ASSESSING THE PROGNOSTIC IMPACT OF 3D CT IMAGE TUMOUR RIND TEXTURE FEATURES ON LUNG CANCER SURVIVAL MODELLING

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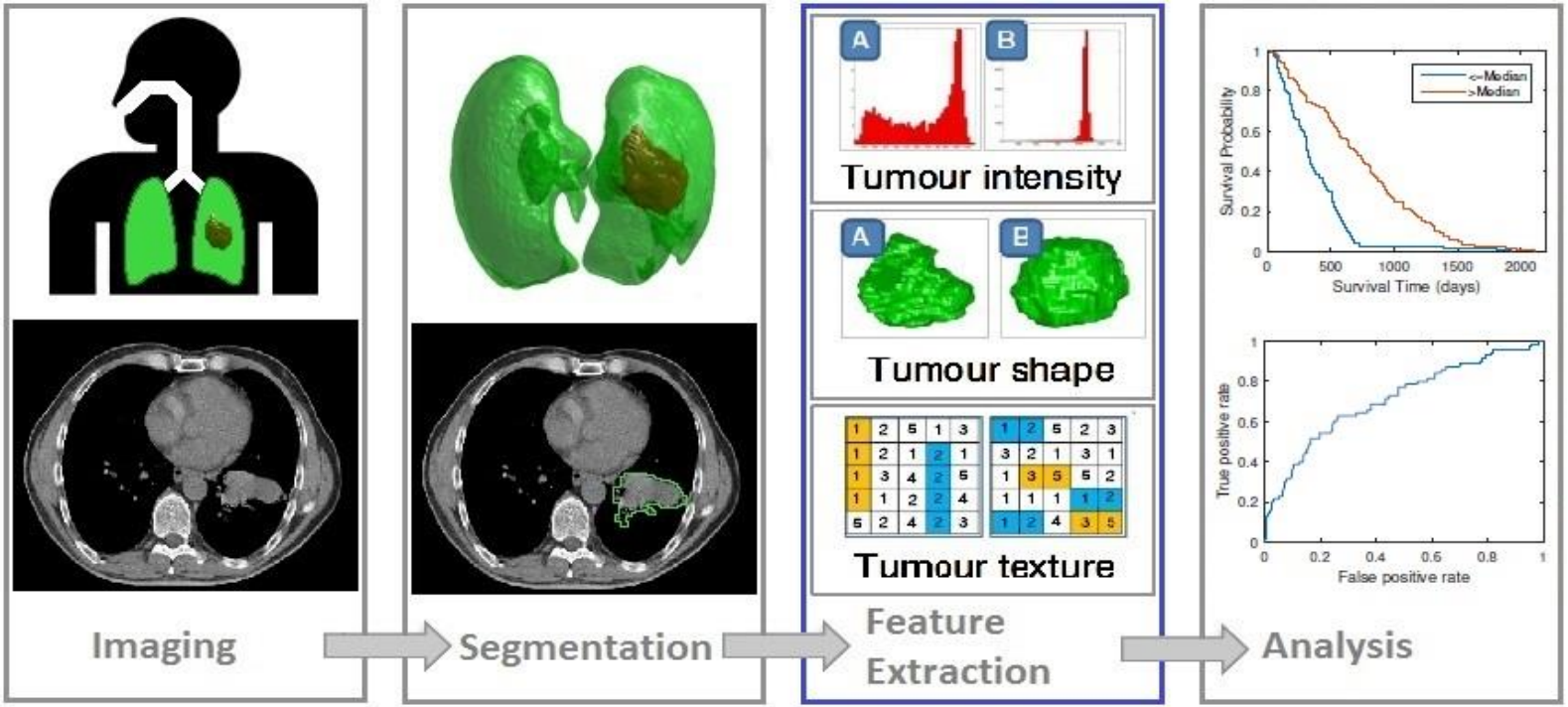
Introduction

- Develop a technique for developing prognostic image characteristics, termed radiomics, for non-small cell lung cancer based on a tumour edge region-based analysis.
- Texture features were extracted from the rind of the tumour in a publicly available 3D CT data set to predict two-year survival.
- Medical experts have expressed a need for this data to be analysed
  - improve treatment planning and improve overall patient survivability.
- Impact of providing personalised automated radiotherapy treatment.

What is Radiomics?

- Radiomics: is the application of textual image processing and data mining in the field of radiology. This is a novel approach to improve treatment outcomes, by finding attributes and features in CT imaging data.



Why Personalised Radiotherapy?

Current Issues

- Patients vary significantly, however clinical trials can't match every variation exactly, hence treatment plans can be incorrect.

Data Mining

- Terabytes of cancer data available to be mined.
- It is proposed that through data mining all data better treatment options can be applied.

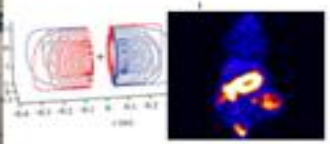
Radiomics

- Radiomics is the proposed method for solving this problem.

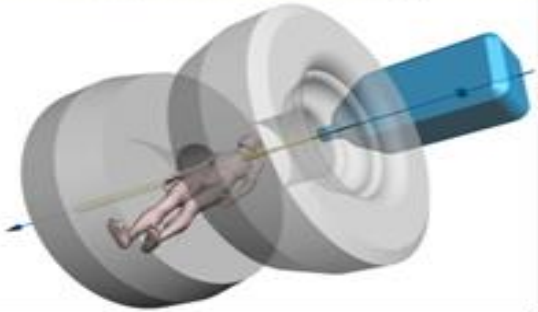
University of Sydney
Real-time imaging and treatment adaptation
Rotating couch development

Liverpool
Ingham Institute
University of NSW
Build research bunker and MRI-linac
Integrated system measurements
Dosimetric validation with EPID
Health technology assessment
Translating research into policy

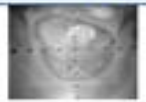
U Queensland
Magnet, gradient coil and RF performance



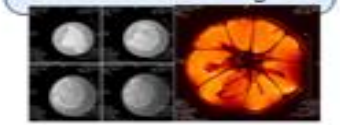
The Australian MRI-linac Program: Improving cancer treatment through real-time image guided adaptive radiotherapy



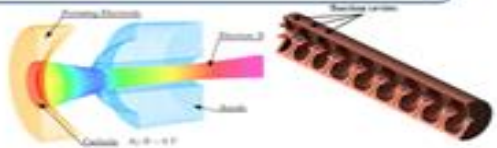
University of Newcastle
Intrafraction monitoring with EPID



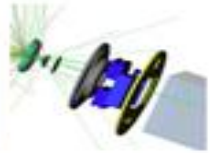
U Western Sydney
Diffusion imaging
Nanoscale contrast agents



Stanford University
Electron gun/waveguide simulations



University of Wollongong
Detector development
Treatment head/patient transport simulations
Proton therapy simulations



Key Challenges

Preprocessing the data

- Remove duplicated data
- Normalise data to ensure it is comparing like to like
- Transform data from DICOM images to MATLAB files for simpler analysis.

Finding Features

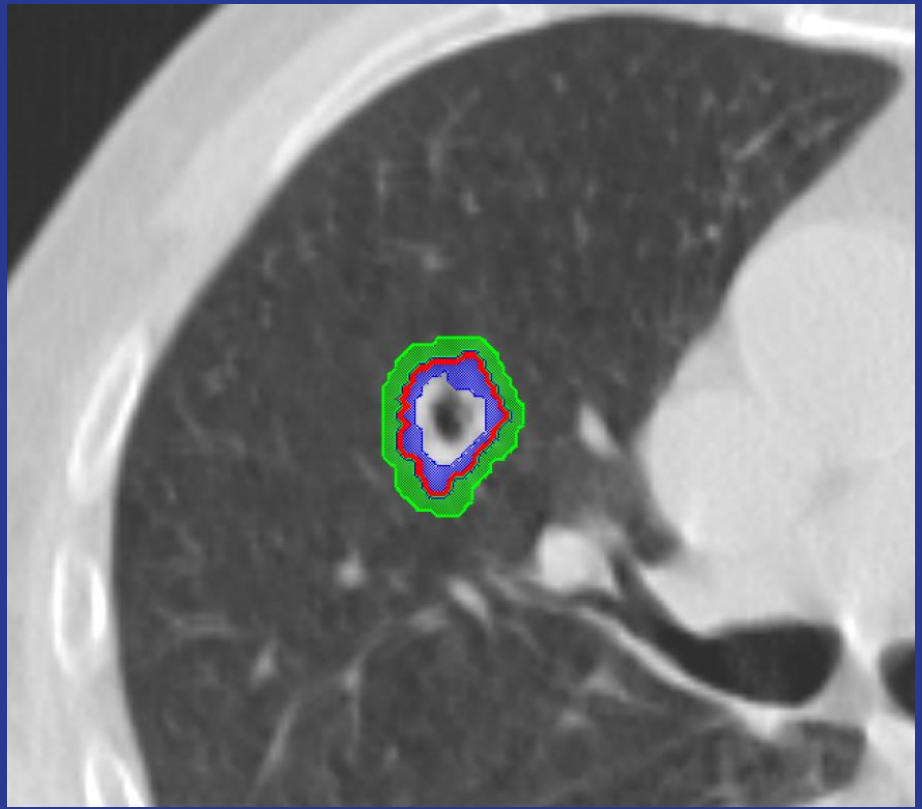
- Discover Radiomic signatures and other textual features to find relationship with 2-year survivability

Modelling the data

- Use data mining and image processing techniques such as Logistic Regression or Support Vector Machines to model data.

Extracting the Rind

Region exploration around the GTV



Deriving the Boundary Masks

To derive the mask, we first define the set of points representing the inside and outside rind, let $\mathbf{x} \in \mathbb{R}^3$ and $\mathbf{z} \in \mathbb{R}^3$ define positions vectors in the 3-Dimensional image set frame. Further, let $\mathcal{V} \subset \mathbb{R}^3$ be the set of all points in the gross tumour volume (GTV) as given by the expert or any other segmented region of interest (ROI) and $\hat{\mathcal{V}} \subset \mathcal{V}$ is defined as all points on the boundary of this region.

Suppose there is a distance function that can be constructed for each ROI, $d(\hat{\mathcal{V}}) : \mathbb{R}^3 \to \mathbb{R}$, which will be defined by the following

$$d(\mathbf{x}, \hat{\mathcal{V}}) = \begin{cases} \min \|\mathbf{x} - \mathbf{z}\|, \ \forall \mathbf{z} \in \hat{\mathcal{V}}, \ \forall \mathbf{x} \notin \mathcal{V} \\ -\min \|\mathbf{x} - \mathbf{z}\|, \ \forall \mathbf{z} \in \hat{\mathcal{V}}, \ \forall \mathbf{x} \in \mathcal{V} \end{cases}$$

Now the outer boundary region can be expressed by the set

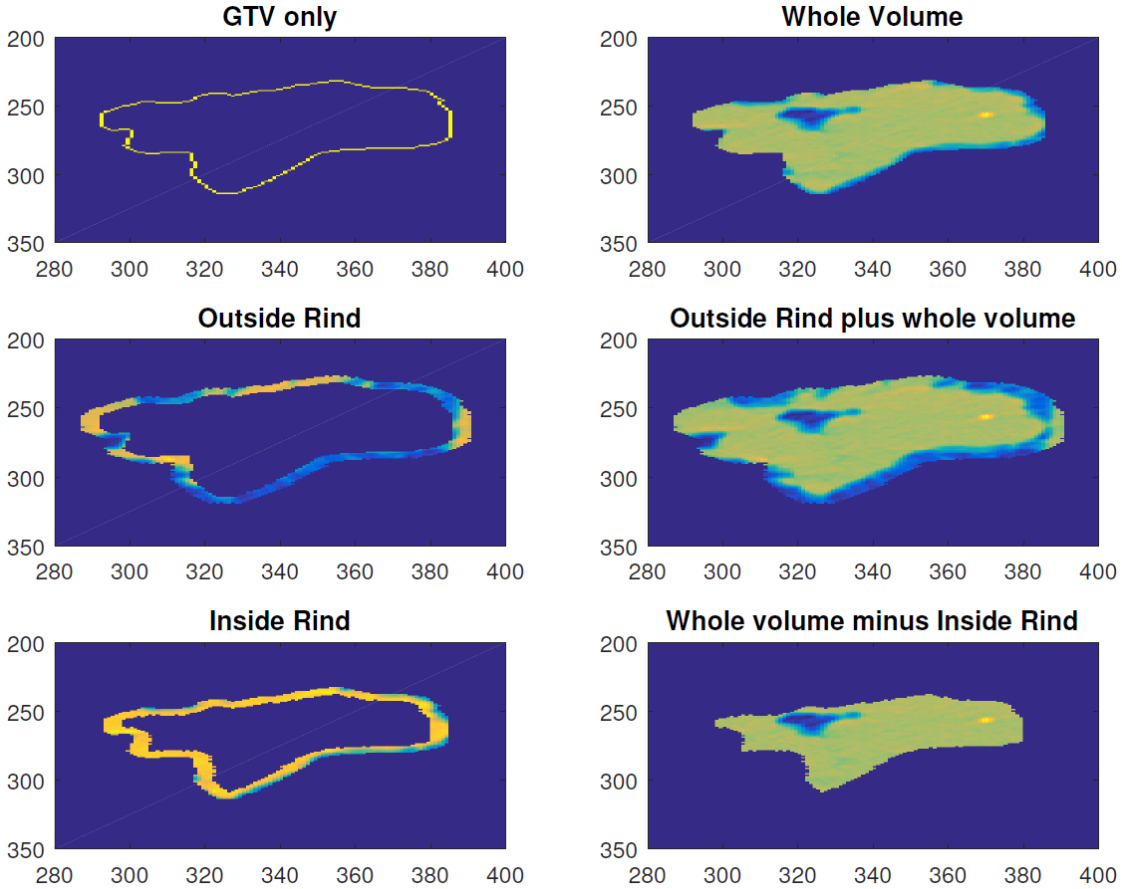
$$S_o = \{\mathbf{x} \mid 0 < d(\mathbf{x}, \hat{\mathcal{V}}) < L\}, \qquad (1)$$

where L is the width of a region that contains all line segments perpendicular to the surface. So is therefore a region external to the ROI. Conversely, we have

$$S_i = \{\mathbf{x} \mid \ -L < d(\mathbf{x}, \hat{\mathcal{V}}) < 0\}, \qquad (2)$$

defining an inner region such that $S_i \subseteq \mathcal{V}$. Colloquially, we refer to the region, $S = \{S_i \cup S_o\}$, as the rind of a given ROI, obtained by expanding or contracting the ROI uniformly from the surface by L.

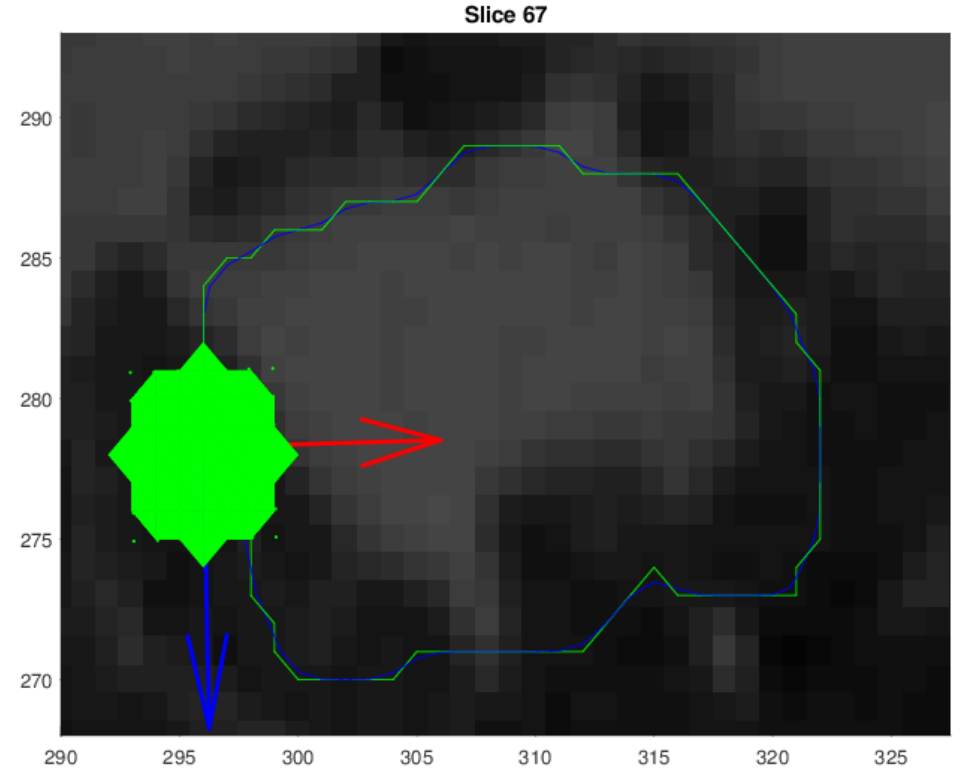
Rind Comparison



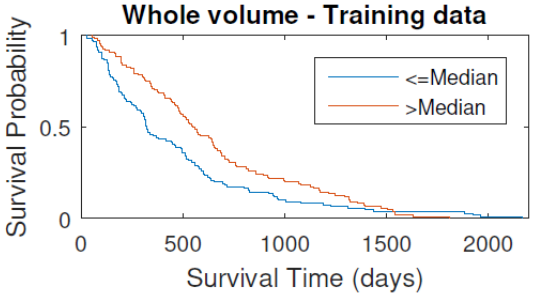
Note: the dark blue background is not included in this analysis.

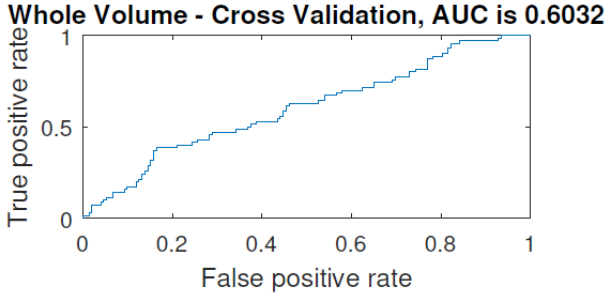
Rind analysis

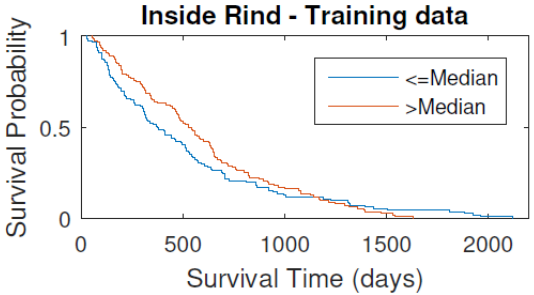
- Logistic Regression

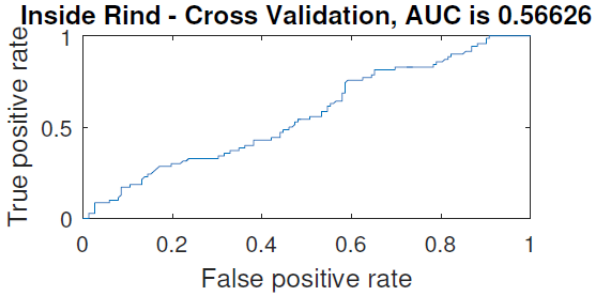


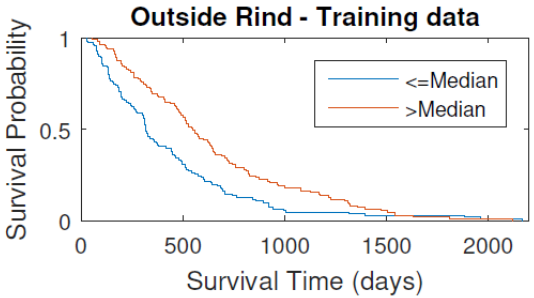
Kaplan Meier Survival Curves – Three Features

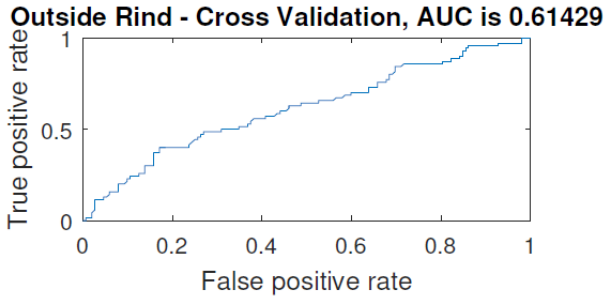




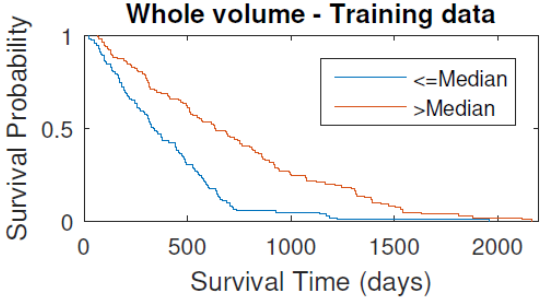


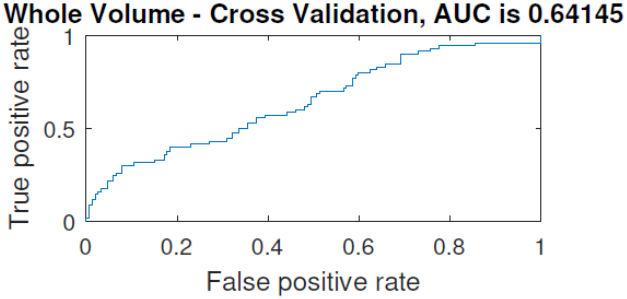


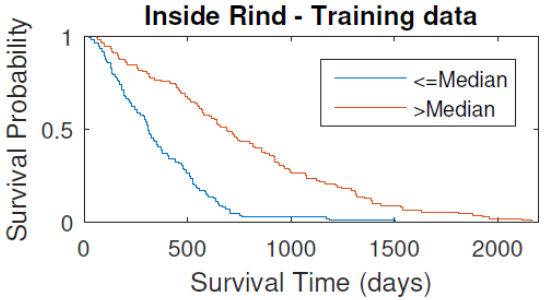


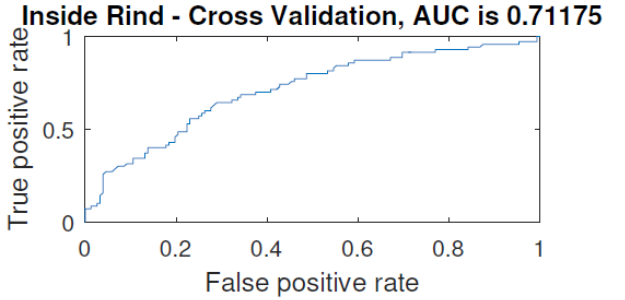


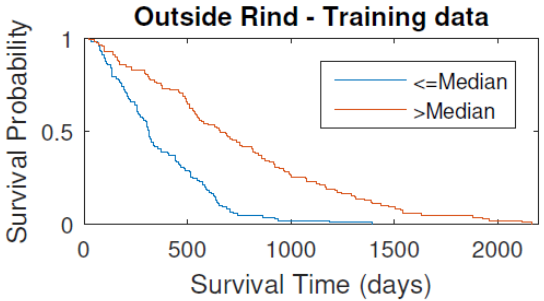
Kaplan Meier Survival Curves – Texture Features

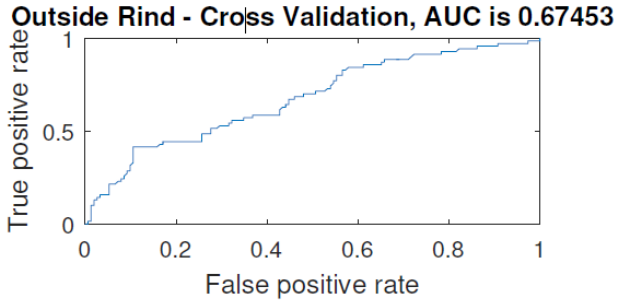












AUC Results from 20 iterations of logistic regression using ten fold cross validation

Volume Analysed	Three Features AUC$\pm\sigma$	Texture Features AUC$\pm\sigma$
Whole vol.	0.589±0.015	0.661±0.016
Inner rind	0.558±0.011	0.679± 0.024
Outer rind	**0.598**±0.011	0.689± 0.015
Outer rind with vol.	0.583±0.013	**0.699**± 0.011
Vol. excl. inner rind	0.584±0.013	0.624± 0.015

Conclusion

- Explored the textual radiomic features in a whole 3D tumour volume, compared to the inside and outside rind of the tumour only, for CT images of NSCLC.
- The derived models were compared against the previous methods of training radiomic signatures that are descriptive of the whole tumour volume.
- Radiomic features derived solely from regions external, but neighbouring, the tumour were shown to also have prognostic value.
- Textual features found within the tumour rinds were very similar to the textures in the entire tumour volume, and this analysis predicted two-year survival with an improved accuracy of 3% for survival classification using textures from the outside rind compared to the whole volume.

Clinical Implications

- It is important to note, that there is significant clinical uncertainty in defining the tumour boundaries of the GTV and that this should be considered when viewing these results.
- These results indicate that while the centre of the tumour is currently the main clinical target for radiotherapy treatment, the tissue immediately around the tumour is also clinically important.

Future Work

- One limitation of this work is in the arbitrary selection of the radiomic features.
- In future work we will use a machine learning algorithm such as convolutional neural networks to determine which radiomic features have the highest prognostic significance for determining two-year survival.
- Furthermore the radiomic features themselves are determined based on general mathematical formulas associated with analysing an image, in a future study we plan to use modern image processing techniques to determine alternative radiomic features.

Questions?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References

[1] P. Lambin, E. Rios-Velazquez, R. Leijenaar, S. Carvalho, R. G. P. M. van Stiphout, P. Granton, C. M. L. Zegers, R. Gillies, R. Boellard, A. Dekker, and H. J. W. L. Aerts, “Radiomics: Extracting more information from medical images using advanced feature analysis,” *Eur. J. Cancer*, vol. 48, no. 4, pp. 441–446, Mar. 2012.

[2] V. Kumar, Y. Gu, S. Basu, A. Berglund, S. A. Eschrich, M. B. Schabath, K. Forster, H. J. W. L. Aerts, A. Dekker, D. Fenstermacher, D. B. Goldgof, L. O. Hall, P. Lambin, Y. Balagurunathan, R. A. Gatenby, and R. J. Gillies, “Radiomics: The process and the challenges,” *Magn. Reson. Imaging*, vol. 30, no. 9, pp. 1234–1248, 2012.

[3] H. J. W. L. Aerts, E. R. Velazquez, R. T. H. Leijenaar, C. Parmar, P. Grossmann, S. Carvalho, J. Bussink, R. Monshouwer, B. Haibe-Kains, D. Rietveld, F. Hoebers, M. M. Rietbergen, C. R. Leemans, A. Dekker, J. Quackenbush, R. J. Gillies, and P. Lambin, “Corrigendum: Decoding tumour phenotype by noninvasive imaging using a quantitative radiomics approach,” *Nat Commun*, vol. 5, Aug. 2014.

[4] A. Dekker, S. Vinod, L. Holloway, C. Oberije, A. George, G. Goozee, G. P. Delaney, P. Lambin, and D. Thwaites, “Rapid learning in practice: A lung cancer survival decision support system in routine patient care data,” *Radiother. Oncol.*, vol. 113, no. 1, pp. 47–53, Oct. 2014.

[5] P. Scovanner, S. Ali, and M. Shah, “A 3-dimensional Sift Descriptor and Its Application to Action Recognition,” in *Proceedings of the 15th ACM International Conference on Multimedia*, 2007, pp. 357–360.

[6] J. Sánchez, F. Perronnin, T. Mensink, and J. Verbeek, “Image Classification with the Fisher Vector: Theory and Practice,” *Int. J. Comput. Vis.*, vol. 105, no. 3, pp. 222–245, 2013.

[7] T. P. Coroller, P. Grossmann, Y. Hou, E. R. Velazquez, R. T. H. Leijenaar, G. Hermann, P. Lambin, B. Haibe-Kains, R. H. Mak, and H. Aerts, “CT-based radiomic signature predicts distant metastasis in lung adenocarcinoma,” *Radiother. Oncol.*, vol. 114, no. 3, pp. 345–350, 2015.

[8] M. Vallières, C. R. Freeman, S. R. Skamene, and I. El Naqa, “A radiomics model from joint FDG-PET and MRI texture features for the prediction of lung metastases in soft-tissue sarcomas of the extremities,” *Phys. Med. Biol.*, vol. 60, no. 14, p. 5471, 2015.