MRO . ART
MODERN RADIATION ONCOLOGY
35° RESIDENTIAL COURSE

INNOVATION AND SUSTAINABILITY IN GYNAECOLOGICAL CANCER CARE

From Pixels to Precision
How AI and Radiomics are personalizing gynaecologic cancer care

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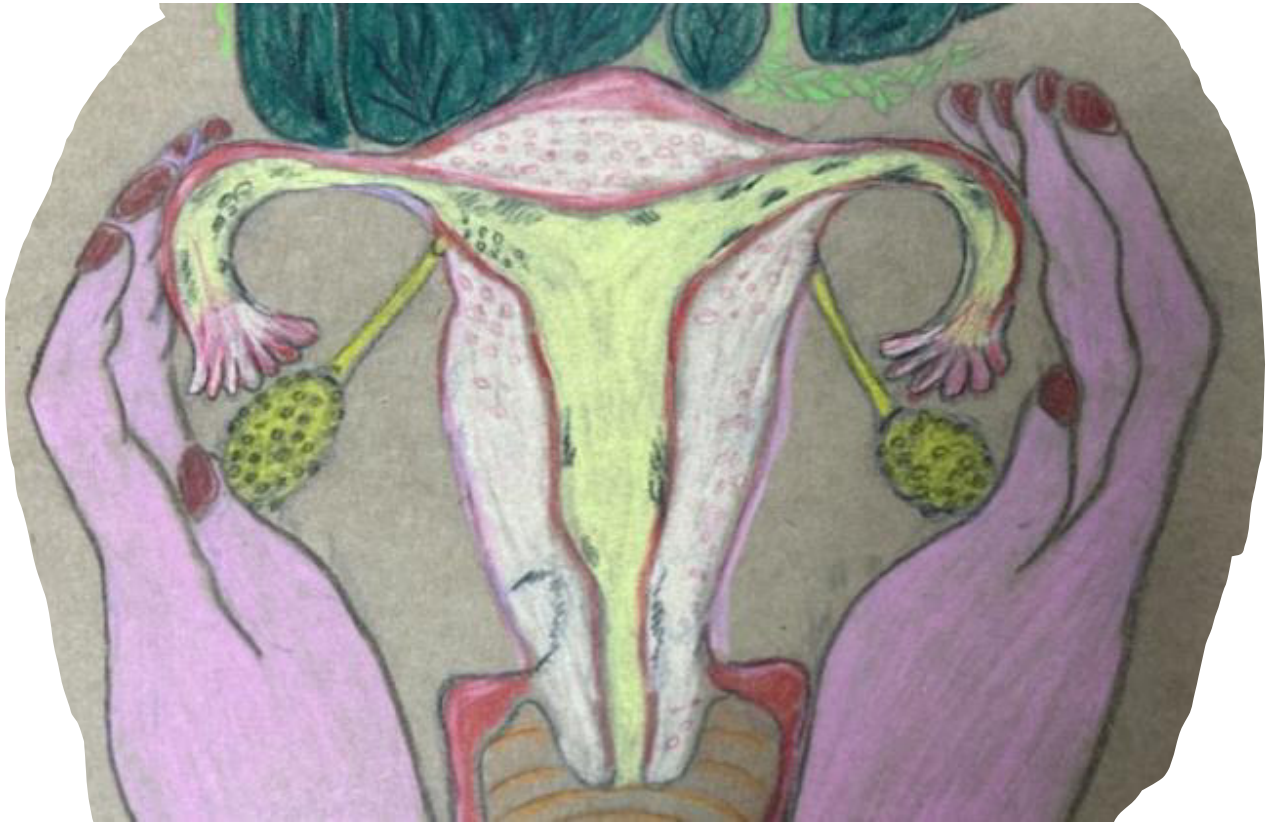
C-ART
Advanced Radiation Therapy

Outline

- Clinical needs
- Applications

  General

  Cancer specific:
  - *endometrial*
  - *cervical*
  - *ovarian*
- Take home messages



Clinical needs

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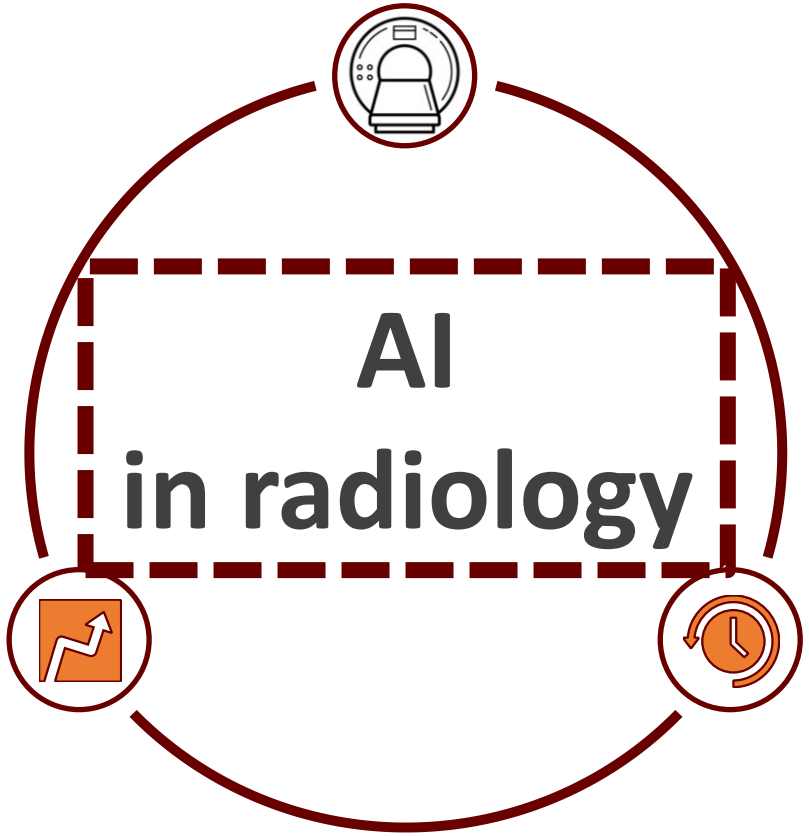
Protocol and Image Acquisition

MR: fasten acquisition CT: dose reduction



Clinical Care

Improve performance in current grey zones to tailor treatment plans

- *improve tumor characterization*
- *identify imaging biomarkers*

Interpretation

Workload Reduction

e.g segmentation

Clinical needs

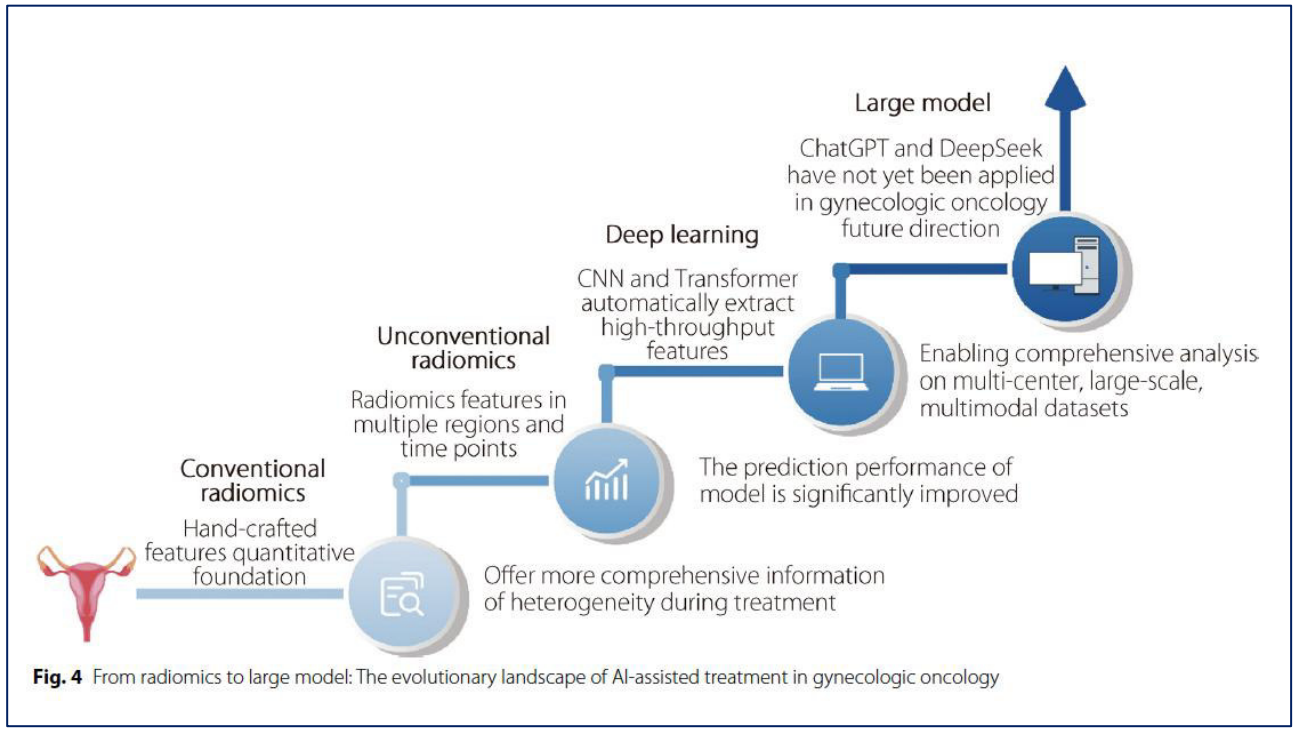


Fig. 4 From radiomics to large model: The evolutionary landscape of AI-assisted treatment in gynecologic oncology

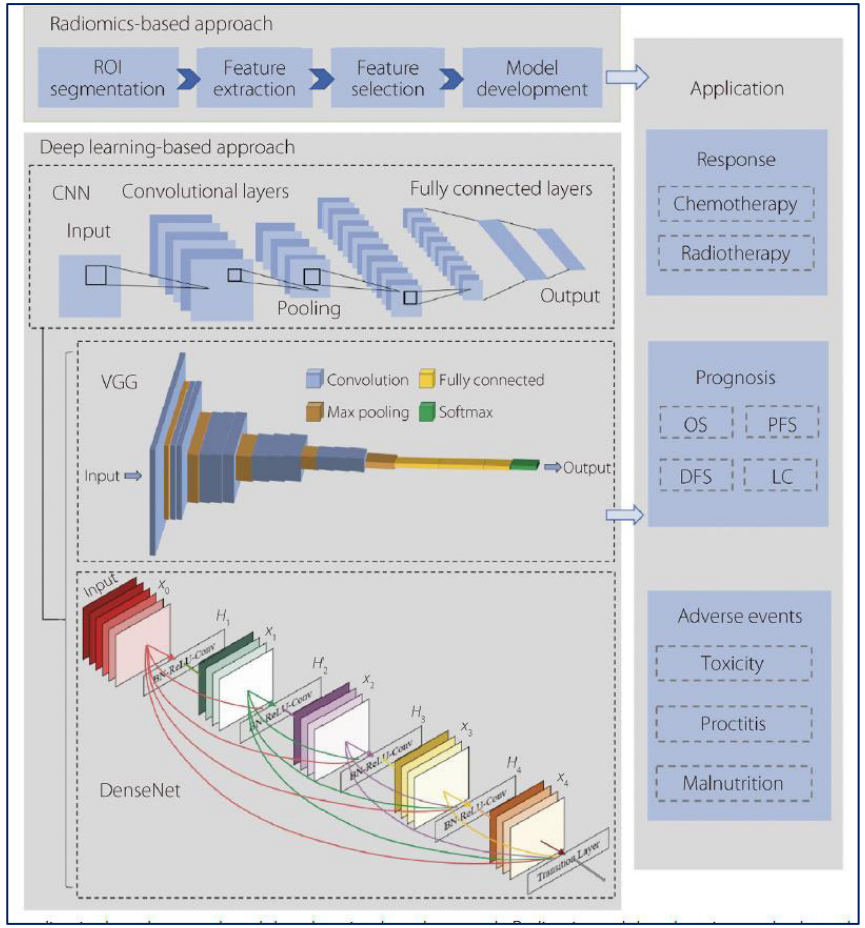
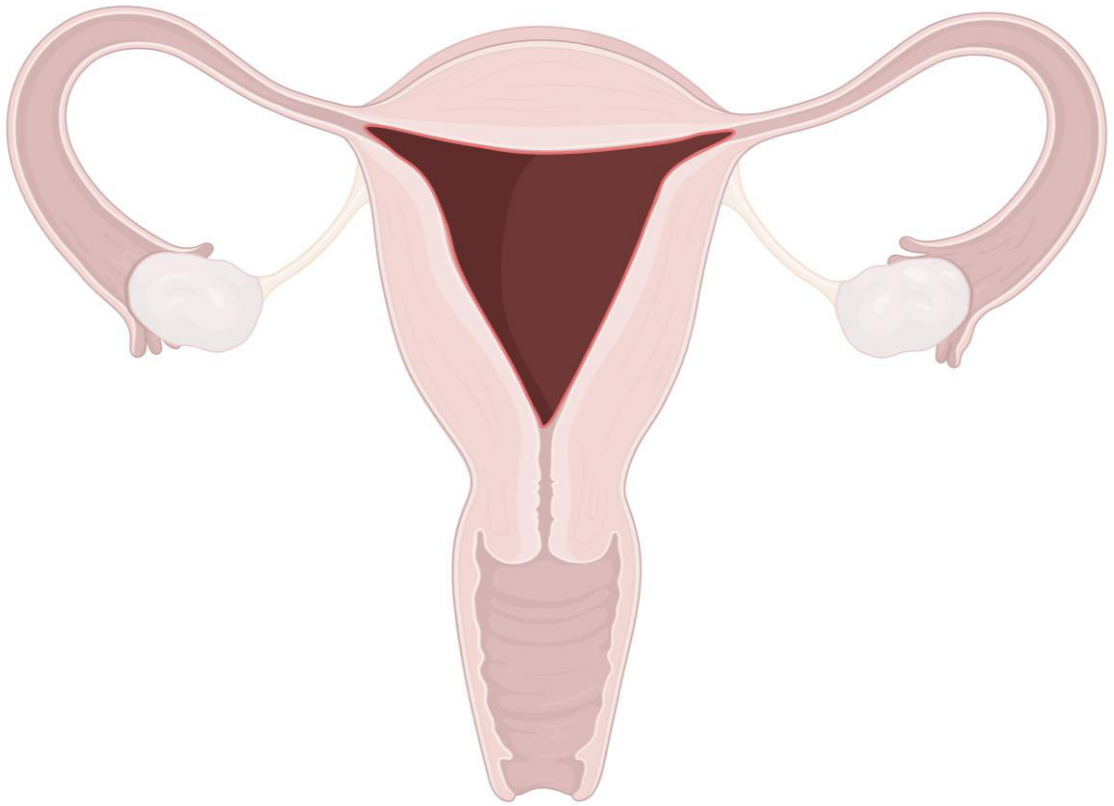
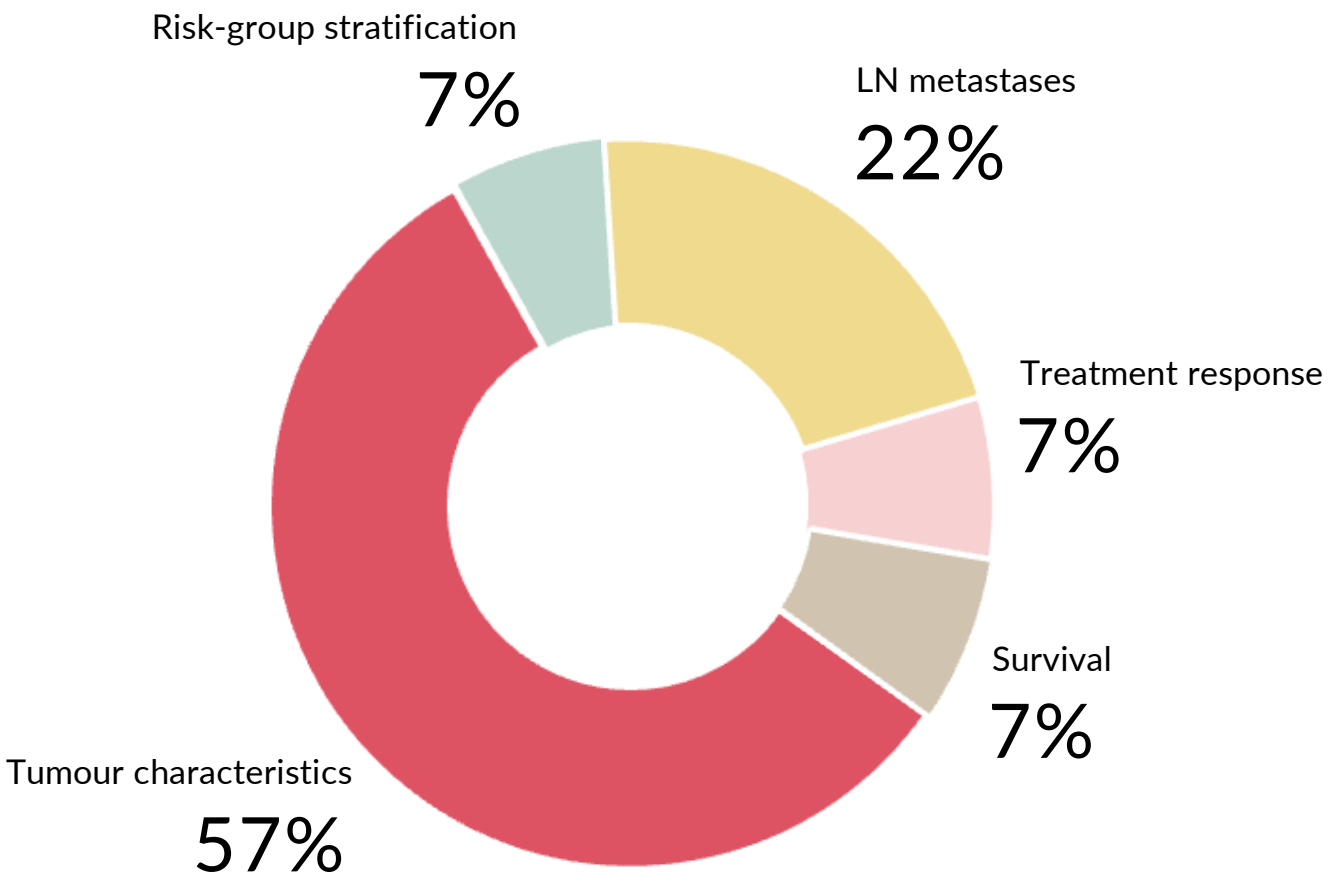


Fig. 2 Workflow for radiomics-based approach and deep learning-based approach. Radiomics and deep learning methods can be used to predict treatment response, prognosis, and adverse events in gynecologic oncology patients. VGG and DenseNet are common CNN networks. CNN, convolutional neural network; VGG, Visual geometry group; OS, Overall survival; PFS, Progression-free survival; DFS, Disease-free survival; LC, Local control

Application
Endometrial cancer





Shrestha P. et al. Gynecol Oncol, 2022

Application

Endometrial cancer – Current status radiomics research

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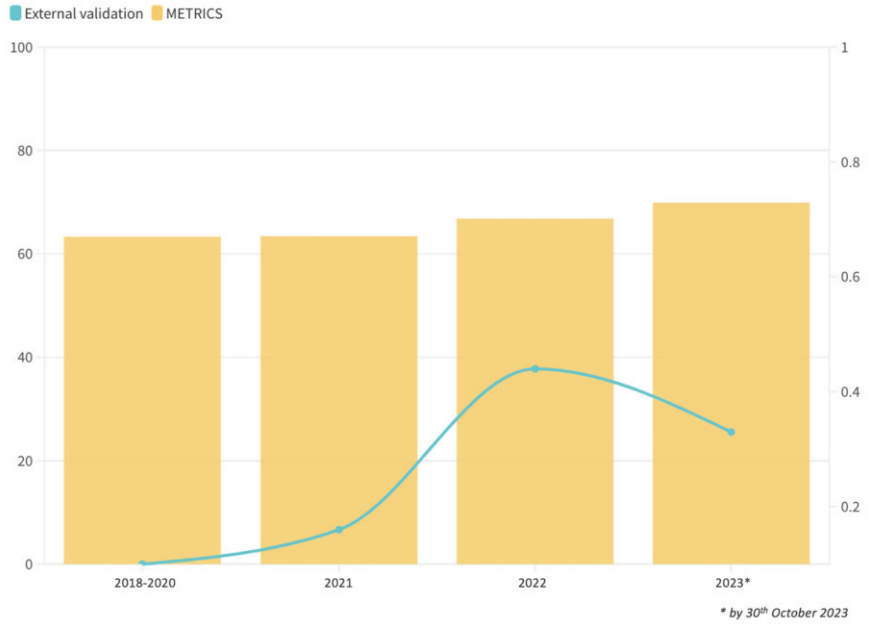
Systematic review:To assess the methodological quality of radiomics-based models

- 68 studies evaluated according to both RQS and METRICS:

  moderate-to-good overall quality



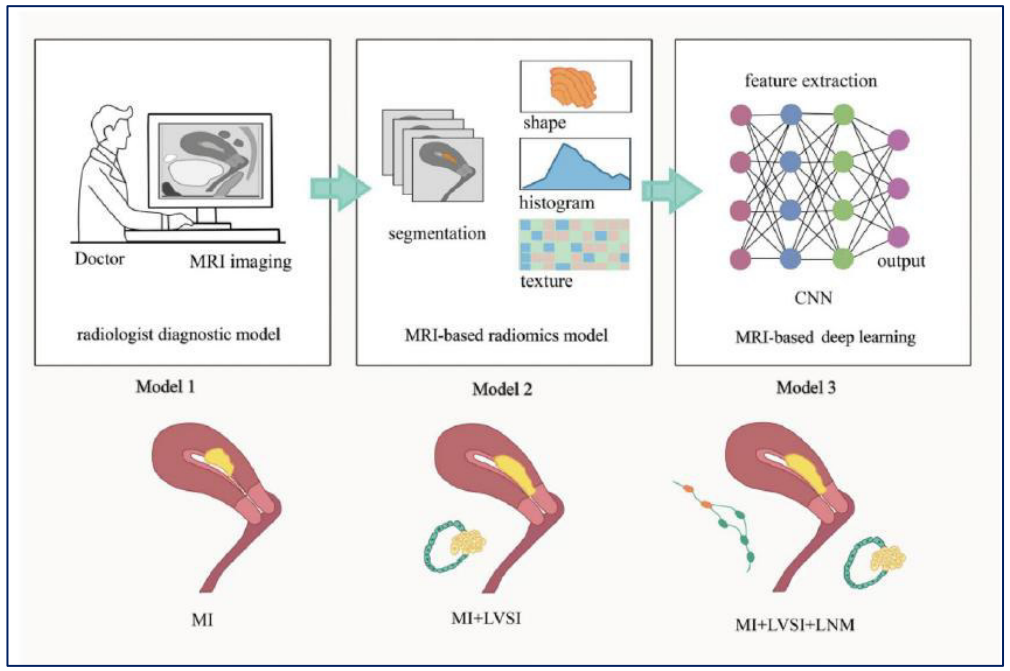
METRICS depicted specific methodological shortcomings:

- ➢ Automatic segmentations
- ➢ Comparison with simple or classical statistical methods
- ➢ External validation (overall 30%, but positive trend)
- ➢ Detection and discussion of biological correlates (18%)

Detecting and discussing biological correlates of radiomics research is critical in endometrial cancer because of the well-established histopathological and molecular characteristics included in the FIGO staging

Application

Endometrial cancer – Preoperative risk stratification



Meta-analysis:

35 papers: 2 DL and 33 radiomics

Median RQS: 12.6 (35%)

Results (sensitivity and specificity)

- **DMI:** 0.80 and 0.85
- **LVSI**: 0.85 and 0.73
- **LNM**: 0.90 and 0.72
- **Grading**: 0.84 and 0.83
- **MSI**: 0.79, 0.85 and 0.89

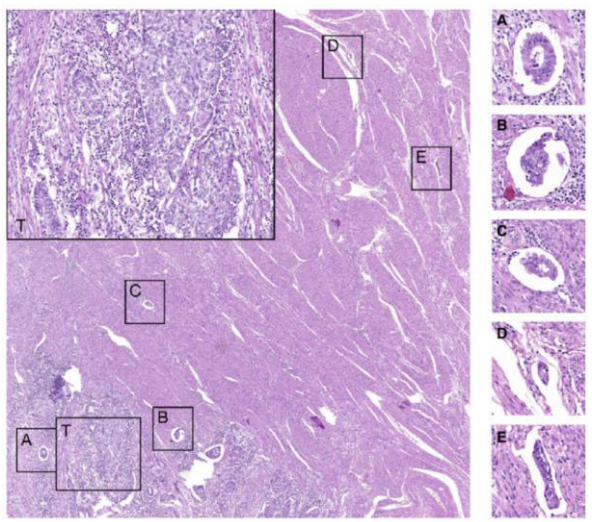
Preoperative MRI-derived ML could help clinicians

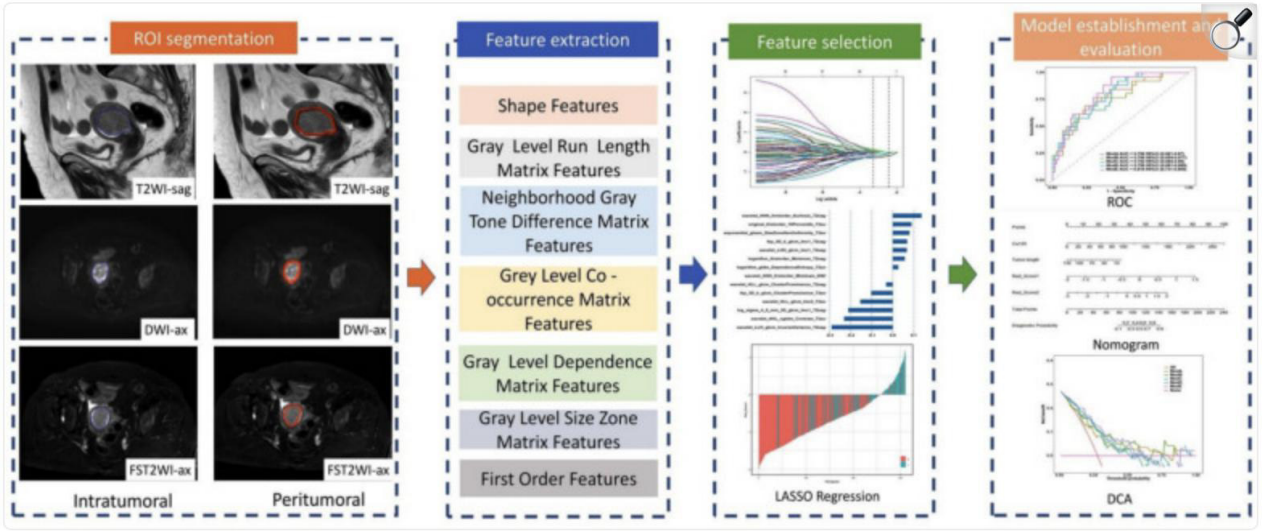
- accurately evaluate EC risk factors
- potentially guiding individual treatment

Gao Y. L. et al. Abdom Radiol, 2025

Application

Endometrial cancer – LVSI





Training set | *Validation set*

Model	AUC(95%CI)	ACC(95%CI)	SEN	SPE	PPV	NPV	AUC(95%CI)	ACC(95%CI)	SEN	SPE	PPV	NPV
Clinical model (ModA)	0.805 (0.740–0.870)	0.779 (0.777–0.780)	0.693	0.824	0.675	0.836	0.766 (0.661–0.870)	0.699 (0.694–0.703)	0.769	0.672	0.476	0.882
Peritumoral radiomics model (ModB)	0.791 (0.729–0.853)	0.737 (0.736–0.739)	0.707	0.754	0.602	0.829	0.766 (0.654–0.877)	0.742 (0.738–0.746)	0.692	0.761	0.529	0.864
Intratumoral radiomics model (ModC)	0.809 (0.748–0.869)	0.724 (0.722–0.725)	0.773	0.697	0.574	0.853	0.782 (0.684–0.880)	0.774 (0.771–0.778)	0.615	0.836	0.593	0.848
Intratumoral + peritumoral radiomics model (ModD)	0.817 (0.759–0.875)	0.793 (0.791–0.794)	0.587	0.901	0.759	0.805	0.788 (0.691–0.885)	0.645 (0.640–0.650)	0.885	0.552	0.434	0.925
Clinical + intratumoral + peritumoral radiomics model (ModE)	0.870 (0.821–0.919)	0.829 (0.828–0.831)	0.707	0.894	0.779	0.852	0.818 (0.731–0.905)	0.677 (0.673–0.682)	0.962	0.567	0.463	0.974

Ma W et al. BMC Cancer, 2025

Application

Endometrial cancer – Preoperative risk stratification

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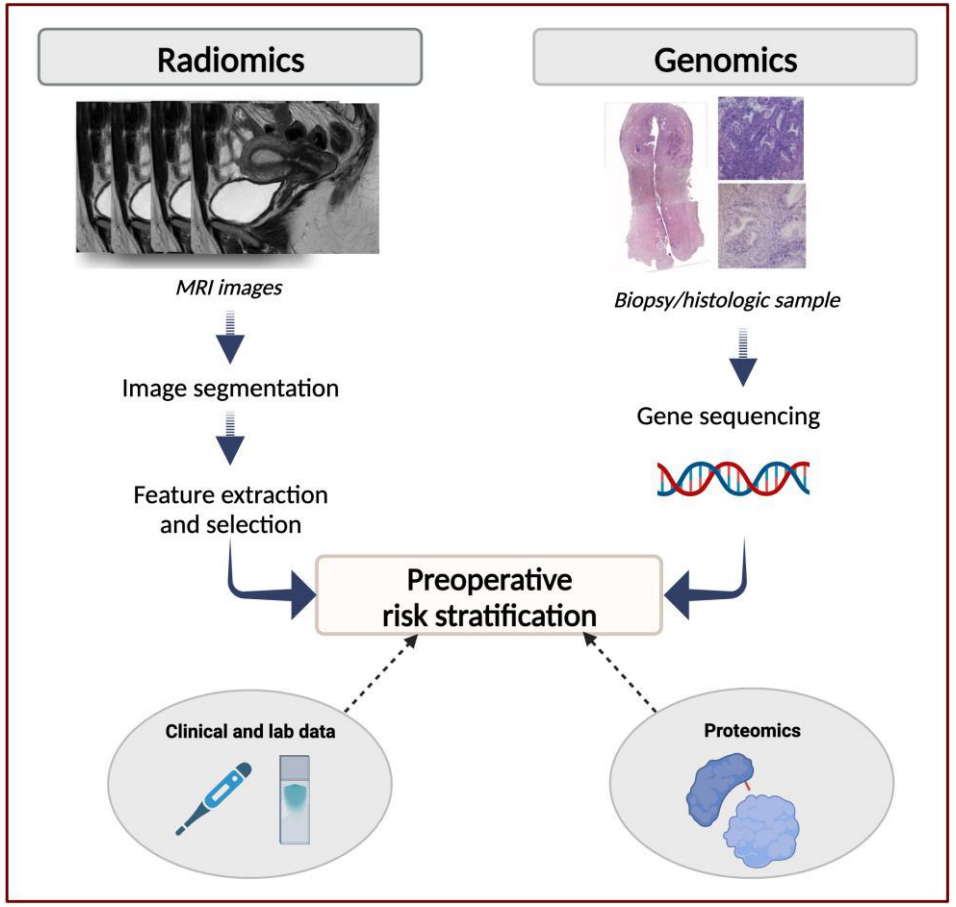
Radiogenomics describes relationships between molecular and imaging phenotypes



Major findings:

- Identification of an 11-gene high-risk signature associated with poor survival → *high copy number/p53-abnormalities*
- Radiomic prognostic index demonstrated strong association with specific genetic alterations:
  → *POLE mutations and p53-abnormalities*
- Moderate accuracy in identifying *MMRd* and tumor mutational burden from CT
- Good accuracy for preoperatory identification of *low-risk EC* according to 2020 ESGO-ESTRO-ESP classification
- Good accuracy for predicting POLEmut, MMRd, NMSP and P53 abn

Hoivik E.A. et al. Commun Biol, 2021; Jacob H. et al, J Clin Med, 2021; Celli V. et al, Cancers, 2022;
Veeraraghavan H. et al. Sci Rep, 2020; Zhou J et al, EJR, 2025

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Endometrial cancer – Preoperative risk stratification

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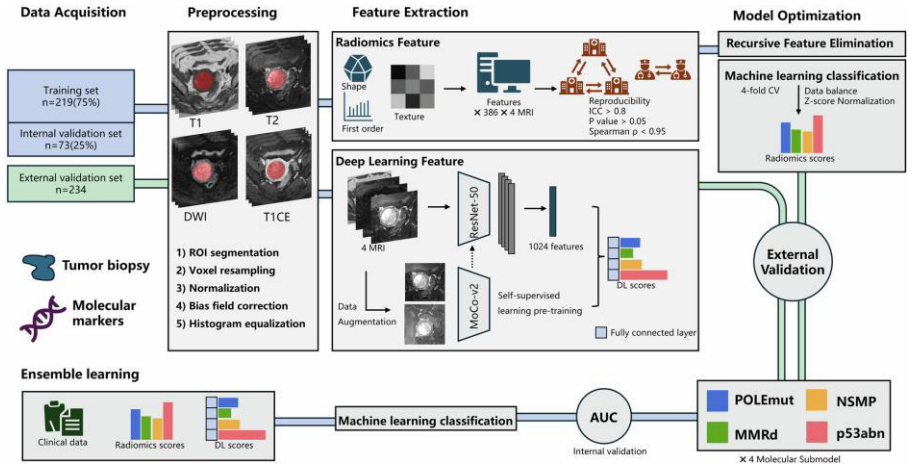

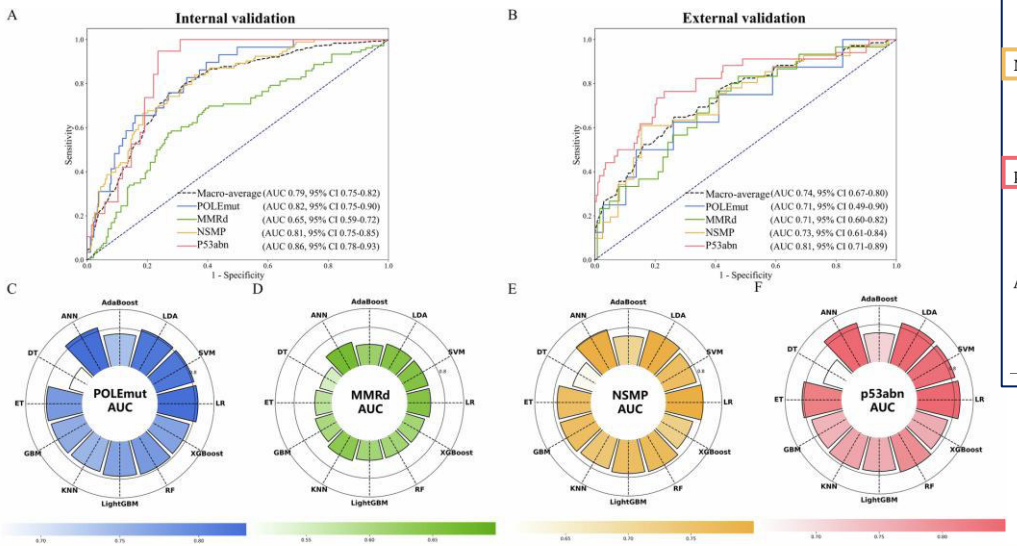

This study aimed to develop and validate a clinical-radiomics deep learning (DL) model based on MRI for EC molecular subtypes classification.

526 patients, from **3 centres. retrospective**

Molecular subtypes	Clinical model (AUC, 95% CI)	Radiomics model (AUC, 95% CI)	DL model (AUC, 95% CI)	Radiomics DL model (AUC, 95% CI)	Clinical-radiomics DL model (AUC, 95% CI)
POLEmut					
Internal validation	0.68 (0.57–0.78)	0.68 (0.57–0.78)	0.76 (0.67–0.84)	0.79 (0.70–0.86)	0.82 (0.75–0.90)
External validation	0.60 (0.42–0.79)	0.73 (0.64–0.82)	0.64 (0.46–0.85)	0.70 (0.47–0.90)	0.71 (0.49–0.90)
MMRd					
Internal validation	0.56 (0.50–0.63)	0.66 (0.59–0.72)	0.61 (0.55–0.68)	0.62 (0.56–0.69)	0.65 (0.59–0.72)
External validation	0.63 (0.52–0.72)	0.67 (0.57–0.78)	0.61 (0.46–0.76)	0.67 (0.60–0.79)	0.71 (0.60–0.82)
NSMP					
Internal validation	0.74 (0.68–0.80)	0.71 (0.64–0.77)	0.66 (0.59–0.72)	0.74 (0.67–0.80)	0.81 (0.75–0.85)
External validation	0.68 (0.59–0.76)	0.69 (0.57–0.81)	0.65 (0.57–0.75)	0.69 (0.56–0.80)	0.73 (0.61–0.84)
p53abn					
Internal validation	0.77 (0.63–0.88)	0.76 (0.67–0.86)	0.68 (0.61–0.76)	0.78 (0.72–0.84)	0.86 (0.78–0.93)
External validation	0.76 (0.66–0.85)	0.72 (0.63–0.81)	0.57 (0.44–0.69)	0.69 (0.59–0.79)	0.81 (0.71–0.89)
Average classification					
Internal validation	0.69 (0.64–0.73)	0.70 (0.66–0.75)	0.68 (0.64–0.72)	0.73 (0.70–0.76)	0.79 (0.75–0.82)
External validation	0.67 (0.60–0.73)	0.70 (0.64–0.75)	0.62 (0.54–0.69)	0.69 (0.62–0.76)	0.74 (0.67–0.80)

Clinical-radiomics DL model based on MRI has the potential to distinguish EC molecular subtypes

Yue W et al, Insights into Imaging, 2025

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Application

Endometrial cancer – Survival prediction

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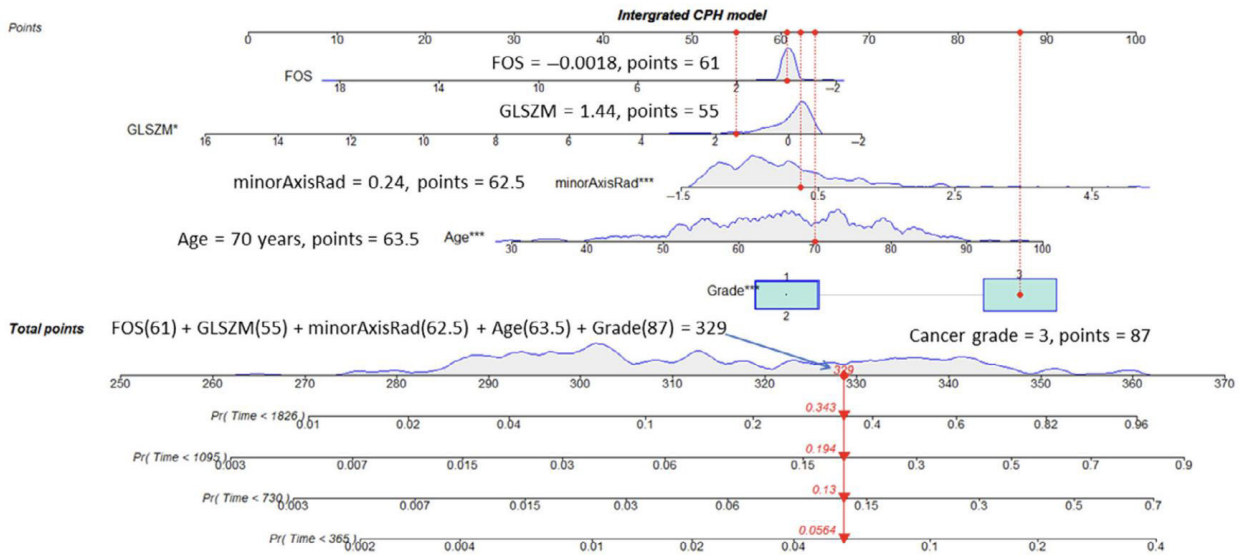
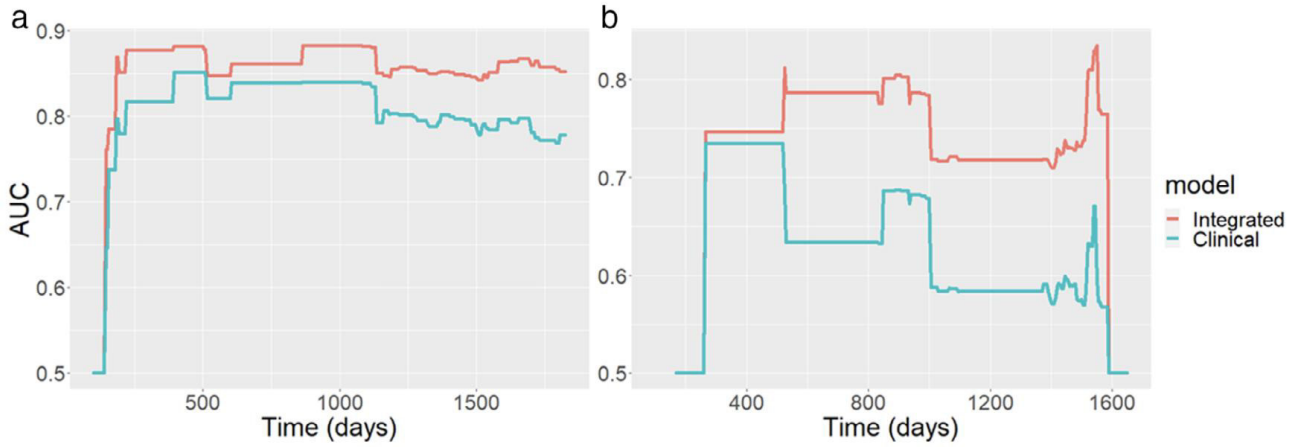
Integrated model combining clinicopathological factors and radiomic features extracted from T2WI

- **495 patients** (330 : 83 : 82) from **15 centres** across UK
- 5 features:
  - *tumor mask minor axis radius (minorAxisRad)*
  - *gray level size zone matrix (GLSZM)*
  - *first order statistics (FOS)*
  - *patient age at diagnosis (Age)*
  - *cancer grade (Grade)*
- Integrated model had a **larger AUC** than the clinical model for all time points

The proposed model with radiomic signatures may serve as a tool to improve estimated survival time in women with EC





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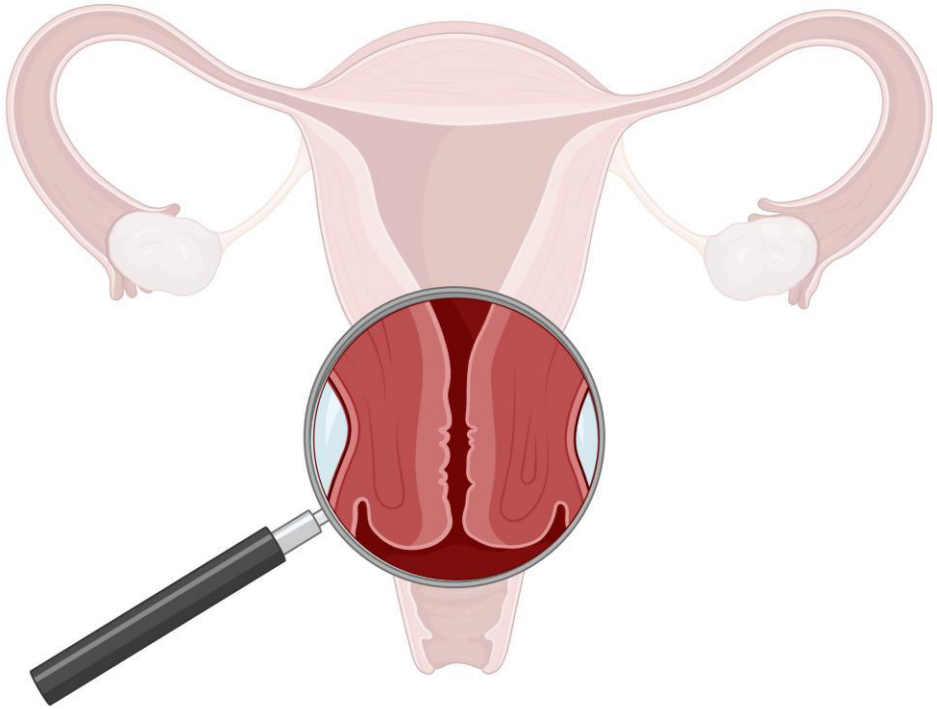
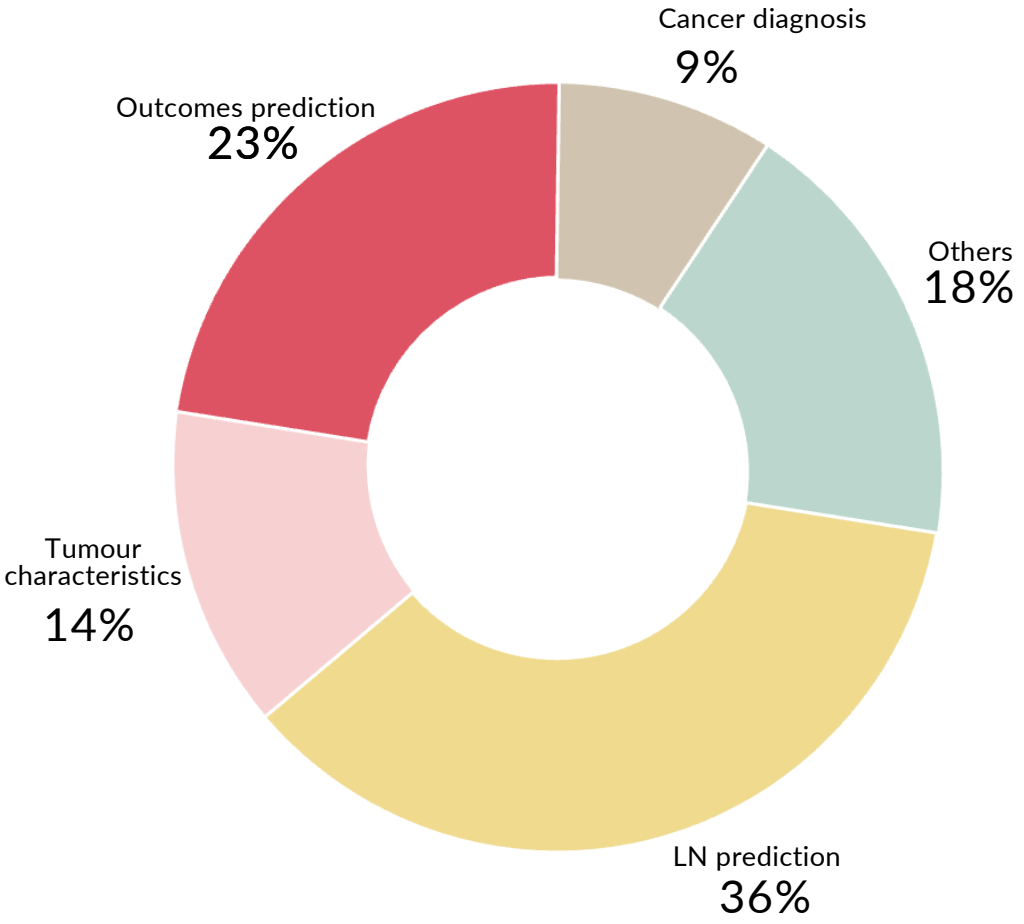
Application
Cervical cancer





Shrestha P. et al. Gynecol Oncol, 2022

Application

Cervical cancer – Lymph-node metastasis

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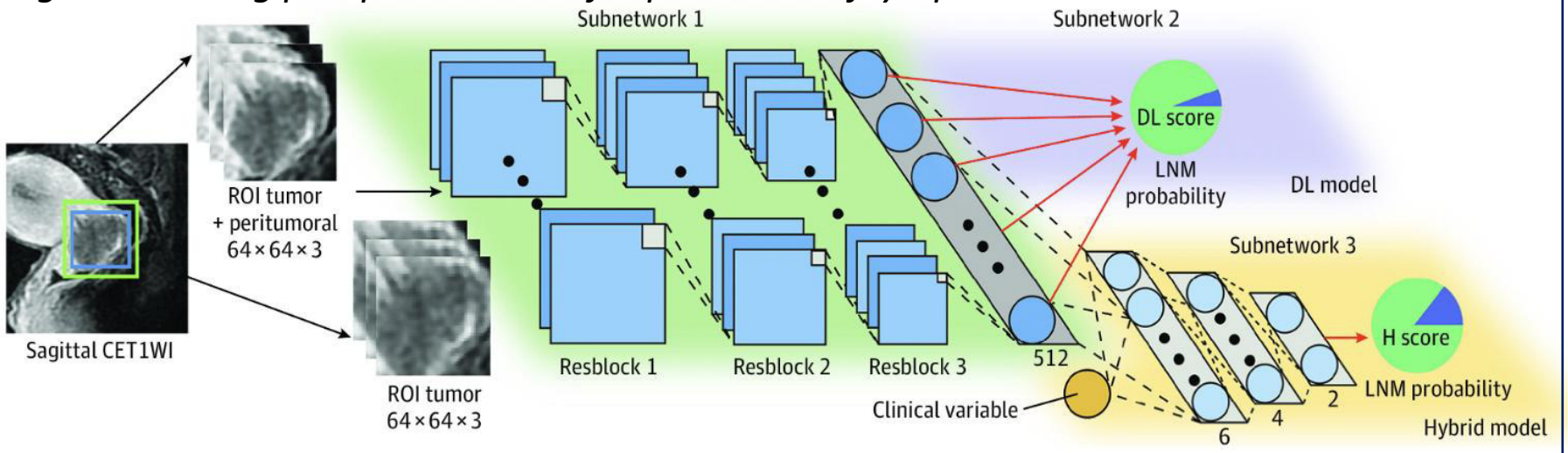
Systematic review:

- 16 studies combining/comparing radiomics and clinical models
- 11 contouring the tumour area; 3 tumour + peritumour; 2 LN
- External validation set in 3/16 only (AUC 0.804 – 0.933)

- Radiomics signatures were predictive of pathological and oncological outcomes, particularly if combined with clinical variables
- These models may tailor and personalize the treatment of each patient with CC

To develop a deep learning model using preoperative MRI for prediction of lymph node metastasis in CC

- 479 Patients (338 : 141)
- Hybrid model: CE-T1WI tumor + peritumoral + MRI-LN status
- **AUC 0.93; sensitivity 90.6%; specificity 87.2%**



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Application
Cervical cancer – Segmentation

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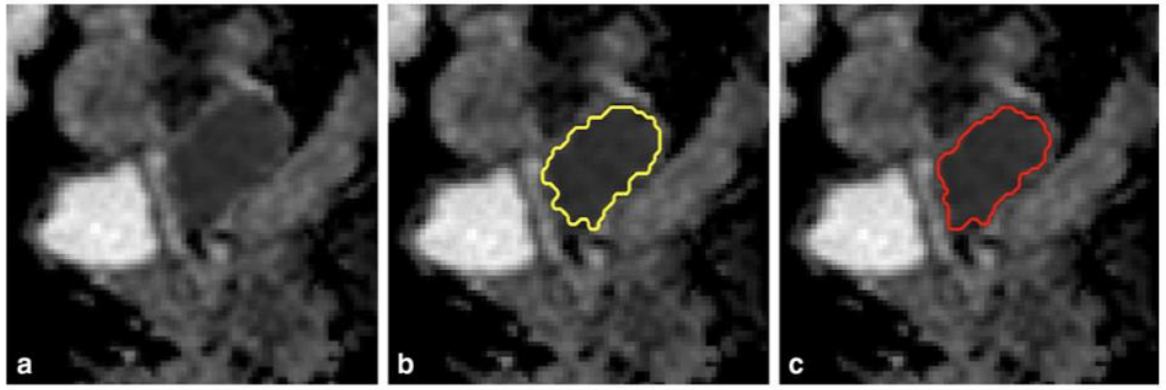
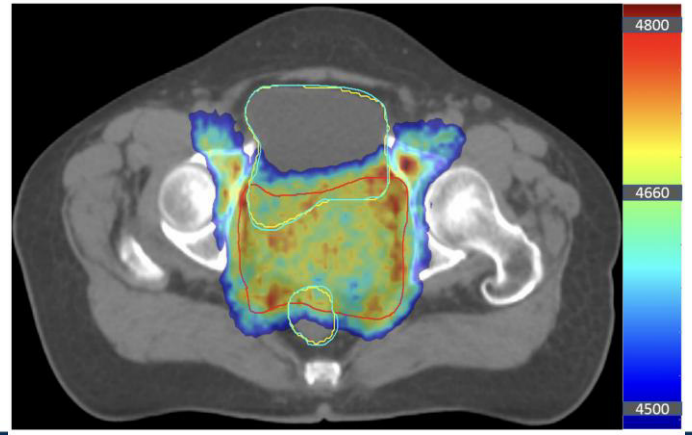
Tumour

- DL-based auto-segmentation
- 160 patients (144 : 25)
- DWI images as input
- **DSC test set: 0.82**
- *DL can perform accurate localization and segmentation of cervical cancer in DWMRI*



Organs at risk

- DL-based auto-segmentation for radiotherapy
- 127 patients (105 : 22)
- High similarity for bladder, femoral head, kidneys, and pelvic bone, (mean **DSC > 0.94**).



Application

Cervical cancer – Prediction of response to CTRT

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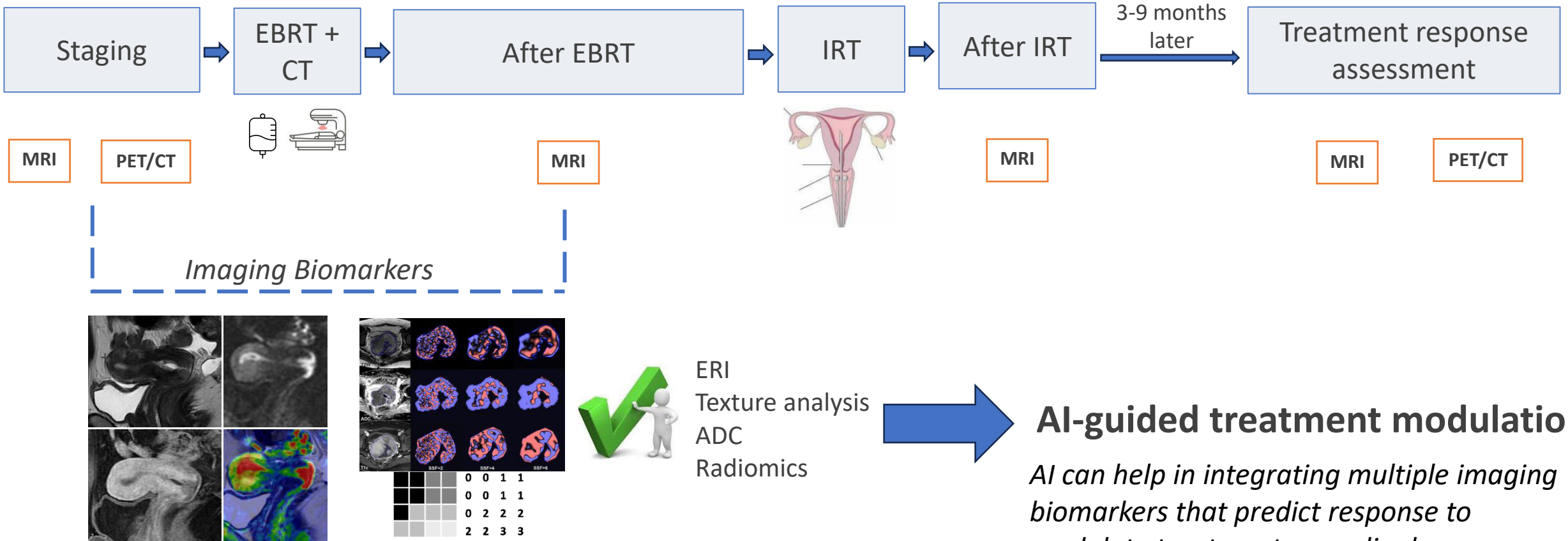
Multi-step imaging-guided treatment:



Application

Cervical cancer – Prediction of response to CTRT

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Radiomics features from both intratumoral and peritumoral regions and lymph nodes to predict the treatment response and prognosis of CC

improve model performance

in comparison to using only radiomics features calculated from the tumor region

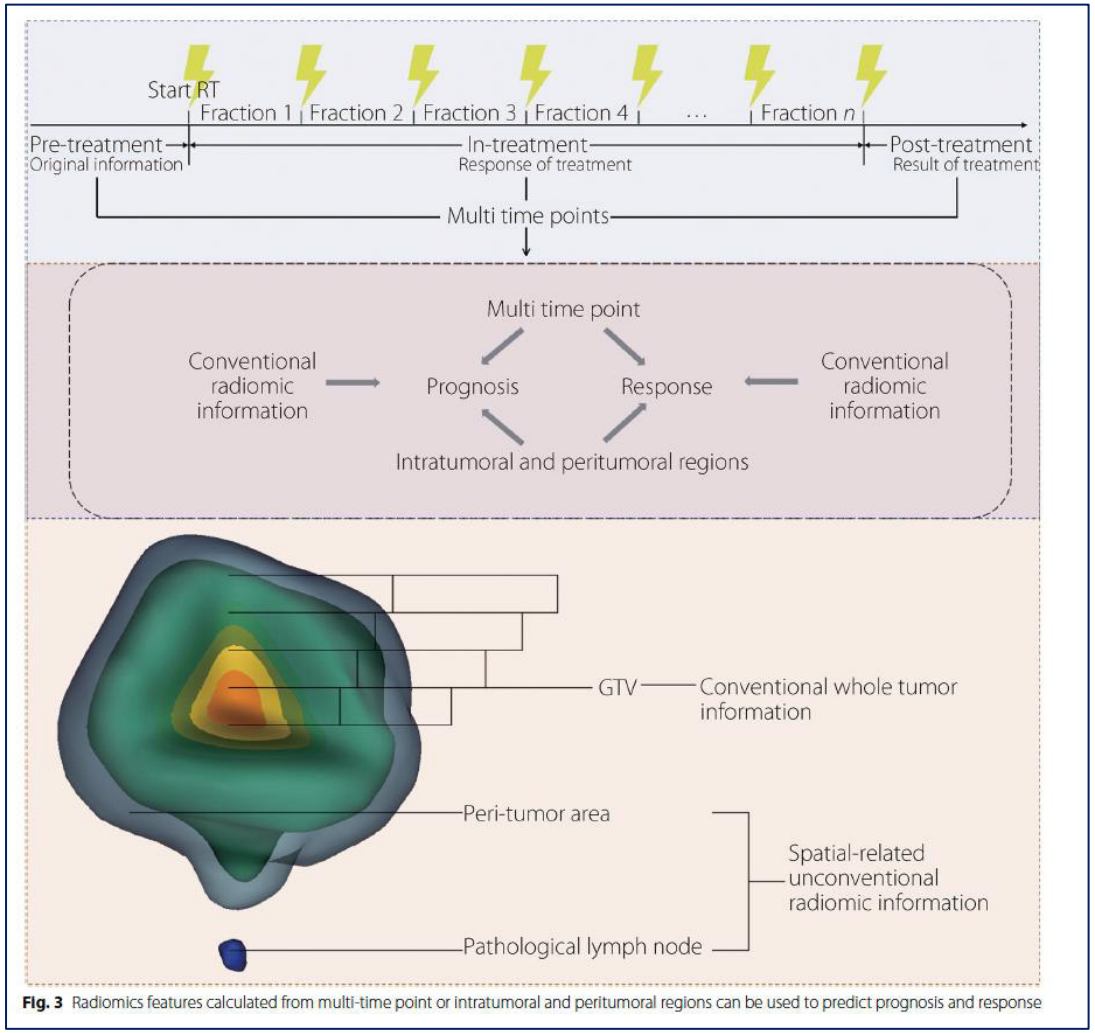

Fig. 3 Radiomics features calculated from multi-time point or intratumoral and peritumoral regions can be used to predict prognosis and response

Guo L et al, *Visual Computing for Industry, Biomedicine, and Art*, 2025

Application

Cervical cancer – Prediction of Progression Free Survival

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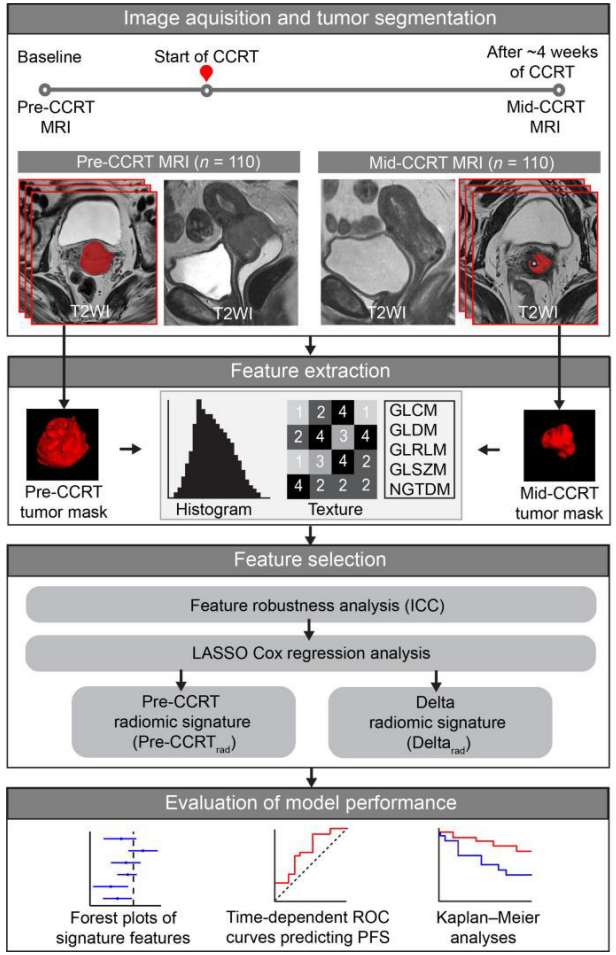
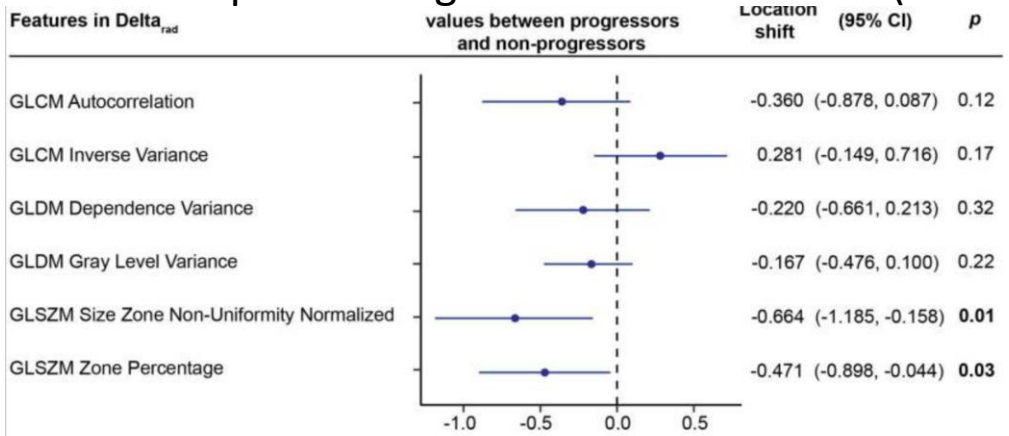
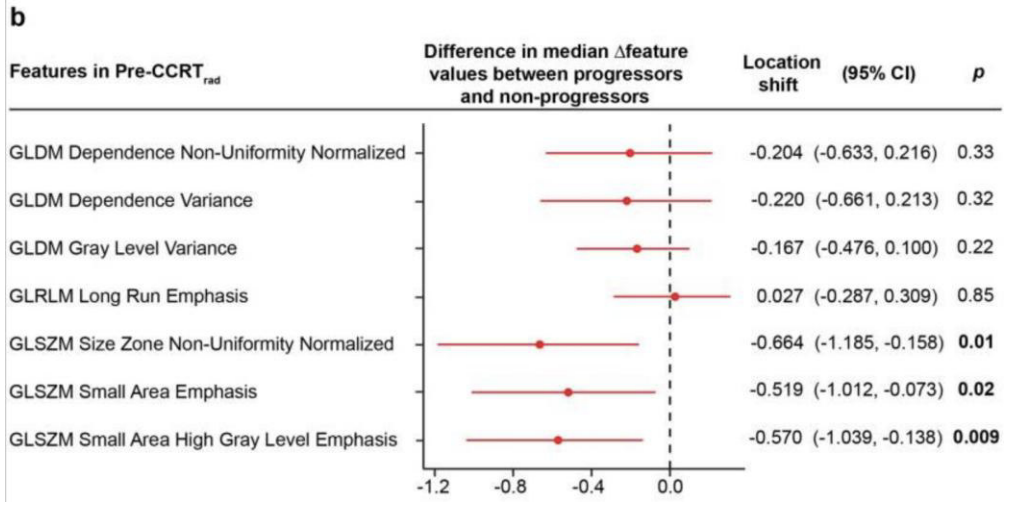
Assess temporal changes in tumor radiomics (Delta Radiomics)



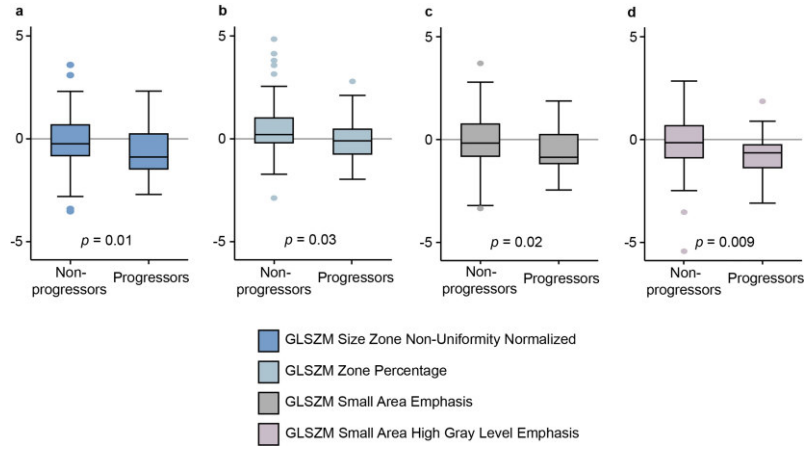




$\text{Delta}_{\text{rad}}$ outperformed:

- $\text{Pre-CCRT}_{\text{rad}}$ (marginally)
- FIGO stage
- $\text{Tumour}_{\text{max}}$

In prediction of **PFS**



4 $\text{Delta}_{\text{rad}}$ *features significantly differed between progressors and non-progressors, being lower in progressors* ($p \leq 0.03$)

Wagner-Larsen KS et al, BMC Cancer, 2025

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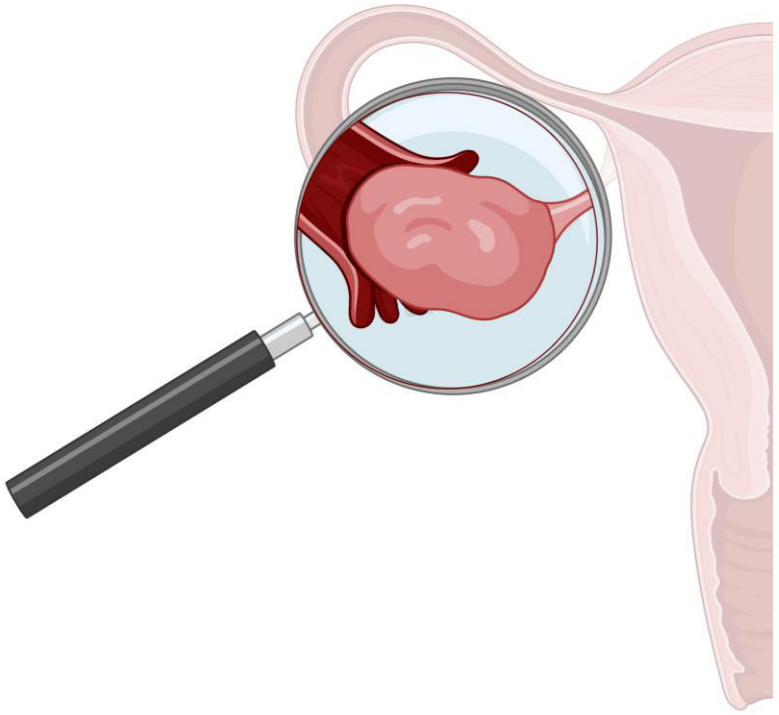
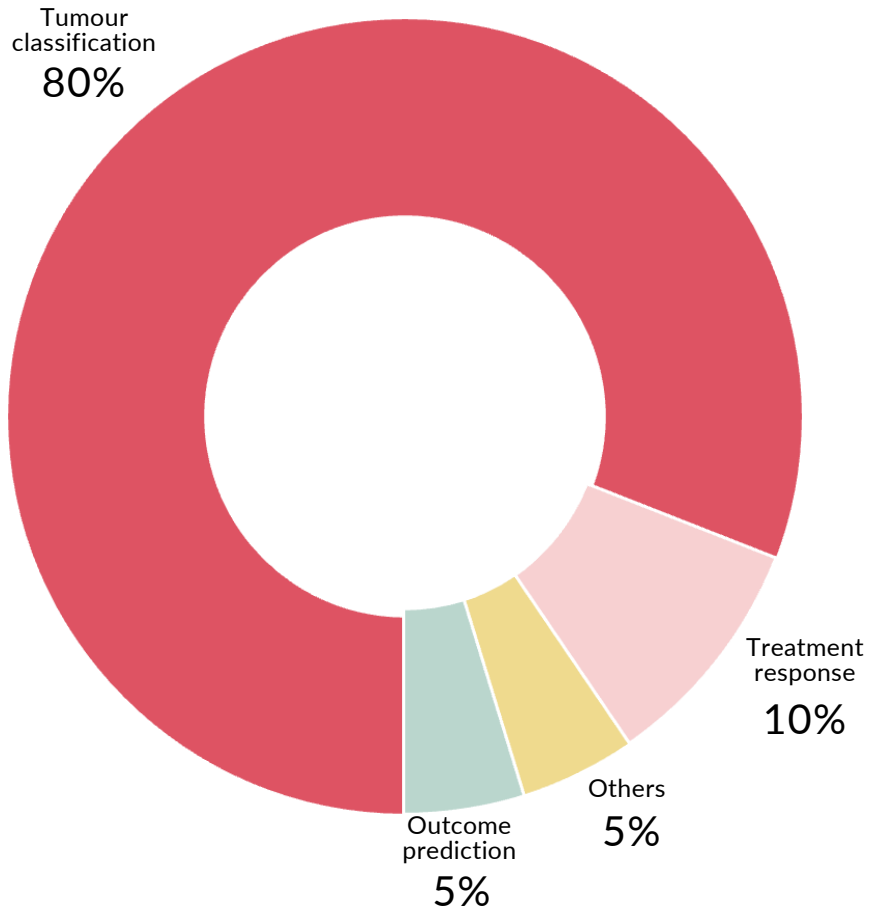
Application

Ovarian cancer





Shrestha P. et al. Gynecol Oncol, 2022

Application

Ovarian cancer – prediction of risk of malignancy

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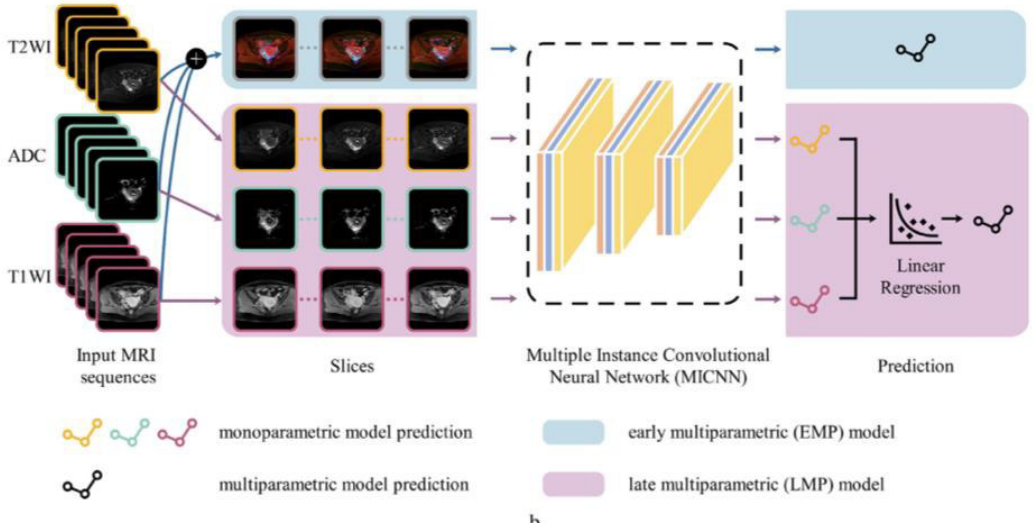
Score	Accuracy (%)	Sensitivity (%)	Specificity (%)
O-RADS MRI	91.0	93.0	92.0
Non contrast MRI Score	94.0	84.9	95.9

3 - 3.6 %
Borderline Tumours (BOTs)

MRI-Based Multiple Instance Convolutional Neural Network for Increased Accuracy in the Differentiation of Borderline and Malignant Epithelial Ovarian Tumors

Junming Jian, PhD,[1,2] Yong'ai Li, MD, PhD,[3] Wei Xia, PhD,[1] Zhang He, MD, PhD,[4] Rui Zhang, MS,[1] Haiming Li, MD,[5] Xingyu Zhao, MS,[1] Shuhui Zhao, MD,[6] Jiayi Zhang, MS,[1] Songqi Cai, MD,[7] Xiaodong Wu, MS,[1] Xin Gao, PhD,[1,2,8*] and Jinwei Qiang, MD, PhD[3*]

- 8 centres
- 501 patients (342 : 159)
- 336 Malignant Tumours; 165 BOTs
- Multiparametric model based on T2-WI, ADC maps and CE-T1WI
- AUC 0.884 (vs 0.797 radiologists)



Developed MICNN models can effectively differentiate BEOT from MEOT and the diagnostic performances (AUCs) were more superior than that of the radiologists' assessments.

Sadowsky E.A., Thommasin-Naggara I. et al. Radiology, 2022; Sahin H. et al. Eur Radiol, 2021
Jian J et al. J Magn Reson Imaging, 2022

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Application

Ovarian cancer – Segmentation

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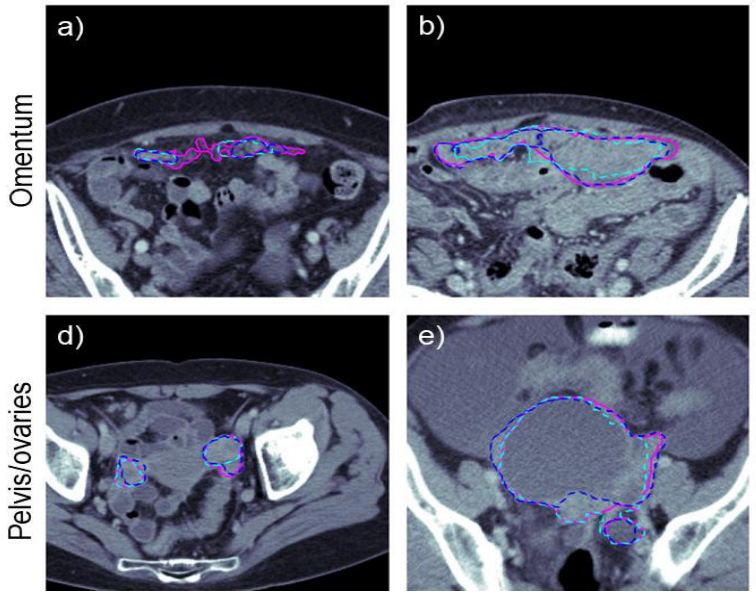
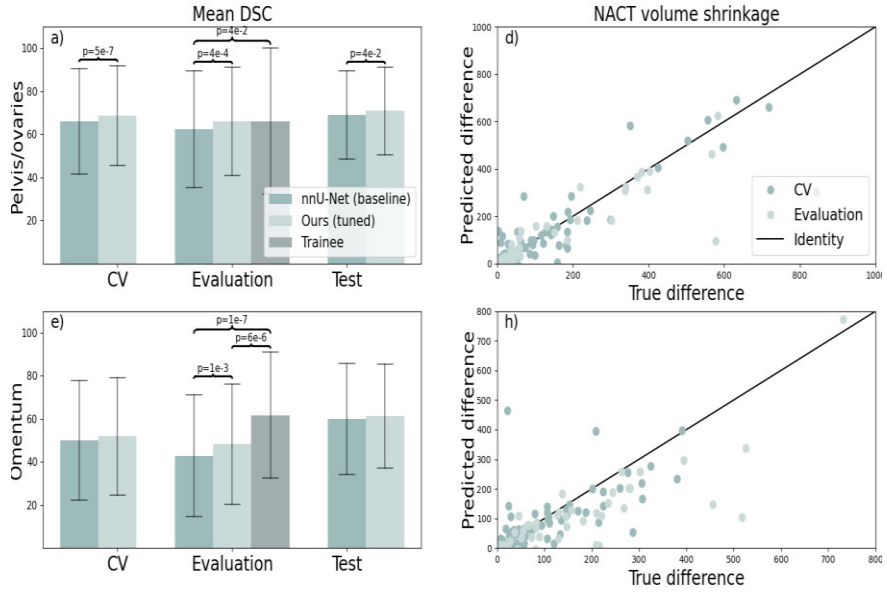
Deep learning-based segmentation of multisite disease in ovarian cancer (pelvis/ovaries and omentum)

- First automated approach for lesion segmentation on CT images
- Automated segmentation of ovarian cancer lesions can be comparable with manual segmentation of trainee radiologists.



Magenta: ground truth, cyan: automated, blue: trainee



Evaluation in terms of DSC and volume shrinkage after treatment.

Automated segmentation of ovarian cancer may be used for volumetric assessments and building complex analysis pipelines

Application

Ovarian cancer – Multiomics data integration for response prediction

Fondazione Policlinico Universitario Agostino Gemelli IRCCS
Università Cattolica del Sacro Cuore

Patient cohort (n=138)

n=92 eligible patients

n=46 External validation

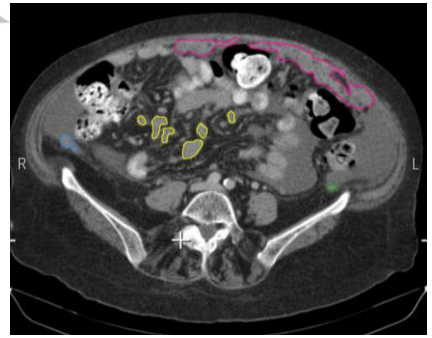
n=72 Training

n=20 Hold-out validation

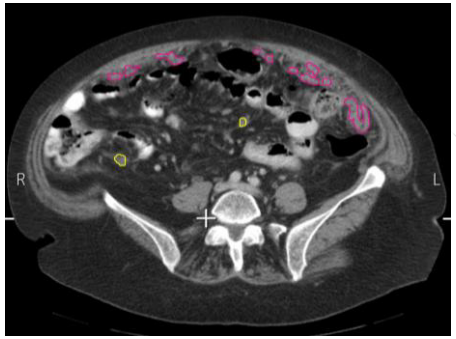
Predict response
to neoadjuvant chemotherapy (NACT)
[change in tumour volume] from baseline scans.

Integrating clinical, blood-based and radiomic biomarker
(CA 125, radiomics, and ctDNA)
From all primary and metastatic lesions

CT scans

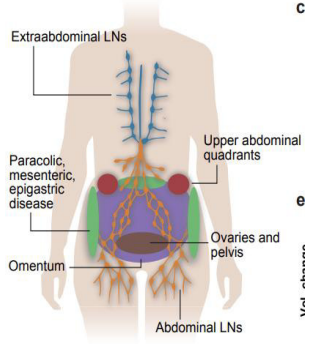


Pre-NACT



Post-NACT

Manual segmentations of whole tumour burden



- *Value of including radiomics data in integrative models of treatment response*
- Future prospective: help stratifying patients

Application

Ovarian cancer – Multiomics data integration for patient stratification

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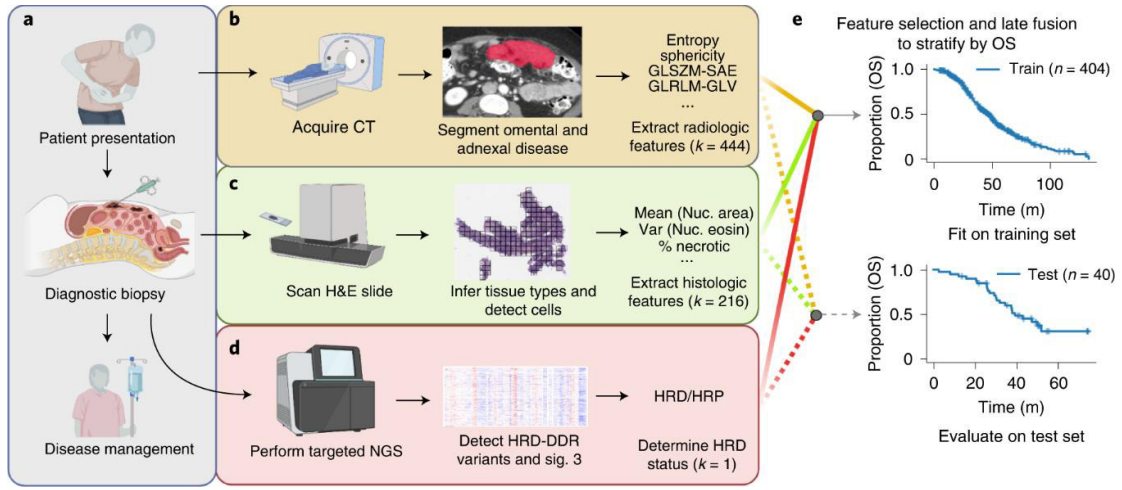
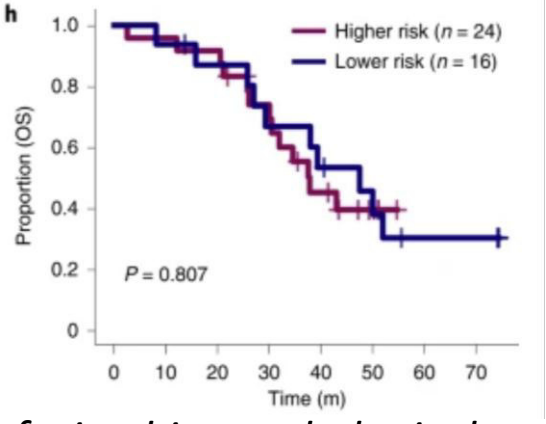
Patient stratification based on multiomics

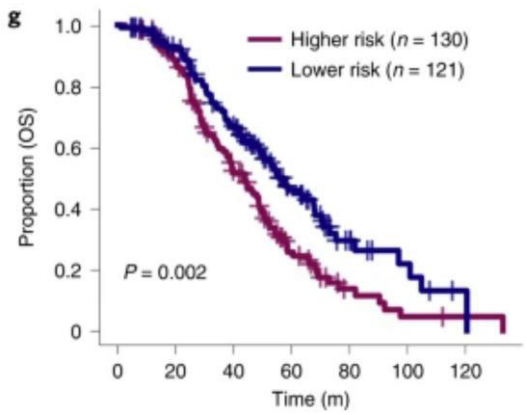
- CT
- H&E tissue sections (dig. Pathology)
- HRD/HRP (NGS)



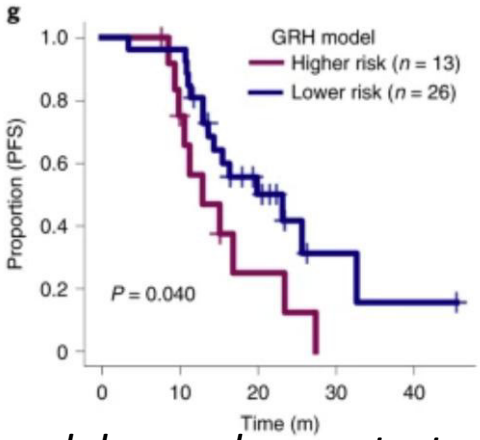
Adnexal radiomics



Omental radiomics



Multimodal data (incl. omental radiomics)



By fusing histopathological, radiologic and clinicogenomic machine-learning models, we demonstrate a promising path toward improved risk stratification of patients with cancer through multimodal data integration

Boehm et al. Nat Cancer 2022

ARC Advanced Radiology Center

Application

Ovarian cancer – survival prediction

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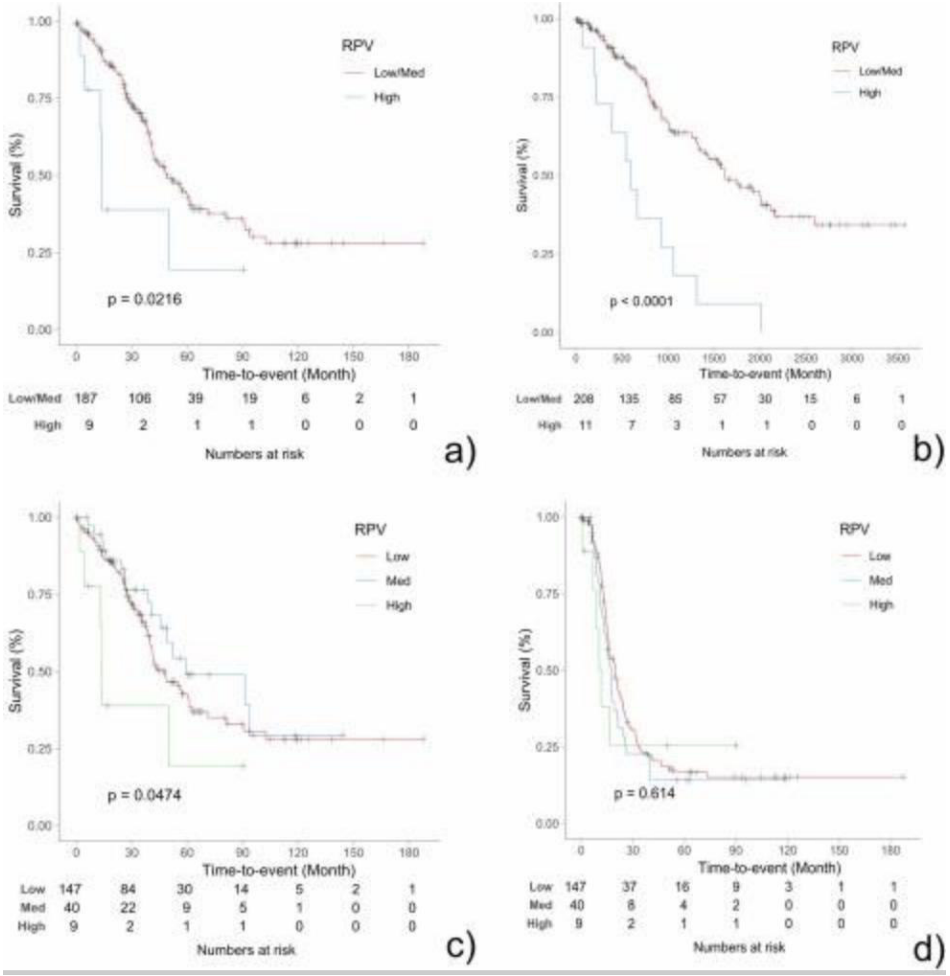

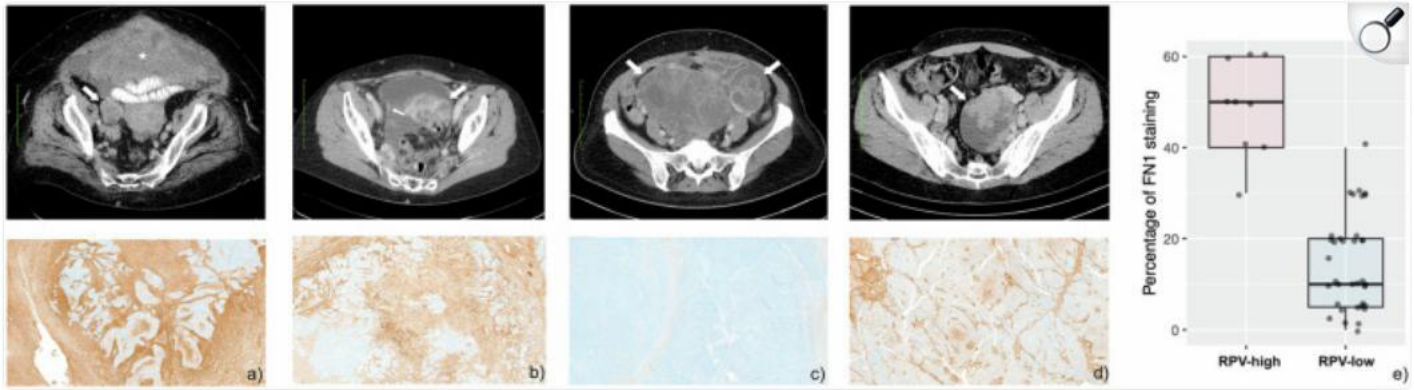

External validation of a radiomic signature (RPV) software

- **RPV-high** patients have **worse OS** (HR 3.17; 95% CI: 1.32–7.60, $p = 0.0099$) after adjusting for known prognostic factors
- RPV-high cases showed a higher percentage of stromal content based on IC fibronectin expression

Patients with HGSOC and Radiomic Prognostic Vector (RPV)-high ovarian mass on pre-operative CT had significantly worse OS following primary surgery and a higher stromal content compared to RPV-low masses

Wenger GJ et al, Eur Radiol, 2024

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Take home messages

- AI is promising for future to tailor individual treatment
  - Identification of complex patterns across diverse data streams
  - Automated integration processes
- Developing robust AI tools using imaging datasets is necessary to quantify imaging biomarkers and improve patient diagnostics and outcomes.

Major challenges

- Multicenter and prospective studies (external validation)
- How best to integrate AI developments into clinical radiology practice
- Reliability for clinical utility

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Thank for your attention

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