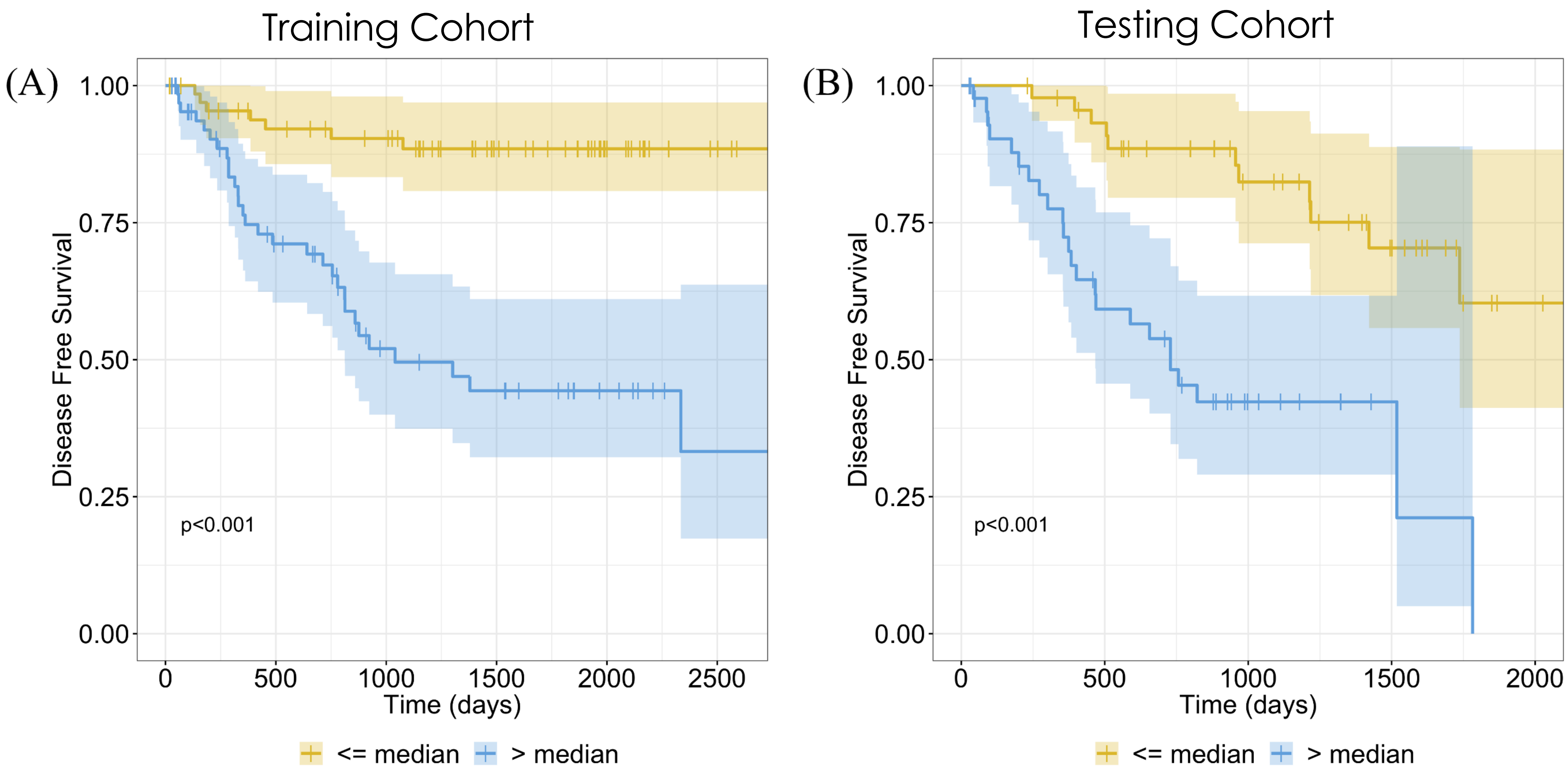
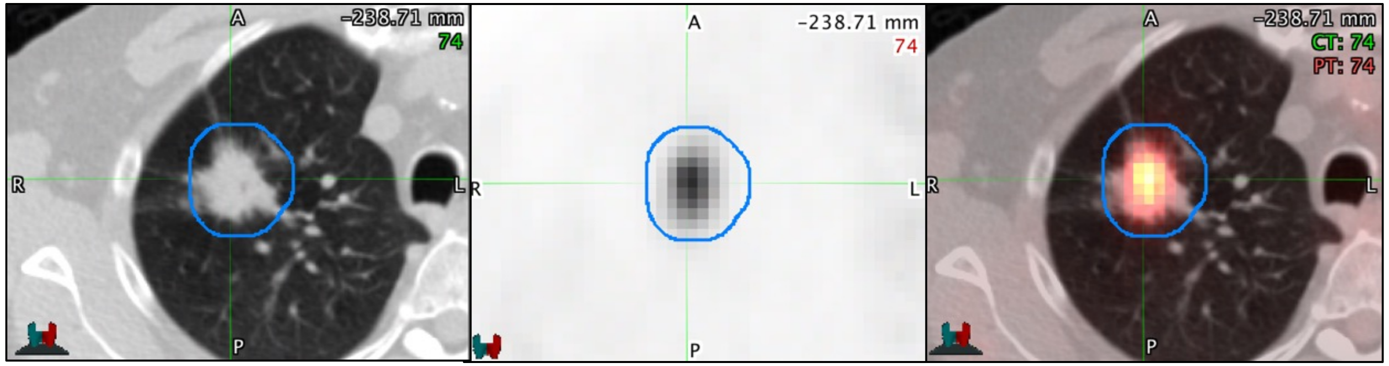
Results: Risk Stratification



Mattonen, et al. Radiology, 2019.

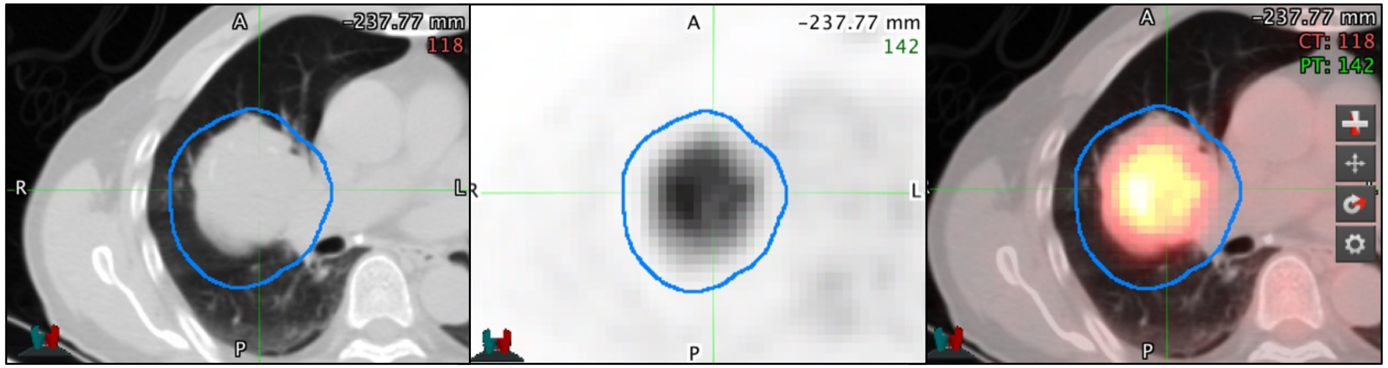
Qualitative Results

(A)



SUV_{max} = 10.3
Stage I
High-Risk Radiomics
Recurrence

(B)

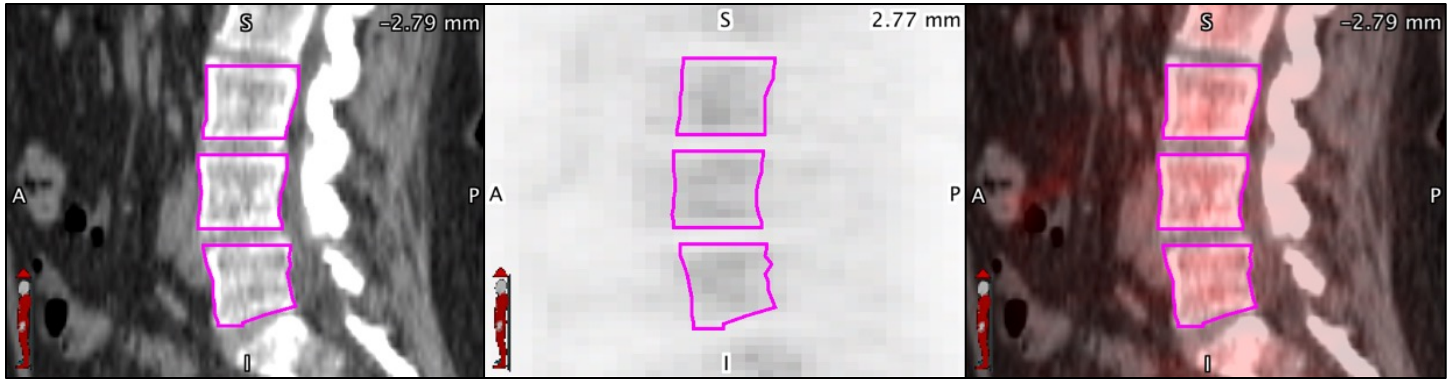


SUV_{max} = 10.1
Stage II
Low-Risk Radiomics
No Recurrence

Mattonen, et al. Radiology, 2019.

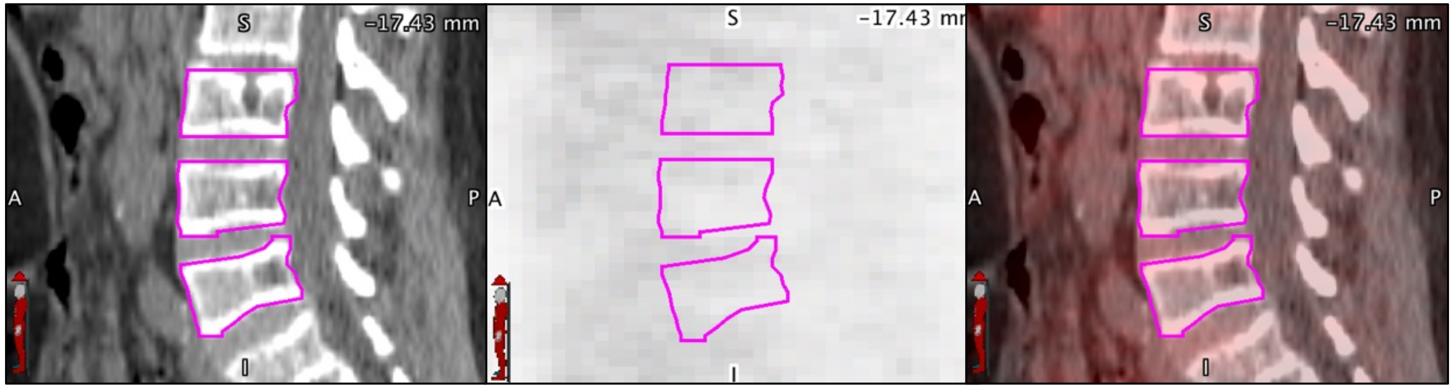
Qualitative Results

(A)



Stage I
High-Risk Radiomics
Recurrence

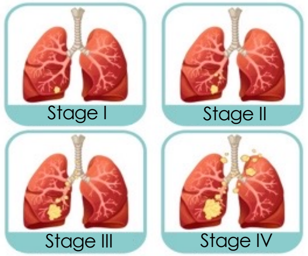
(B)



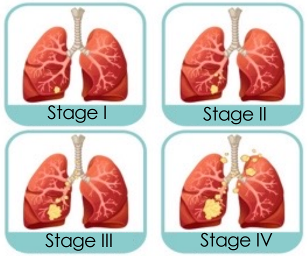
Stage III
Low-Risk Radiomics
No Recurrence

Mattonen, et al. Radiology, 2019.

Results: Summary



Concordance = 0.69 [0.60-0.77]



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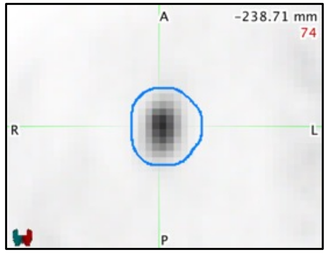
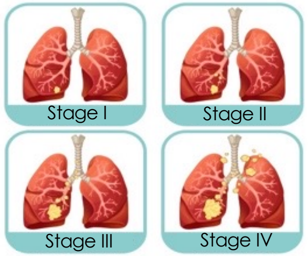


Concordance = 0.75 [0.67-0.82]



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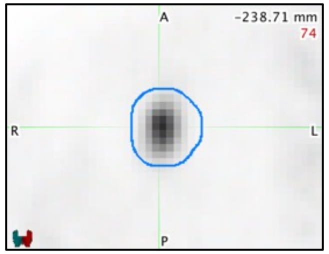

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Concordance = 0.78 [0.70-0.85]

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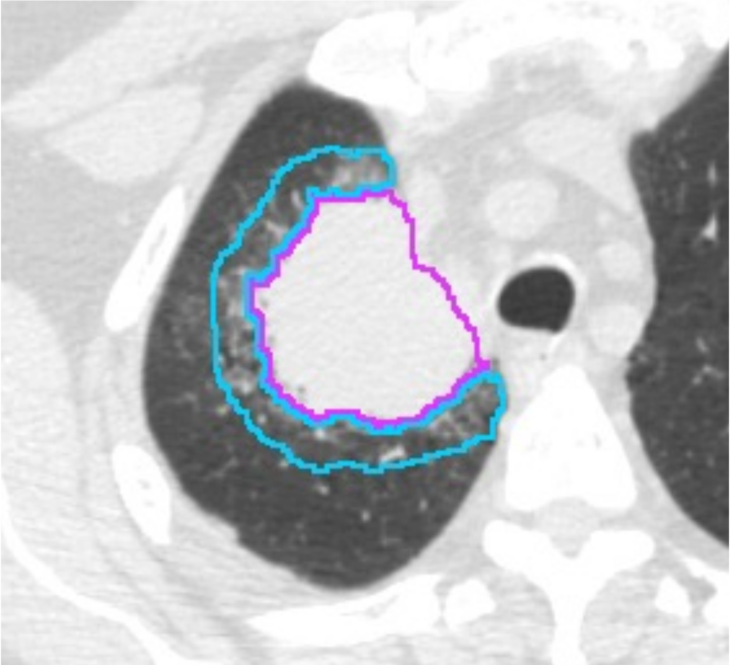
CAN ADDING CT FEATURES IMPROVE PERFORMANCE?

Jaryd Christie, CAMPEP PhD Candidate

Tumor and Peri-tumoral CT Segmentation

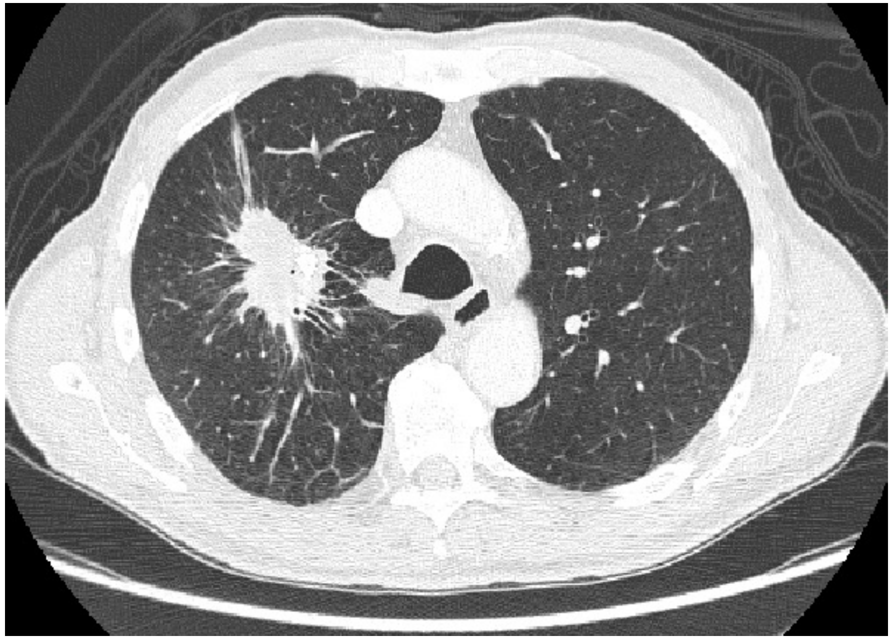
- MATLAB based-GUI for semi-automatic tumor segmentation on CT



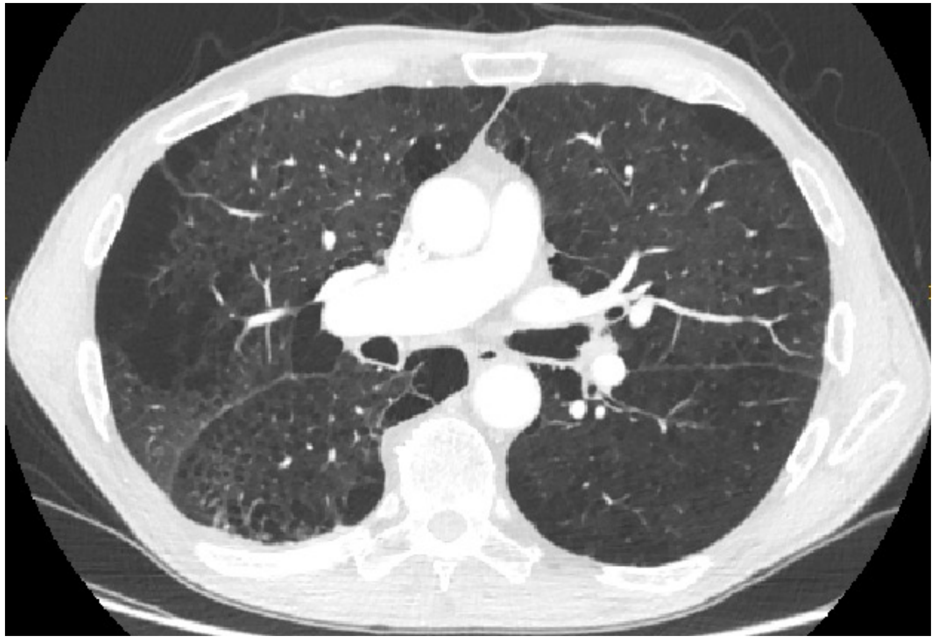
Christie, Jaryd R., et al. Vol. 12036. SPIE, 2022.
https://github.com/baines-imaging-mattonen-lab/CT-Lung-Tumour-Segmentation

Qualitative Features

- Tumour features that describe the location and geometry
- Features which characterize the lung tissue, bronchi, and lumen



Spiculated



Severe Emphysema

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Results: Feature Selection

- **Seven** selected features:
  - **One** clinical feature
    - **Stage**
  - **Six** radiomic features (3 texture, 3 first-order)
    - **Three CT (2 Tumour, 1 Peritumoural)**
    - **Three PET (2 Peritumoural, 1 Bone Marrow)**

Results: Model Evaluation

- Training: **Stage** vs **Radiomics + Stage**
  - **Concordance: 0.67** [95% CI: 0.58 – 0.76] vs **0.78** [95% CI: 0.70-0.86]
  - **$p < 0.005$**
- Testing: **Stage** vs **Radiomics + Stage**
  - **Concordance: 0.60** [95% CI: 0.48 – 0.74] vs **0.76** [95% CI: 0.59-0.87]
  - **$p = 0.008$**
- Radiomics model significantly stratified patients into high- and low-risk of recurrence

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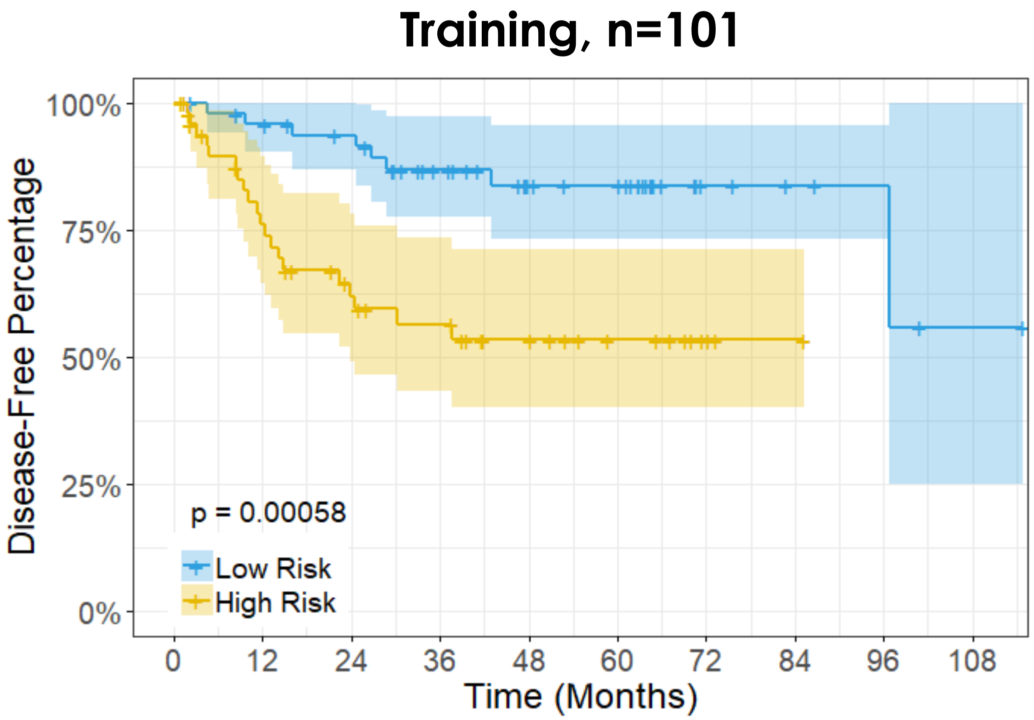
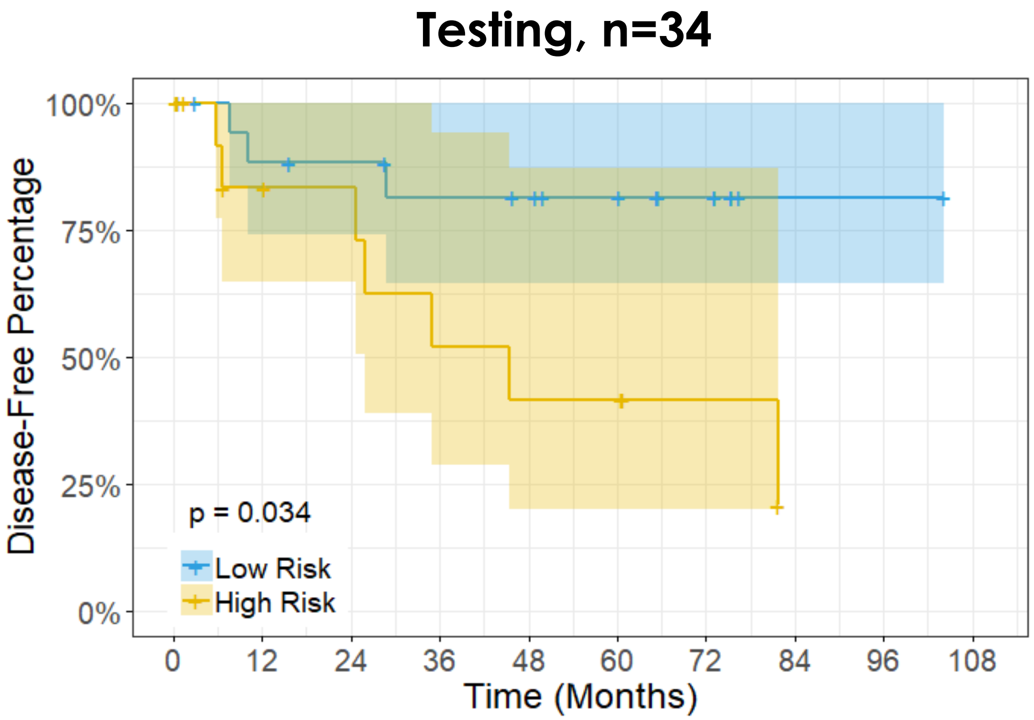
Results: Risk Stratification



Concordance = 0.78



Concordance = 0.76

Conclusions

- These radiomics based tools have the potential to identify NSCLC patients at a higher risk of recurrence and may add clinical utility for risk stratification.
- This assist physicians in distinguishing patients who may benefit from adjuvant or more aggressive personalized treatment options.

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Next Steps

- Collaborations for external validation of models.
- Implementation of standardized radiomics features and open-source software

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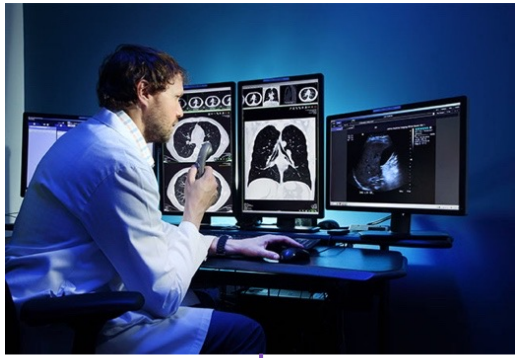
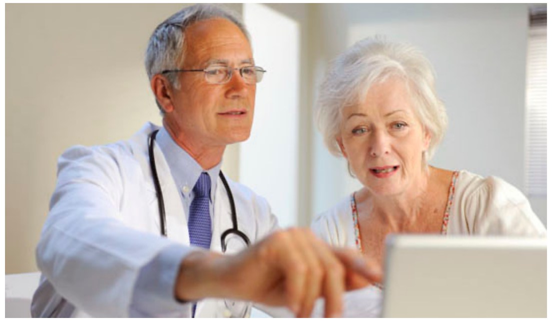
Translational Cancer Imaging

Computer-Aided Decision Support



Improve Patient Outcomes



Adapted from:
Lambin P, et al. Eur J Cancer. (2012) 48:441-446.

AFFILIATIONS

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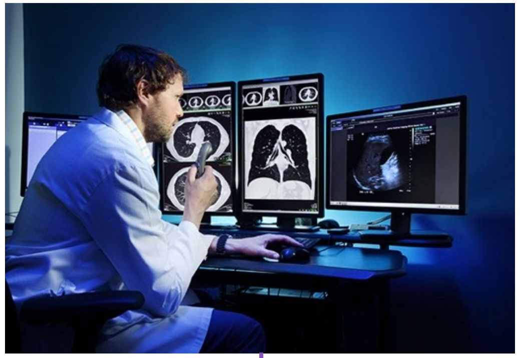
Translational Cancer Imaging

Computer-Aided Decision Support



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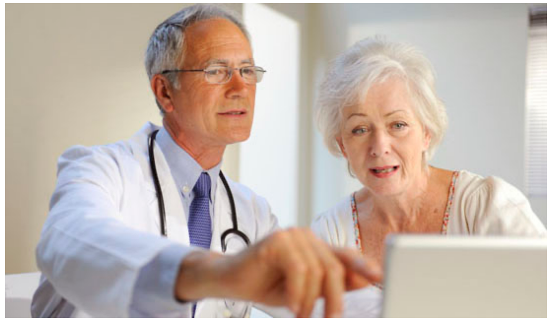

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