

Applications of AI-powered Chest Imaging

서울대학교병원 영상의학과

임우현

AI for Lung Cancer

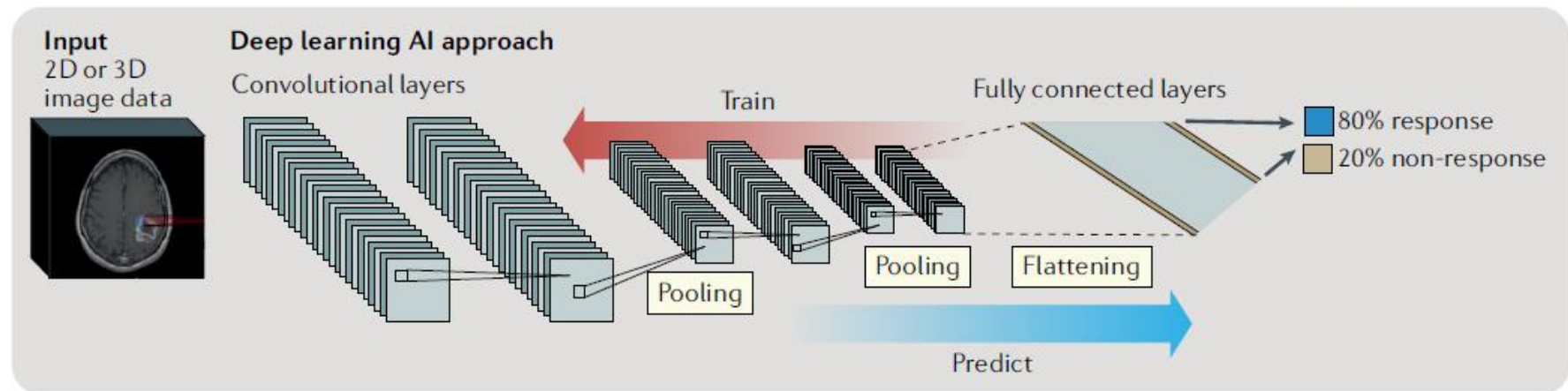
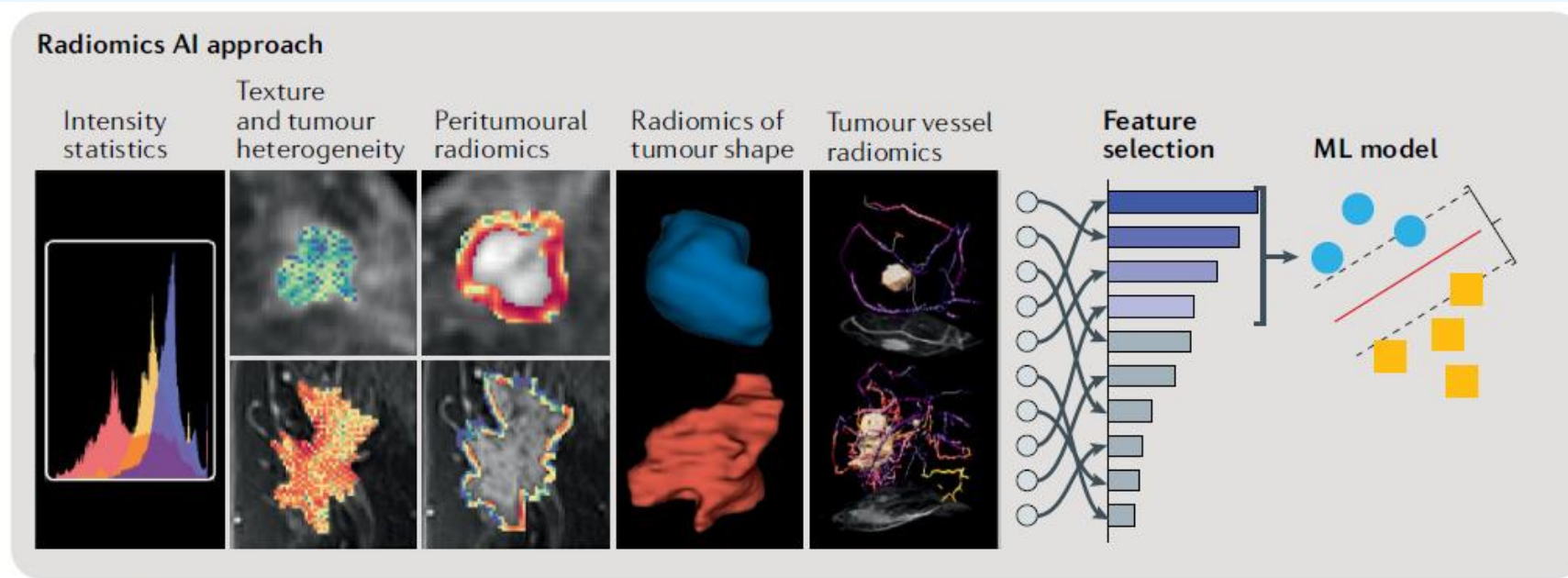
- **Purpose**

- Detection: CXR, CT, MRI, PET/CT
- Selection: patient, procedure type, lesion
- Prediction: malignancy risk, genetic mutation, PD-L1 expression, treatment response
- Prognostication: recurrence, survival

- **Tool**

- DL
- Radiomics

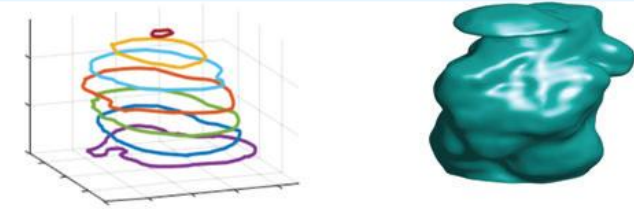
Radiomics vs. DL



Radiomics

Class of feature	Features	Common examples
Intensity-based measures and first-order statistics	Direct physical or functional measures from fully quantitative modalities, and basic statistical measures characterizing the distribution of intensity values within a region	Mean, median, standard deviation, skewness and kurtosis of image intensity values, attenuation values on CT ^{162,163} , maximum standardized uptake value on FDG-PET ³⁸
Heterogeneity and texture	Features of spatial arrangement and local heterogeneity of image intensity values	Grey-level co-occurrence matrix ⁴⁴ , grey-level run length matrix ¹⁶⁴ , local binary patterns ¹⁶⁵ , Gabor wavelets ¹⁶⁶ , Laws' energy measures ⁴⁵
Shape and volume	Measure of 2D or 3D tumour morphology	Volume, surface-to-volume ratio, sphericity, compactness, fractal dimensionality ¹⁶⁷
Peritumoural radiomics	Characterization of TME through application of radiomic features (such as texture) within the surrounding TME	Textural heterogeneity of the peritumoural radius surrounding a tumour ⁵⁸ , stroma ¹⁶⁸ , lymph nodes ¹⁶⁹ , potential metastatic sites ¹⁰⁹
Radiomics of tumour vascularity	Measurements of the function or shape of the tumour-associated vasculature	Vessel tortuosity and structural organization ^{78,170,171} , kinetic and textural measures of tumour vessels ¹⁷²

Shape



First order features

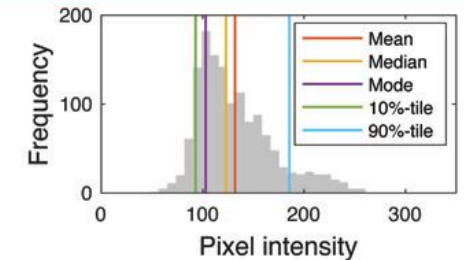
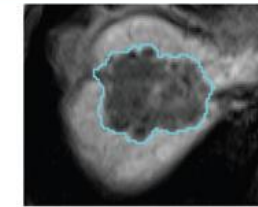


Image texture

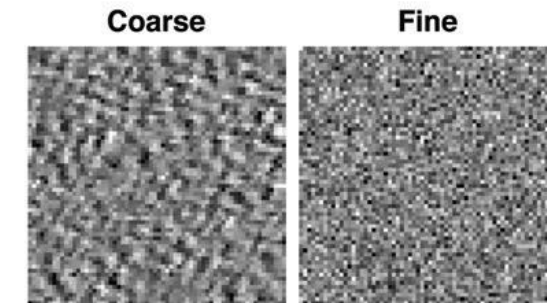
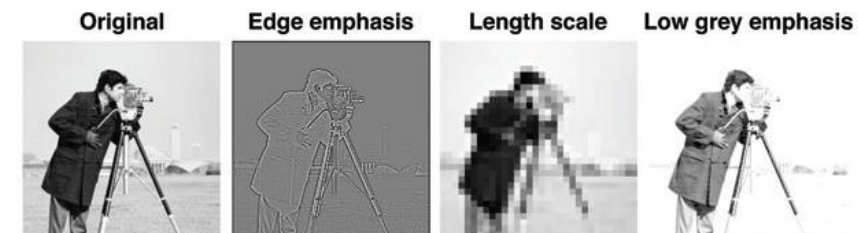


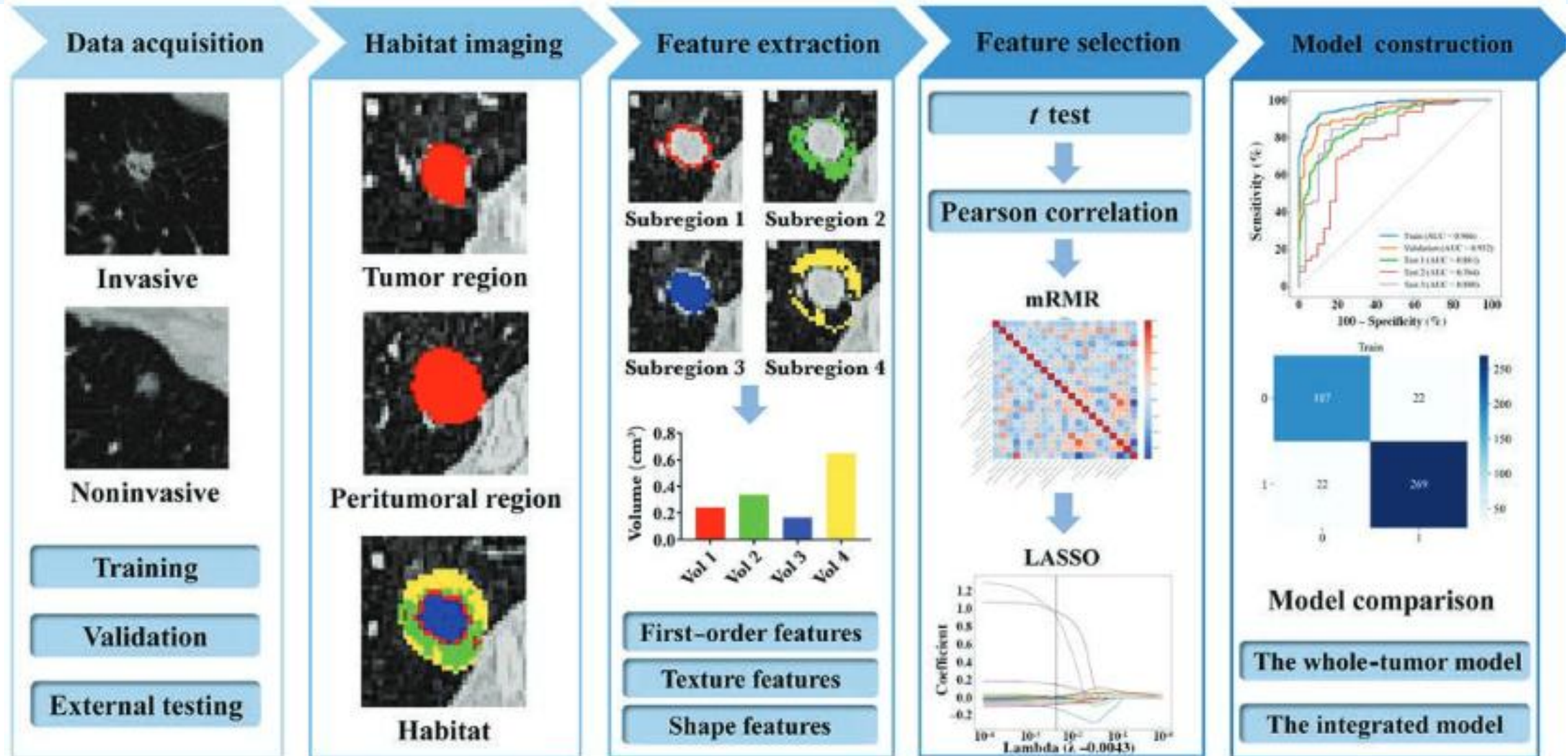
Image filters



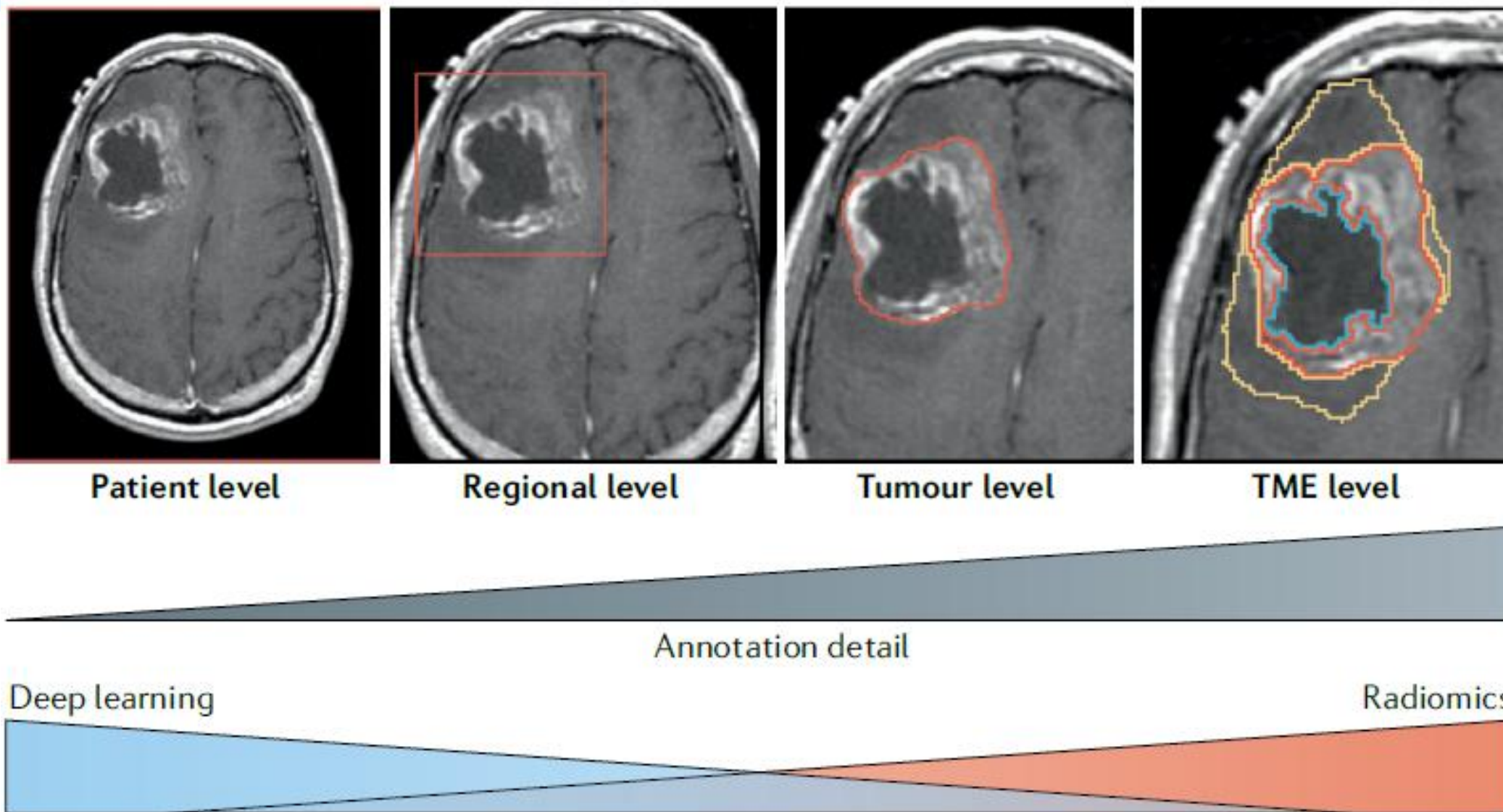
Bera et al. Nat Rev Clin Oncol 2022;19:132–146

Shur et al. Radiographics 2021;41:1717–1732

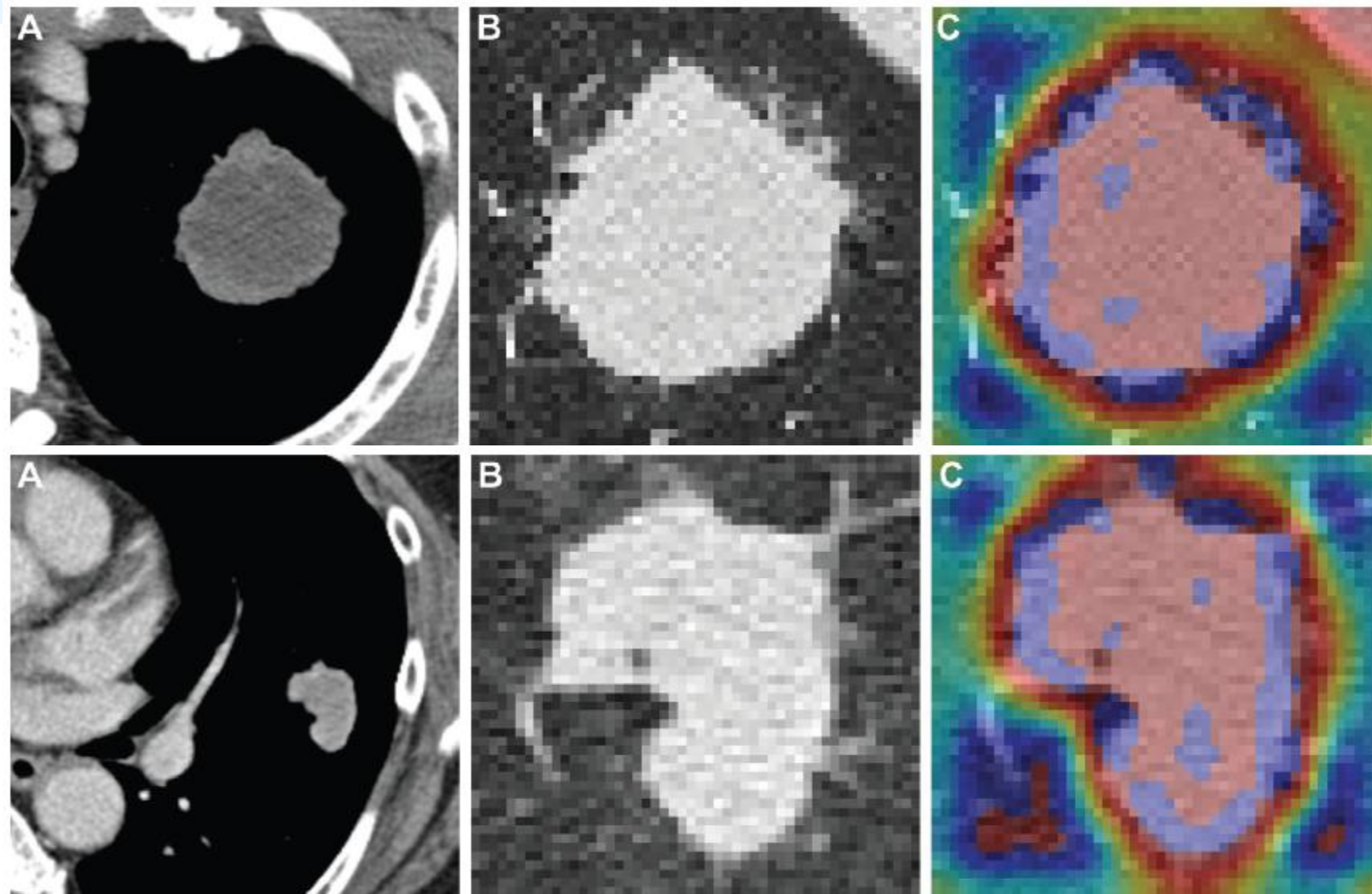
Radiomics



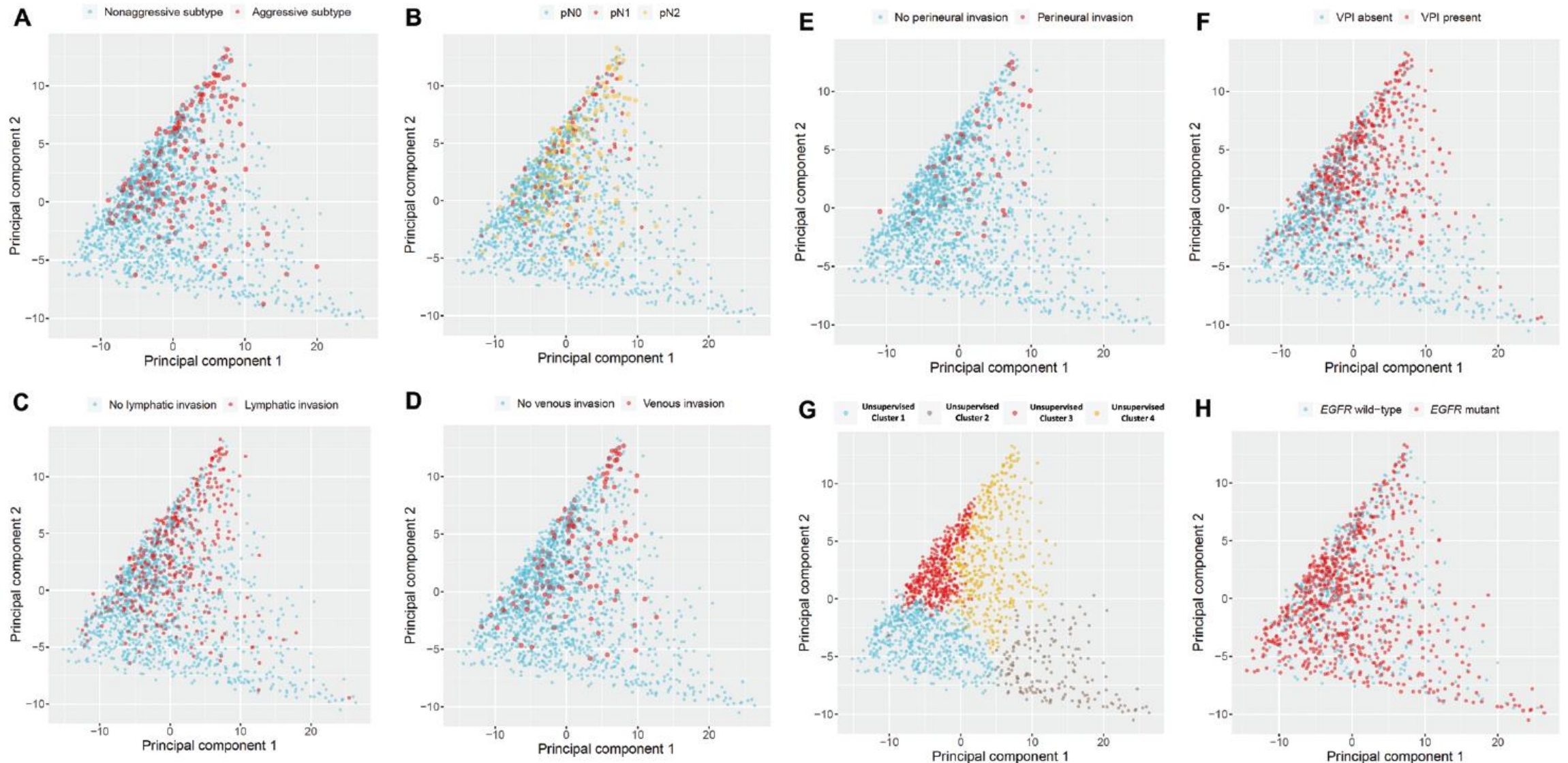
Radiomics vs. DL



Prediction of Aggressiveness



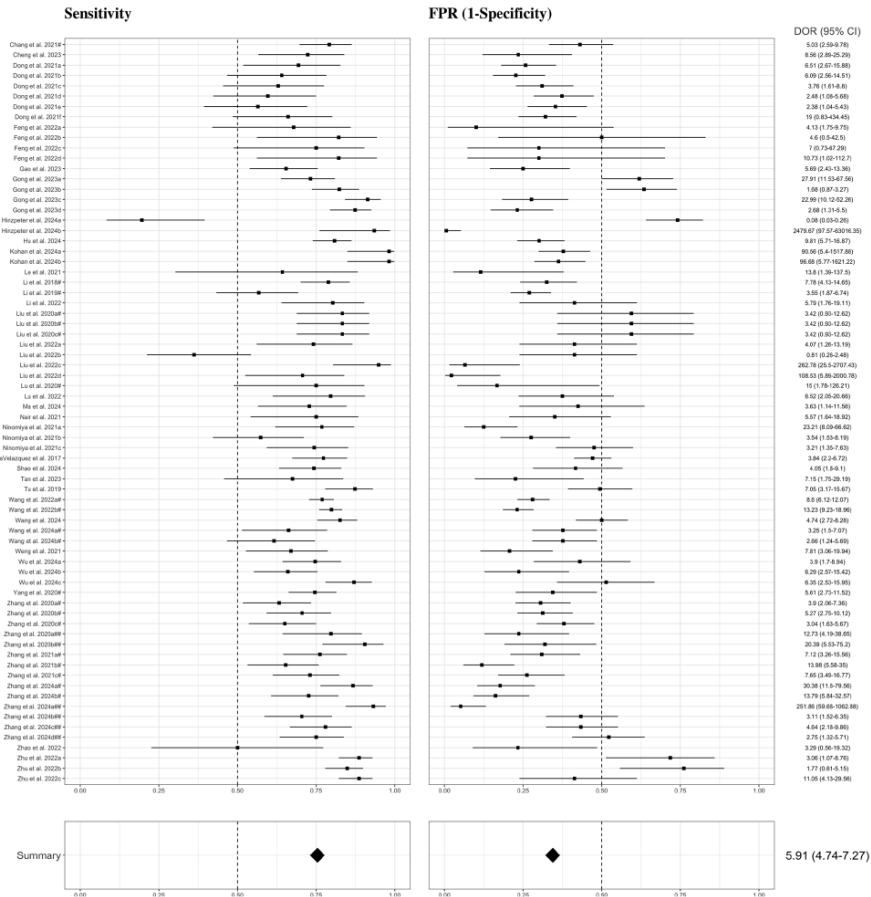
Prediction of Aggressiveness



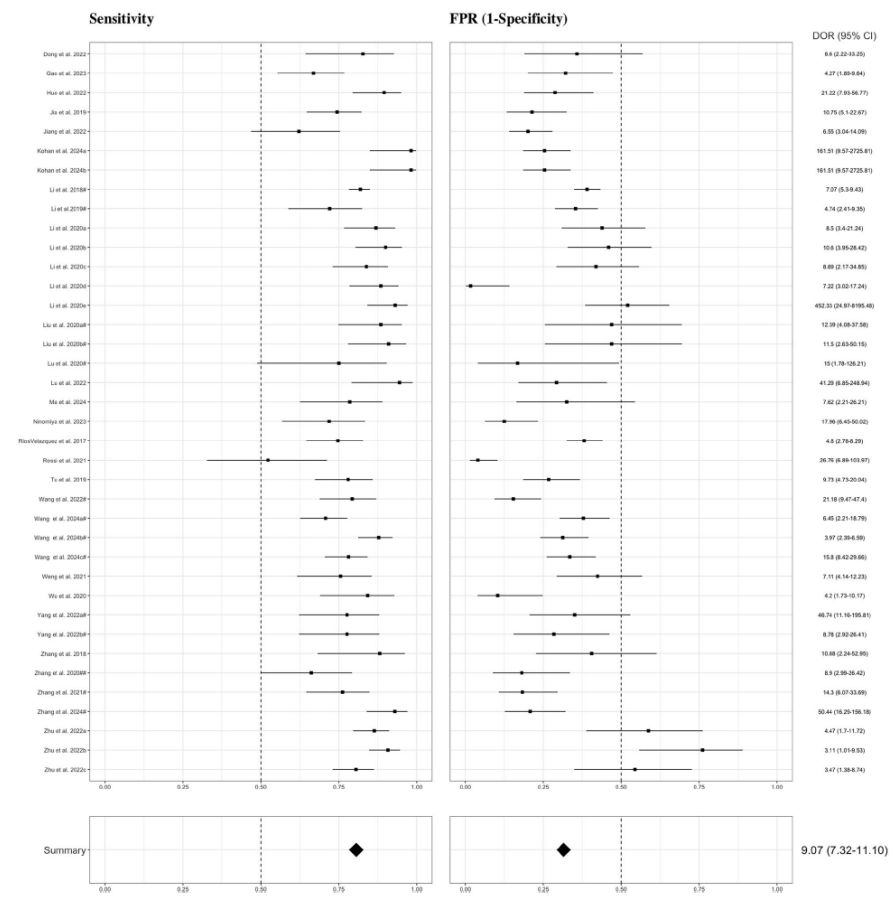
Prediction of Genetic Mutation

Onco-genic Driver	Radiomic Features	Imaging Modality	Reported Sensitivity / Specificity	Key References
EGFR	Air bronchograms, pleural retraction, small lesion size, absence of fibrosis	CT	~ 70–85% / 65–80%	[28]
KRAS G12C	Round tumor shape, nodules in non-tumor lobes, smoking history	CT	~ 65–75% / 60–80%	[28]
ALK	Central location, absence of pleural tail, large pleural effusions, disorganized vasculature	CT	~ 68–80% / 62–78%	[42]
BRAF V600E	Spiculated margins, subsolid nodules, cavitation, heterogeneity on PET	CT, PET	Limited data	[50]
HER2	Ground-glass opacities, ill-defined margins, multifocal lesions	CT	Not reported	[63]
ROS1	Peripheral location, lobulated margins, high FDG uptake, distinctive vasculature	CT, PET	Not reported	[52, 53, 64]
NTRK	Well-circumscribed nodules, minimal necrosis, homogeneous enhancement	CT	Not reported	[65]
MET	Large tumor size, irregular margins, high metabolic activity on FDG-PET	CT, PET	Not reported	[66]
RET	Well-defined nodules, peripheral location, moderate FDG uptake	CT, PET	Not reported	[52]

Prediction of Genetic Mutation

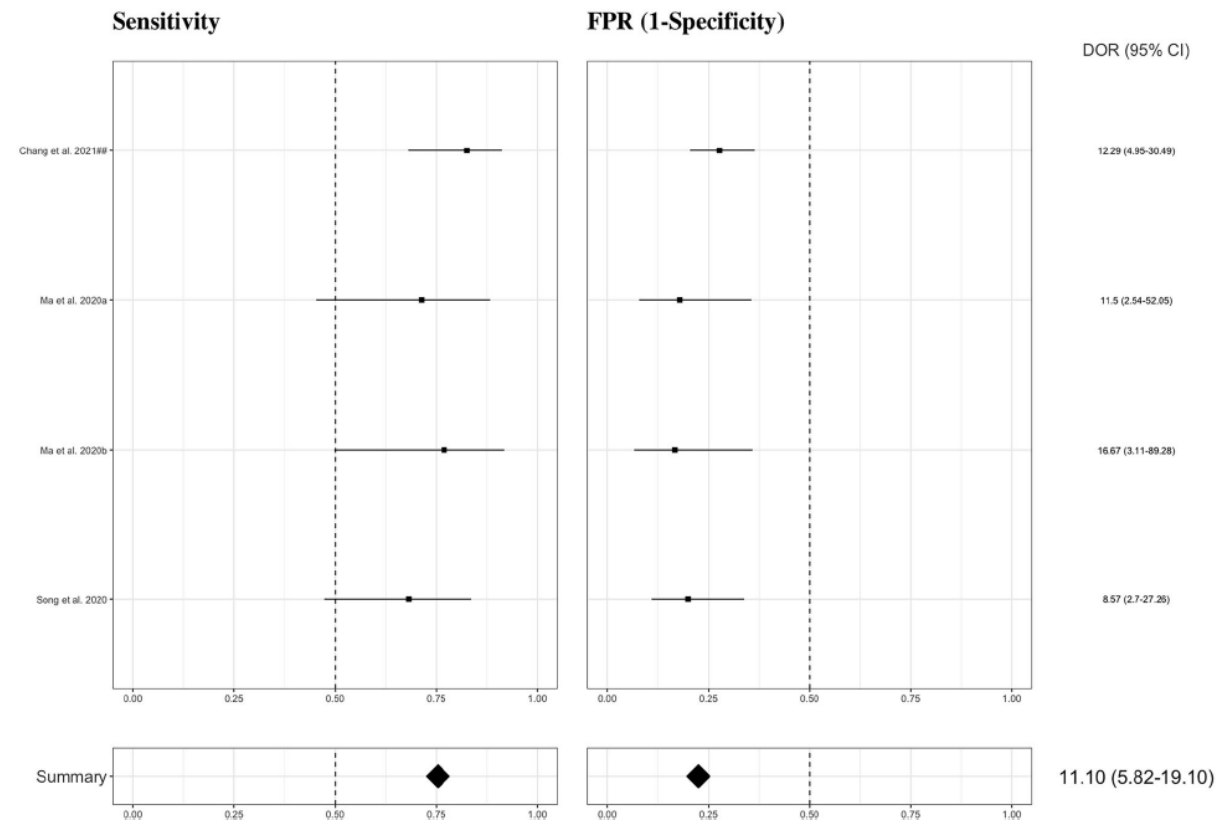


EGFR, Radiomics model
 Pooled sensitivity: 0.754 (95% CI: 0.727–0.780)
 Pooled specificity: 0.656 (95% CI: 0.619–0.692)



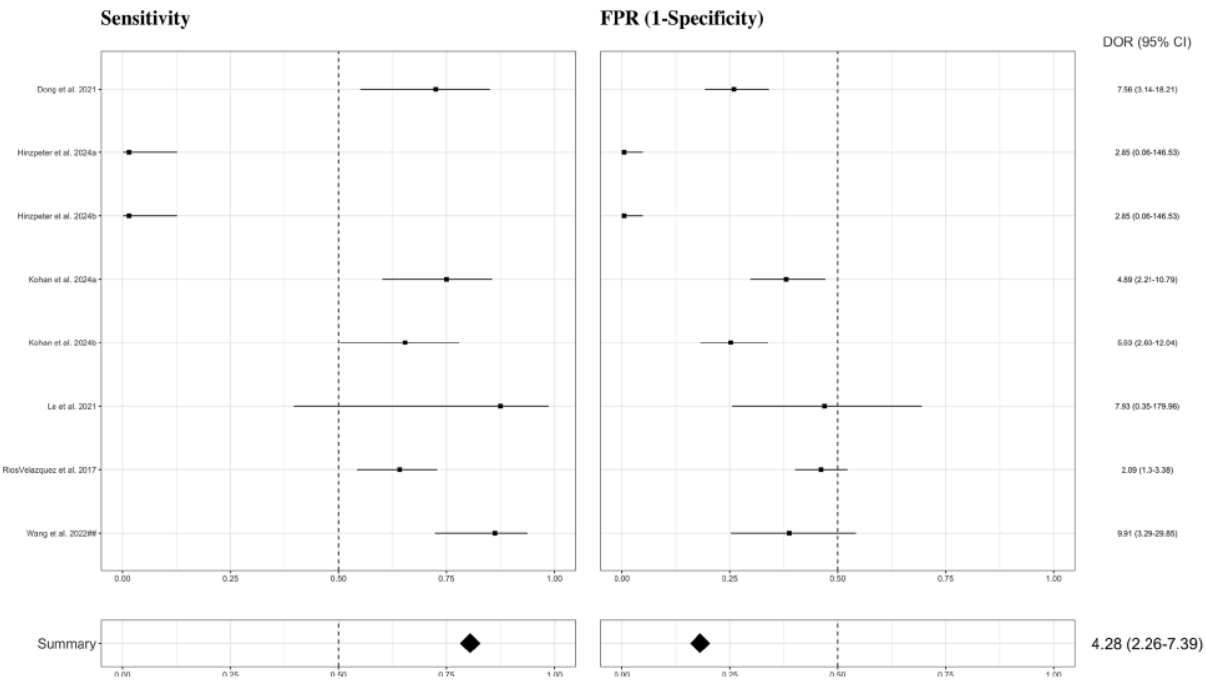
EGFR, Combined model (radiomics + clinical)
 Pooled sensitivity: 0.806 (95% CI: 0.776–0.833)
 Pooled specificity: 0.685 (95% CI: 0.636–0.730)

Prediction of Genetic Mutation



ALK

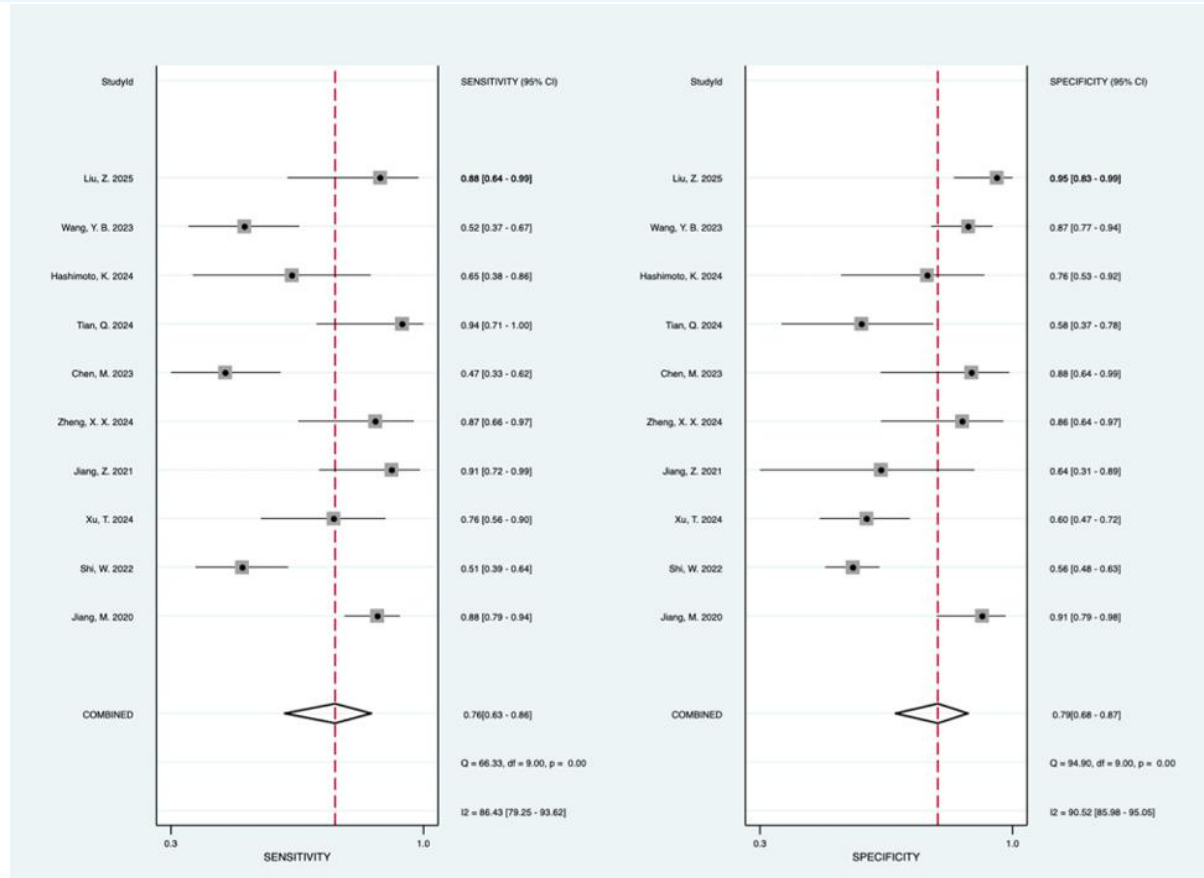
Pooled sensitivity: 0.754 (95% CI: 0.638–0.841)
Pooled specificity: 0.775 (95% CI: 0.698–0.837)



KRAS

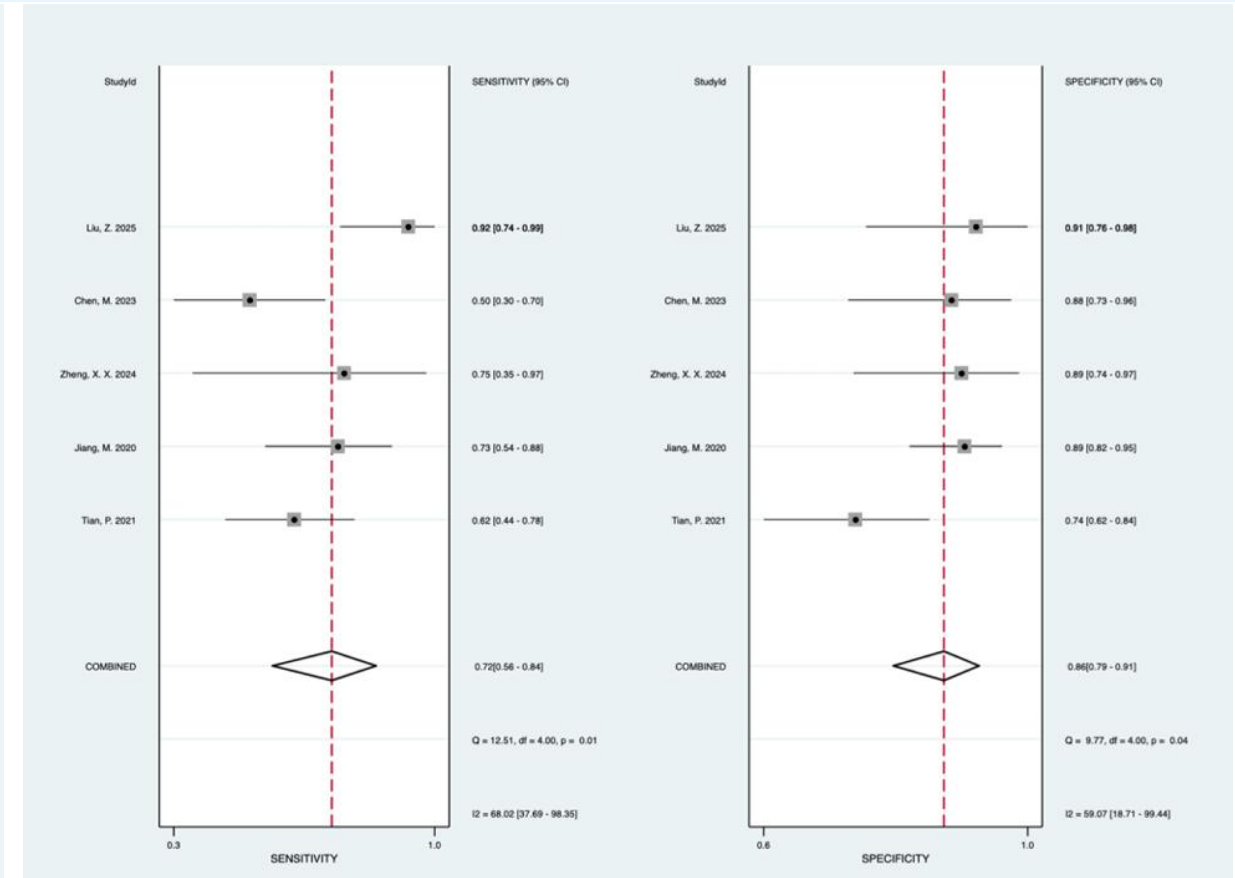
Pooled sensitivity: 0.475 (95% CI: 0.153–0.820)
Pooled specificity: 0.819 (95% CI: 0.539–0.946)

Prediction of PD-L1 Expression



TPS1

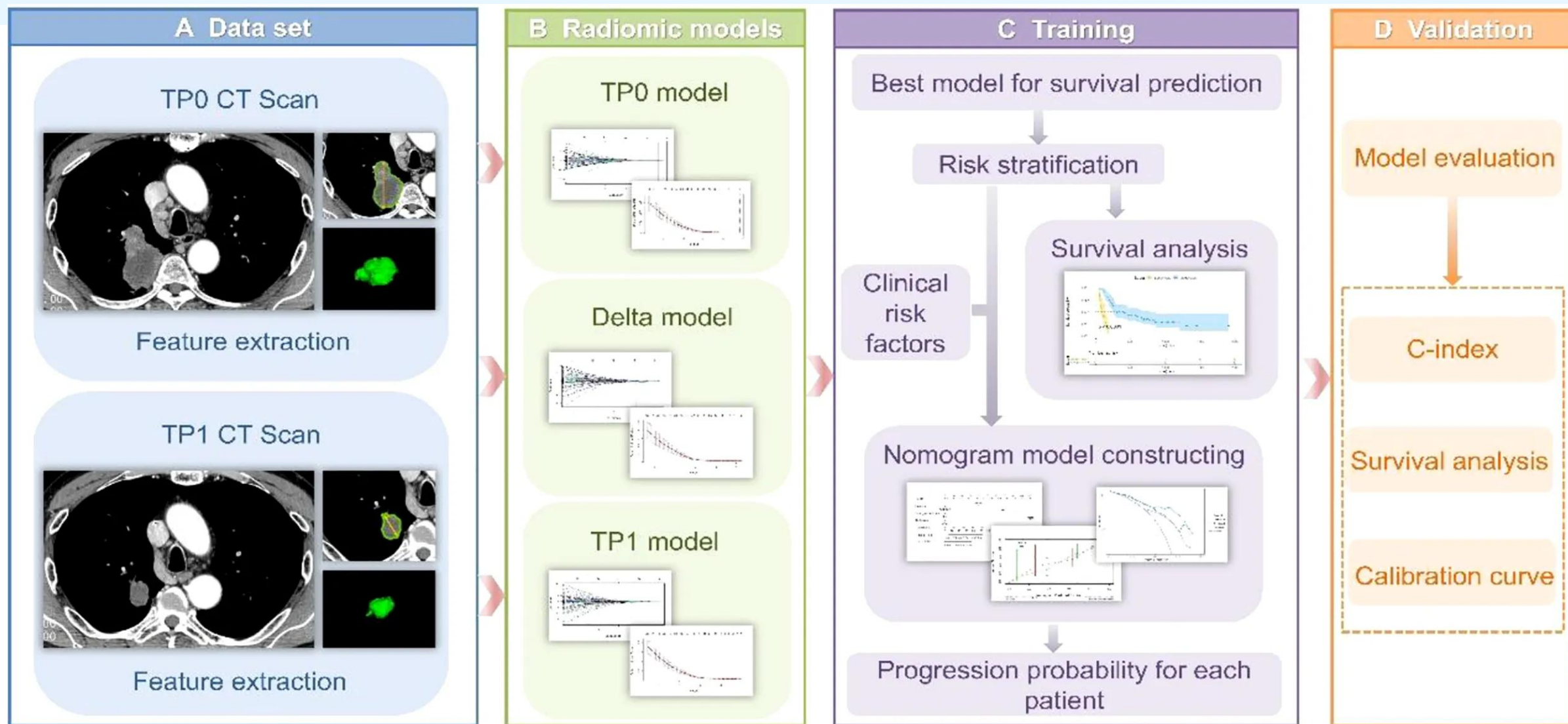
Pooled AUC: 0.85
Pooled sensitivity: 0.76
Pooled specificity: 0.76



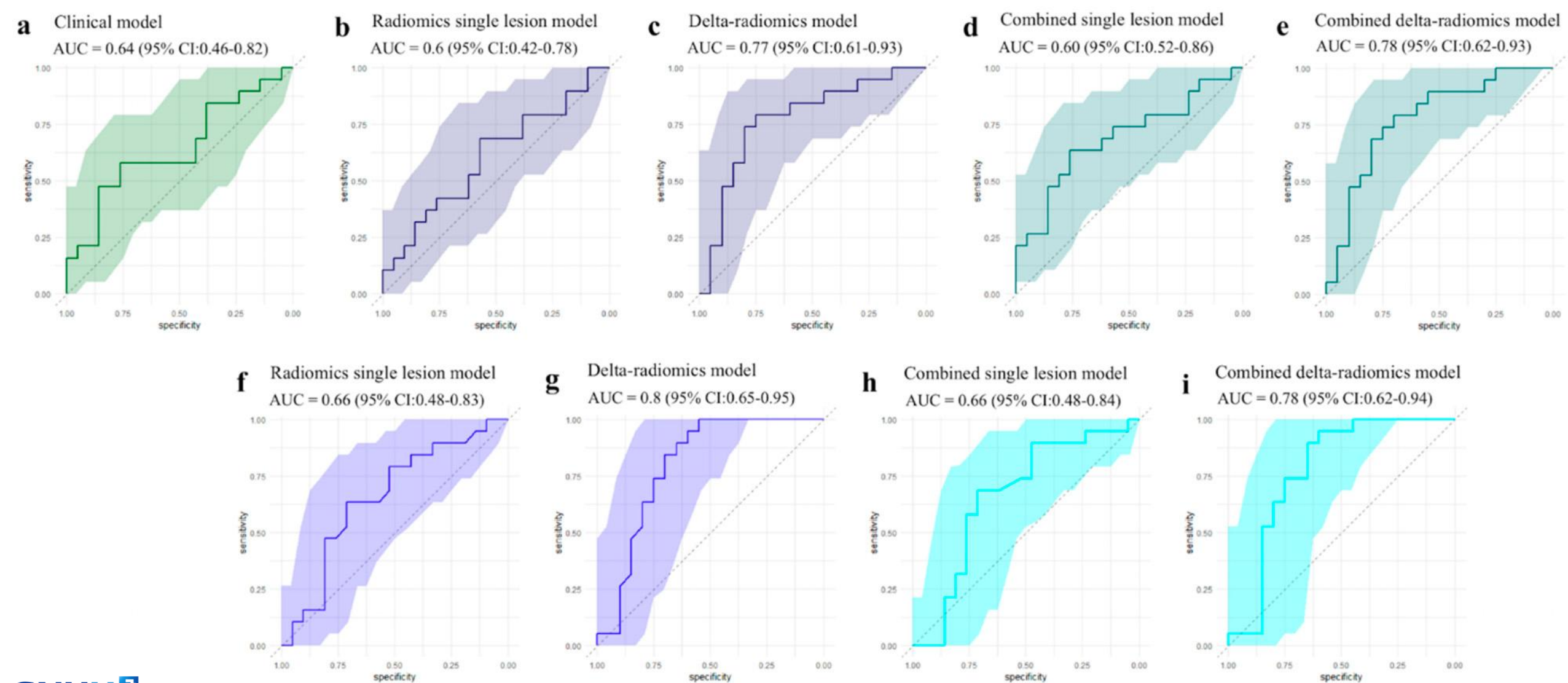
TPS50

Pooled AUC: 0.88
Pooled sensitivity: 0.72
Pooled specificity: 0.76

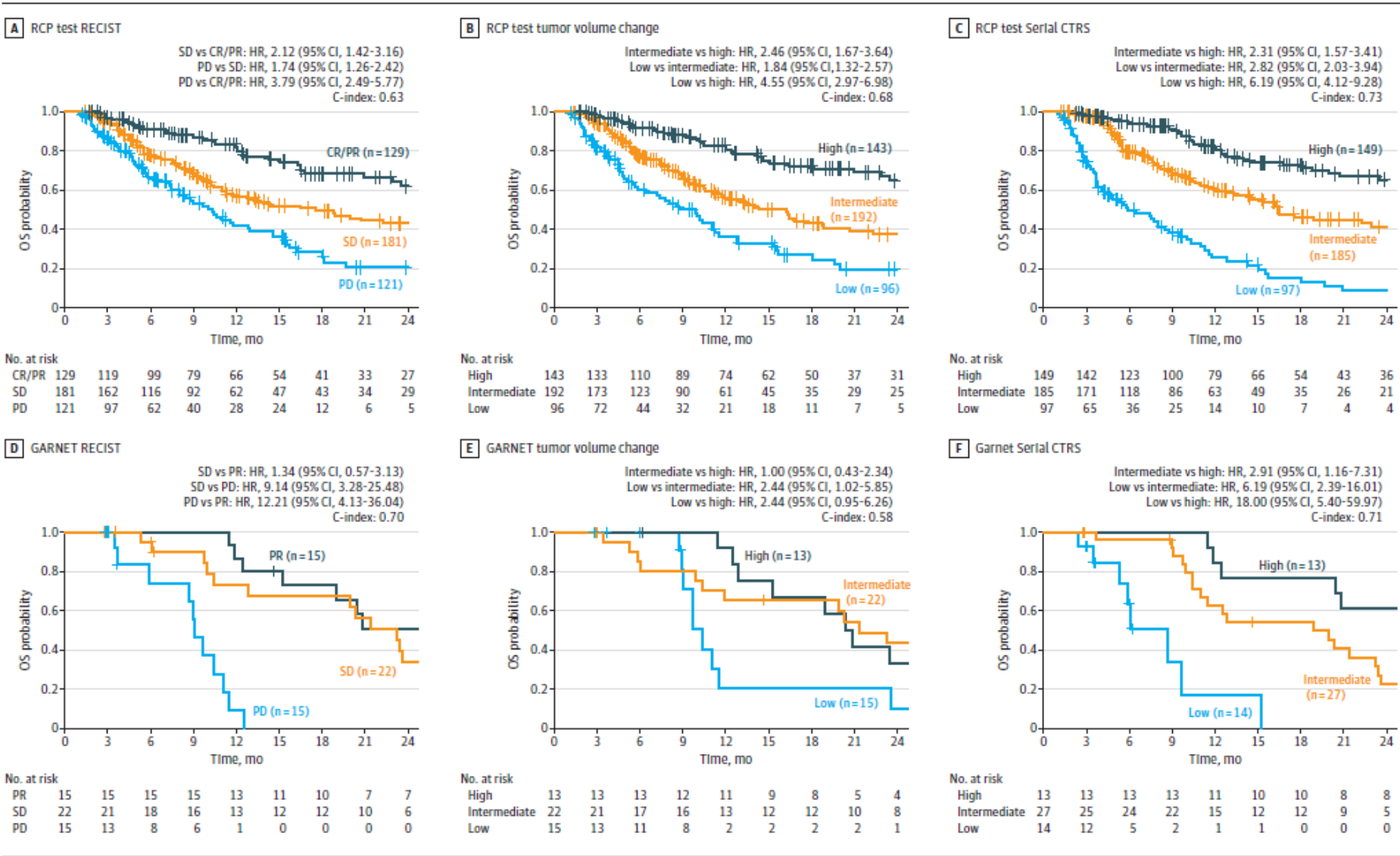
Treatment Response



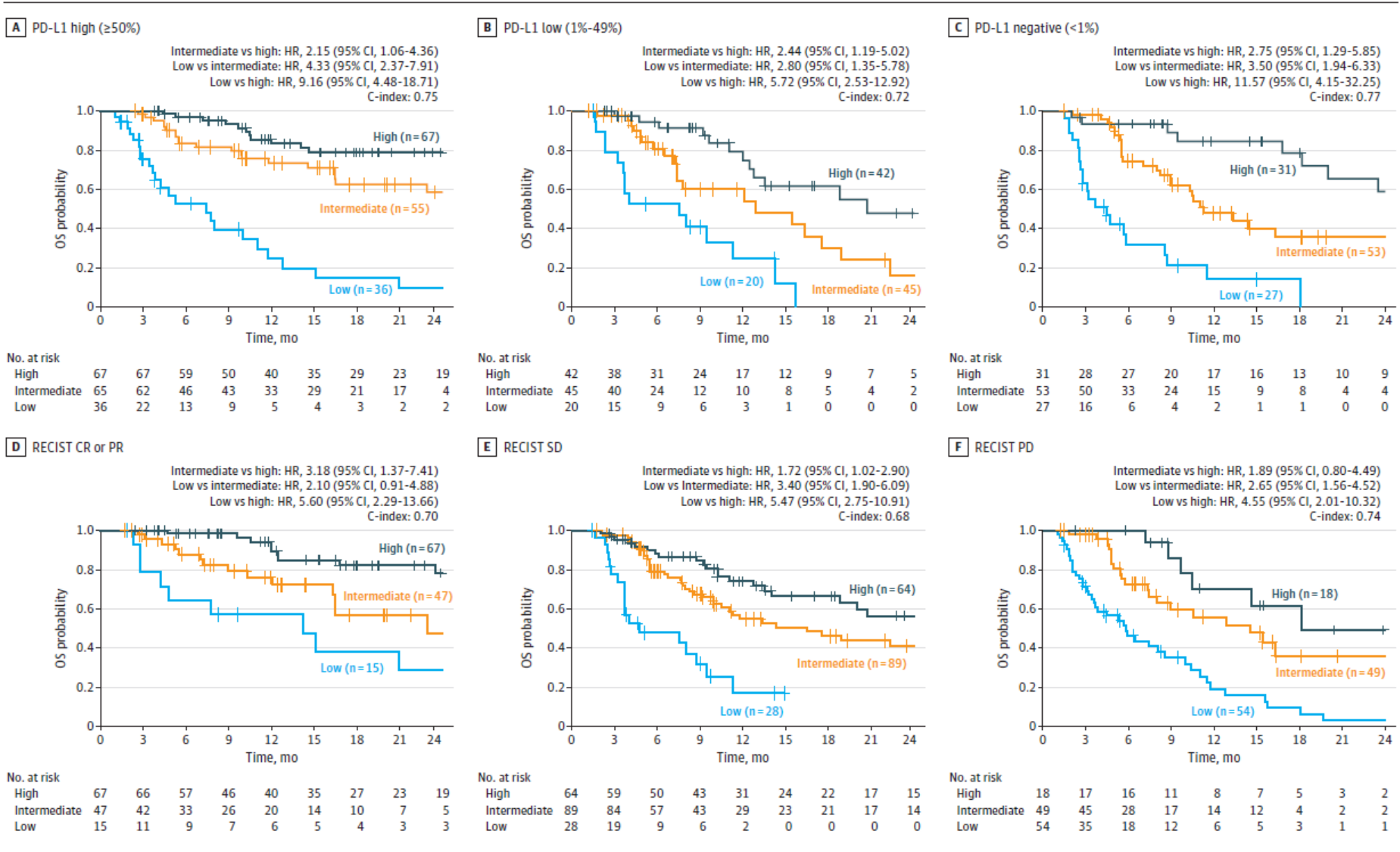
Treatment Response



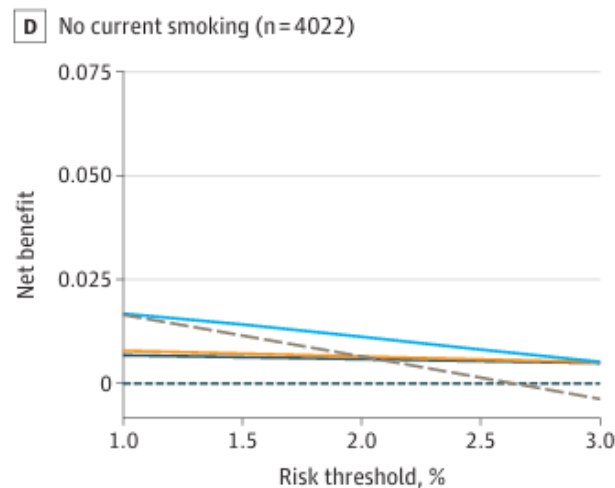
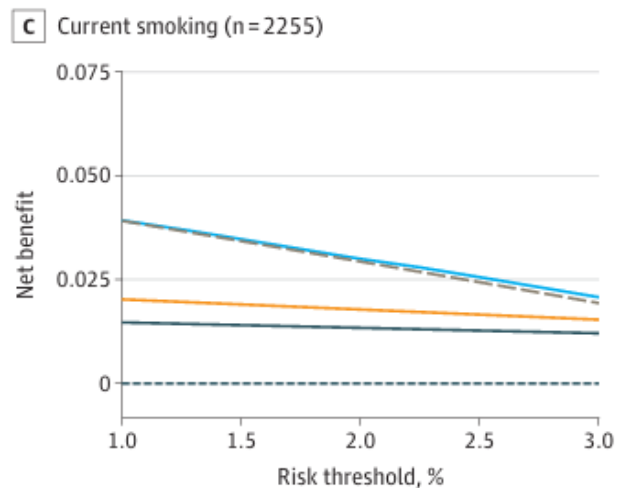
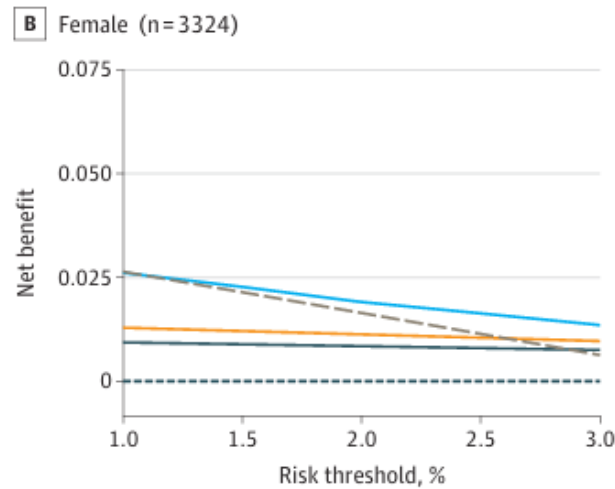
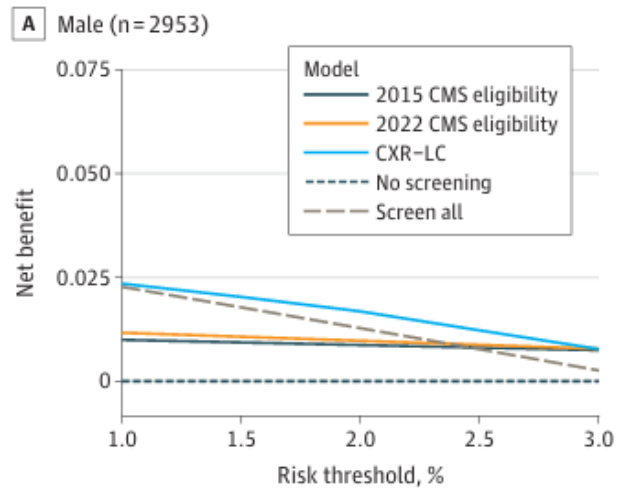
Treatment Response



Treatment Response



Real World?



Study Overview

Brief Summary

The goal of this clinical trial is to evaluate whether an AI tool that alerts providers to patients at high 6-year risk of lung cancer based on their chest x-ray images will improve lung cancer screening CT participation. The main question it aims to answer is: Does the AI tool improve lung cancer screening CT participation at 6 months after the baseline outpatient visit?

The intervention is an alert to the provider to discuss lung cancer screening CT eligibility, for patients considered at high risk of lung cancer based on CXR-LC AI tool. Intervention and non-intervention arms will be compared to determine if lung cancer screening CT participation increases.

Individuals who are considered high-risk by the tool, but who do not meet the Medicare/USPSTF pack-year or quit-date lung screening eligibility criteria may be offered research lung screening CT.

Official Title

Deep Learning Using Routine Chest X-Rays and Electronic Medical Record Data to Identify High Risk Patients for Lung Cancer Screening CT

Study Start (Actual) ⓘ

2025-05-20

Primary Completion (Estimated) ⓘ

2027-07-01

Study Completion (Estimated) ⓘ

2027-07-01

Enrollment (Estimated) ⓘ

1500

Study Type ⓘ

Interventional

Phase ⓘ

Not Applicable

Real World?

Study Overview

Brief Summary

This research study aims to investigate methods for enhancing lung cancer screening. The study will investigate whether an artificial intelligence (AI) tool, known as Sybil, can aid in predicting the risk of lung cancer. The investigators will also examine whether expanding the screening criteria (based on the guidelines of the Potter and American Cancer Society (ACS)) can help identify individuals at risk who are not currently included in the U.S. Preventive Services Task Force (USPSTF) guidelines.

Detailed Description

This is a prospective, non-randomized, multi-cohort implementation study designed to evaluate the feasibility, acceptability, and outcomes of Sybil AI, an AI-based lung cancer risk prediction model, in both guideline-eligible and expanded-eligibility populations undergoing low-dose CT (LDCT) lung cancer screening (LCS). The study includes two interventional cohorts (Cohorts 1 & 2). Aim 1 of the study is to prospectively apply Sybil AI risk scores to a cohort that meets the USPSTF lung screening criteria and the expanded eligibility (Potter & ACS) and evaluate patient comprehension and acceptability. Aim 2 of the study is to collect and analyze blood-based biospecimens to identify immunometabolic biomarkers and assess their integration with Sybil AI and the Brock model for improved risk stratification.

Study Start (Actual) ⓘ

2026-03-12

Primary Completion (Estimated) ⓘ

2028-02

Study Completion (Estimated) ⓘ

2038-02

Enrollment (Estimated) ⓘ

2500

Study Type ⓘ

Interventional

Phase ⓘ

Not Applicable

Project description

[DE](#) [EN](#) [ES](#) [FR](#) [IT](#) [PL](#)

Evaluating strategies in lung cancer screening

Lung cancer (LC) is the main cause of cancer deaths in the EU, claiming 338 000 lives each year. The crucial next method to prevent a great number of these deaths is low-dose CT (Computer Tomography) screening for lung cancer. However, its implementation meets several obstacles resulting in limited and slow use while the need is at perhaps 25 million CT screens annually in Europe, and there are many uncertainties related to the most optimal and cost-effective strategy to apply. Personalised treatment based on the baseline CT result can reduce LC mortality and harm associated with screening; it can also significantly reduce costs. The EU-funded 4-IN THE LUNG RUN project consists of a randomised controlled trial engaging 24 000 individuals aiming to evaluate when it is safe to increase risk-based screening intervals after a negative baseline CT. It is a multi-center implementation trial in 5 countries, with an additional focus on individual optimal recruitment and smoking cessation strategies, co-morbidity reducing strategies (like the use of a calcium score for CVD), and biomarkers.

[Show the project objective](#)

Fields of science (EuroSciVoc) ⓘ

[social sciences](#) > [sociology](#) > [demography](#) > [mortality](#)

[humanities](#) > [history and archaeology](#) > [history](#)

[natural sciences](#) > [chemical sciences](#) > [inorganic chemistry](#) > [alkaline earth metals](#)

[medical and health sciences](#) > [clinical medicine](#) > [oncology](#)

[Suggest new fields of science](#) ▾



Project Information

4-IN THE LUNG RUN

Grant agreement ID: 848294

[Project website](#)

DOI ⓘ

[10.3030/848294](#)

Project closed

EC signature date

6 December 2019

Start date

1 January 2020

End date

31 December 2025

Funded under

SOCIETAL CHALLENGES - Health, demographic change and well-being

Total cost ⓘ

€ 7 999 948,75

EU contribution ⓘ

€ 7 999 948,75

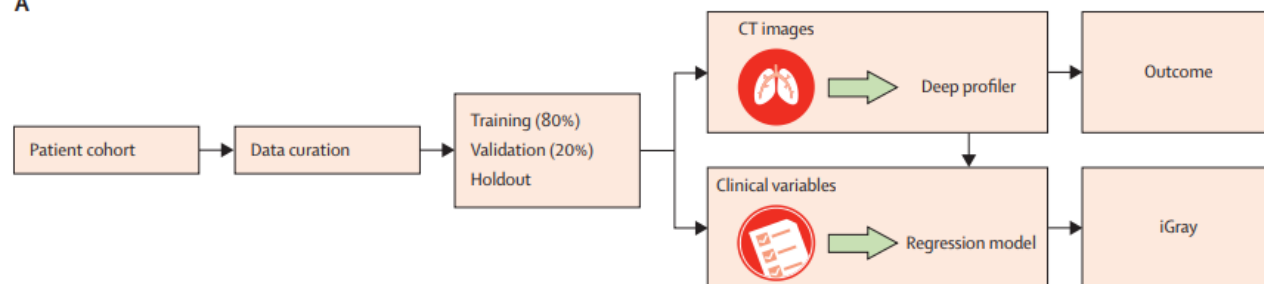
Coordinated by

ERASMUS UNIVERSITAIR MEDISCH CENTRUM
ROTTERDAM
Netherlands



Real World?

A



Study Overview

Brief Summary

This phase II trial tests the effectiveness and safety of artificial intelligence (AI) to determine dose recommendation during stereotactic body radiation therapy (SBRT) planning in patients with primary lung cancer or tumors that has spread from another primary site to the lung (metastatic). SBRT uses special equipment to position a patient and deliver radiation to tumors with high precision. This method may kill tumor cells with fewer doses over a shorter period and cause less damage to normal tissue. Even with the high precision of SBRT, disease persistence or reappearance (local recurrence) can still occur, which could be attributed to the radiation dose. AI has been used in other areas of healthcare to automate and improve various aspects of medical science. Because the relationship of dose and local recurrence indicates that dose prescriptions matter, decision support systems to help guide dose based on personalized prediction AI algorithms could better assist providers in prescribing the radiation dose of lung stereotactic body radiation therapy treatment.

Detailed Description

PRIMARY OBJECTIVE:

I. To obtain preliminary evidence of efficacy (reduction in local failure free survival) in patients receiving SBRT to the lung with personalized artificial intelligence dose guidance (Deep Profiler + iGray).

Study Start (Actual) ⓘ

2023-11-20

Primary Completion (Estimated) ⓘ

2026-08-01

Study Completion (Estimated) ⓘ

2031-08-01

Enrollment (Estimated) ⓘ

70

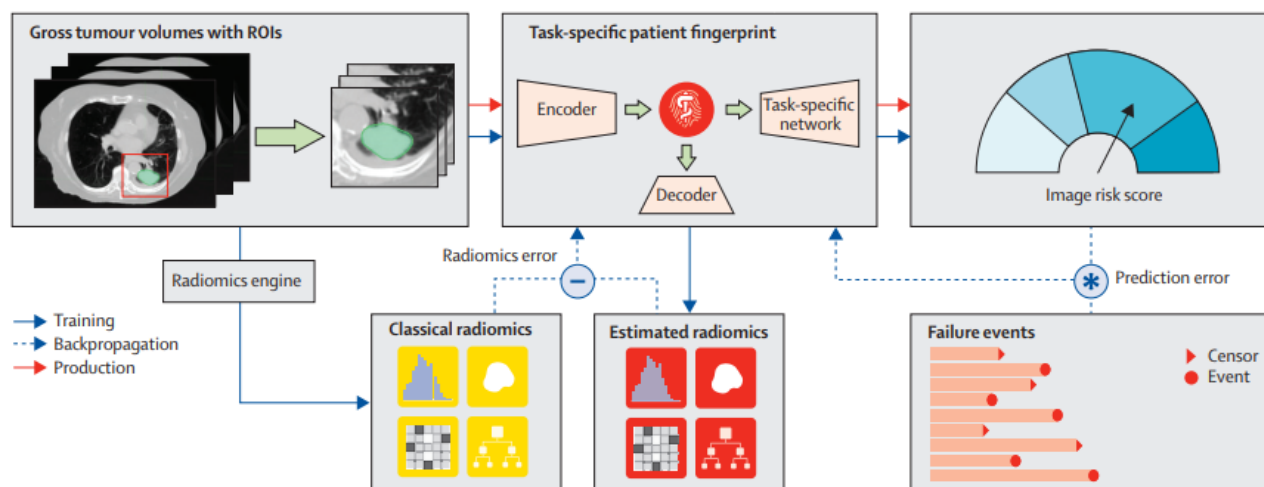
Study Type ⓘ

Interventional

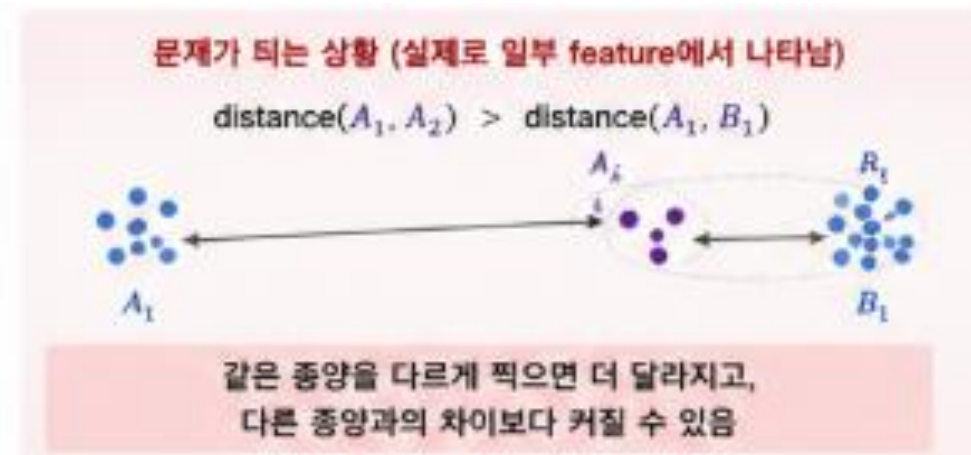
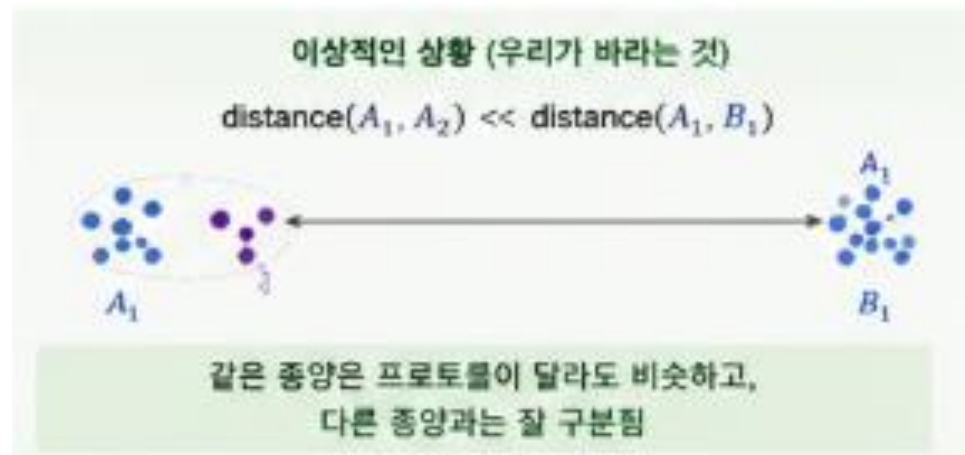
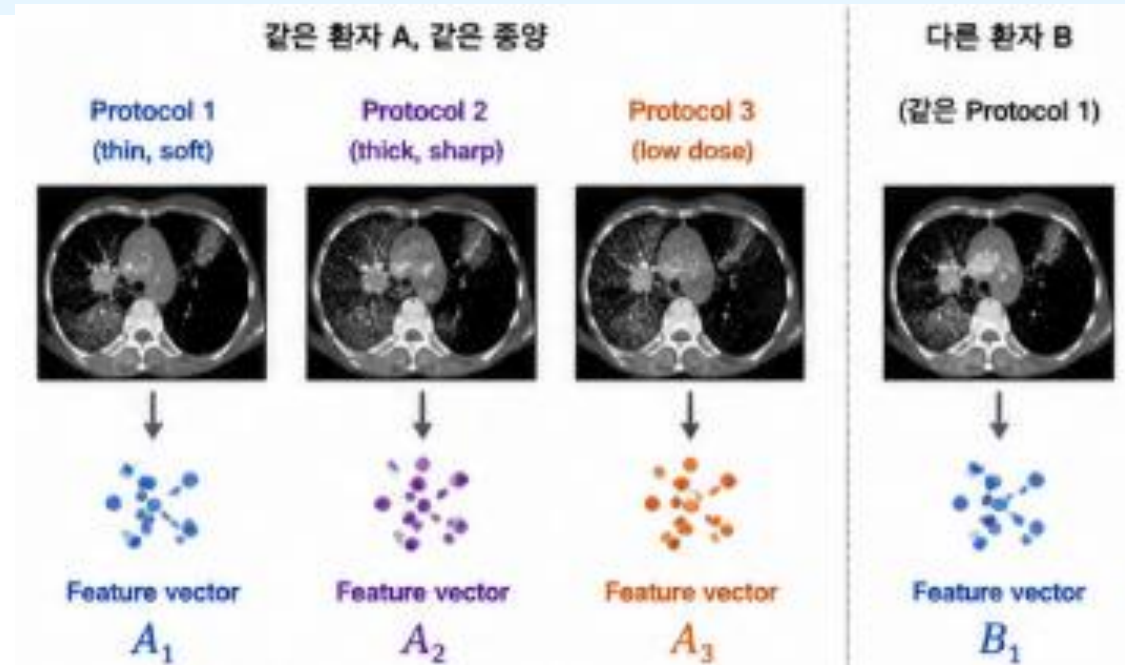
Phase ⓘ

Not Applicable

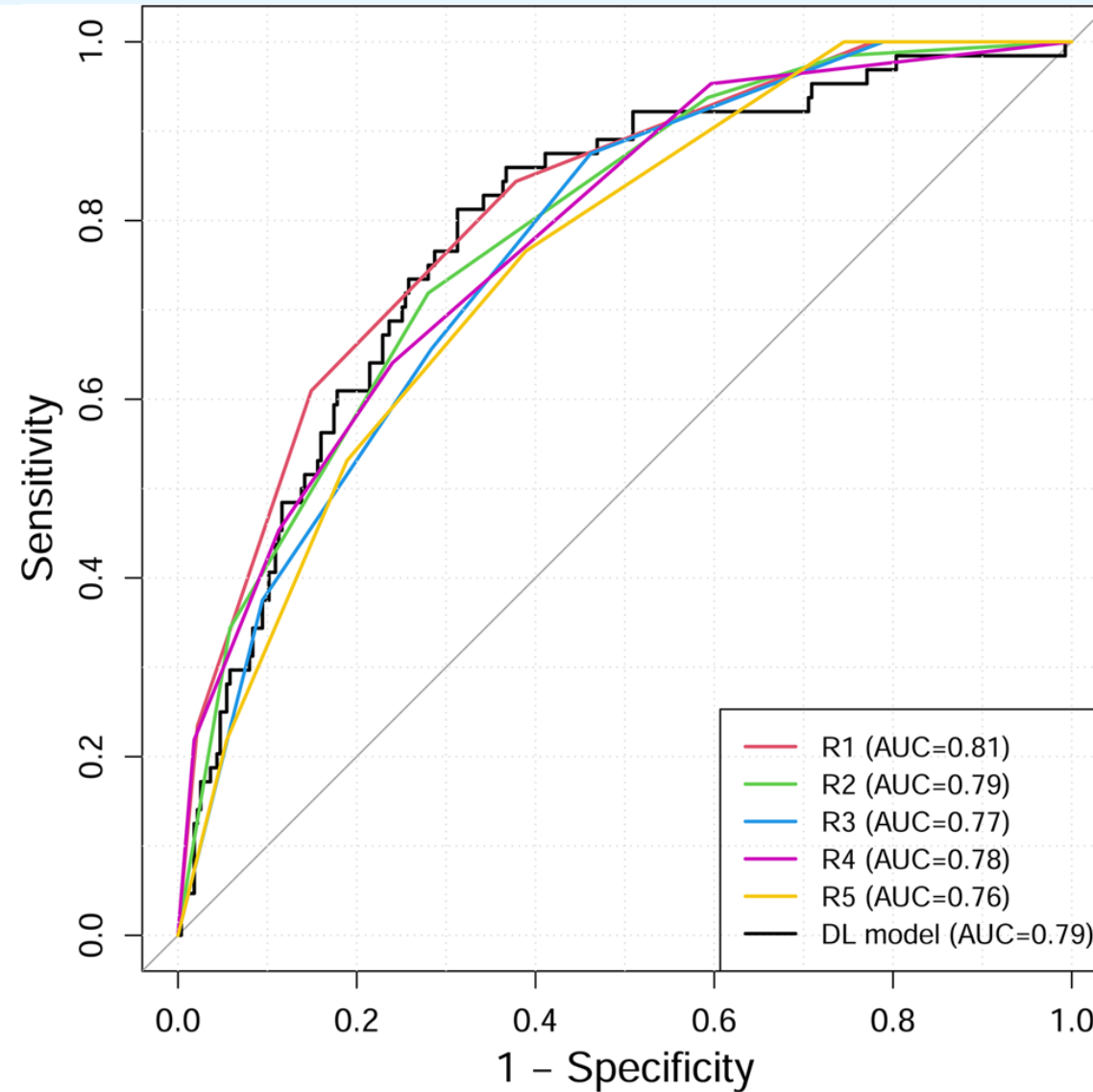
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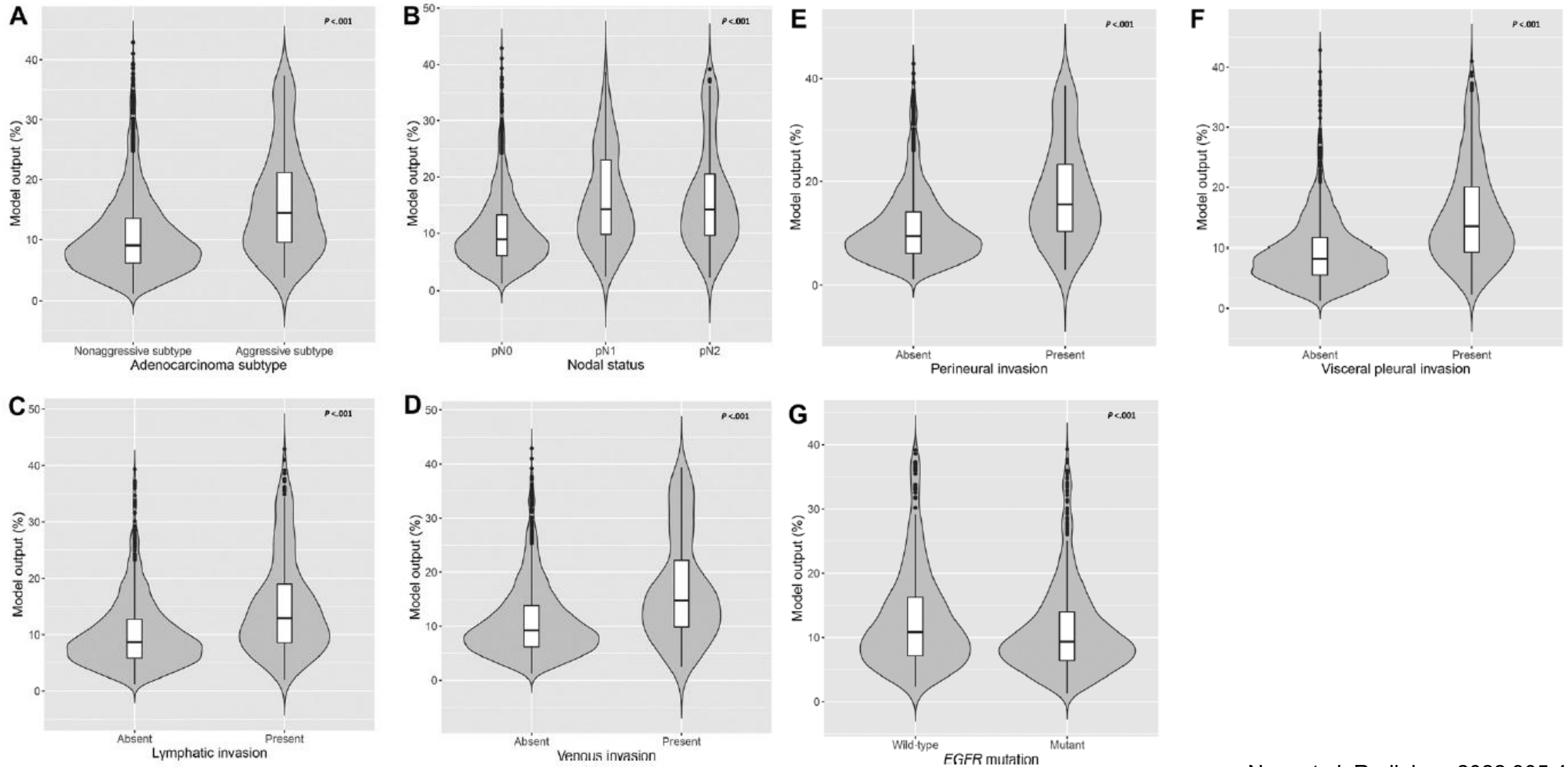
Real World?



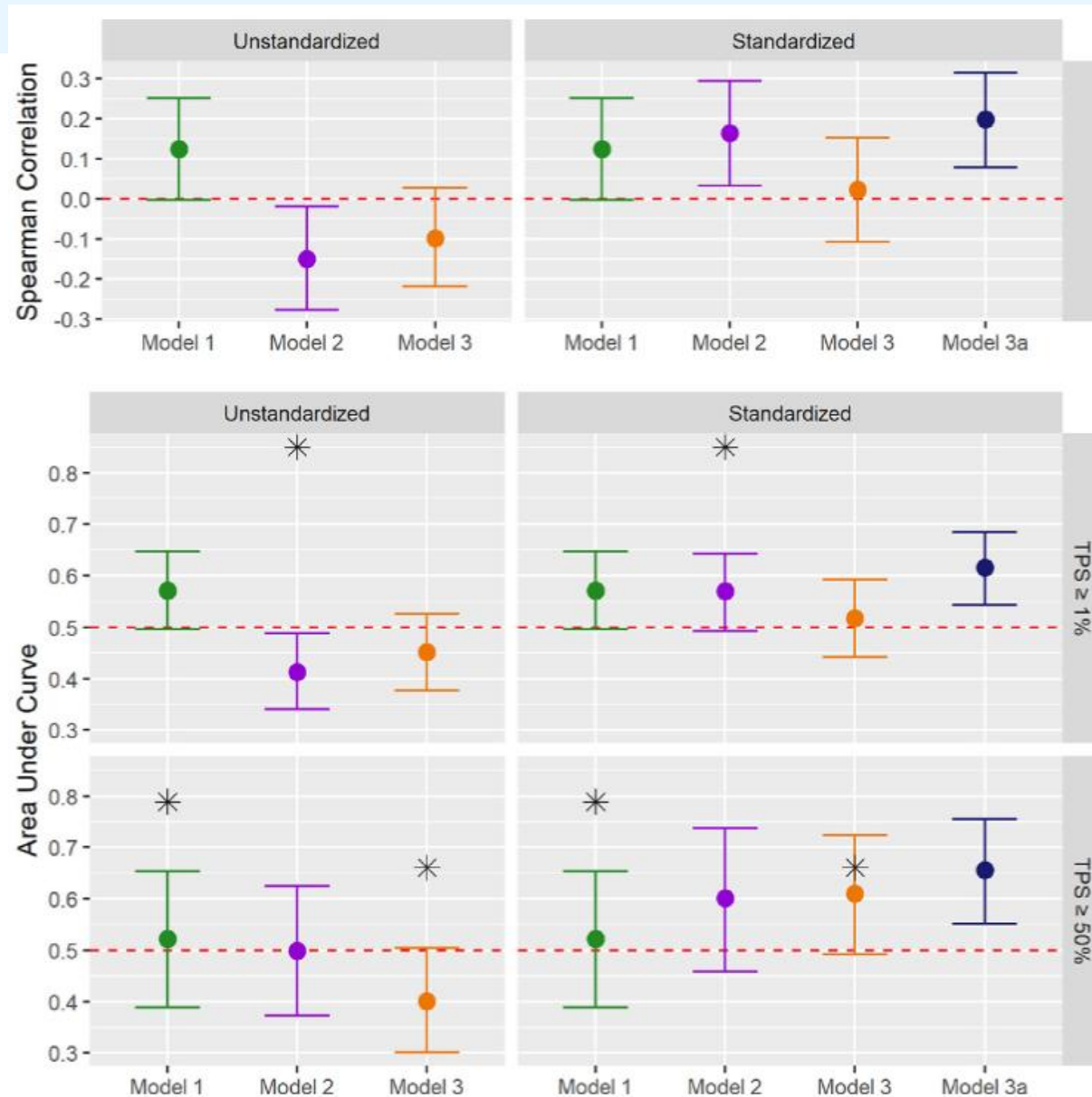
Real World?



Real World?



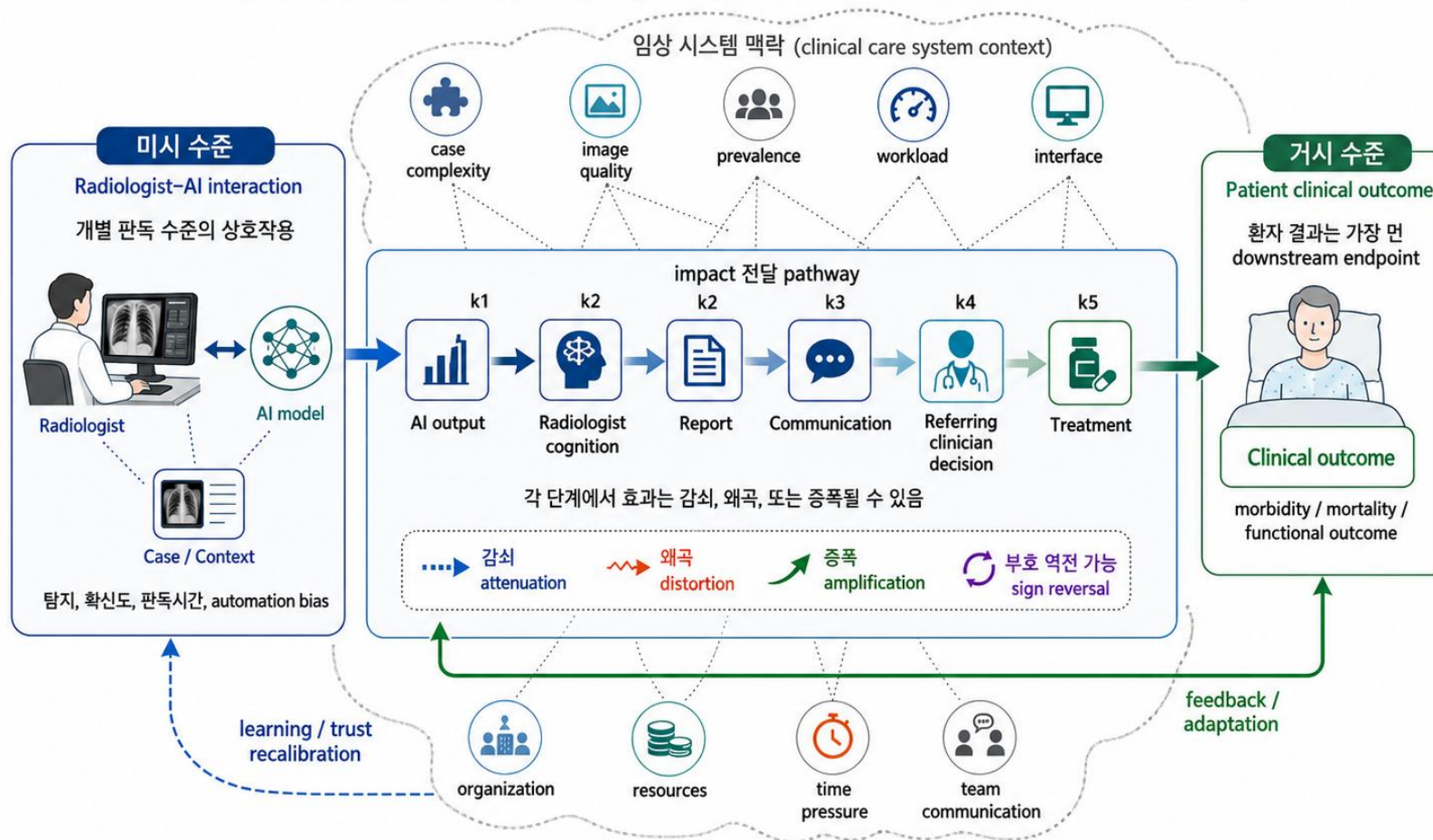
Real World?



Real World?

Radiologist-AI impact가 patient outcome으로 전달되는 과정

개별 판독 상호작용에서 임상 시스템 전반으로 (From individual interaction to the clinical care system)



$$\text{AI impact on outcome} \approx \Delta \text{AI} \times k_1 \times k_2 \times k_3 \times k_4 \times k_5$$

즉, AI의 임상효과는 알고리즘 자체보다 전체 care pathway와 sociotechnical system에 의해 결정된다.

Virtual Scenario 1-1 (EGFR in ADC)

- **Pre-test probability of EGFR mutation in Korea: 43.3%**
- **Expected performance of a predictive model (AUC): 0.801 vs. 0.9**
- **Expected sensitivity and specificity (equal-variance binormal ROC):**
 - Balanced model: 72.5% & 72.5% (AUC 0.801) vs. 81.8% & 81.8% (AUC 0.9)
 - High-sensitivity model: 90.0% & 46.6% (AUC 0.801) vs. 90.0% & 70.2% (AUC 0.9)
 - High-specificity model: 46.6% & 90.0% (AUC 0.801) vs. 70.2% & 90.0% (AUC 0.9)
- **Expected PPV and NPV:**
 - Balanced model: 66.8% & 77.5% (AUC 0.801) vs. 77.4% & 85.4% (AUC 0.9)
 - High-sensitivity model: 56.3% & 85.9% (AUC 0.801) vs. 69.8% & 90.2% (AUC 0.9)
 - High-specificity model: 78.1% & 68.8% (AUC 0.801) vs. 84.3% & 79.8% (AUC 0.9)

Virtual Scenario 1-2 (EGFR in ADC)

- **Pre-test probability of EGFR mutation in Korea: 43.3%**
- **False-negative rate of biopsy-driven EGFR mutation test: 5% vs. 10%**
- Post-test probability of EGFR mutation in biopsy-negative patients: 3.7% vs. 7.1%
- Expected performance of a predictive model (AUC): 0.801 vs. 0.9
- **Re-biopsy yield (using a high-specificity model):**
 - 5% False-negative rate of biopsy: 15.1% (AUC 0.801) vs. 21.1% (AUC 0.9)
 - 10% False-negative rate of biopsy: 26.2% (AUC 0.801) vs. 34.9% (AUC 0.9)
- **Number needed to re-biopsy (using a high-specificity model):**
 - 5% False-negative rate of biopsy: 6.6 (AUC 0.801) vs. 4.7 (AUC 0.9)
 - 10% False-negative rate of biopsy: 3.8 (AUC 0.801) vs. 2.9 (AUC 0.9)

Virtual Scenario 1-3 (EGFR in ADC)

- **Pre-test probability of EGFR mutation in Korea: 43.3%**
- **Performance of liquid biopsy-driven EGFR mutation test: sensitivity of 66%, specificity of 96%**
- Post-test probability of EGFR mutation in biopsy-negative patients: 21.3%
- Expected performance of a predictive model (AUC): 0.801 vs. 0.9
- **Post-test probability of EGFR mutation in biopsy-negative and CT model positive-patients (using a sensitivity model):**
 - AUC 0.801: 31.3%
 - AUC 0.9: 45.0%

Virtual Scenario 2-1 (PD-L1 in NSCLC)

- **Pre-test probability of PD-L1: 60.4% (TPS $\geq$ 1%), 29.1% (TPS $\geq$ 50%)**
- **Expected performance of a predictive model (AUC): 0.85 (TPS $\geq$ 1%), 0.88 (TPS $\geq$ 50%)**
- **Expected sensitivity and specificity (equal-variance binormal ROC):**
 - Balanced model: 76.8% & 76.8% (TPS $\geq$ 1%), 79.7% & 79.7% (TPS $\geq$ 50%)
 - High-sensitivity model: 90.0% & 57.3% (TPS $\geq$ 1%), 90.0% & 64.8% (TPS $\geq$ 50%)
 - High-specificity model: 57.3% & 90.0% (TPS $\geq$ 1%), 64.8% & 90.0% (TPS $\geq$ 50%)
 - Meta-analysis: 76% & 79% (TPS $\geq$ 1%), 72% & 86% (TPS $\geq$ 50%)
- **Expected PPV and NPV:**
 - Balanced model: 83.5% & 68.5% (TPS $\geq$ 1%), 61.7% & 90.5% (TPS $\geq$ 50%)
 - High-sensitivity model: 76.3% & 79.0% (TPS $\geq$ 1%), 51.2% & 94.0% (TPS $\geq$ 50%)
 - High-specificity model: 89.7% & 58.0% (TPS $\geq$ 1%), 72.7% & 86.2% (TPS $\geq$ 50%)

Virtual Scenario 2-2 (PD-L1 in NSCLC)

- **Pre-test probability of PD-L1: 60.4% (TPS $\geq 1\%$), 29.1% (TPS $\geq 50\%$)**
- **False-negative rate of biopsy-driven PD-L1 expression test: 15% (TPS $\geq 1\%$), 24% (TPS $\geq 50\%$)**
- Post-test probability of PD-L1 expression in biopsy-negative patients: 18.6% vs. 9.0%
- Expected performance of a predictive model (AUC): 0.85 (TPS $\geq 1\%$), 0.88 (TPS $\geq 50\%$)
- **Re-biopsy yield (using a high-specificity model):**
 - TPS $\geq 1\%$: 56.7%
 - TPS $\geq 50\%$: 39.0%
- **Number needed to re-biopsy (using a high-specificity model):**
 - TPS $\geq 1\%$: 1.8
 - TPS $\geq 50\%$: 2.6

AI Application for Lung Cancer

- Reducing intra-observer and inter-observer variability
- Potential for measuring intratumoral heterogeneity
- Potential for predicting aggressiveness
- Inherent limitation in predicting microscopic changes
- Technical variability vs. Variability d/t biological signal
- Various clinical scenarios; Limited real-world validation
- Population, Intervention, Comparison, Outcome

Thank You for Attention