Associazione Italiana Radioterapia e Oncologia clinica

Società Italiana di Radiobiologia

RADIOMIC FEATURE RELEVANCE IN THE PREDICTION OF PATHOLOGICAL FEATURES OF PROSTATE CANCER

IEO Istituto Europeo di Oncologia

Dr. Maria Giulia Vincini

Division of Radiation Oncology,

IEO, European Institute of Oncology, IRCSS, Milan, Italy

UNIVERSITÀ DEGLI STUDI DI MILANO

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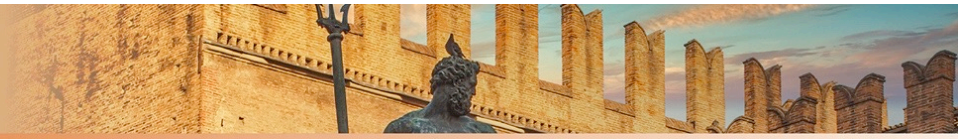


DICHIARAZIONE

Relatore: MARIA GIULIA VINCINI

Come da nuova regolamentazione della Commissione Nazionale per la Formazione Continua del Ministero della Salute, è richiesta la trasparenza delle fonti di finanziamento e dei rapporti con soggetti portatori di interessi commerciali in campo sanitario.

- Posizione di dipendente in aziende con interessi commerciali in campo sanitario **(NIENTE DA DICHIARARE)**
- Consulenza ad aziende con interessi commerciali in campo sanitario **(NIENTE DA DICHIARARE)**
- Fondi per la ricerca da aziende con interessi commerciali in campo sanitario **(NIENTE DA DICHIARARE)**
- Partecipazione ad Advisory Board **(NIENTE DA DICHIARARE)**
- Titolarità di brevetti in compartecipazione ad aziende con interessi commerciali in campo sanitario **(NIENTE DA DICHIARARE)**
- Partecipazioni azionarie in aziende con interessi commerciali in campo sanitario **(NIENTE DA DICHIARARE)**
- Altro

Background

Multiple risk classification systems with sub-ottimal prognostic performances → **under/over treatment**

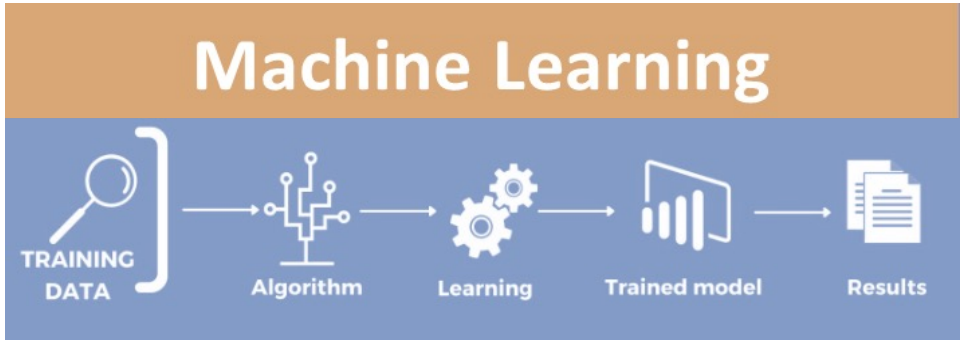
The lack of a-priori deeper characterization makes difficult to determinate accurately and non-invasively PCa aggressiveness at the time of the first diagnosis in order to guide treatment decision

Pre-treatment prostate cancer risk stratification systems by different organizations

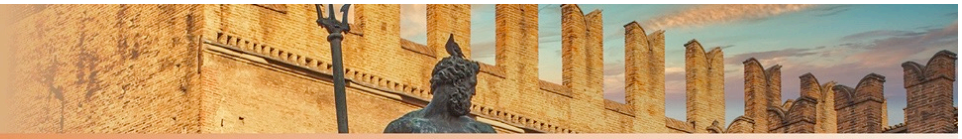
Organization	Very Low risk/Low risk	Intermediate risk (favorable and unfavorable)	High risk/Very high risk
D'Amico (22) **AUA (23)** **EAU (24)**	T1-T2a and GS ≤6 and PSA ≤10	T2b and/or GS =7 and/or PSA >10–20 not low-risk	≥T2c or PSA >20 or GS 8–10
GUROC* (25) **NICE (26)**	T1-T2a and GS ≤6 and PSA ≤10	T1-T2 and/or Gleason ≤7 and/or PSA ≤20 not low-risk	≥T3a or PSA >20 or GS 8–10
CAPSURE* (27)	T1-T2a and GS ≤6 and PSA ≤10	T2b and/or GS =7 and/or PSA >10–20 not low-risk	T3-4 or PSA >20 or GS 8–10
NCCN (28)	T1-T2a and GS 2–6 and PSA ≤10 not very low-risk AND very-low risk category: T1c and GS ≤6 and PSA <10 and Fewer than 3 biopsy cores positive and ≤50% cancer in each core	T2b or T2c and/or GS =7 and/or PSA >10–20 not low-risk	T3a or PSA >20 or GS 8–10 not very high risk AND very high-risk category: T3b-4
ESMO (29)	T1-T2a and GS ≤6 and PSA <10	Not high risk and not low risk	T3-4 or PSA >20 or GS 8–10

Aims

- **Primary endpoint:**
  - Non-invasive prediction of PCa **pathological characteristics** with mathematical models integrating radiological, clinical and radiomics features



- **Secondary endpoints: focus on radiomic features**
  - Investigate **radiomic contribution**
  - Investigate **leading features**
  - Exploring **model behaviour across patients subgroups**



Patients

*"A total of **949 prostate cancer (PCa) patients** who had undergone multiparametric magnetic resonance imaging (**mp-MRI**) and **radical prostatectomy at the IEO** (European Institute of Oncology IRCSS, Milan, Italy) between 2015 and 2018 were retrospectively included."*

Inclusion criteria:

- ✓ Age ≥ 18 years
- ✓ histological proven diagnosis of Prostate Cancer
- ✓ **multiparametric magnetic resonance (mp-MRI) performed c/o IEO**
- ✓ **radical prostatectomy performed c/o IEO**
- ✓ availability of pre- and post-surgery clinical and radiological data
- ✓ written consent to the anonymous use of clinical data for educational and scientific purposes

Exclusion criteria: any hormone therapy prior to surgery.

Methods

Radiomic features extraction:

- All images acquired at IEO
- Extraction from T2 weighted
- Whole prostate segmented with an **internally-developed learning autosegmentation tool**

ORIGINAL ARTICLE Open Access

Quality assurance for automatically generated contours with additional deep learning

Lars Johannes Isaksson[1*], Paul Summers[2], Abhir Bhalerao[3], Sara Gandini[4], Sara Raimondi[4], Matteo Pepa[1], Mattia Zaffaroni[1], Giulia Corrao[1,5], Giovanni Carlo Mazzola[1,5], Marco Rotondi[1,5], Giuliana Lo Presti[4], Zaharudin Haron[6], Sara Alessi[2], Paola Pricolo[2], Francesco Alessandro Mistretta[7], Stefano Luzzago[7], Federica Cattani[8], Gennaro Musi[5,7], Ottavio De Cobelli[5,7], Marta Cremonesi[9], Roberto Orecchia[10], Giulia Marvaso[1,5], Giuseppe Petralia[5,11] and Barbara Alicja Jereczek-Fossa[1,5]

Input

Clinical variables: Age, Comorbidities, risk class, PSA, cT, cN, GS pre-op, ISUP pre-op

Radiomic features

Radiological variables (mpMRI): pirads, EPE, ADC, volume

M1. *Clinical features*

M2. *Clinical + radiological*

M3. *Clinical + radiomics*

M4. *Clinical + radiological + radiomics*

Output

- pT
- pN
- Residual surgical margin
- Post-op GS
- Post-op ISUP
- Biochemical progression
- Clinical progression

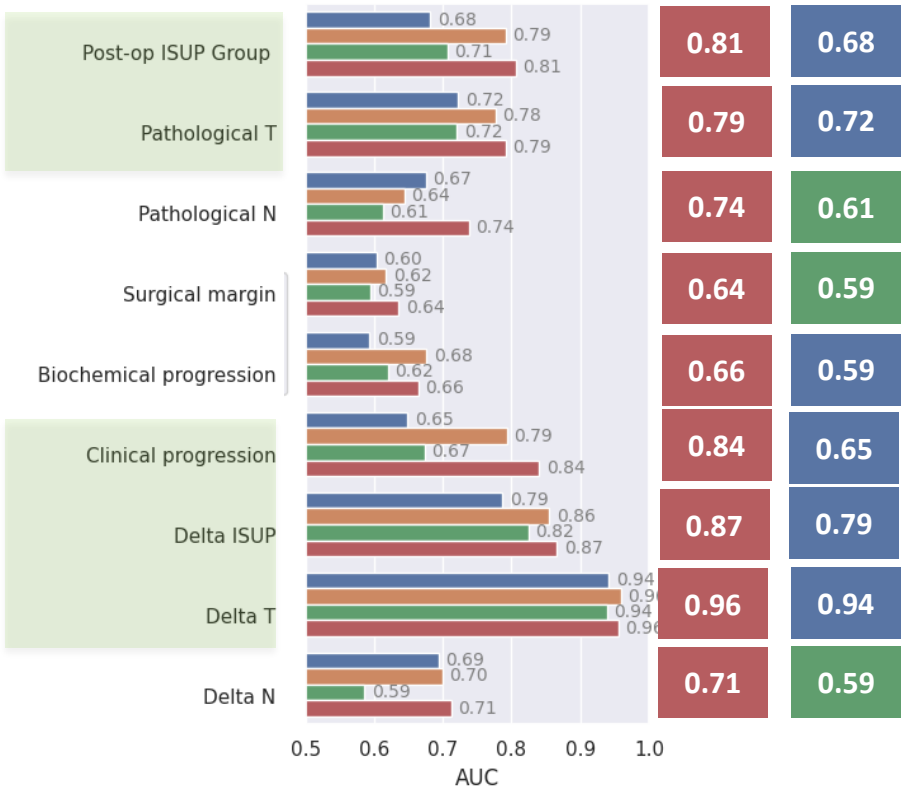
Results – Models performance

MODEL 1: Clinical

MODEL 2: Clinical + Radiological

MODEL 3: Clinical + Radiomic

MODEL 4: All Variables



radiological variables improve the performance by a **substantial margin** (**blue** vs. **orange**).

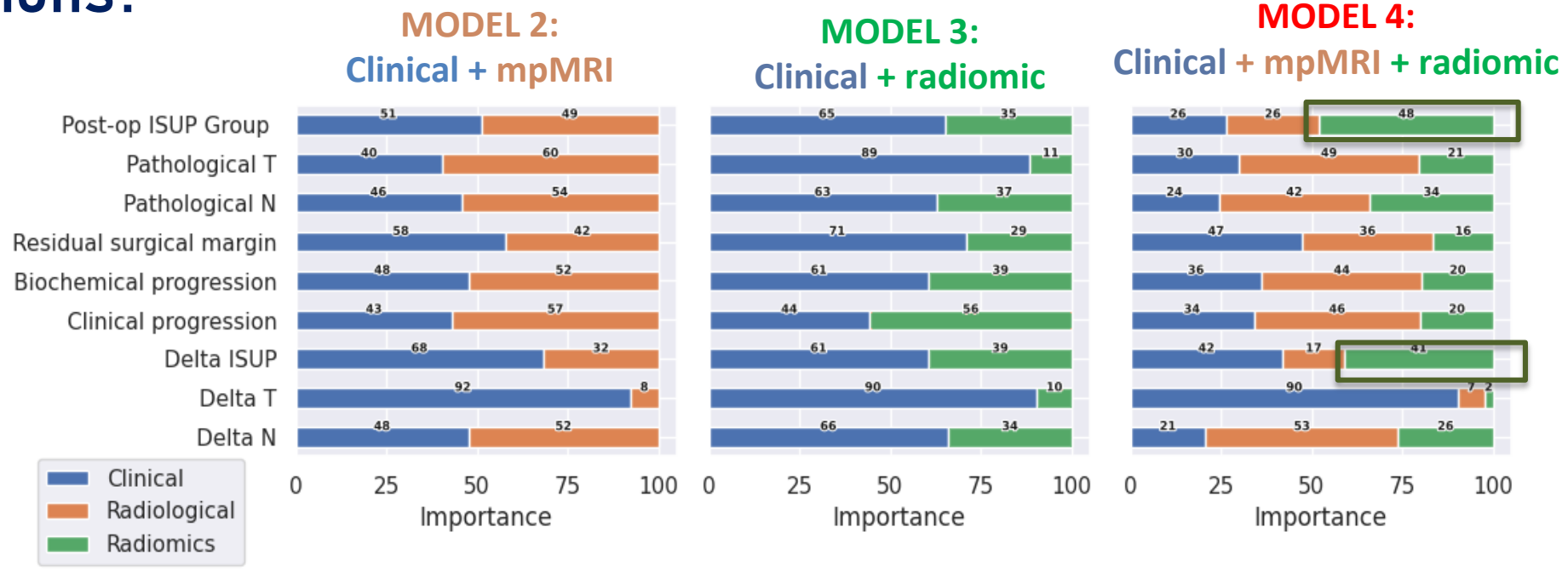
The radiomic variables appear to improve the performance by a small margin (**blue** vs. **green** and **orange** vs. **red**),

Mean AUC 0.78

→ Inclusion of radiomics seems to give a **boost** in models performance, although small

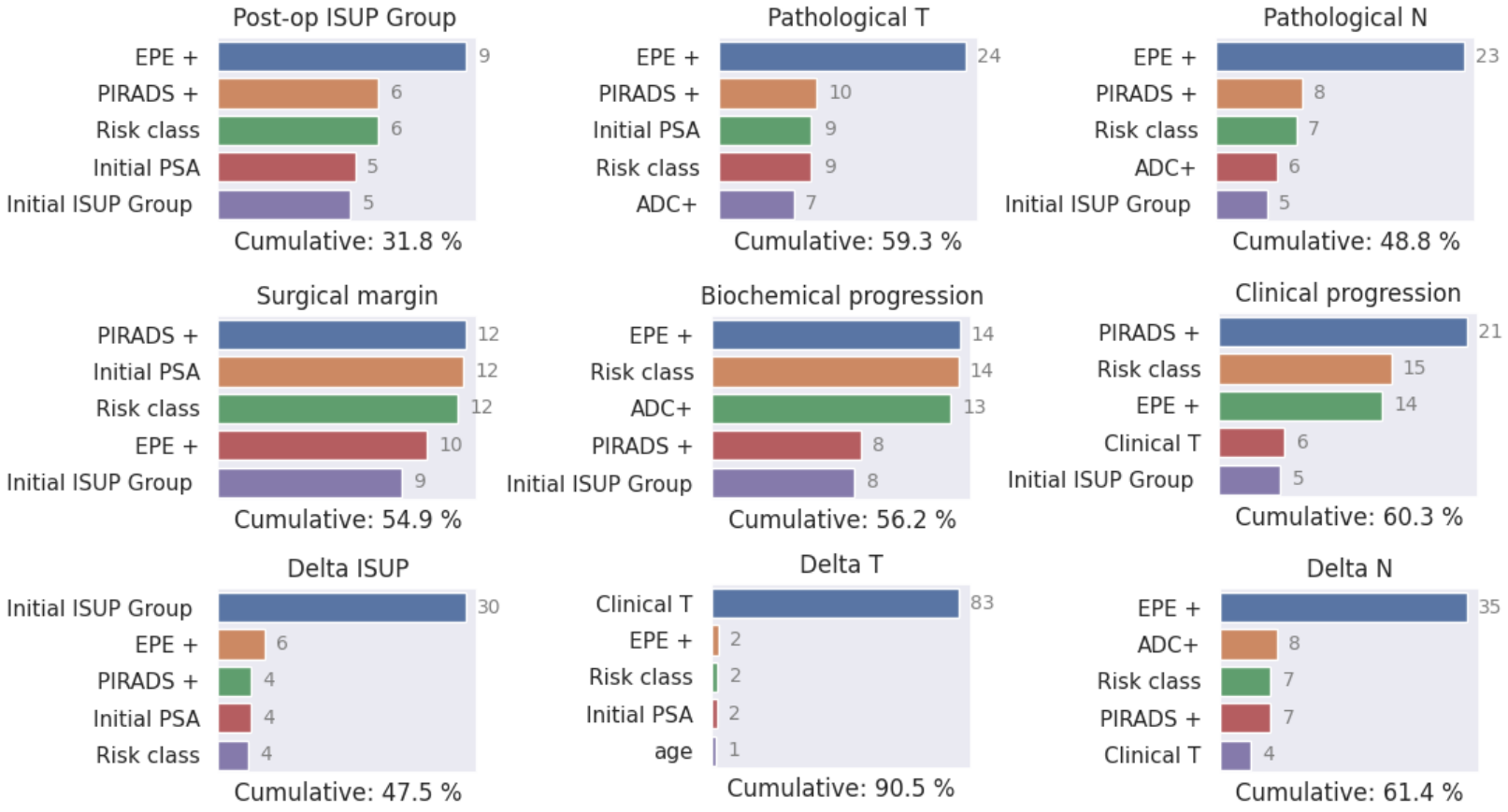
Results - Do the radiomic features actually influence the decisions of the model? On what variables does the model base its decisions?

Cumulative feature importance of different groups of variables



Results – On what variables does the model base its decisions?

MODEL 4.
TOP 5 used features



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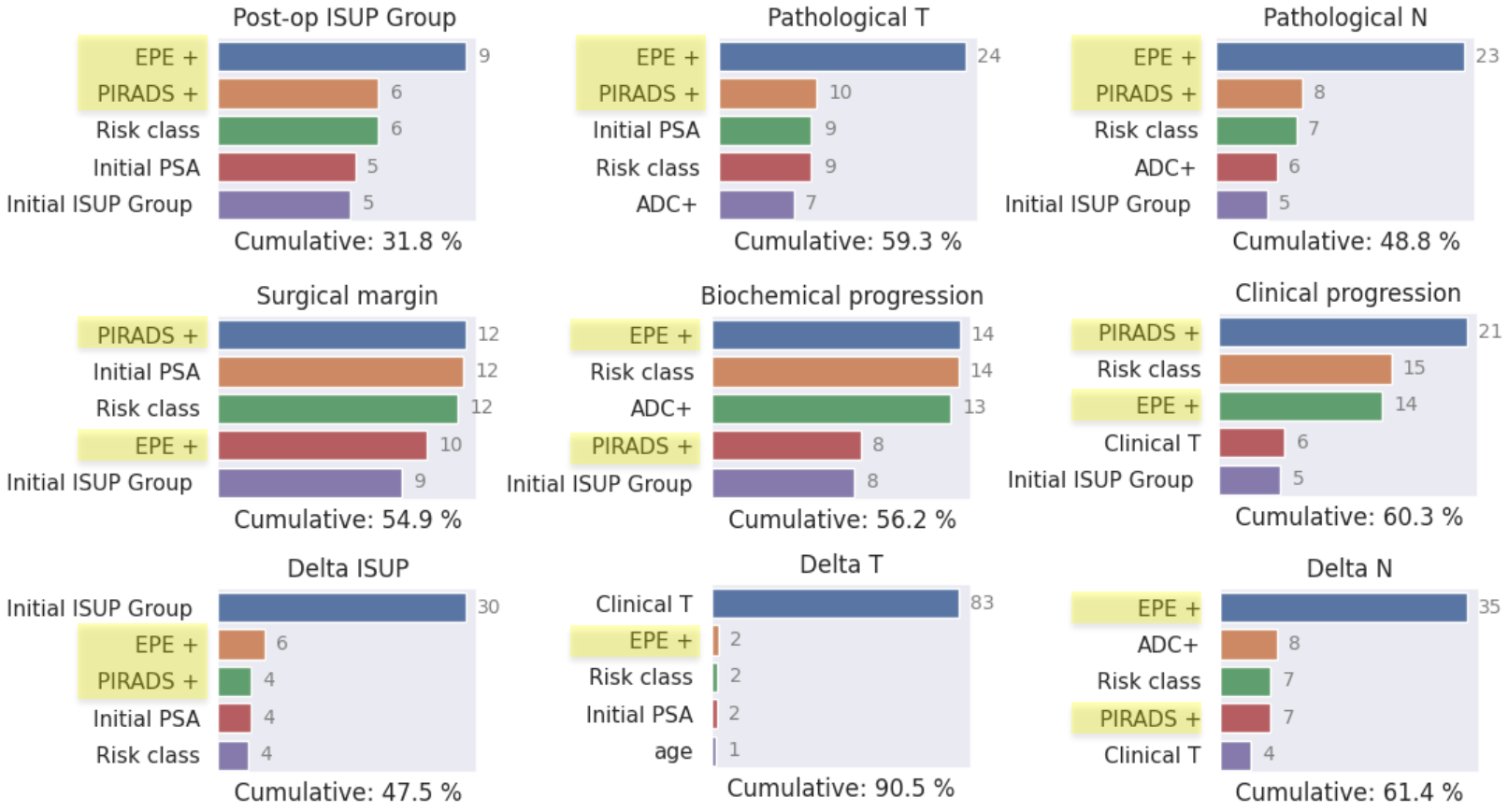
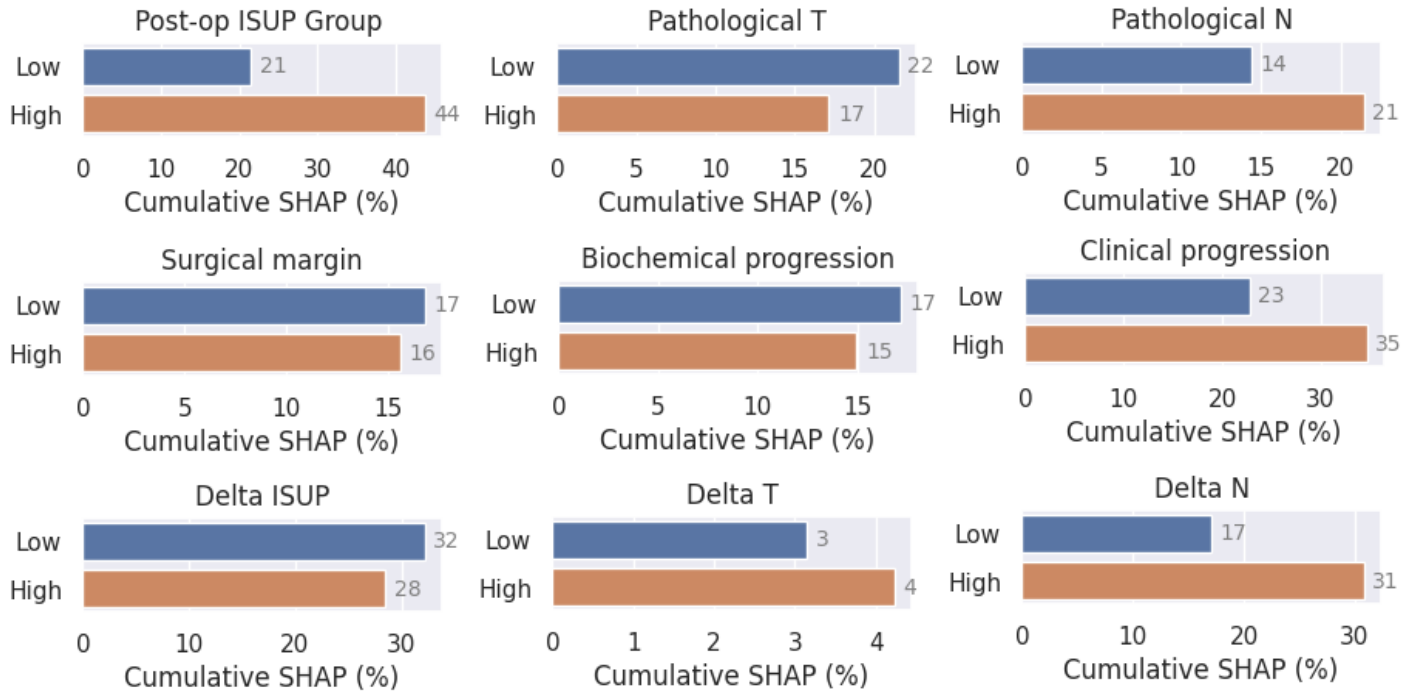


Results – Does radiomics play a specific role for low/high-risk patients?

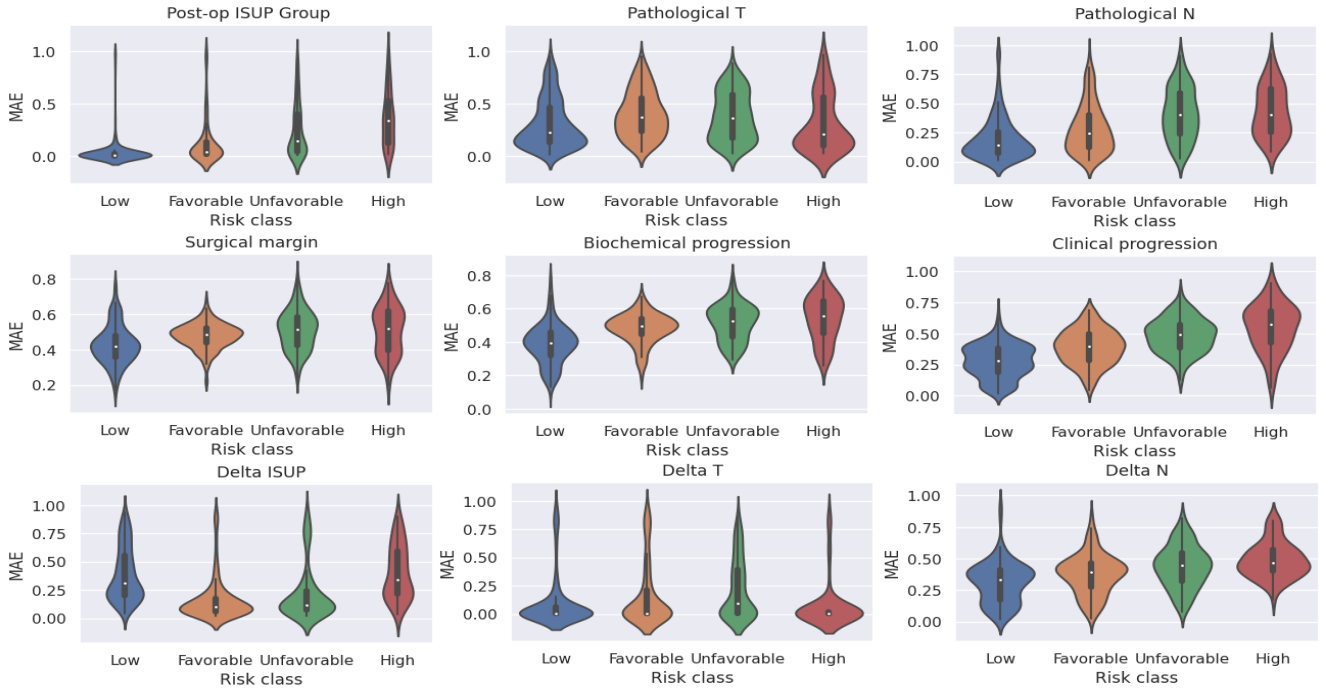
MODEL 4.
SHAP value distribution for different class-risk group



Results – Is there a performance difference between the low-risk and high-risk patients?

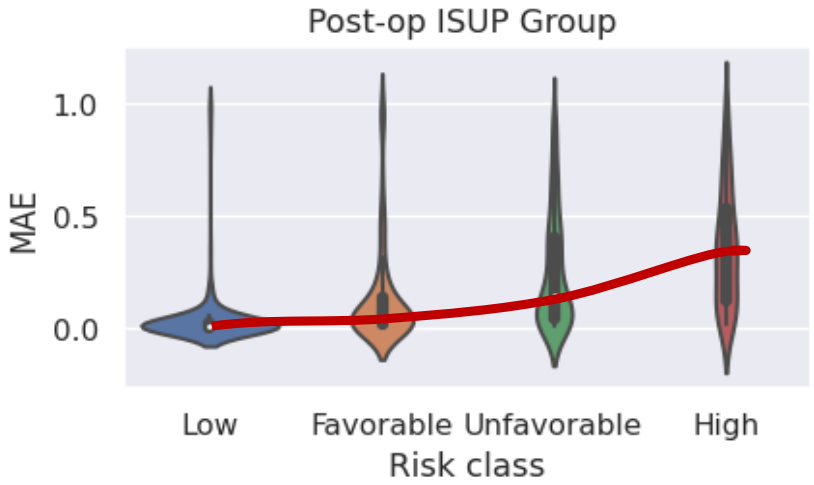
MODEL 4.

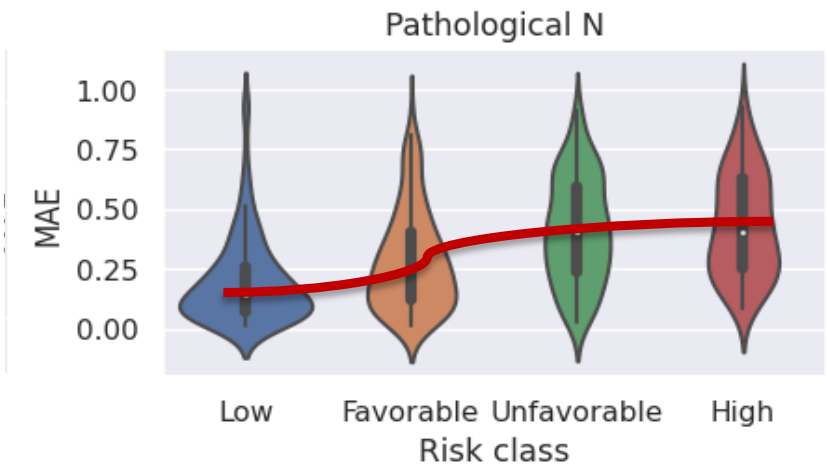
MAE values distribution for different class-risk group



Results – Is there a performance difference between the low-risk and high-risk patients?

MODEL 4.
MAE values distribution for different class-risk group





Results – Model 4 Comparison with clinical workflow

Clinical workflow	≤ 3 predicted	≥ 4 predicted	Model 4	≤ 3 predicted	≥ 4 predicted
≤ 3 true	877	0	ISUP ≤ 3 true	841	36
≥ 4 true	**67**	1	ISUP ≥ 4 true	**46**	22

*Confusion matrices for **ISUP** prediction*

Clinical workflow	≤ 2 predicted	≥ 3 predicted	Model 4	≤ 2 predicted	≥ 3 predicted
≤ 2 true	568	14	cT ≤ 2 true	463	119
≥ 3 true	**319**	48	cT ≥ 3 true	**141**	226

*Confusion matrices for **pathological T (pT)** prediction*

Clinical workflow	0 predicted	1 predicted	Model 4	0 predicted	1 predicted
0 true	493	2	cN = 0 true	408	87
1 true	**76**	0	cN = 1 true	**36**	40

*Confusion matrices for **pathological N (pN)** prediction*

Take home messages

- **mp-MRI variables** are fundamental for model performances (PI-RADS and EPE)
- Models can provide clinicians with pathological information prior to surgery, helping identify the correct stage of the disease and guiding the clinical course **(tailored treatment)**

→ **potential benefit of mathematical models for pathological features prediction in Pca**

WHAT ABOUT RADIOMICS?

- **Radiomics features bring a measurable boost** in model performance, **although small**

→ explore the use of additional **mp-MRI sequences for radiomic features extraction**

The possibility shown by these models to improve risk stratification and drive treatment-decision process is promising and warrant further efforts

Thank you for your kind attention

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