LungNet: Shallow CNN models for NSCLC

PRITAM MUKHERJEE

In collaboration with

Mu Zhou, Edward Lee, Sandy Napel, Simon Wong,

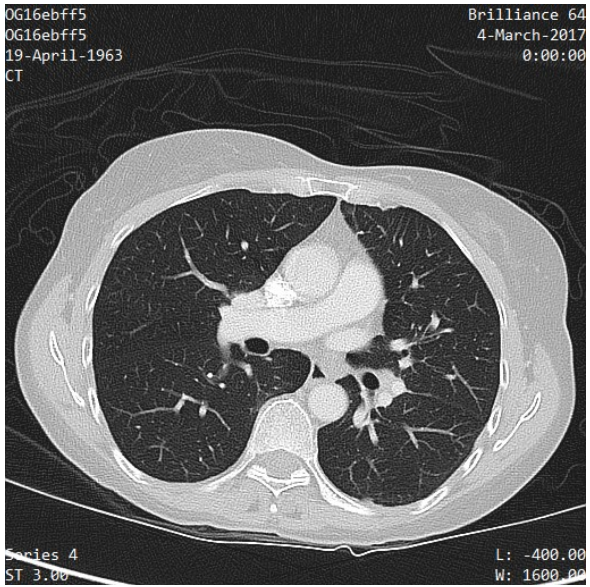
Ann Leung and Olivier Gevaert, Stanford University,

Anne Schicht and Alexander Thieme, Charité Universitätsmedizin, Berlin

Yoganand Balagurunathan and Robert Gillies, Moffitt Cancer Center

Motivation

- Lung cancer is the most fatal malignancy in adults worldwide
- 85% of lung cancers are Non Small Cell Lung Cancers (NSCLC)
- Lung Computed Tomography (CT) scans are routinely used in clinical practice
- Can we use lung CTs for prognostication, patient stratification?
- **Our target**: Overall Survival



Data: Multi-institutional Cohort

We collected lung CT image data from **four** institutions:

- Cohort 1 from Stanford Hospital (n=129)
  - Now publicly available on TCIA: http://doi.org/10.7937/K9/TCIA.2017.7hs46erv
- Cohort 2 from Moffitt Cancer Center (n=185)
  - Soon to be made available
- Cohort 3 from MAASTRO Clinic, The Netherlands (n=311)
  - Publicly available on TCIA: http://doi.org/10.7937/K9/TCIA.2015.PF0M9REI
- Cohort 4 from Charité – Universitätsmedizin, Berlin (n=84)

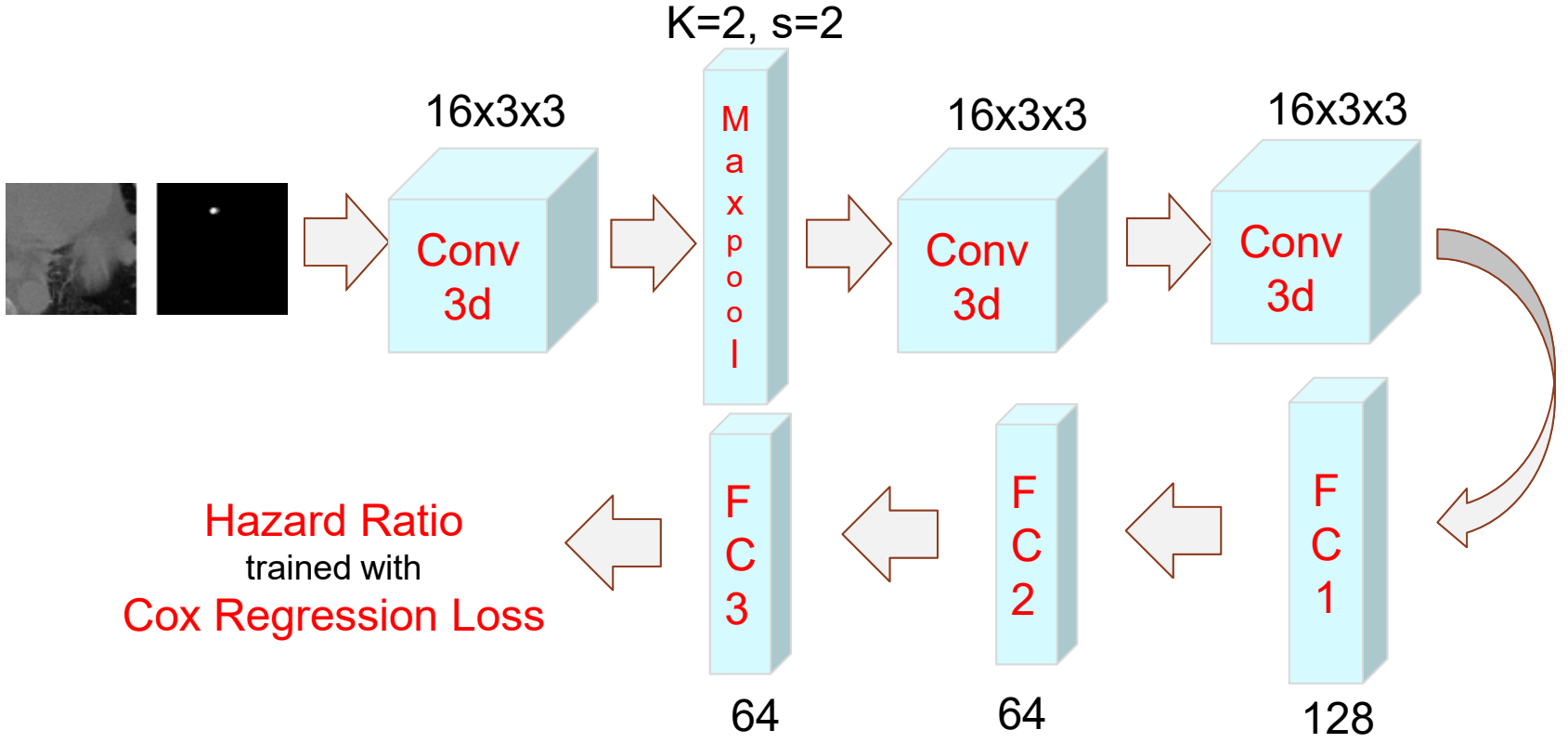
Data: Patient characteristics

Characteristic	Institutional Cohorts			
	Cohort 1	Cohort 2	Cohort 3	Cohort 4
Number of patients	129	185	311	84
Age (yrs, Mean ± SD)	69.40 ± 8.47		67.65 ± 10.13	67.05 ± 9.07
Sex (n Male, %)	101 (78.3%)	82 (44.3%)	220 (70.7%)	64 (76.2%)
Smoking history	20 (15.5%)	38 (20.5%)		
Histology				
Adenocarcinoma	100 (77.5%)	107 (57.8%)	32 (10.3%)	36 (42.9%)
Squamous Carcinoma	29 (22.5%)	50 (27%)	84 (27%)	44 (52.4%)
Other histology type(s)		28 (15.2%)	195 (62.7%)	4 (4.8%)
Survival time (dys, Mean)	889	1021	609	944
Survival time (dys, Std)	671	504	457	710
Staging status				
Stage 1	67	97	81	5
Stage 2	42	32	26	10
Stage 3	15	38	73	69
Stage 4	5	18	131	0

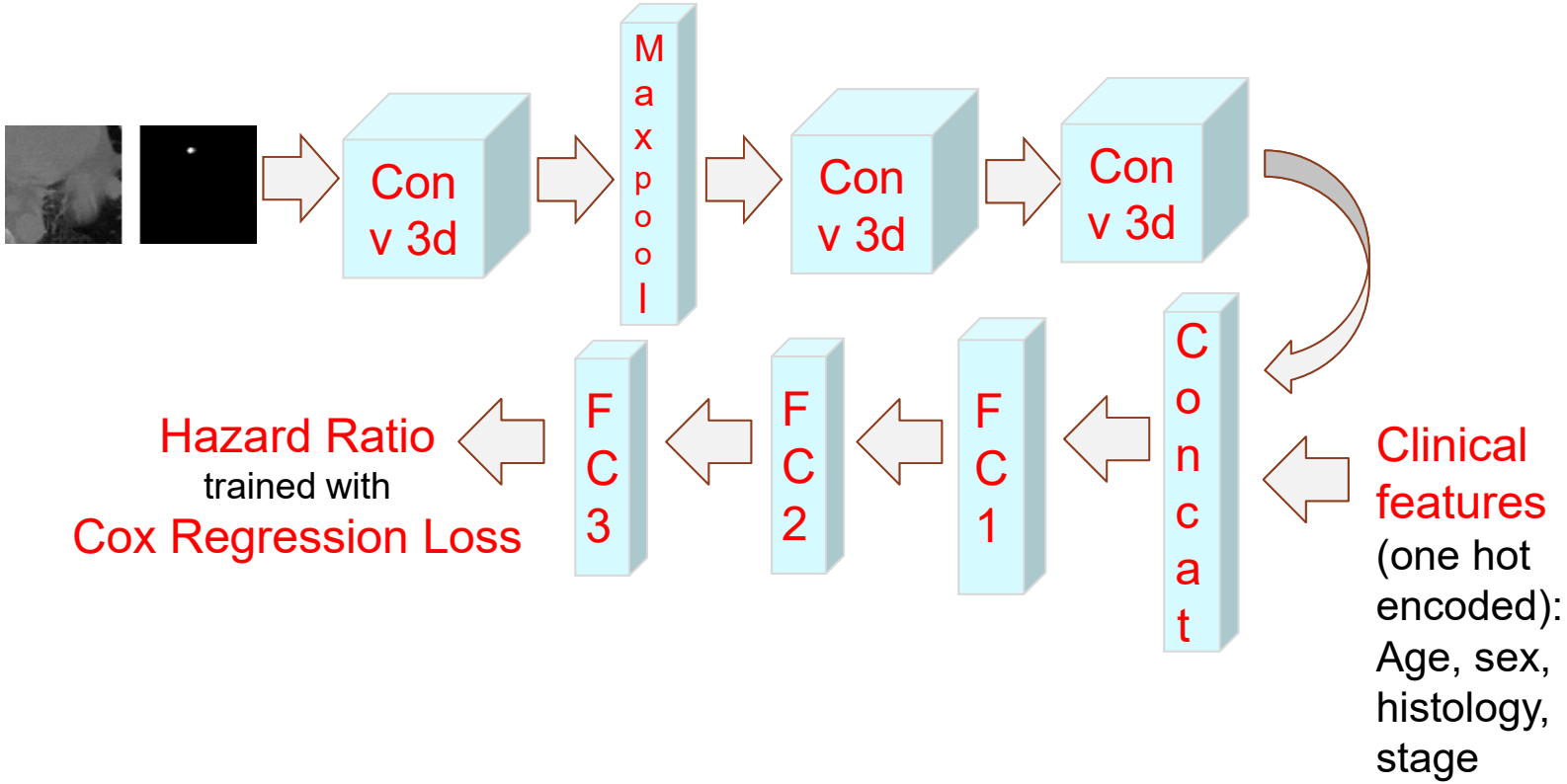
Methodology

- Convolutional Neural Networks
- Nodules segmented by radiologists
- Input: 3D patch containing the nodule and corresponding masks and clinical variables (optional)
- Output: Hazard ratio that can be used to stratify patients
- Data augmentation:
  - Random flips
  - Random crops
  - Random brightness change
  - Addition of a small amount of noise
  - Small rotations

Model Architecture: Imaging Only



Model Architecture: With Clinical features



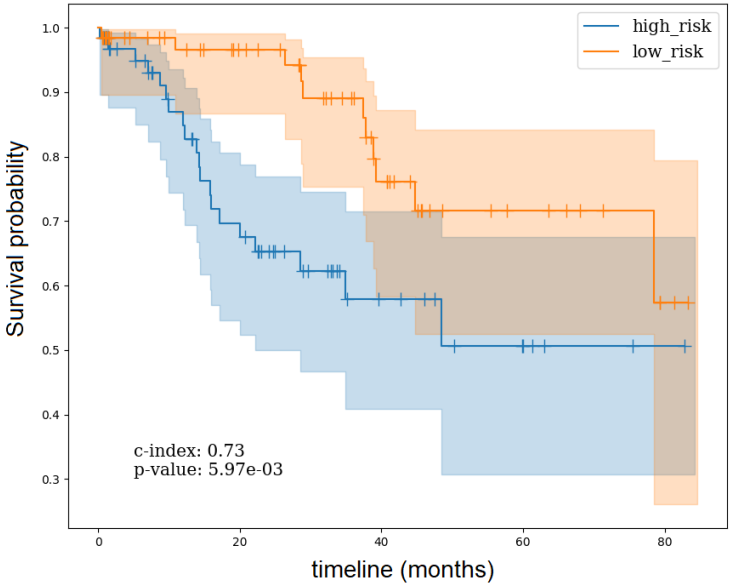
Training and Validation

- 80-20 train-validation split while training
- Monitor the validation loss while training and save best models
- Training for 100 epochs with a *cyclic learning rate*, batch size=64
- Round-robin training and testing with cohorts 1, 2 and 3
- Train on two cohorts and test on the third
- Cohort 4 is used for external validation
  - Model trained on cohorts 1, 2 and 3
  - Tested on cohort 4
- Cox Proportional hazards models with clinical features (sex, age, histology, stage) for benchmarking with same training/validation method

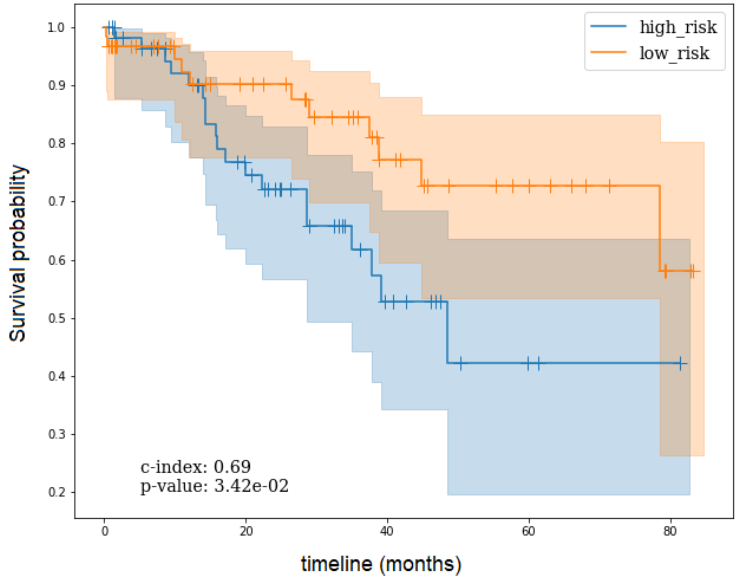
Results: Stratification of patients into risk groups

Cohort 1

LungNet



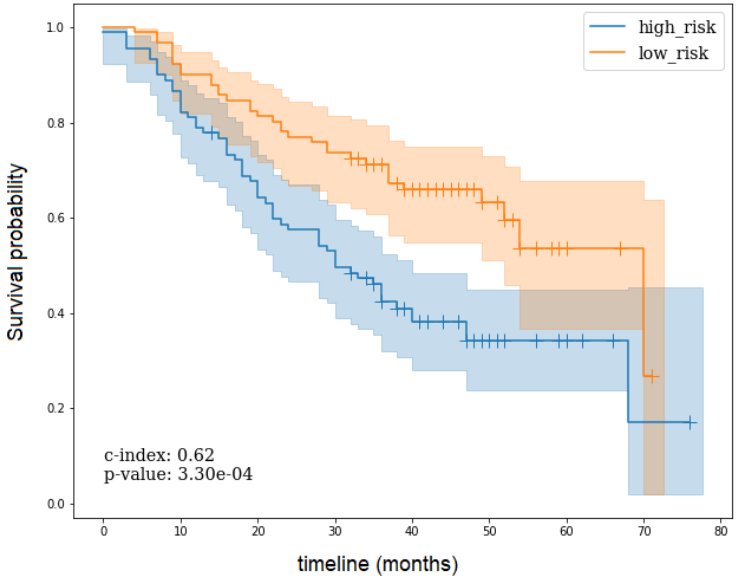
Clinical model



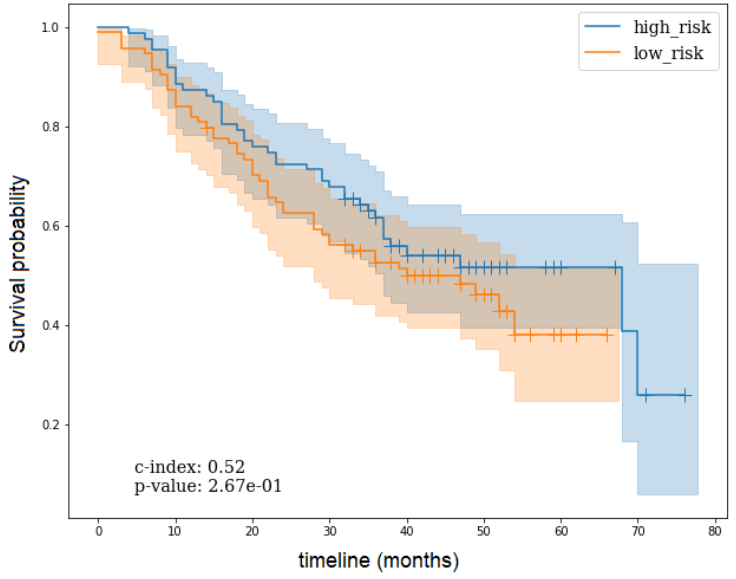
Results: Stratification of patients into risk groups

Cohort 2

LungNet



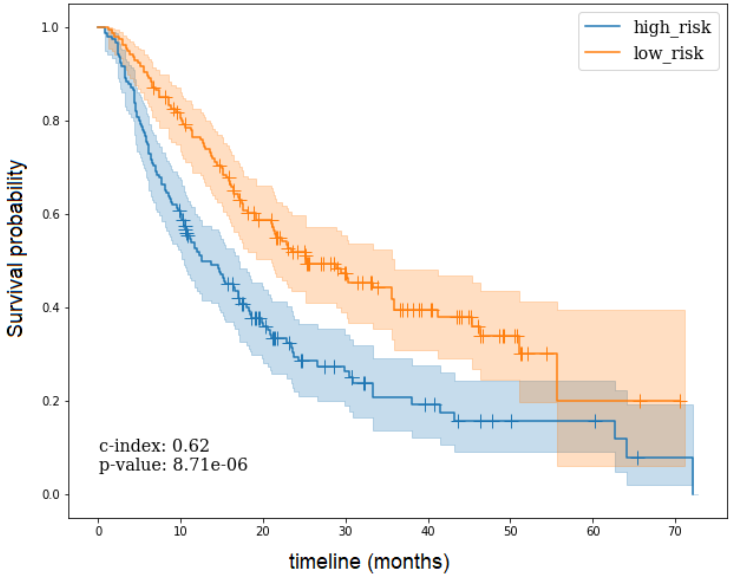
Clinical model



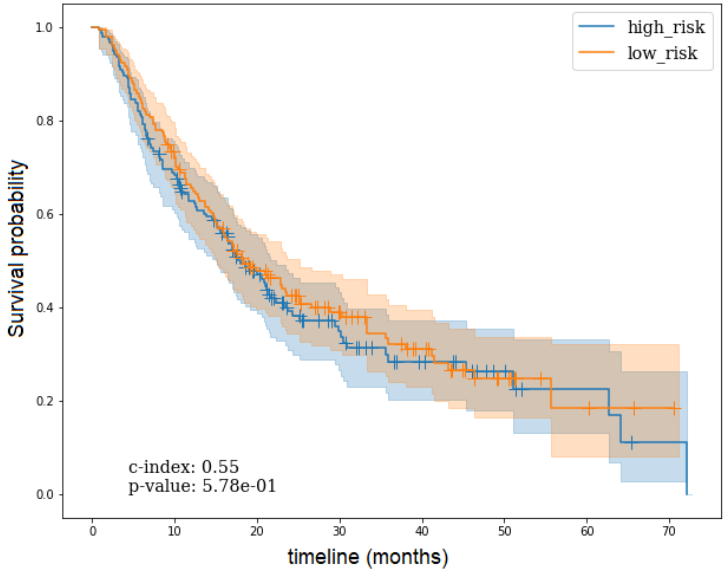
Results: Stratification of patients into risk groups

Cohort 3

LungNet



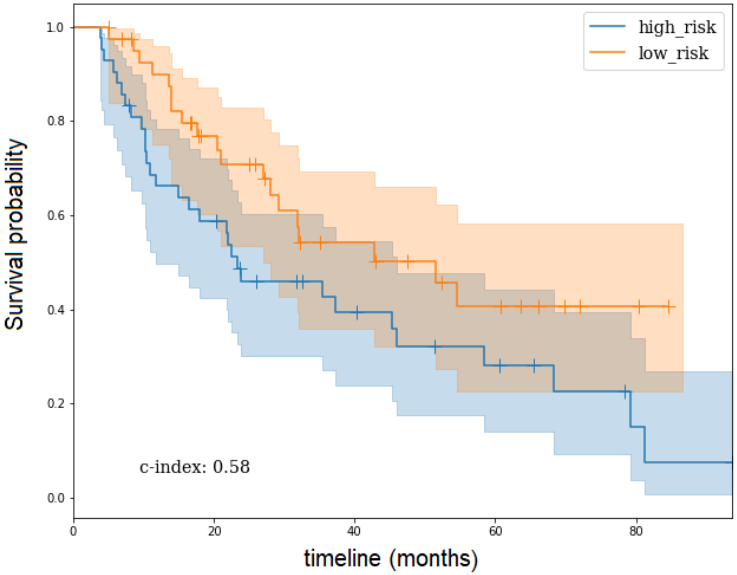
Clinical model



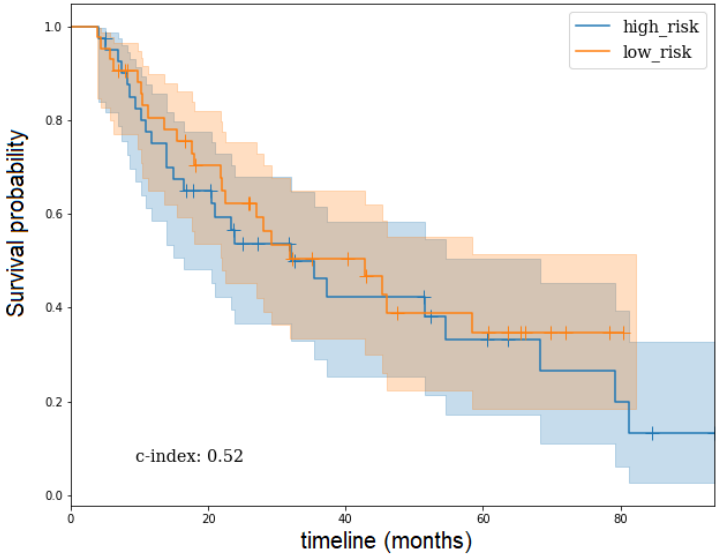
Results: Stratification of patients into risk groups

Cohort 4

LungNet

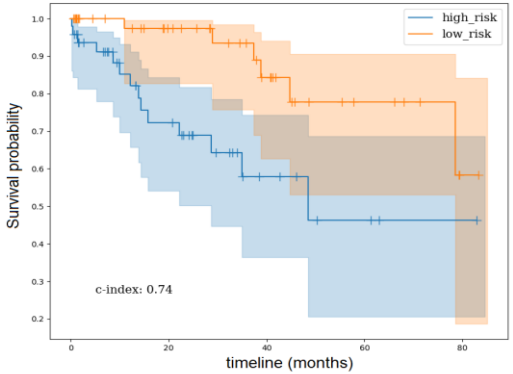


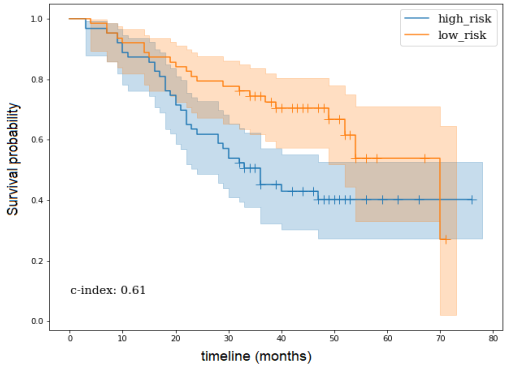
Clinical model



Results: Stratifying Early Stage (stages 1 and 2) Cancer

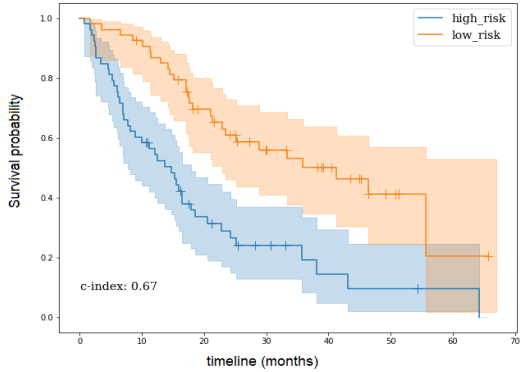
Cohort 1





Cohort 2

Cohort 3



Stanford University

Results: Takeaways and Caveats

- Adding clinical data did not improve model performance
- Performed reasonably well on early stage cancers as well
- Separate models for adenocarcinoma and SCC?
  - Not enough data unfortunately
- Inter-reader variability of segmentations not analyzed
  - Random crops for robustness
- Variability in CT acquisition parameters not explicitly analyzed
  - Random brightness shifts and small added noise
- **Ultimately seems to generalize quite well across institutions!**

Additional Slide 1: Cox Regression Loss

- θ: parameters to train
- h_θ: prediction of the model
- E: event of interest
- T_i: time at which the event occurs for sample i
- $R(T_i)$: set of samples which have not seen E until T_i

$$l(\theta) = -\frac{1}{N_{E=1}} \sum_{i:E_i=1} \left(h_\theta(x_i) - \log \sum_{j \in R(T_i)} e^{h_\theta(x_j)} \right)$$

Additional Slide 2: Learning rate modifier

Rationale: escape saddle points by increasing learning rate in a cyclic fashion – may allow faster convergence