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

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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%

SEER Stat Fact Sheets: Lung and Bronchus Cancer.
The Role of Imaging

Computed Tomography (CT)  Positron Emission Tomography (PET)
The Role of Imaging

Computed Tomography (CT)  Positron Emission Tomography (PET)

3 cm

SUVmax = 9
Radiomics

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

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

Positron Emission Tomography (PET)

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

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

Pre-Treatment Imaging → Segmentation → Radiomic Feature Extraction → Clinical Information → Machine Learning

Risk Stratification

High Risk of Failure

Low Risk of Failure

Computer-Aided Risk Stratification

Radiomic Feature Extraction

Clinical Information

Machine Learning

Pre-Treatment Imaging

Segmentation

High Risk of Failure

Low Risk of Failure

Risk Stratification

Proportion Not Progressing

Time (days)
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
Methods: Bone Marrow Segmentation

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

Radiomic Feature Extraction

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

GitHub: ripl/3d_qifp
Methods: Model Training

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

Clinical
Methods: Model Training

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

Stage I  Stage II  Stage III  Stage IV

Clinical  Tumour Plus Penumbra
Methods: Model Training

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

Clinical + Tumour Plus Penumbra + Bone Marrow
# Results: Multivariate Model

Clinical + Tumor + Bone Marrow

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

Results: Risk Stratification

(A) Training Cohort

(B) Testing Cohort

Qualitative Results

SUV\(_{\text{max}}\) = 10.3
Stage I
High-Risk Radiomics
Recurrence

SUV\(_{\text{max}}\) = 10.1
Stage II
Low-Risk Radiomics
No Recurrence
Qualitative Results

(A) Stage I
High-Risk Radiomics
Recurrence

(B) Stage III
Low-Risk Radiomics
No Recurrence
Results: Summary

Concordance = 0.69 [0.60-0.77]

Concordance = 0.75 [0.67-0.82]

Concordance = 0.78 [0.70-0.85]
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

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
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
Results: Risk Stratification

Training, n=101

Concordance = 0.78

Testing, n=34

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.
Next Steps

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

Computer-Aided Decision Support

Improve Patient Outcomes

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Translational Cancer Imaging

Computer-Aided Decision Support

Improve Patient Outcomes