BAINES IMAGING

RADIOMICS AND MACHINE LEARNING FOR OROPHARYNGEAL CANCER

Sarah A. Mattonen, Ph.D.

Assistant Professor, Depts. of Medical Biophysics and Oncology, Western University

Baines Research Chair in Translational Cancer Imaging

Scientist, Lawson Health Research Institute
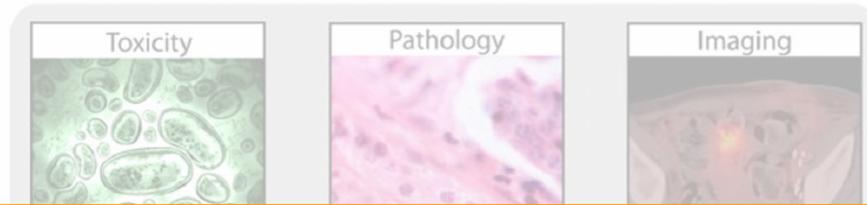
Translational Cancer Imaging

Computer-Aided Decision Support

Improve Patient Outcomes

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

BAINES IMAGING

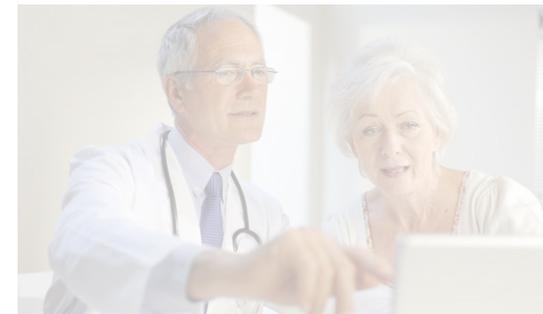sarah.mattonen@uwo.ca

Research Focus

Clinical Decision Making

To develop, evaluate, and translate clinically relevant quantitative image analysis tools supporting diagnosis, treatment, and response assessment in oncology.
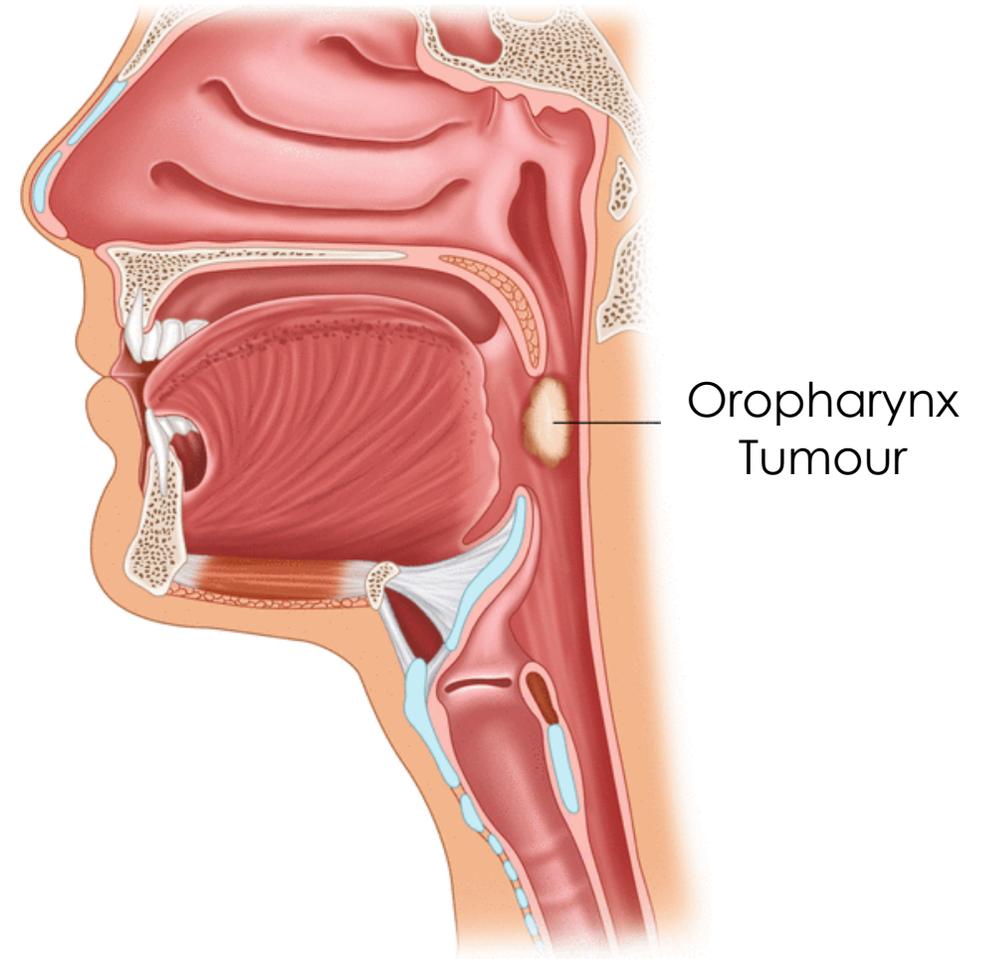
Toxicity

Pathology

Imaging

Genomics

Proteomics

Treatment Decision

**Improve Patient Outcomes**

BAINES IMAGING

sarah.mattonen@uwo.ca

Oropharyngeal Cancer

► Oropharyngeal cancer is the fastest-rising incident cancer in Canada

► This increase is due to rapidly increasing rates of oral infection with the human papilloma virus (HPV)

Oropharynx Tumour

Radiomics

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

Image

Segmentation

Feature Extraction

Machine Learning
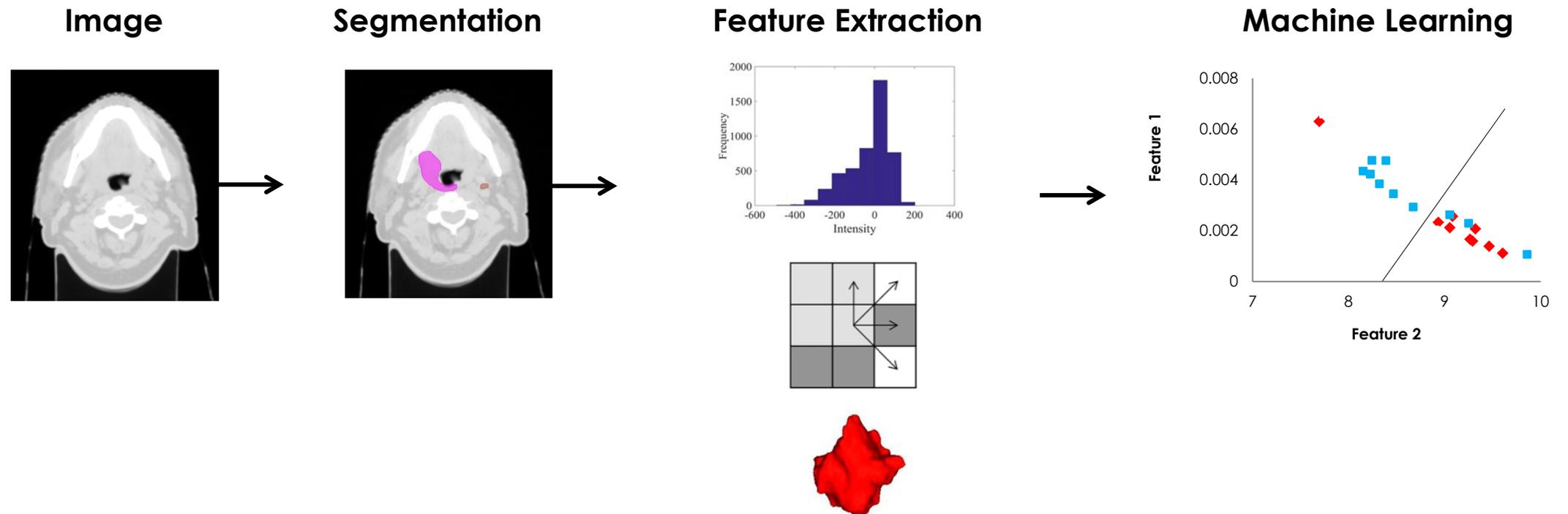
HOW CAN WE CREATE REPRODUCIBLE RADIOMIC MODELS?

Dataset

► 363 patients with oropharyngeal cancer

► Treated with chemoradiation at the London Regional Cancer Program between 2013 and 2018
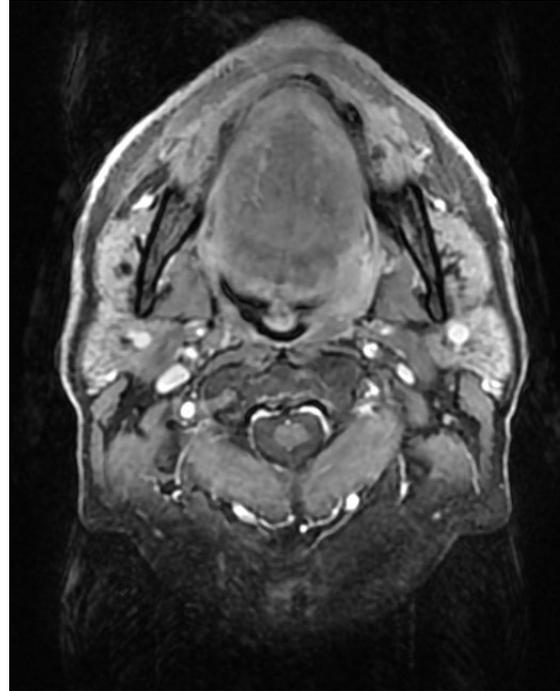
► Planning CT +/- MRI with target volume contours
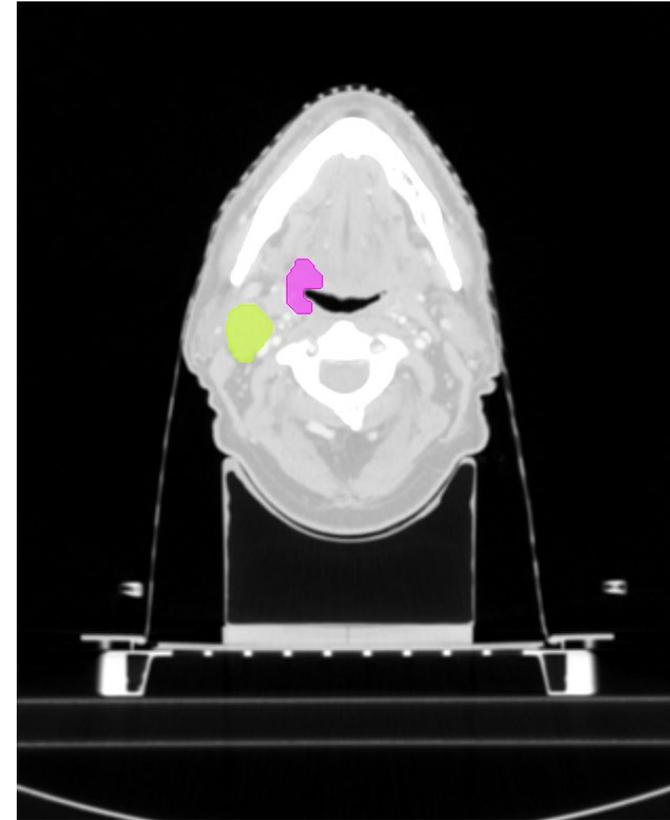
Imaging Challenges for Reproducibility

► Variability in Imaging

► Variability in Contouring

► Contrast

► CT Artifacts

Imaging Variability
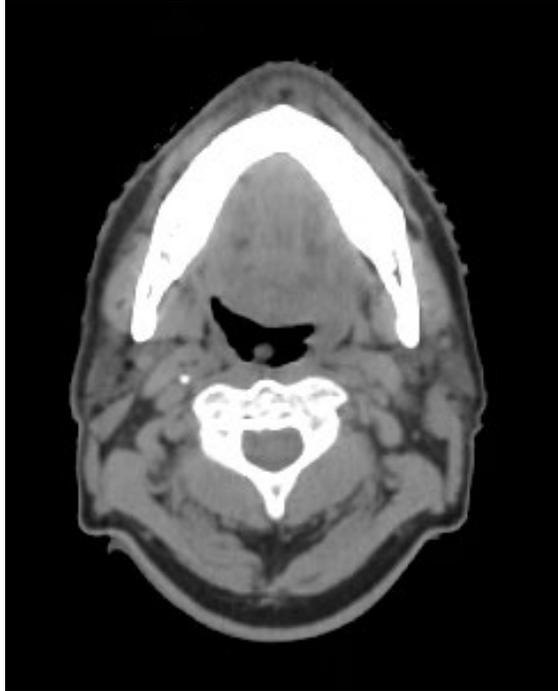
CT

T1-MRI

T2-MRI

Imaging Variability

BAINES IMAGING

sarah.mattonen@uwo.ca
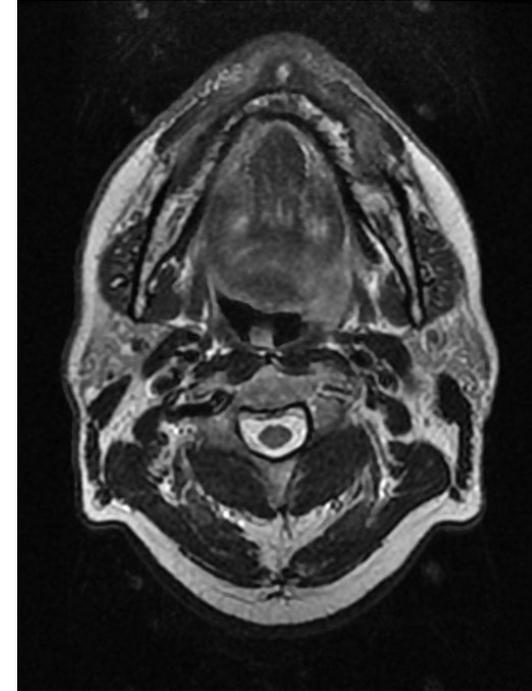
Imaging Variability
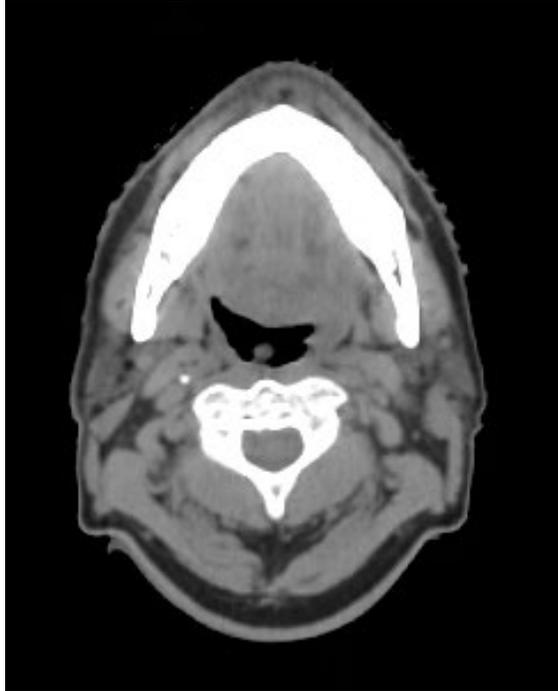
CT
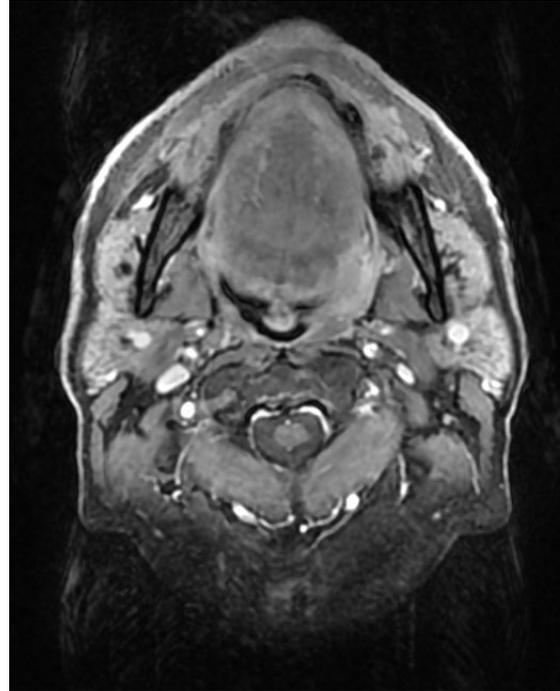
T1-MRI

T2-MRI

Contour Naming and Variability

► Gross Tumor Volume (GTV)
  > Primary and/or nodes

sarah.mattonen@uwo.ca
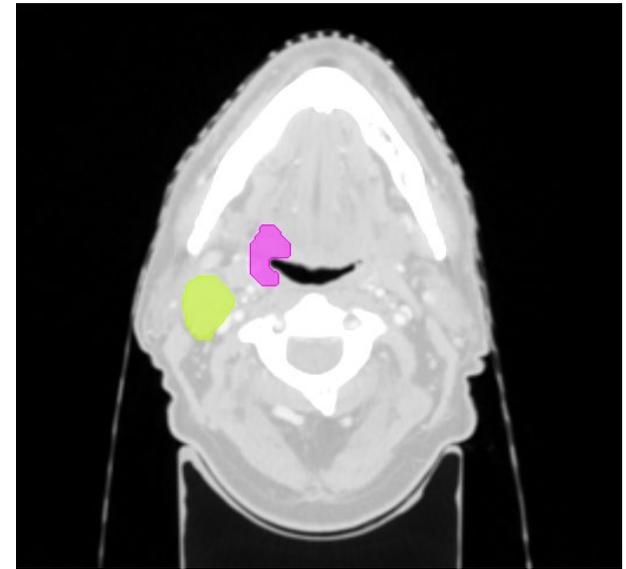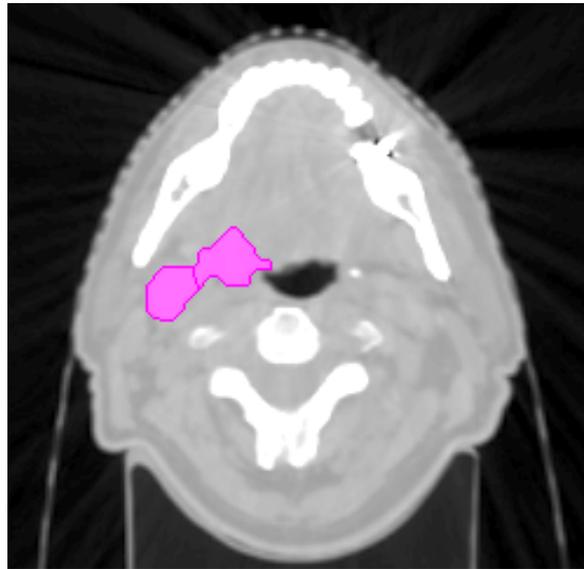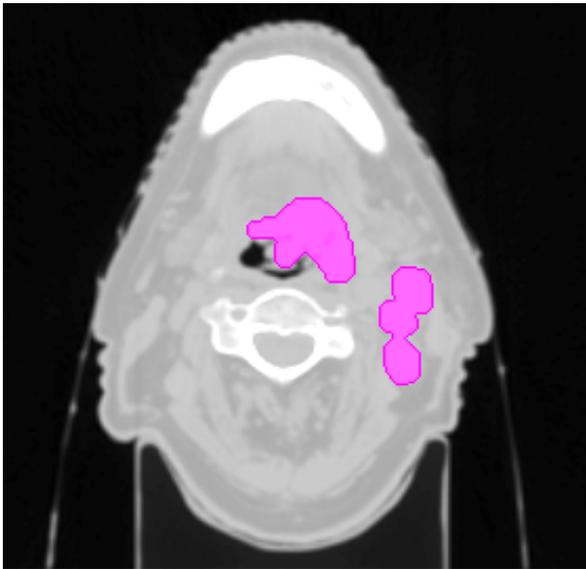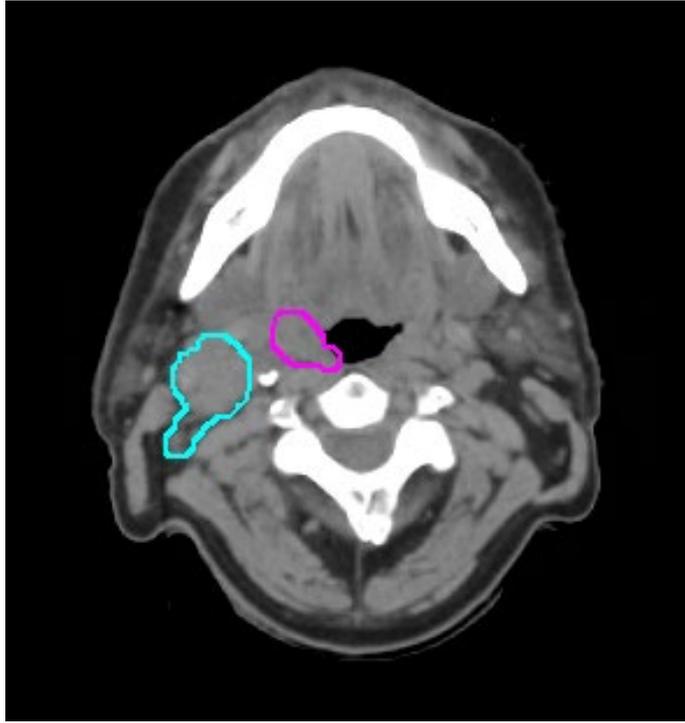
Contrast

No Contrast
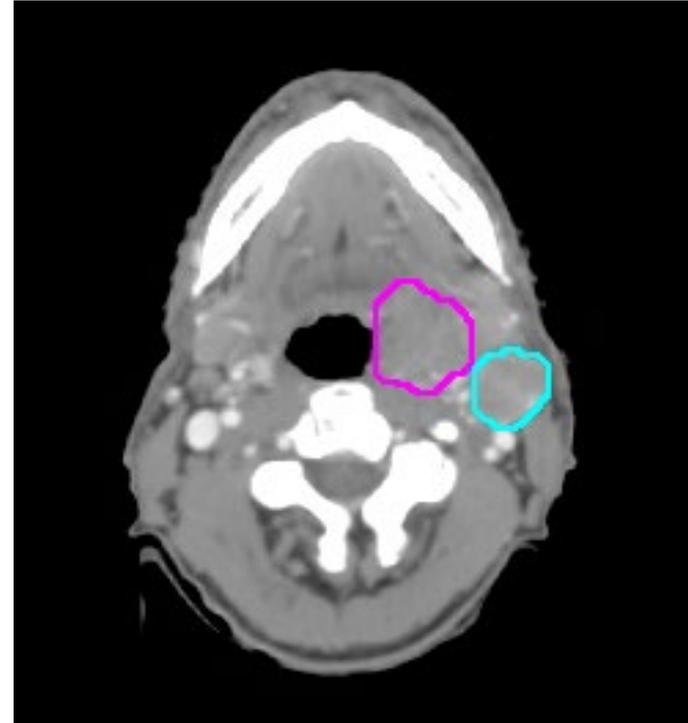
Contrast

CT Artifacts
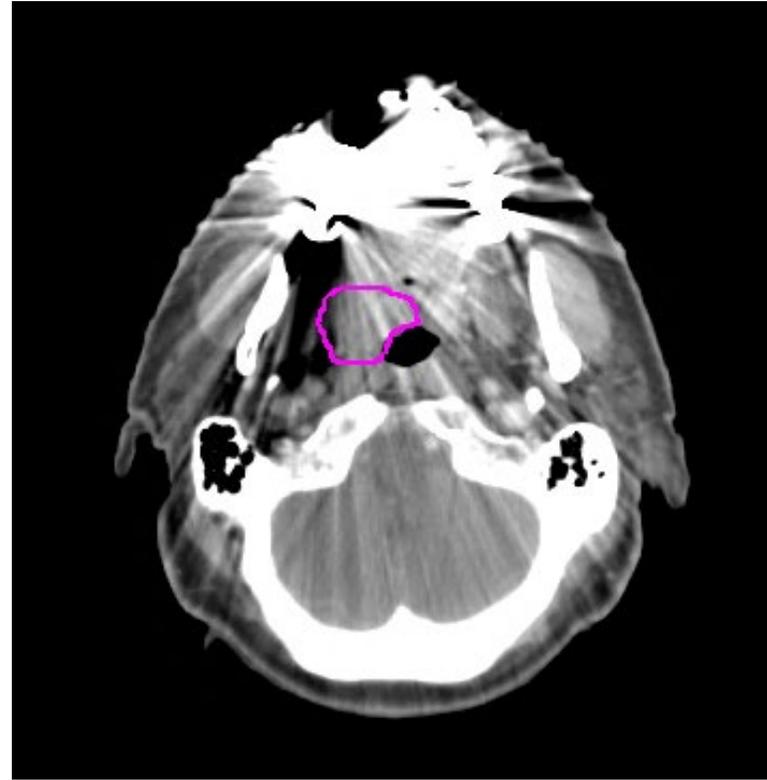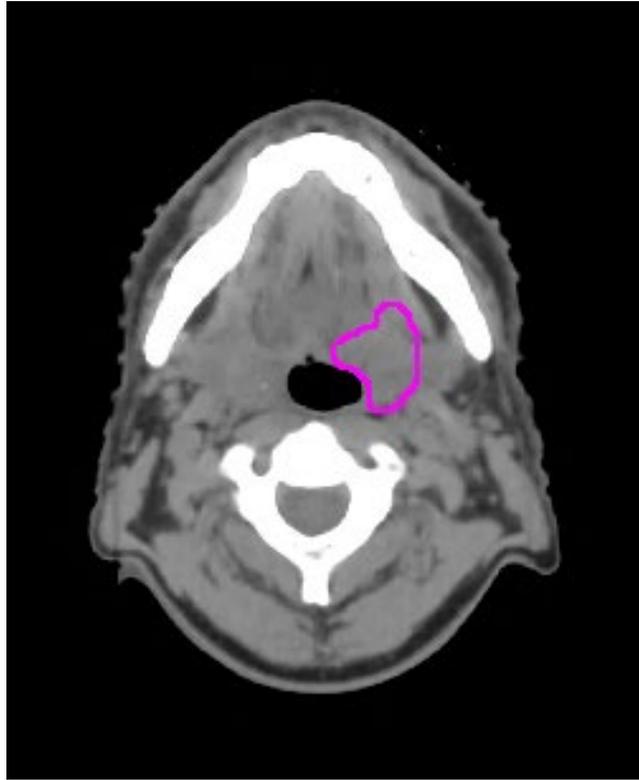
CT Artifacts

DentalArtifactModel

Dental artifact Classification in H&N CT

PYTORCH   NETRON

Welch, Mattea L., et al. *Physics in Medicine & Biology* 65.3 (2020): 035017.

sarah.mattonen@uwo.ca

Imaging Challenges for Reproducibility

► Variability in Imaging

► Variability in Contouring

► Contrast

► CT Artifacts

HOW CAN VALIDATE EXISTING RADIOMIC MODELS?

BAINES IMAGING — sarah.mattonen@uwo.ca

HOW CAN WE VALIDATE EXISTING RADIOMIC MODELS?

Philipp Guevorguian
Medical Biophysics
BMSc Student
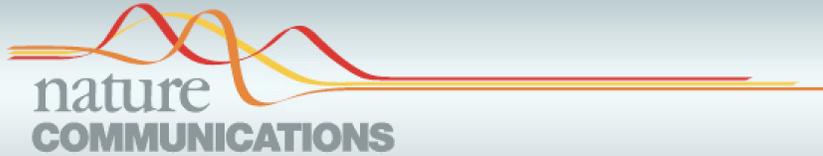
BAINES IMAGING

sarah.mattonen@uwo.ca

Validation of Existing Models

Decoding tumour phenotype by noninvasive imaging using a quantitative radiomics approach

Hugo J.W.L. Aerts[1,2,3,4,*], Emmanuel Rios Velazquez[1,2,*], Ralph T.H. Leijenaar[1], Chintan Parmar[1,2], Patrick Grossmann[2], Sara Carvalho[1], Johan Bussink[5], René Monshouwer[5], Benjamin Haibe-Kains[6], Derek Rietveld[7], Frank Hoebers[1], Michelle M. Rietbergen[8], C. René Leemans[8], Andre Dekker[1], John Quackenbush[4], Robert J. Gillies[9] & Philippe Lambin[1]

Prognostic Radiomics Signature

► Features were extracted on a lung cancer dataset (Lung1)

► **Cox model** was built to predict **overall survival** using four radiomic features:
    1. First order energy
    2. Compactness
    3. Gray level run length matrix (GLRLM) gray level non-uniformity
    4. Wavelet (HLH) GLRLM gray level non-uniformity

► This signature was validated on two cohorts of patients with head and neck cancer

Aerts et al, Nature Communications, 5(1):1-9

BAINES IMAGING

sarah.mattonen@uwo.ca

Validation of Existing Models
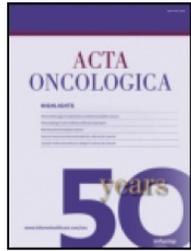
Acta Oncologica

External validation of a prognostic CT-based radiomic signature in oropharyngeal squamous cell carcinoma

Ralph T. H. Leijenaar, Sara Carvalho, Frank J. P. Hoebers, Hugo J. W. L. Aerts, Wouter J. C. van Elmpt, Shao Hui Huang, Biu Chan, John N. Waldron, Brian O'sullivan & Philippe Lambin

Original article

Vulnerabilities of radiomic signature development: The need for safeguards

Mattea L. Welch [a,f,i], Chris McIntosh [e,f,i], Benjamin Haibe-Kains [a,c,i,j], Michael F. Milosevic [b,e,i], Leonard Wee [g], Andre Dekker [g], Shao Hui Huang [b,i], Thomas G. Purdie [b,e,f,i], Brian O'Sullivan [b,i], Hugo J.W.L. Aerts [h], David A. Jaffray [a,b,d,e,f,i,*]

[a] Department of Medical Biophysics, University of Toronto; [b] Department of Radiation Oncology, University of Toronto; [c] Ontario Institute of Cancer Research, Toronto; [d] IBBME, University of Toronto; [e] Radiation Medicine Program, Princess Margaret Cancer Centre, Toronto; [f] The Techna Institute for the Advancement of Technology for Health, Toronto, Canada; [g] Department of Radiation Oncology (MAASTRO), GROW Research Institute, Maastricht University, the Netherlands; [h] Dana-Farber Cancer Institute, Brigham and Women's Hospital, Harvard Medical School, Boston, USA; [i] Princess Margaret Cancer Centre, University Health Network; and [j] Vector Institute, Toronto, Canada

BAINES IMAGING

sarah.mattonen@uwo.ca

Validation of Existing Models

▶ **Pyradiomics** was used to extract radiomic features on Lung1 and our local OPC dataset

▶ A **Cox model** was built to predict **overall survival (OS)** based on four radiomic features:
  1. First order energy
  2. Compactness
  3. Gray level run length matrix (GLRLM) gray level non-uniformity
  4. Wavelet (HLH) GLRLM gray level non-uniformity

Challenges with Validation of Existing Models

► Radiomic feature extraction:
  > Inconsistency / updates to feature equations
  > In-house vs. open-source software
  > Parameters

$$Compactness1 = \frac{V}{\sqrt{\pi}A^{\frac{3}{2}}}$$

$$Compactness1 = \frac{V}{\sqrt{\pi}A^{\frac{2}{3}}}$$

◆◆ BAINES IMAGING

Challenges with Validation of Existing Models

► Model validation:
  > Model weights are not reported
  > Median threshold for risk group stratification not reported
  > Software variability

Coefficients of Cox Model from Lung1 Dataset

Feature	Aerts et al, 2014 (Reported in Leijenaar et al, 2015)	Welch et al, 2018	London
First-Order Energy	2.42E-11	1.74E-11	6.62E-11
Compactness	-5.38E-03	-1.65E+01	-8.32E00
GLRLM Gray Level Non-Uniformity	-1.47E-04	4.95E-05	1.50E-05
HLH GLRLM Gray Level Non-Uniformity	9.39E-06	2.81E-06	2.76E-05

Coefficients of Cox Model from Lung1 Dataset

Feature	Aerts et al, 2014 (Reported in Leijenaar et al, 2015)	Welch et al, 2018	London
First-Order Energy	2.42E-11	1.74E-11	6.62E-11
Compactness	-5.38E-03	-1.65E+01	-8.32E00
GLRLM Gray Level Non-Uniformity	-1.47E-04	4.95E-05	1.50E-05
HLH GLRLM Gray Level Non-Uniformity	9.39E-06	2.81E-06	2.76E-05

Coefficients of Cox Model from Lung1 Dataset

Feature	Aerts et al, 2014 (Reported in Leijenaar et al, 2015)	Welch et al, 2018	London
First-Order Energy	2.42E-11	1.74E-11	6.62E-11
Compactness	-5.38E-03	-1.65E+01	-8.32E00
GLRLM Gray Level Non-Uniformity	-1.47E-04	4.95E-05	1.50E-05
HLH GLRLM Gray Level Non-Uniformity	9.39E-06	2.81E-06	2.76E-05

Cox Model – London Dataset

▶ Concordance = 0.69 [95% CI: 0.61– 0.77]
> Log-rank p<0.001

Feature	Coefficient	p-value
First-Order Energy	-4.44E-9	p=0.052
Compactness	-1.02E2	**p=0.005***
GLRLM Gray Level Non-Uniformity	-9.75E-4	p=0.214
HLH GLRLM Gray Level Non-Uniformity	9.47E-4	**p=0.026***

Considerations in Head and Neck Radiomics

► Impact of radiomic features on:
  > Segmentation variability
  > CT artifacts

► Open-source software

► Detailed description of all methodology:
  > Image acquisition
  > Radiomic feature extraction
  > Machine learning modeling

► **Radiomics Quality Score (RQS)** and **Image Biomarker Standardization Initiative (IBSI)**

Future Opportunities

- ► Incorporation of clinical data

- ► Integration of dosimetric information

- ► Prospective data collection

- ► Collaboration and validation of models

Future Opportunities

- ▶ Incorporation of clinical data

- ▶ Integration of dosimetric information

- ▶ Prospective data collection

- ▶ Collaboration and validation of models

Imaging and machine learning applications have the potential to make real changes to clinical practice!

AFFILIATIONS

FUNDING AGENCIES

Acknowledgements

Department of Otolaryngology, Western University

Department of Oncology, Western University

Anthony Nichols, MD

Kathleen Surry, PhD

Pencilla Lang, MD, PhD

David Palma, MD, PhD

@MattonenLab

http://www.bainesimaging.com/

BAINES IMAGING

sarah.mattonen@uwo.ca

Translational Cancer Imaging

Computer-Aided Decision Support

Improve Patient Outcomes

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

BAINES IMAGING

sarah.mattonen@uwo.ca