Generalizability of Radiomics-based Progression Risk Models in Immunotherapy-treated mNSCLC Subjects

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INTRODUCTION

- Radiomics has shown promise in improving prognostication in metastatic non-small cell lung cancer (mNSCLC) subjects treated with immunotherapy (IO).
- However, ensuring generalizability across different centers still represents an open challenge to clinical adoption.
- We sought to develop and test the generalizability of a radiomics model aimed at predicting risk of progression in IO treated subjects with mNSCLC.

METHODS

- Pretreatment CT scans of IO treated mNSCLC subjects and with known outcome data were collected from a single institution (Discovery cohort) to develop the model.
- Radiomics features were extracted from the segmentation of the largest lung tumor lesion.
- The 8 most predictive radiomics features were selected using a least absolute shrinkage and selection operator (LASSO) Cox regression
- A survival random forest algorithm was used to train a radiomics risk model
  - via 5-fold cross-validation
  - using censored progression-free survival (PFS) data.
- To test if the model was predictive of IO outcome, we evaluated it in a cohort of mNSCLC subjects treated with 1L chemotherapy (Chemo cohort).
- To test model generalizability, we used a publicly available retrospective cohort of pretreatment CT scans of mNSCLC treated with IO and with known PFS data from an independent institution (External cohort).
- Risk models were evaluated by splitting the data into high and low risk groups, and evaluating the hazard ratios (HR) and log rank test p-values between the predicted risk groups.

SUMMARY

- PFS risk model trained on nMSCLC IO cohort generalizes to both external IO cohort, and same institution chemotherapy cohort
- The model predicts generalizable prognostic features rather than therapy-specific benefit

RESULTS

Figure 1. KM Curve for Discovery Cohort

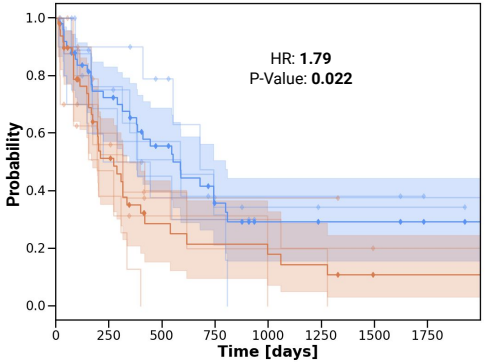

Figure 1. KM curve shows the PFS curves for patients in predicted high and low risk groups within the 5 validation folds inside the discovery cohort. 95% Confidence intervals are shown. The results of the final trained model on the full discovery cohort is the darkest line.

Discovery Cohort Demographics

- 108 Patients
- Median PFS 11.5 months
- 51% Female
- Average age of 68
- 100% First line therapy
- 62% IO+Chemo / 38% IO-monotherapy

Figure 2. KM Curve for External Cohort

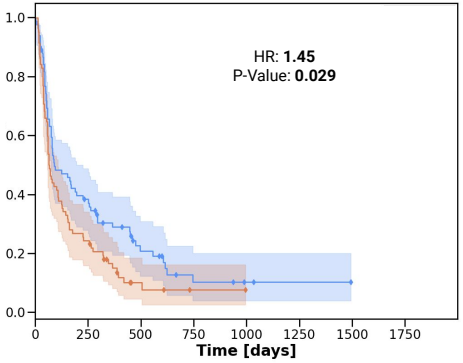

Figure 2. KM curve shows the PFS curves for patients in predicted high and low risk groups within the external cohort. 95% Confidence intervals are shown.

External Cohort Demographics

- 174 Patients
- Median PFS 2.7 months
- 52% Female
- Average age of 68
- 33% First line therapy
- 9% IO+Chemo / 91% IO-monotherapy

Figure 3. KM Curve for Chemotherapy cohort

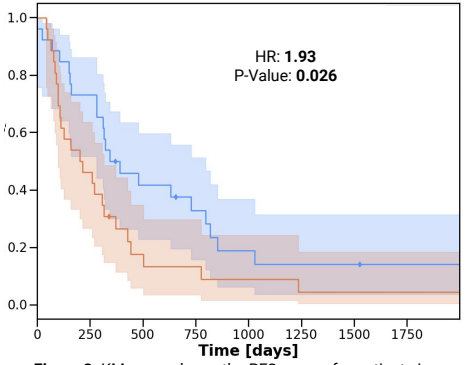

Figure 3. KM curve shows the PFS curves for patients in predicted high and low risk groups within the chemo therapy cohort. 95% Confidence intervals are shown.

Chemotherapy Cohort Demographics

- 55 Patients
- Median PFS 10.3 months
- 45% Female
- Average age of 65
- 100% First line therapy

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