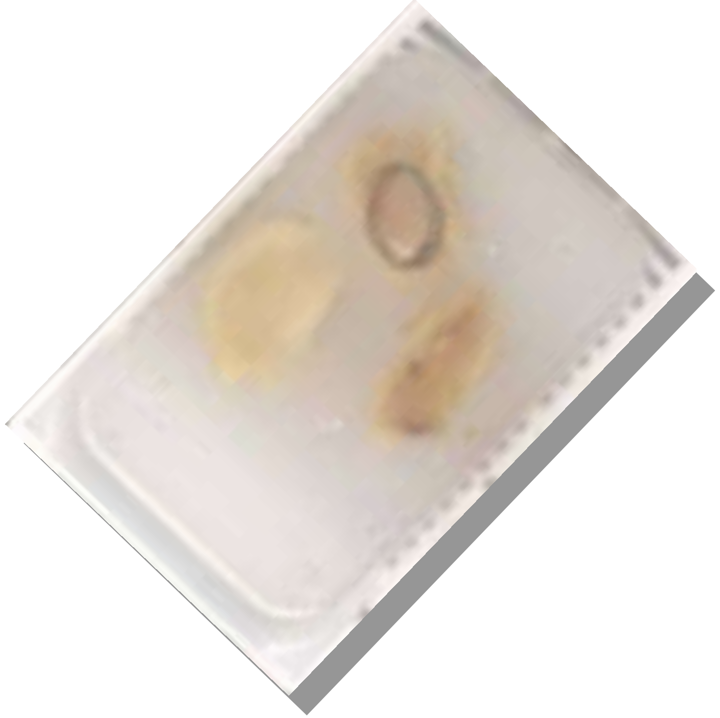
AI in Pathology

Junya Fukuoka, MD. PhD
Nagasaki University Graduate School of Biomedical Sciences
Kameda Medical Center

COI

- Have stocks of Pathology Institute Corp. and PathPresenter
- Research funding from Sony, Sakura Finetech, Astellas Pharm
- Advisory board of ContextVision and N Lab

病理診断って？　病理医って？



United States / Population

327.2 million

2018

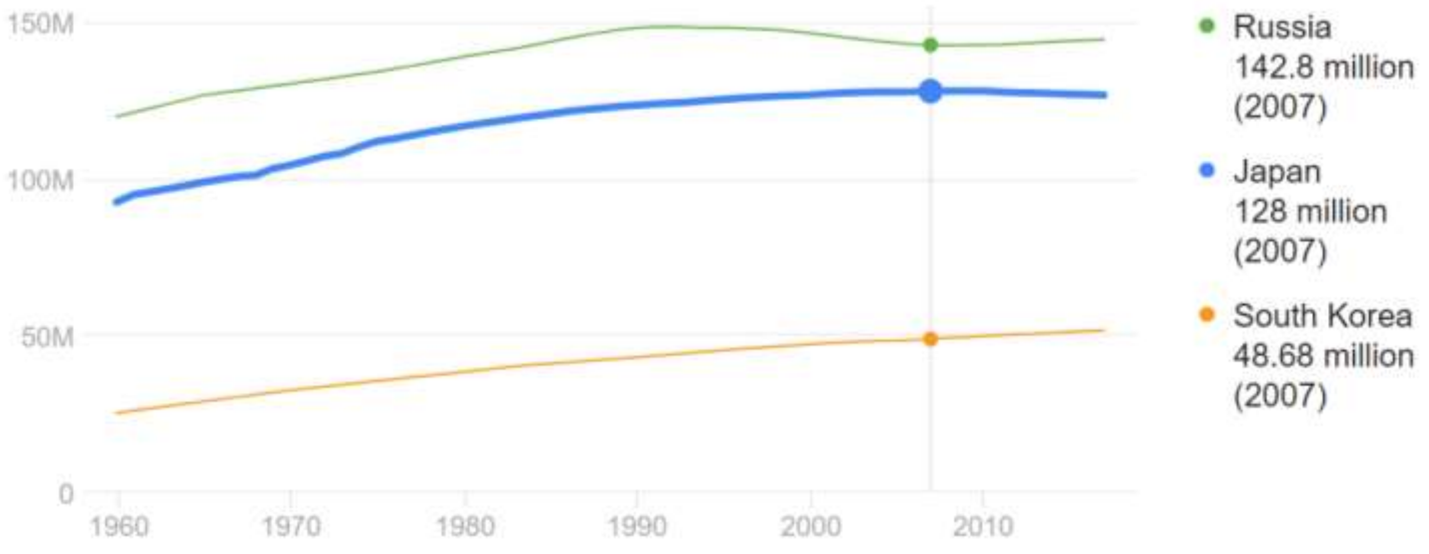
Pathologists: ≒

18000 (USA) (1/18K)

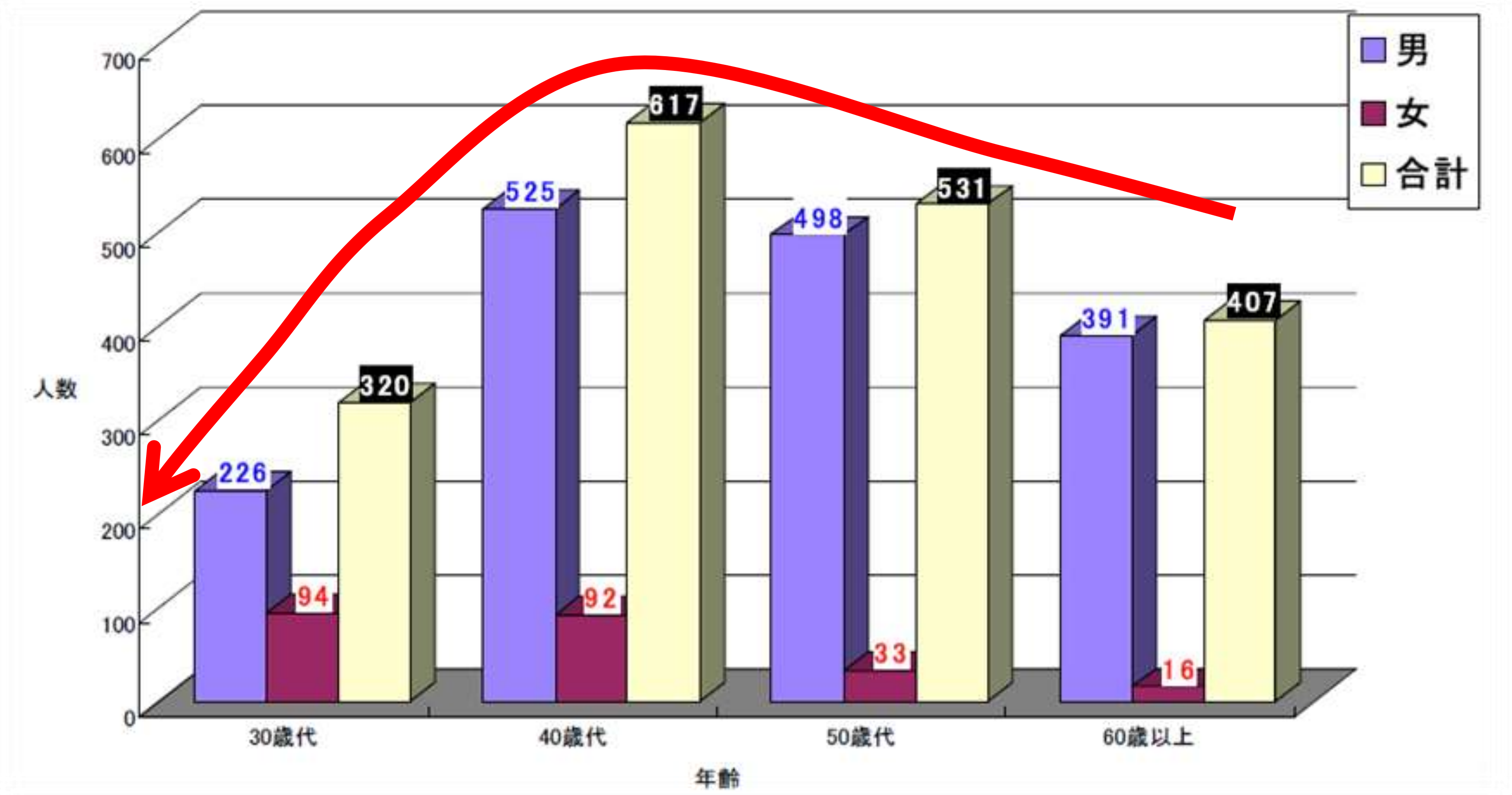
2200 (Japan) (1/58K)

Japan / Population

126.8 million (2017)

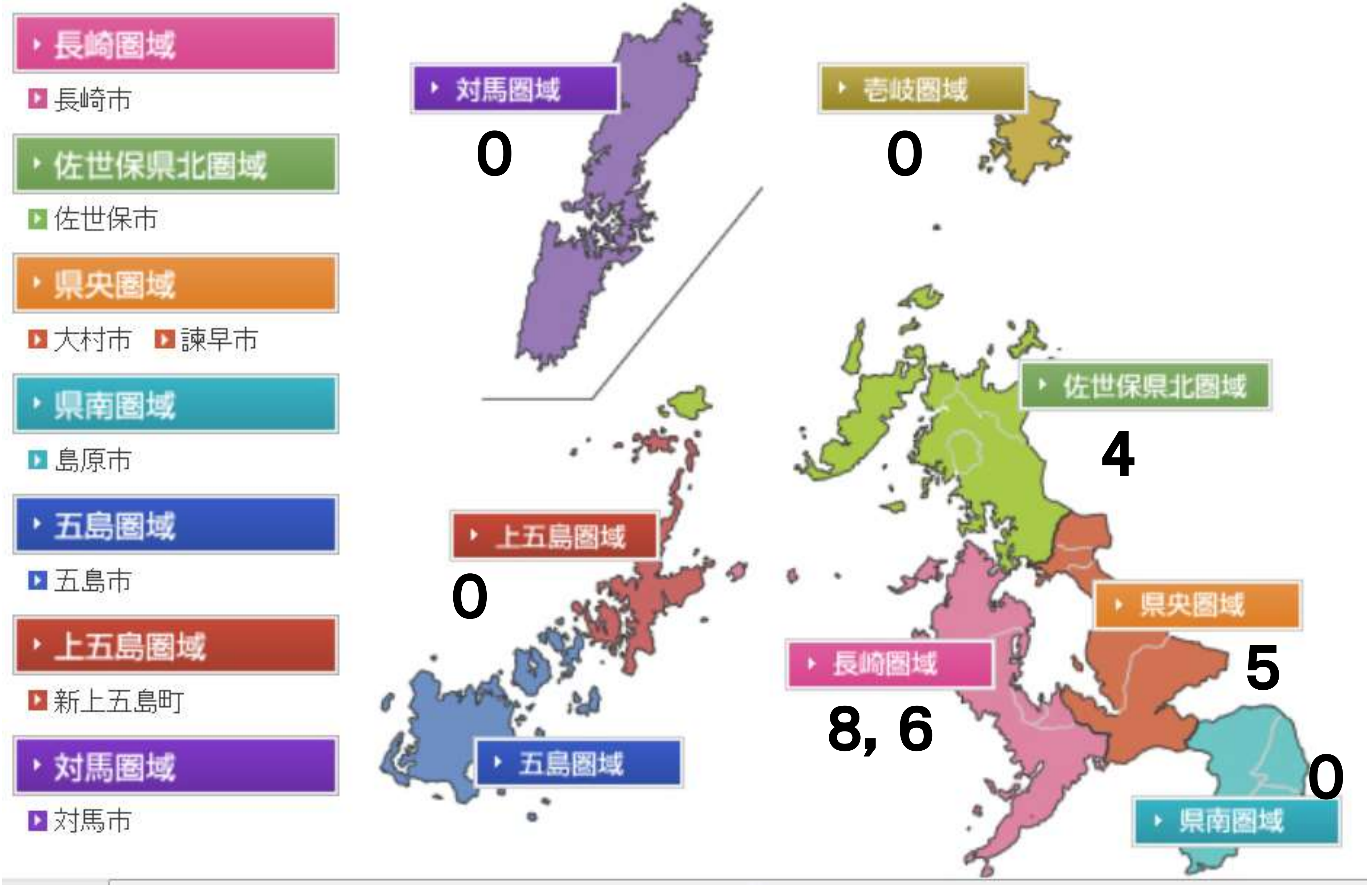


A serious shortage of pathologists and the need for pathology training centers



Sasaki T et al， at JSP meeting

２０１２



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県央圏域
大村市
諫早市
県南圏域
島原市
五島圏域
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新上五島町
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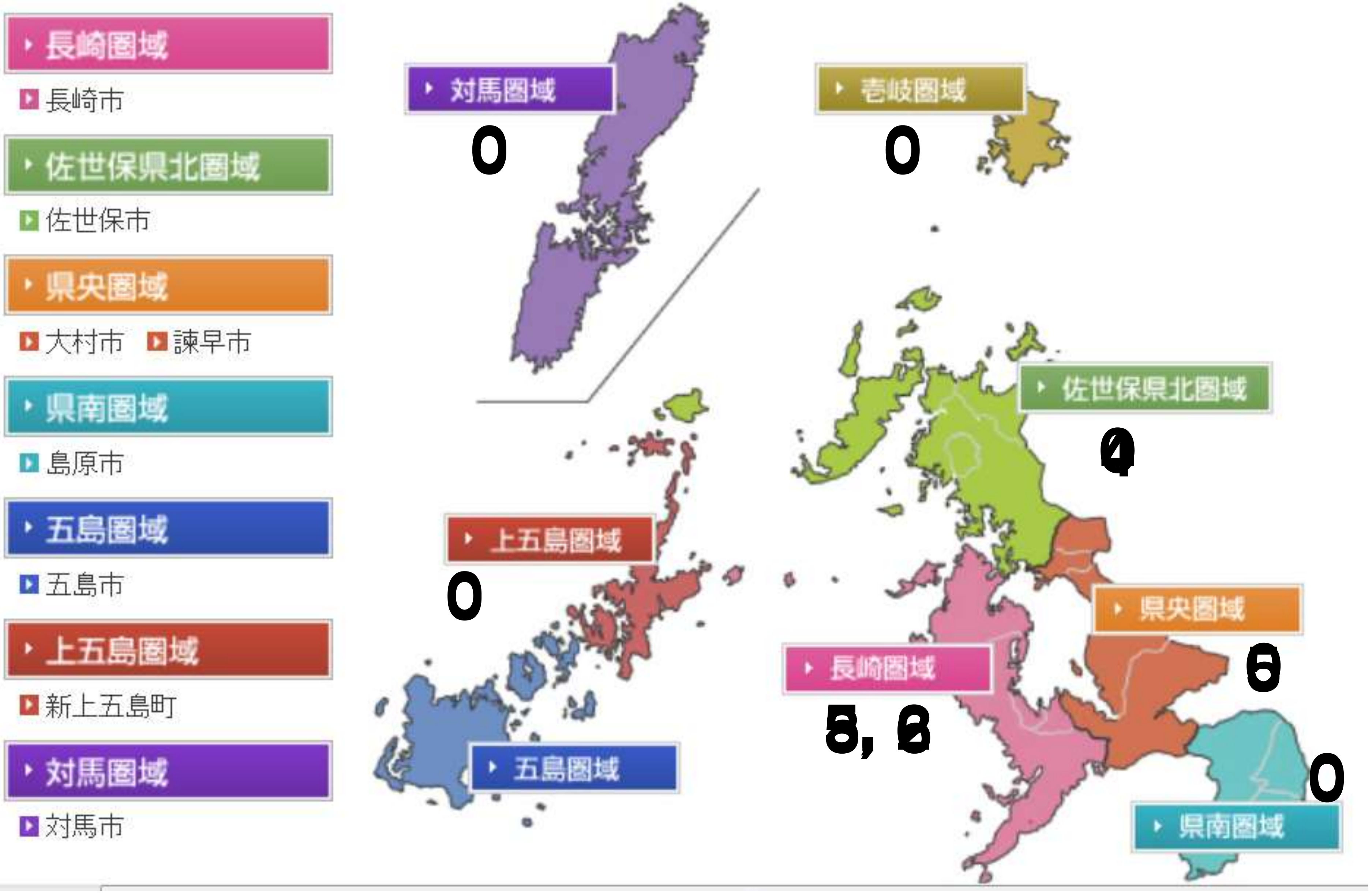
２０２２



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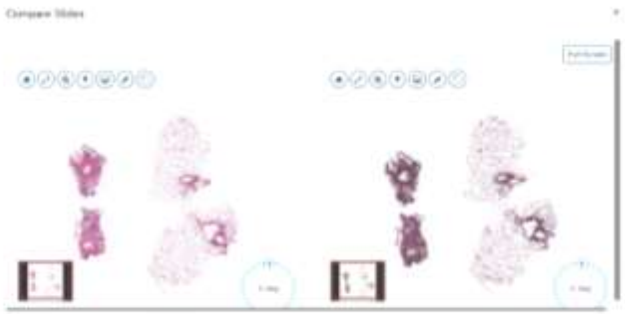
県南圏域
五島圏域

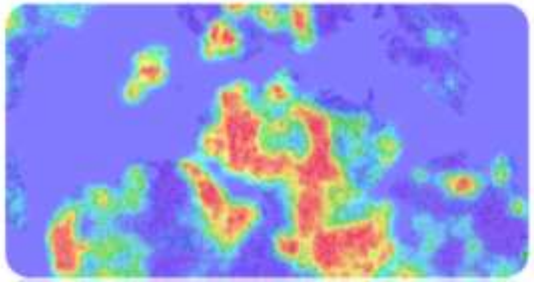
Today's talk (Digital Pathology and AI)

1.Introduction of Digital Pathology



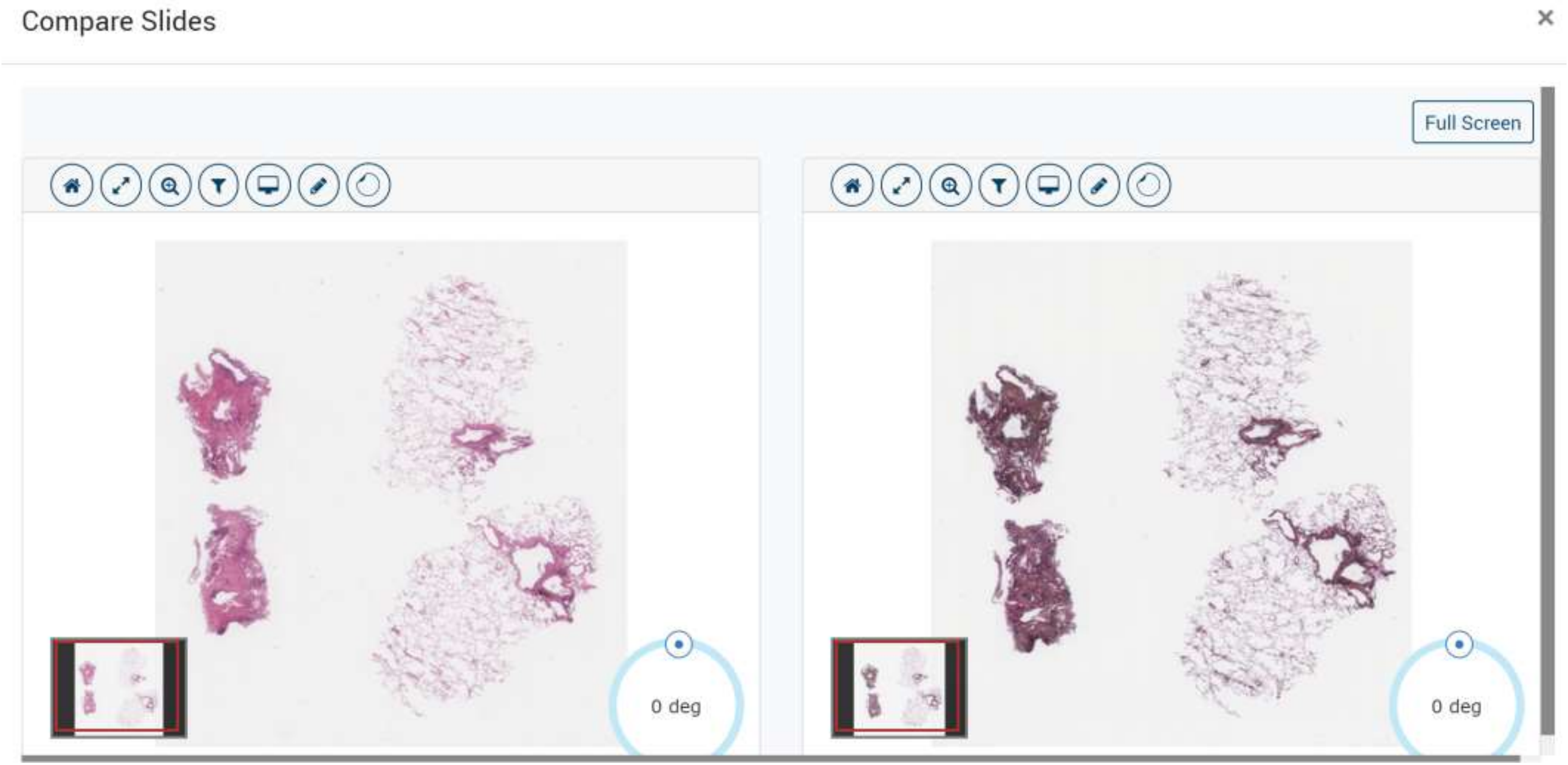
2. Digital Consultation improves diagnosis

3. Artificial intelligence in Pathology

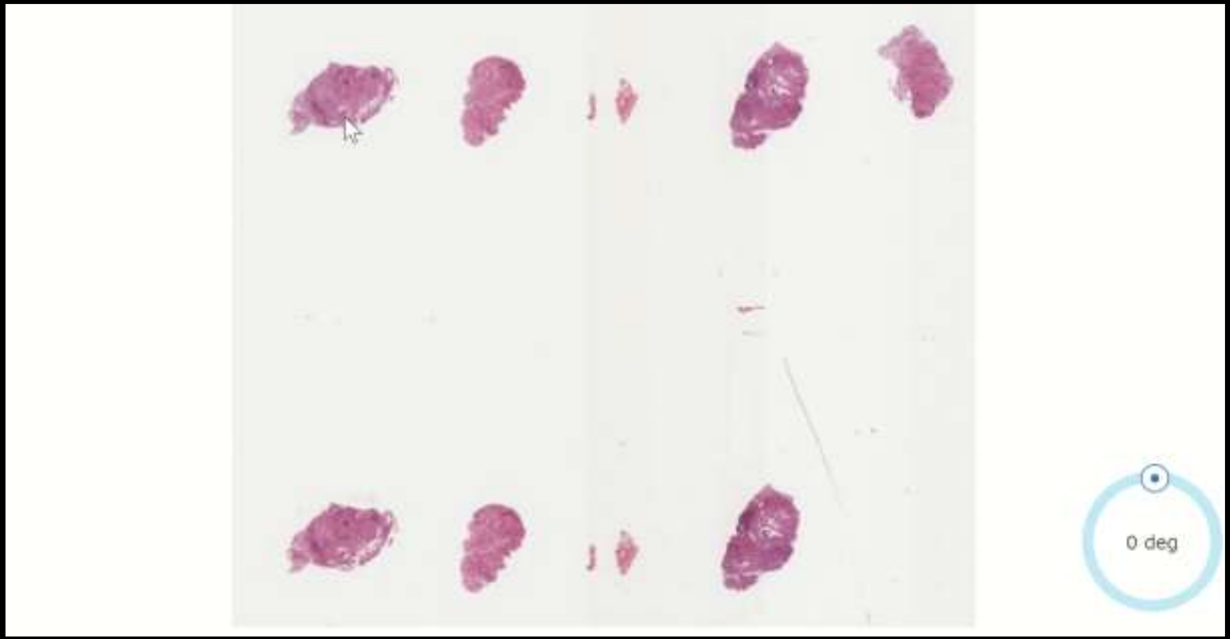


4. Introduction of 19th JSDP 2020 in Nagasaki

1.Introduction of Digital Pathology



Microscope ⇒ Digital pathology



159
ライフ
73
ブラウザ
Extras
37
レファレンス
ホーム
Slack
55,542

Installation of 16 multiheaded microscope 2014/4

Nagasaki・Kameda Path-NET

2. Digital Consultation improves diagnosis

Question:

If pathologists are not so good, the prognosis of the patients will be..

A) Poorer
B) Same
C) Better

Question:

If pathologists are not so good, the prognosis of the patients will be..

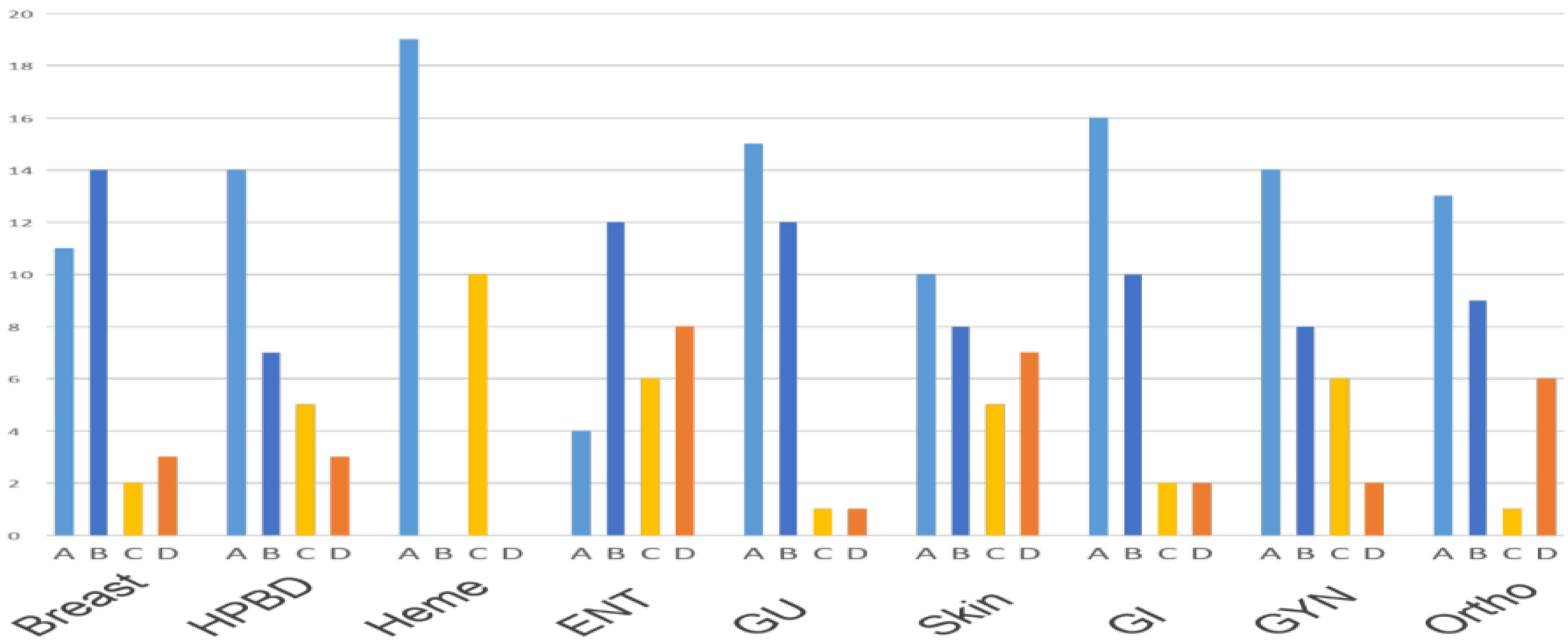
A) Poorer
B) Same
C) Better

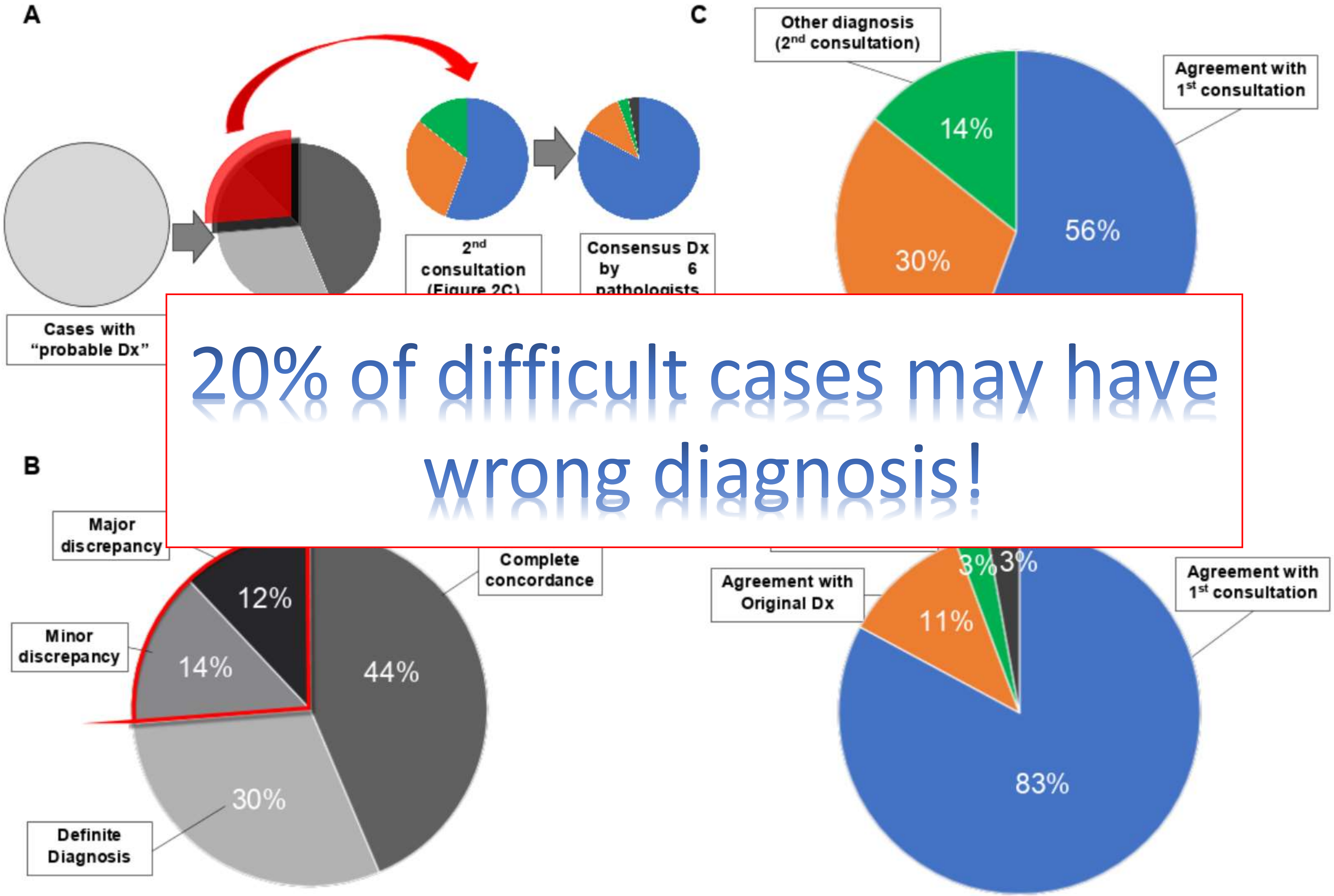
Judgment of “Benign” is harder

Frequency of "challenging cases"

	Nagasaki Univ		Community Hsp	
	2010	2013	2010	2013
No of cases	8301	8828	4267	4101
pathologists	9	13	1	2
double check	no	yes	no	no
suspected	42	115	53	215
suspicious	7	24	0	3
possible	3	16	0	2
probable	3	13	0	0
probably	416	106	0	0
	471	274	53	220
percentage	6%	3%	1%	5%

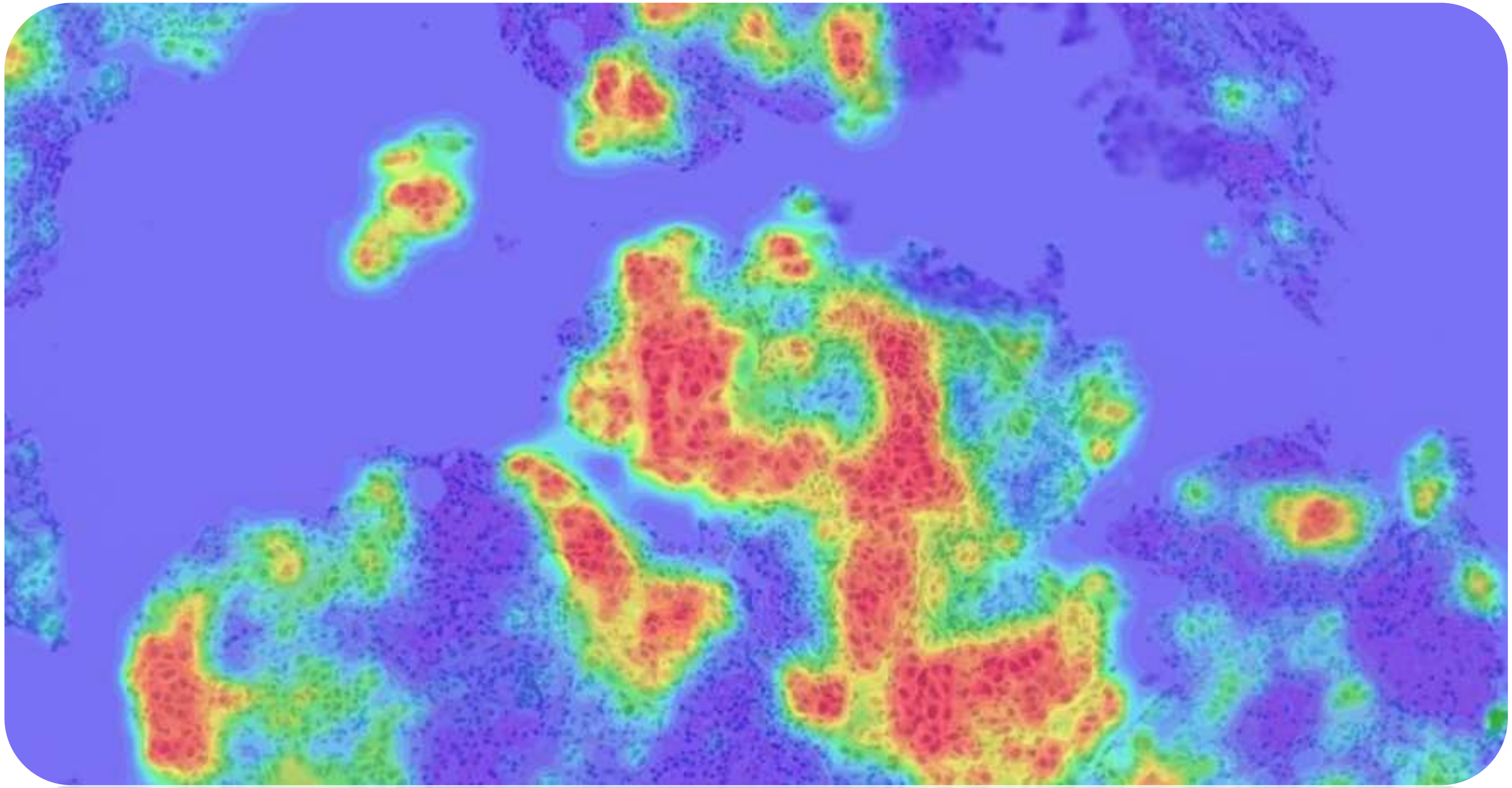
Changes after Expert Consultation





20% of difficult cases may have wrong diagnosis!

3. Artificial intelligence in Pathology



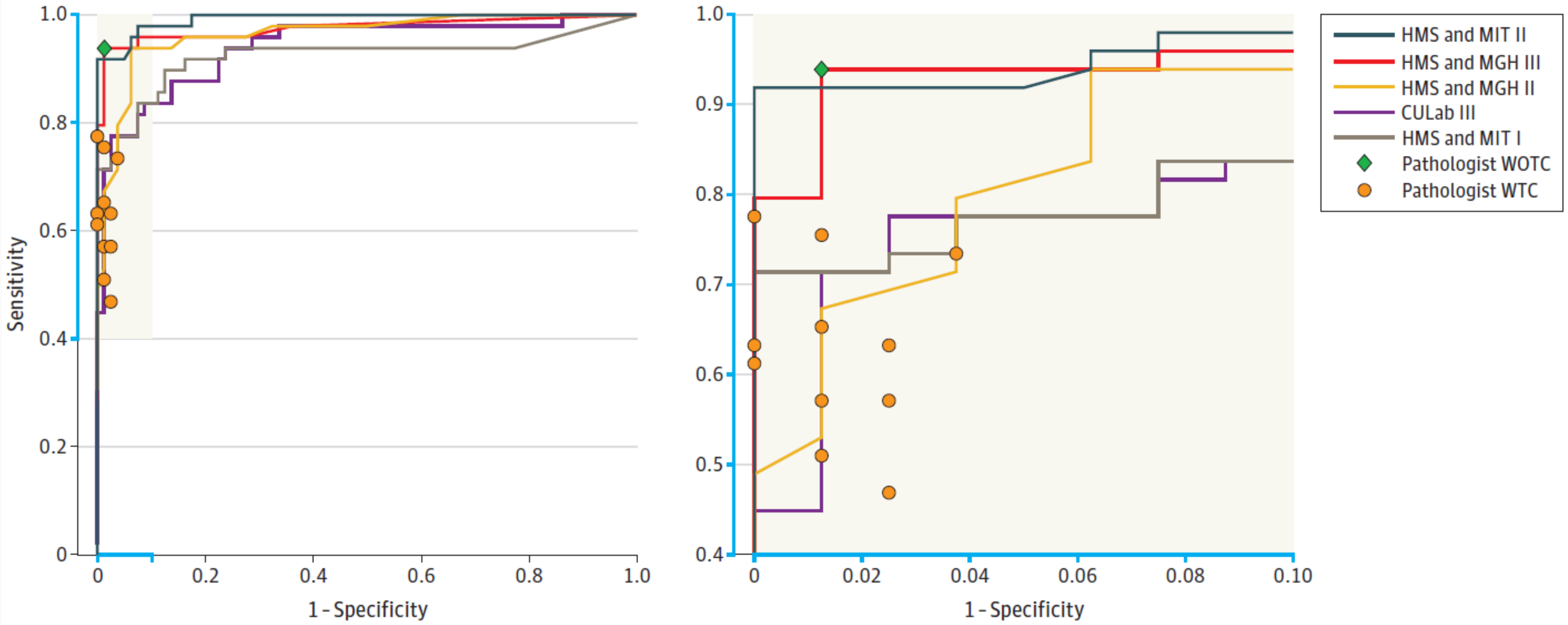
Research

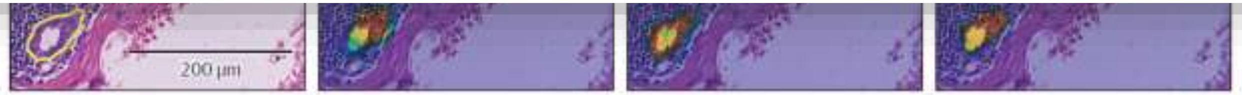
JAMA | Original Investigation

Diagnostic Assessment of Deep Learning Algorithms for Detection of Lymph Node Metastases in Women With Breast Cancer

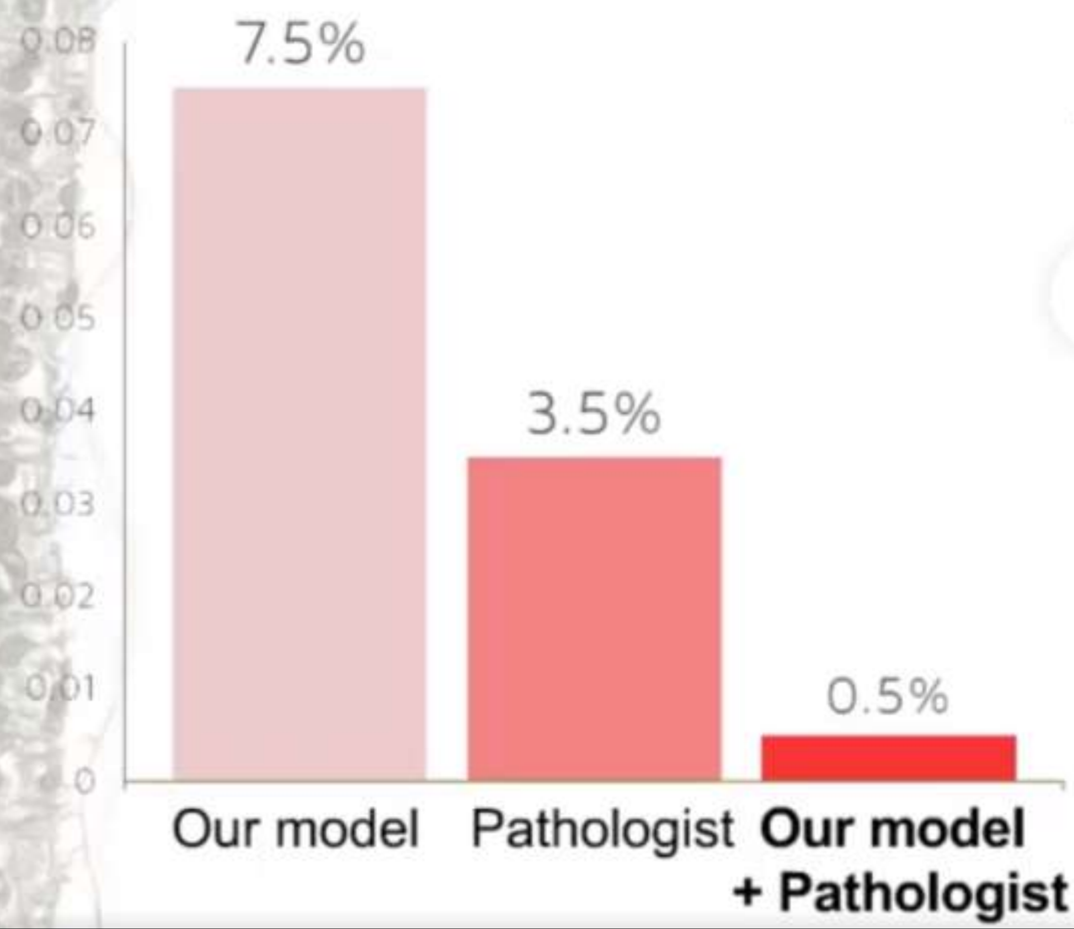
Figure 3. ROC Curves of the Top-Performing Algorithms vs Pathologists for Metastases Classification (Task 2) From the CAMELYON16 Competition

A Comparison of top 5 machine learning system teams and pathologists





Deep Learning vs Pathologist



The **combination** of a pathologist and the Beck Lab deep learning system **reduces error rate** by 85% **to 0.5%.**

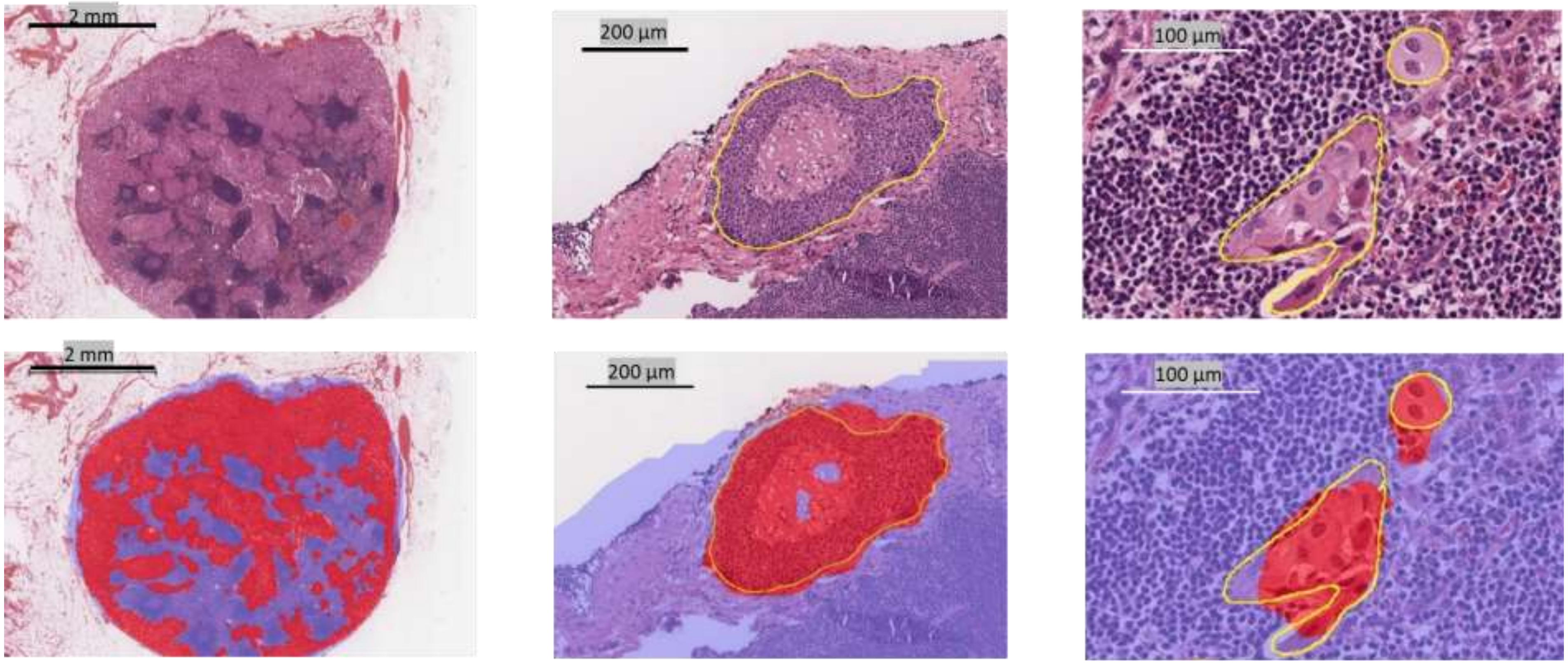
ELSEVIER

The American Journal of PATHOLOGY

Detection of Lung Cancer Lymph Node Metastases from Whole-Slide Histopathologic Images Using a Two-Step Deep Learning Approach

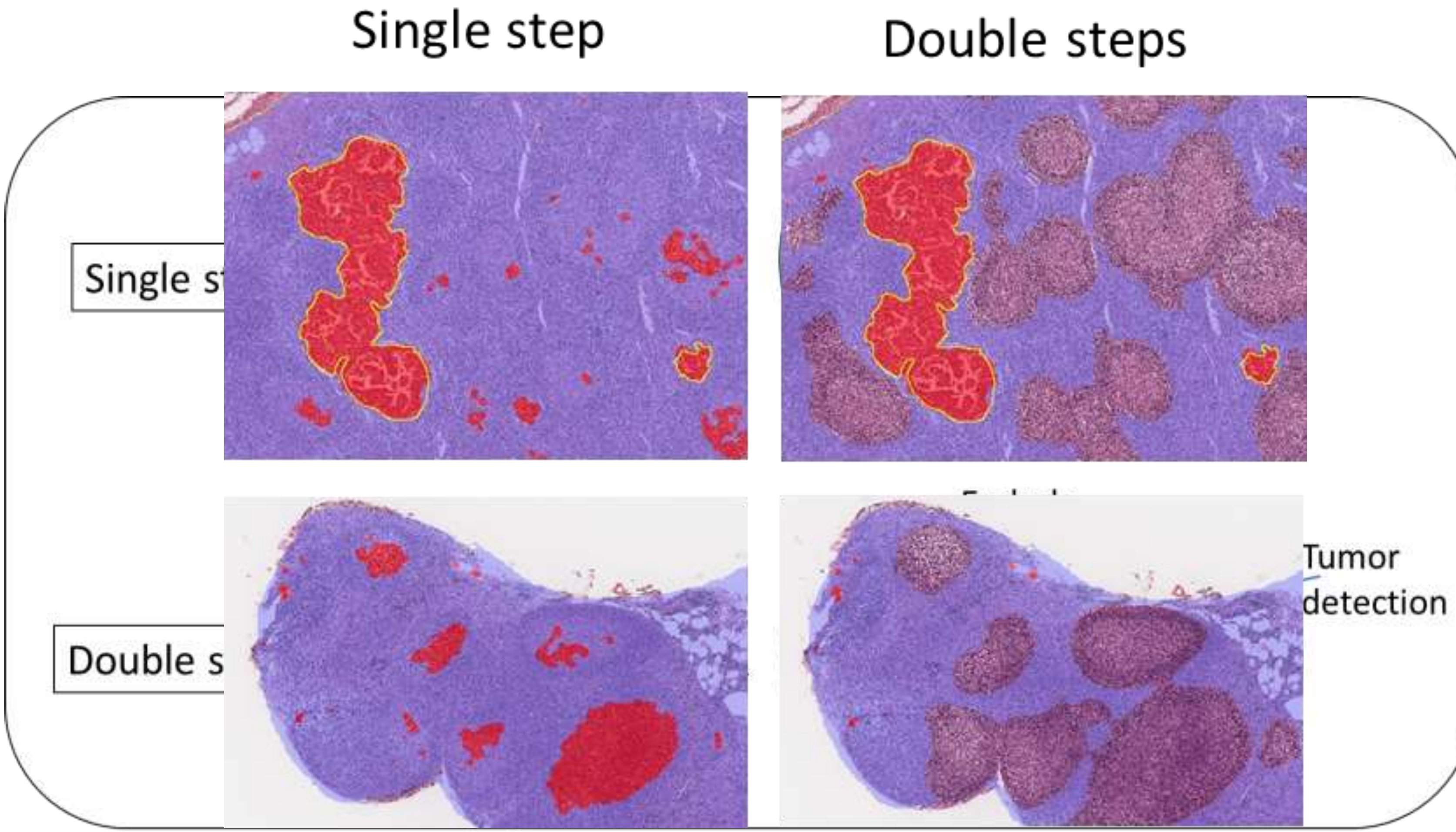
Hoa Hoang Ngoc Pham,* Mitsuru Futakuchi,* Andrey Bychkov,*† Tomoi Furukawa,* Kishio Kuroda,* and Junya Fukuoka*†

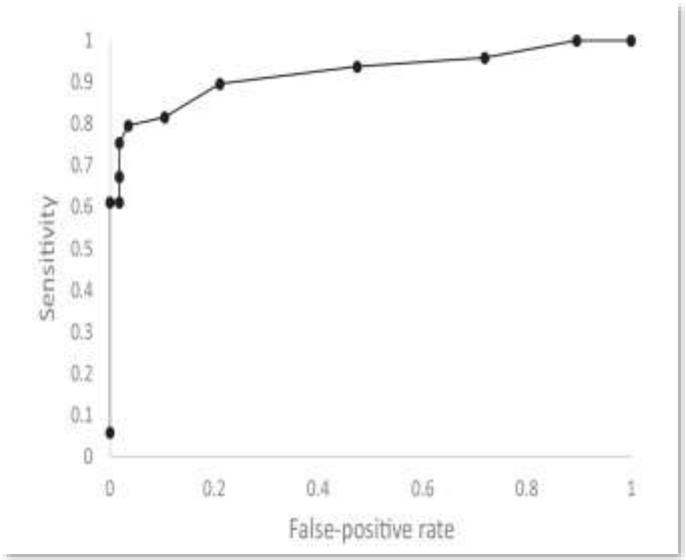
From the Department of Pathology, Nagasaki University Graduate School of Biomedical Sciences, Sakamoto, Nagasaki; and the Department of Pathology,† Kameda Medical Center, Kamogawa, Chiba, Japan*



Macro-metastasis Micro-metastasis Isolated tumor cells

Difficult to remove pseudo-positive





Research Article

Hindawi

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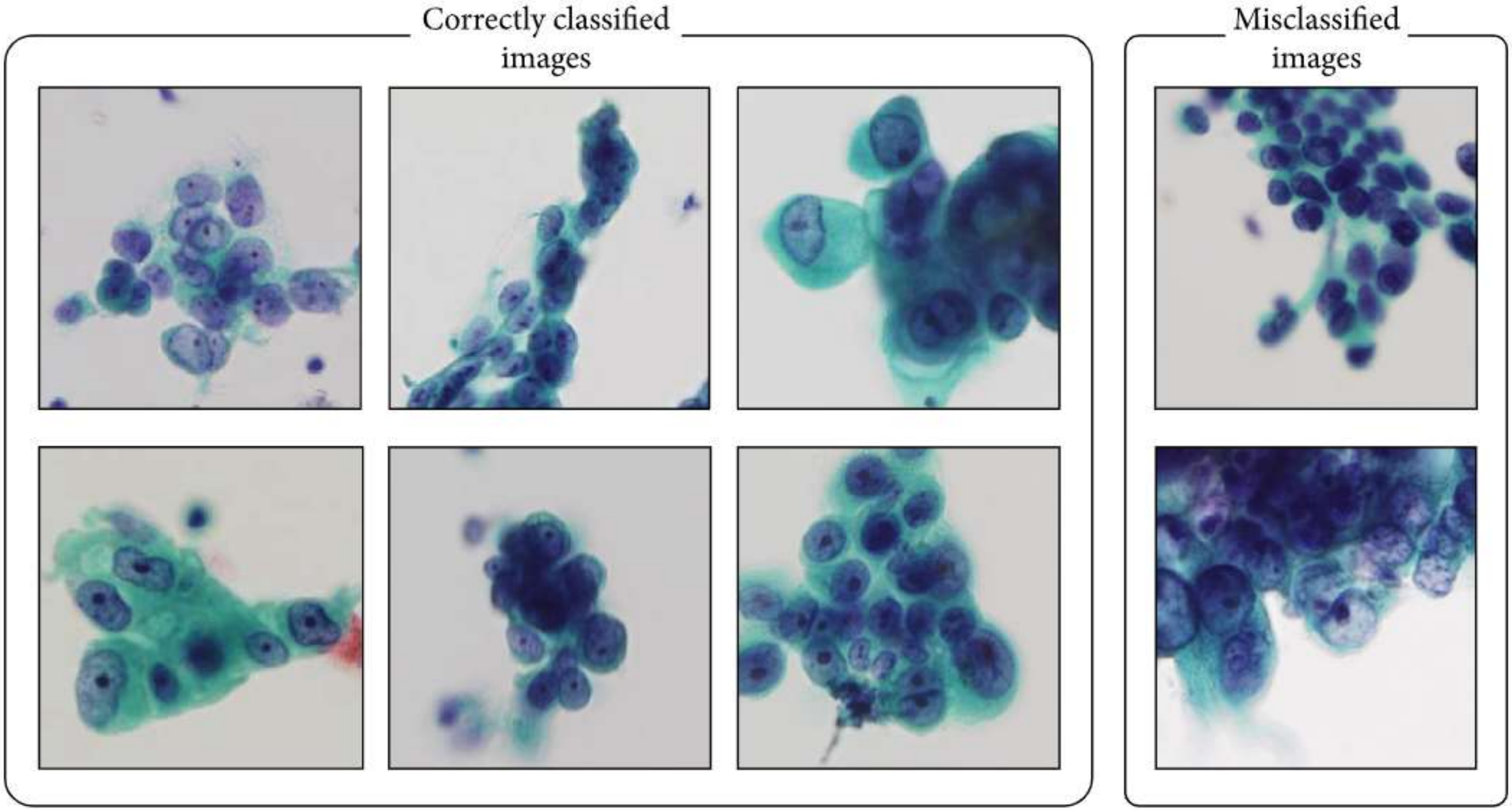
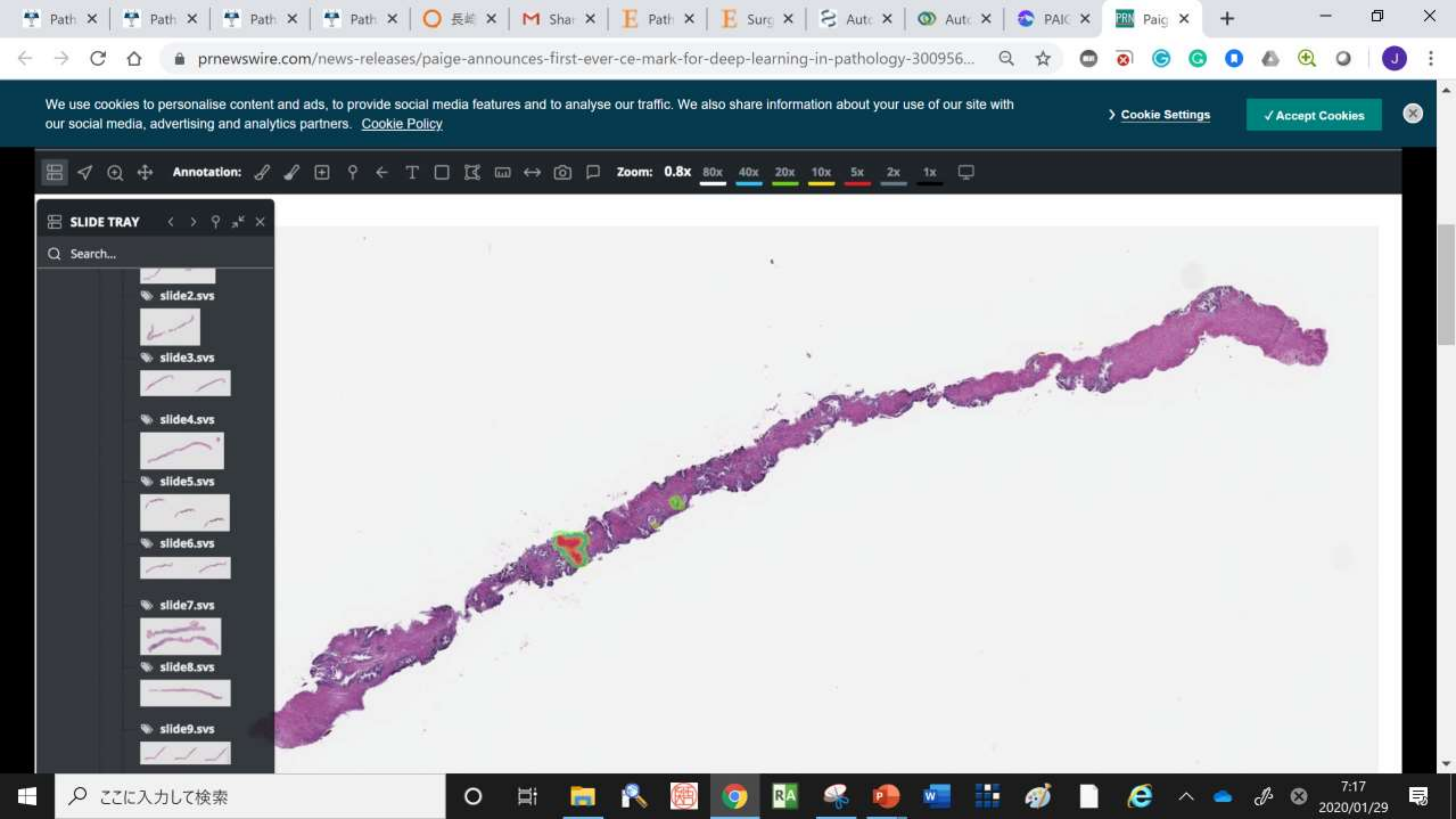


(a) Adenocarcinoma


prnewswire.com/news-releases/paige-announces-first-ever-ce-mark-for-deep-learning-in-pathology-300956...
We use cookies to personalise content and ads, to provide social media features and to analyse our traffic. We also share information about your use of our site with our social media, advertising and analytics partners. Cookie Policy
Cookie Settings
✓ Accept Cookies
Annotation:
Zoom: 0.8x
80x
40x
20x
10x
5x
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1x
SLIDE TRAY
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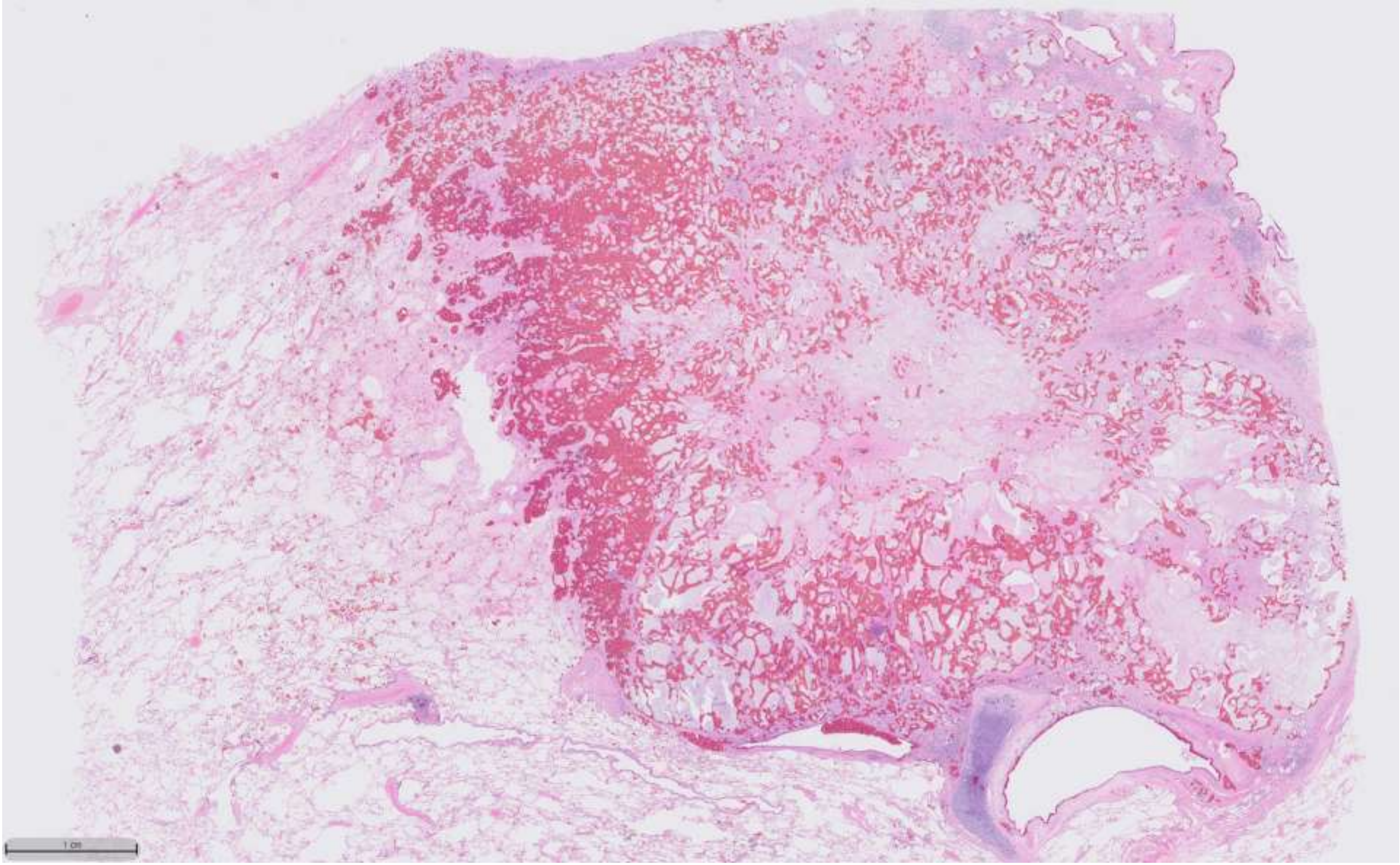
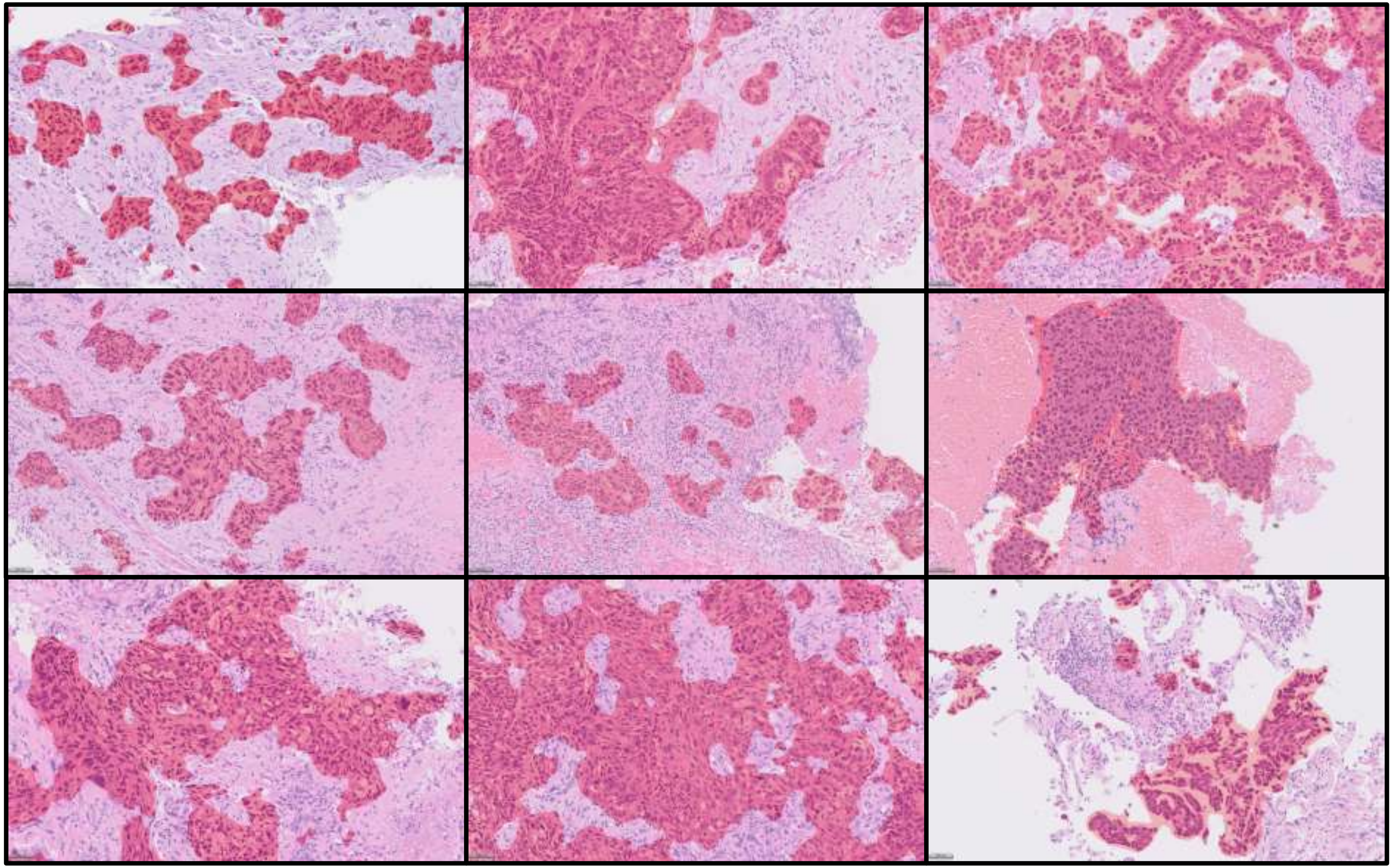
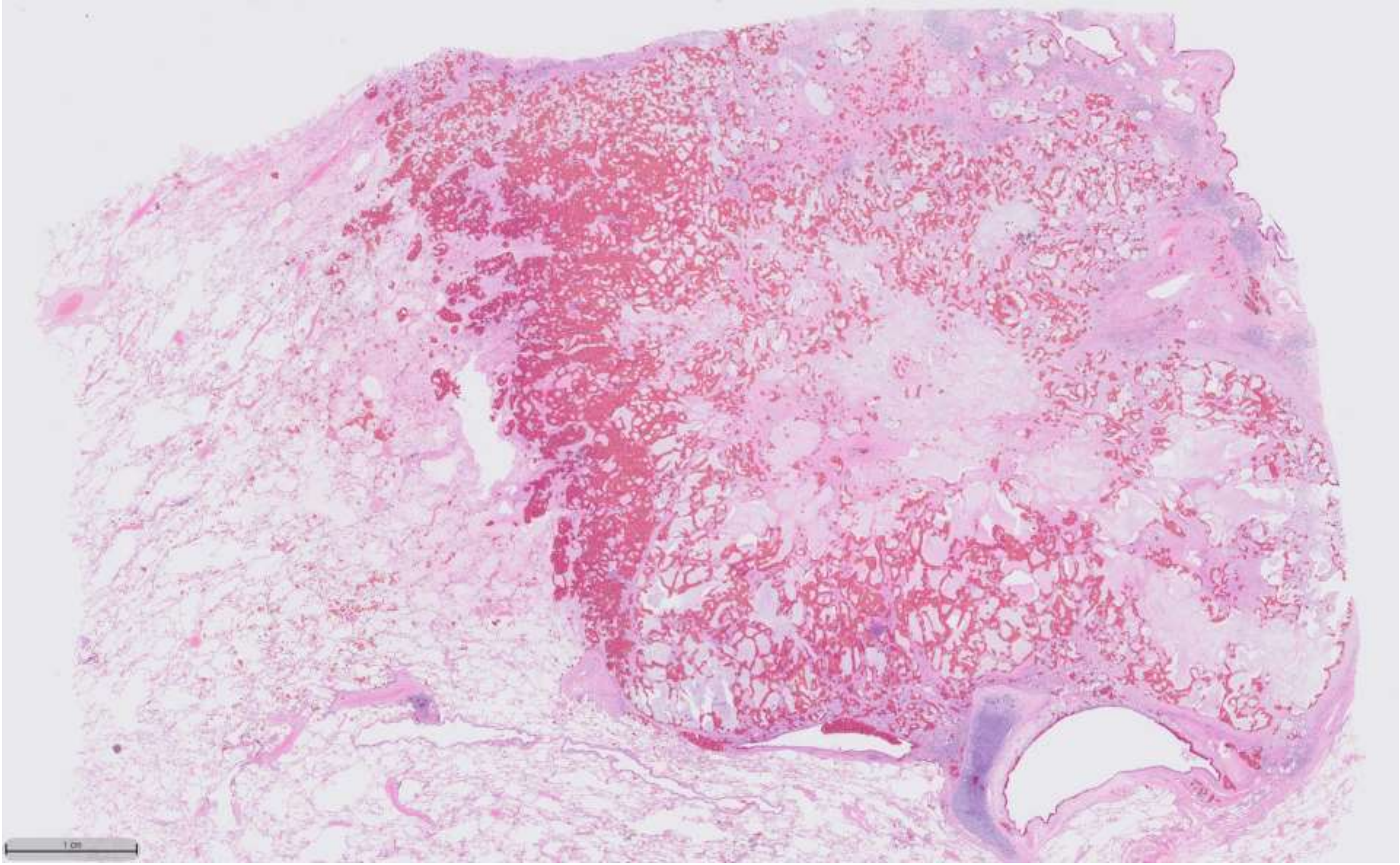
2020/01/29


1 cm

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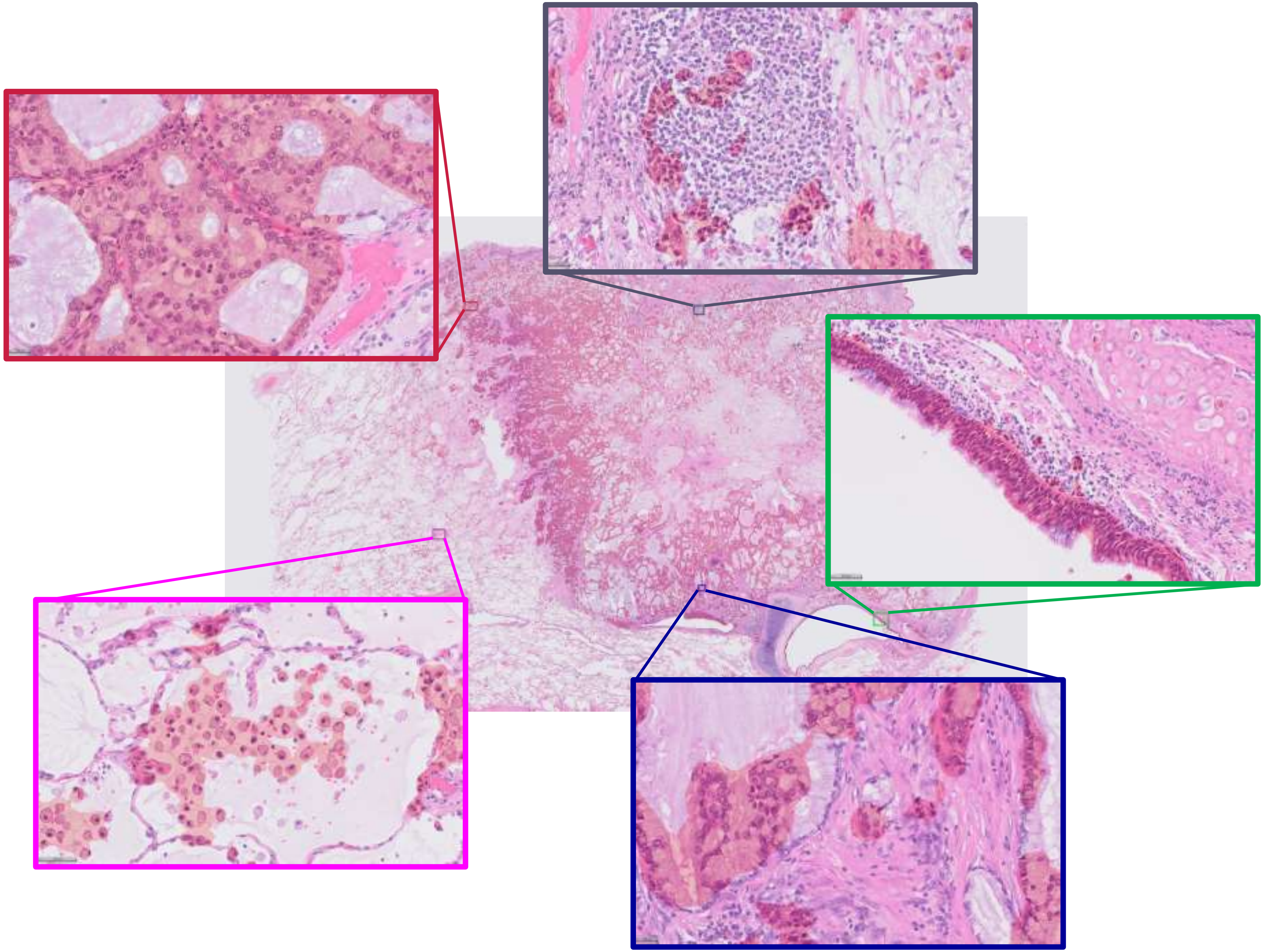
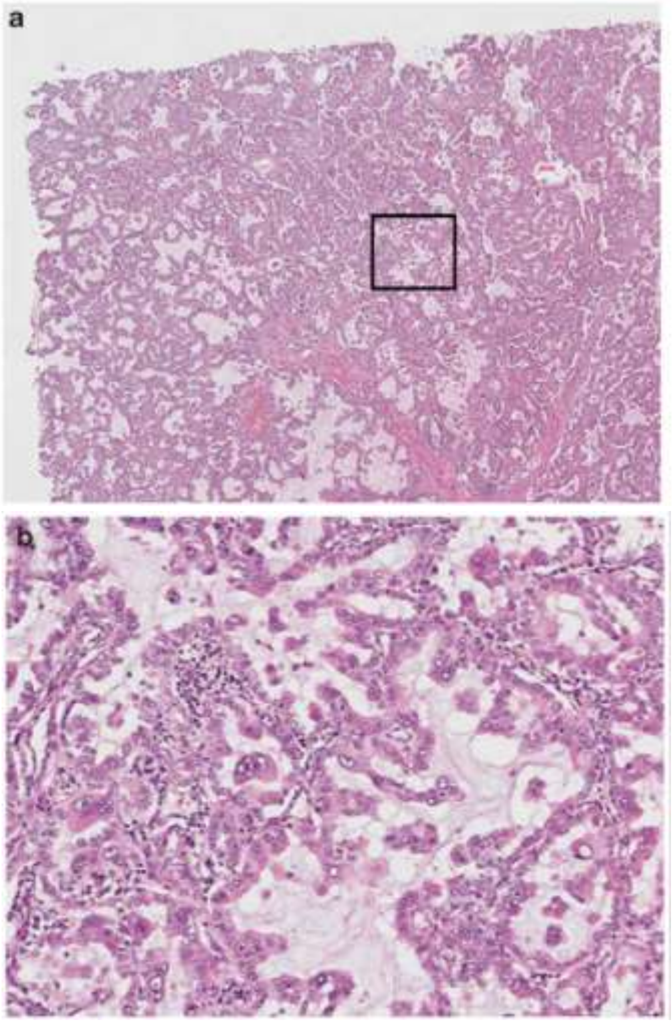
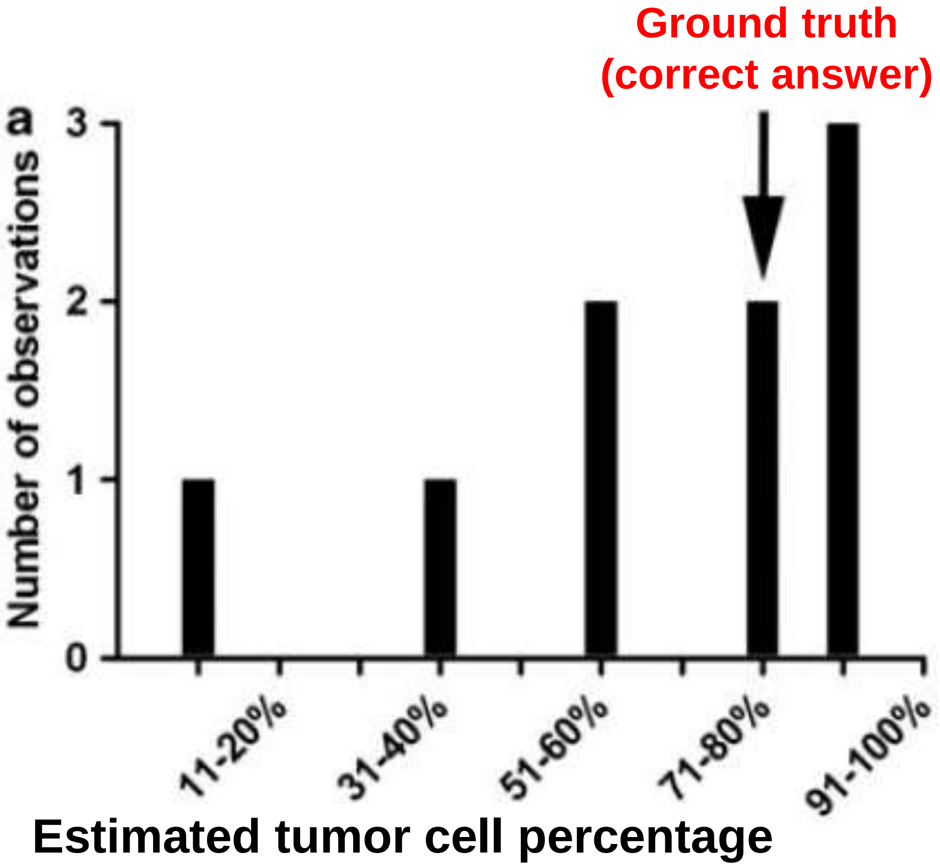


Tumor% by pathologists…



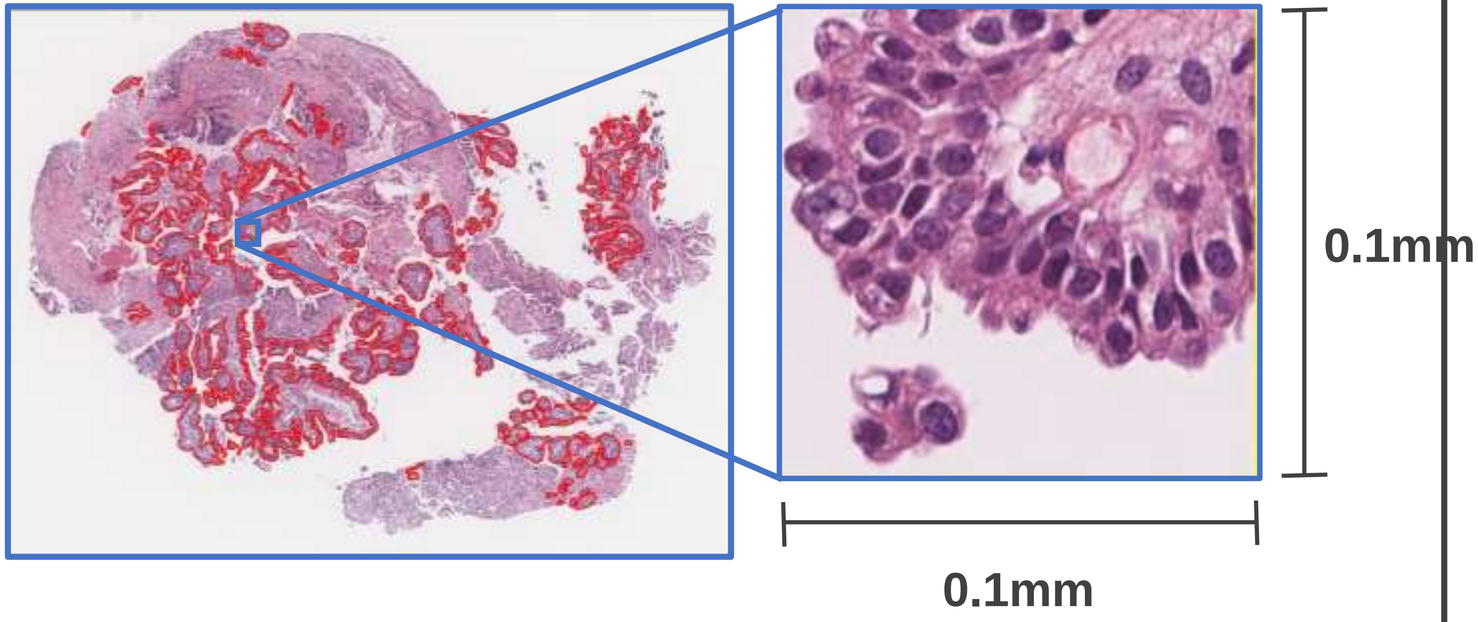
Estimation result of cancer cell ratio
by nine pathologists



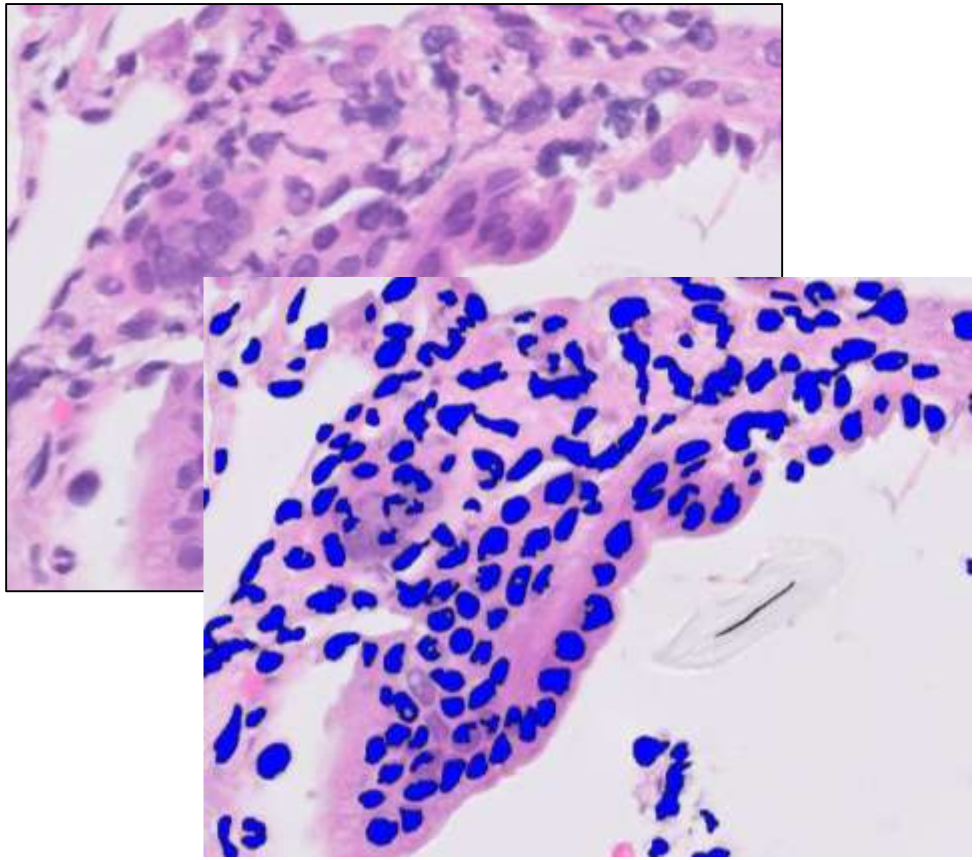
[3] Alexander JJ Smits, et. al., Modern Pathology, 24 (2014) 168

Our routine AI: Tumor Cell Count workflow

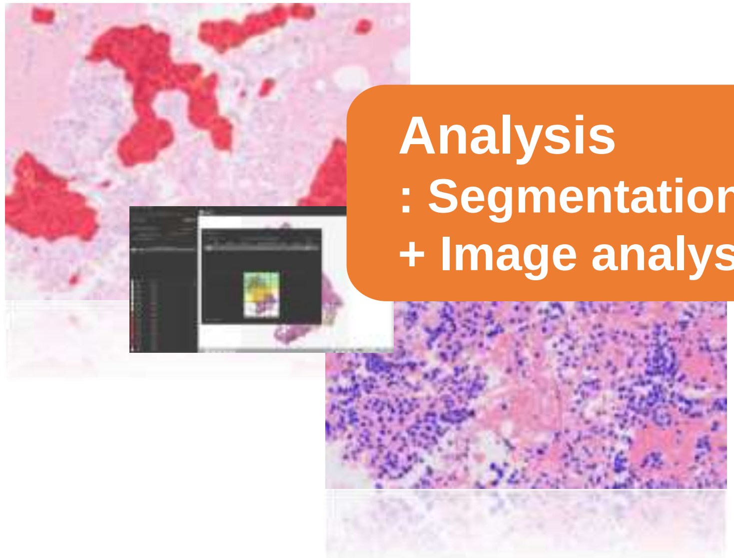
Segmentation by Deep Learning



Nuclei counting by Image Analysis



Validation: protocol of tumor cell count



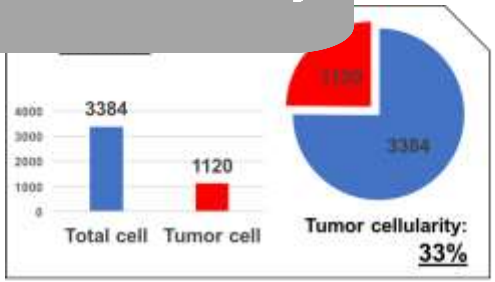
01

Analysis
: Segmentation
+ Image analysis

02

03

Calculation of tumor cellularity



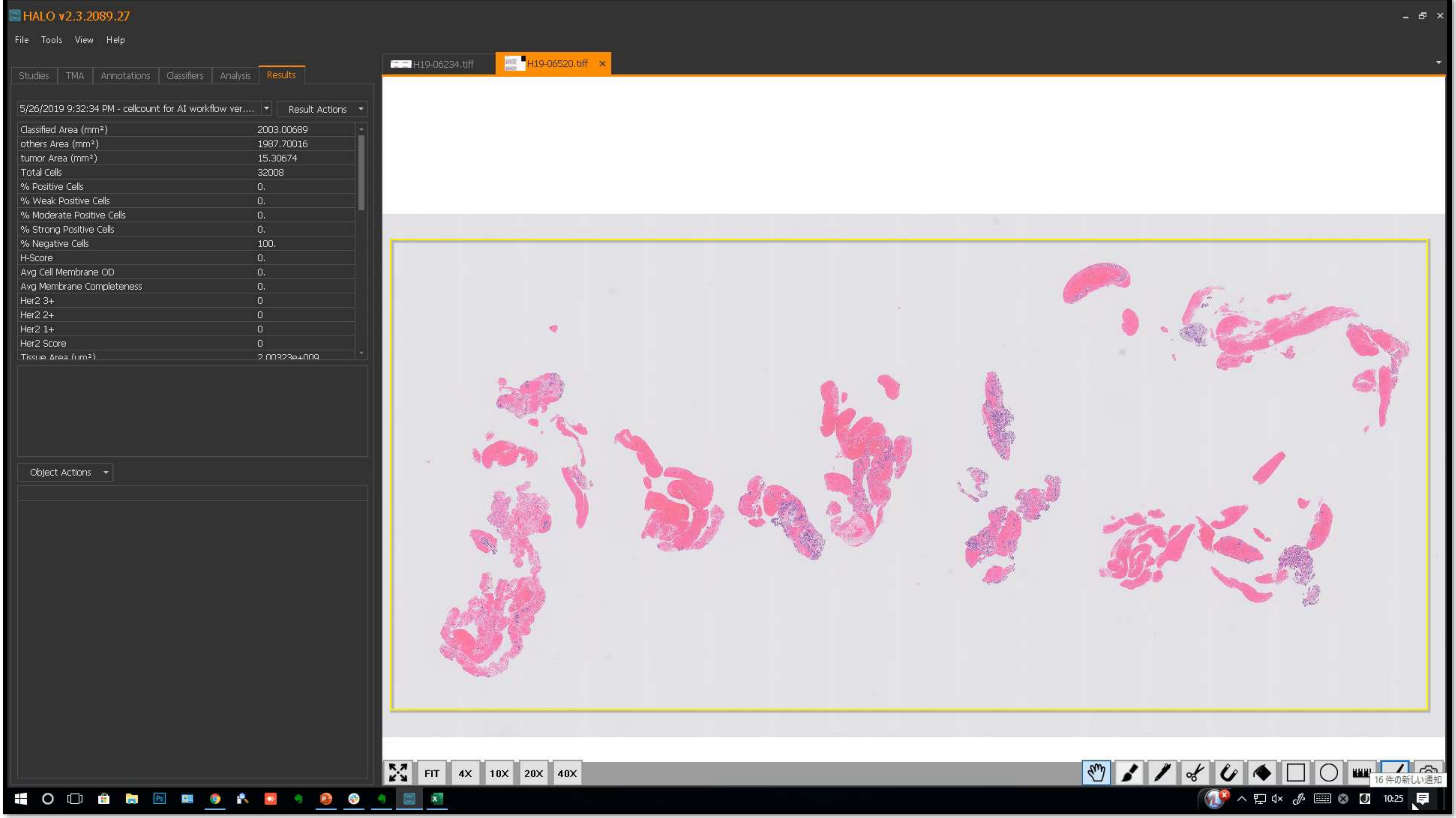
04

Review by Pathologists

<u>"Good"</u>
more than 90% accuracy

<u>"Fair"</u>
70~90% accuracy

<u>"Poor"</u>
less than 70% accuracy


HALO v2.3.2089.27
File Tools View Help
Studies TMA Annotations Classifiers Analysis Results
H19-06234.tiff
H19-06520.tiff
5/26/2019 9:32:34 PM - cellcount for AI workflow ver....
Result Actions
Classified Area (mm²) 2003.00689
others Area (mm²) 1987.70016
tumor Area (mm²) 15.30674
Total Cells 32008
% Positive Cells 0.
% Weak Positive Cells 0.
% Moderate Positive Cells 0.
% Strong Positive Cells 0.
% Negative Cells 100.
H-Score 0.
Avg Cell Membrane OD 0.
Avg Membrane Completeness 0.
Her2 3+ 0
Her2 2+ 0
Her2 1+ 0
Her2 Score 0
Tissue Area (μm²) 2.00323e+009
Object Actions
FIT
4X
10X
20X
40X
16 件の新しい通知
10:25

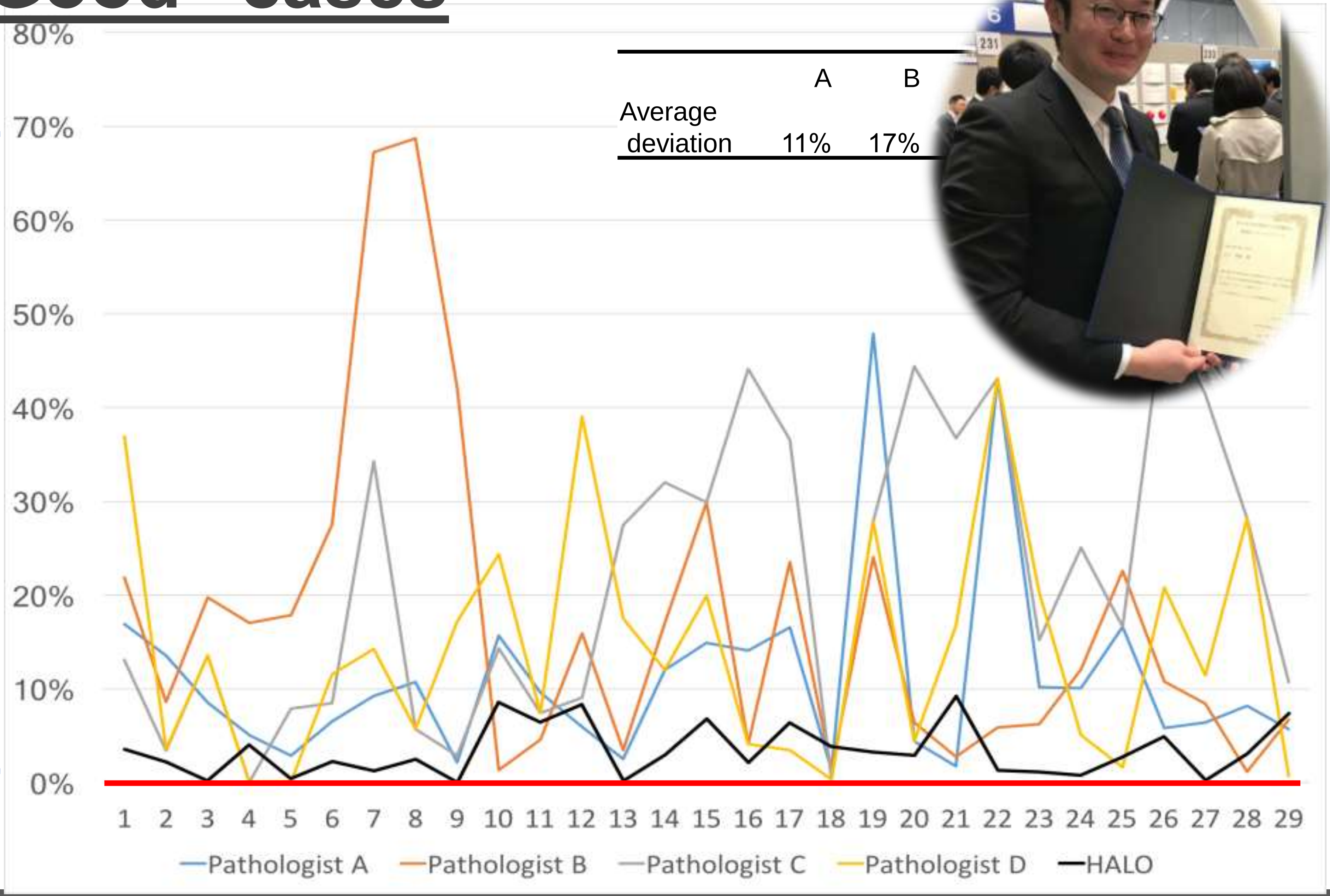
Results: "Good" cases

Deviation from gold standard in each "excellent" case

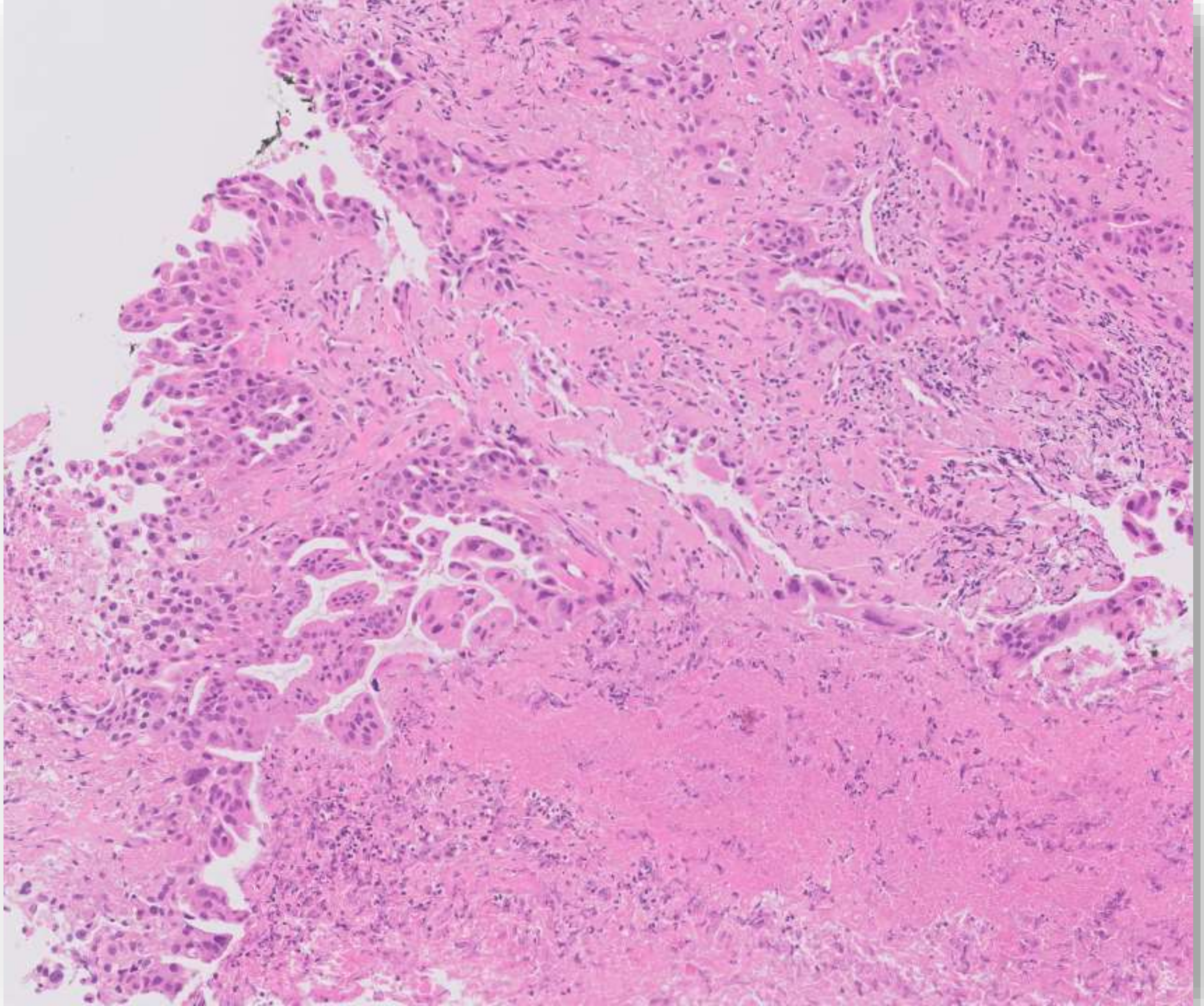
Pathologists

HALO →

Ground Truth (0%) →

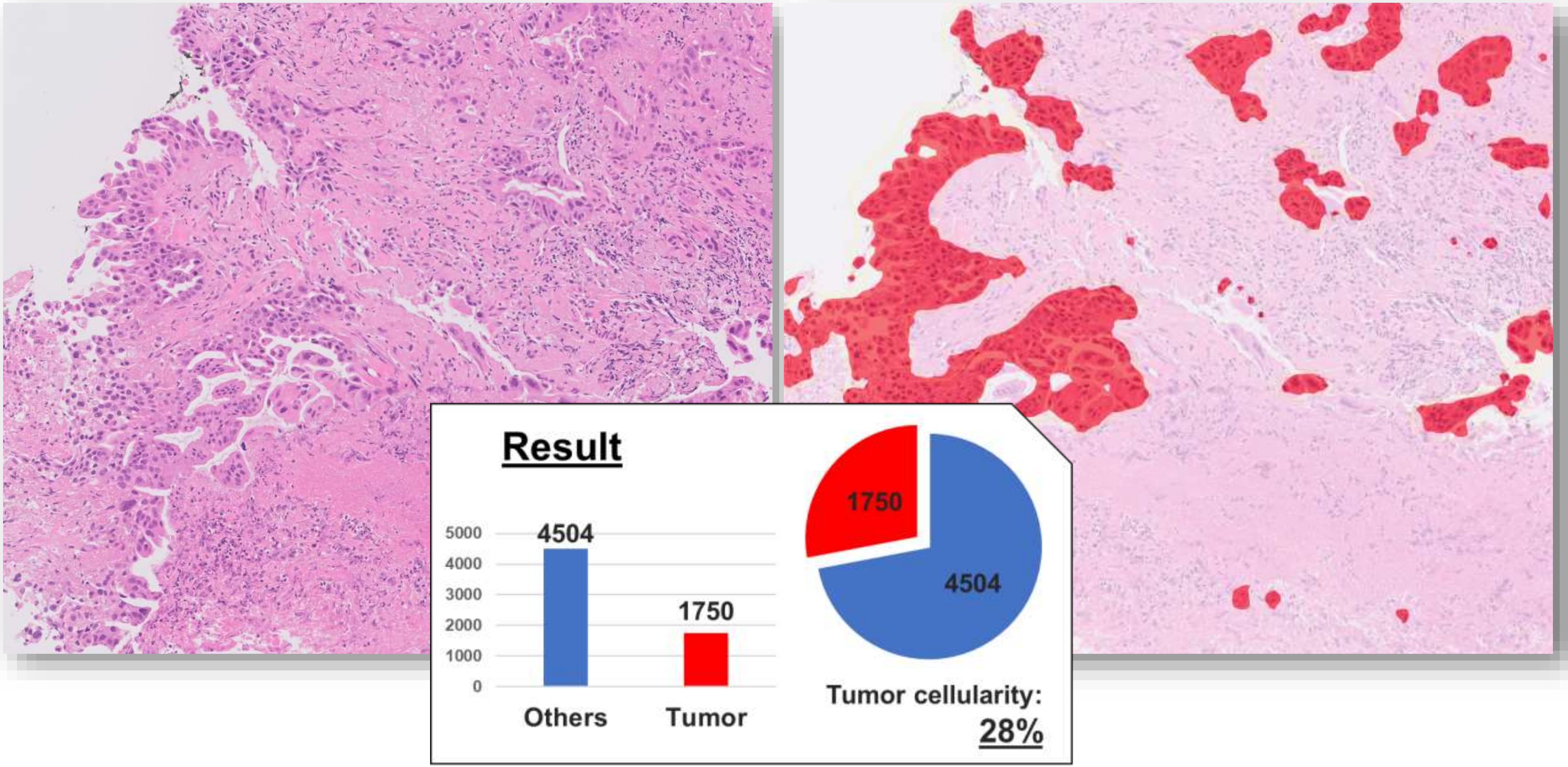


	A	B
Average deviation	11%	17%



How do you think?
% of Cancer cells
(by nuclei)

① <5%
② 5-10
③ 11-15
④ 16-20
⑤ 21-25
⑥ 25-30
⑦ 31-35
⑧ 36-40
⑨ >41


Result
5000
4000
3000
2000
1000
0
4504
1750
Others
Tumor
1750
4504
Tumor cellularity:
28%

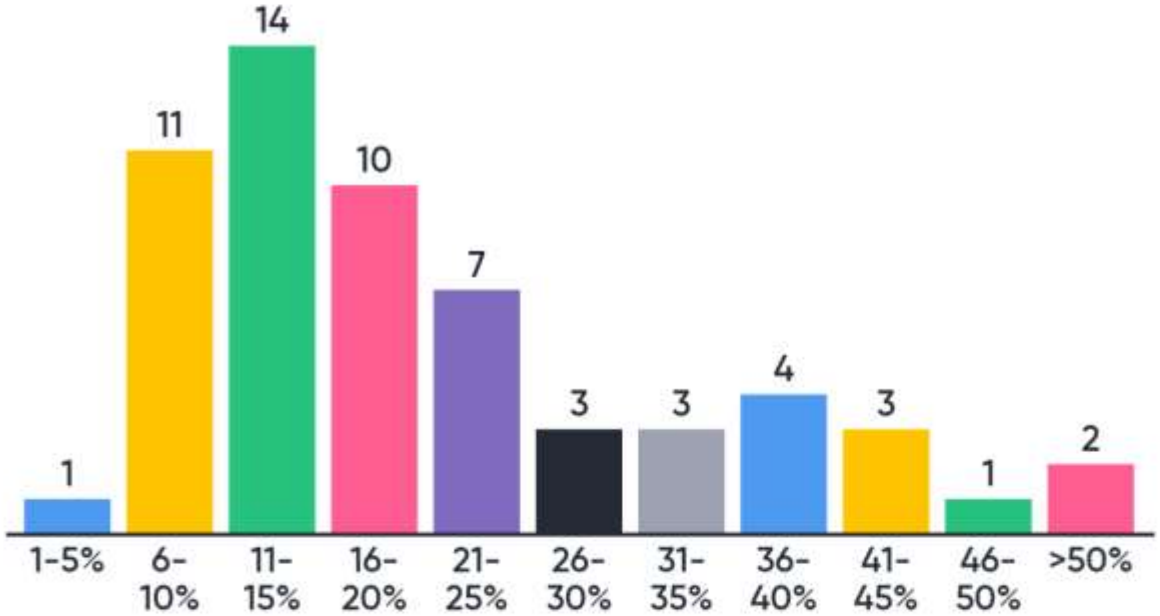
Taiwan2019_9_1 - Mentimeter

mentimeter.com/s/1a639c10303226d17e46a72c38ed134a/62a6bfd7cd3d

Go to **www.menti.com** and use the code **38 66 00**

Mentimeter

% of tumor cells by nuclear?



Show image

59

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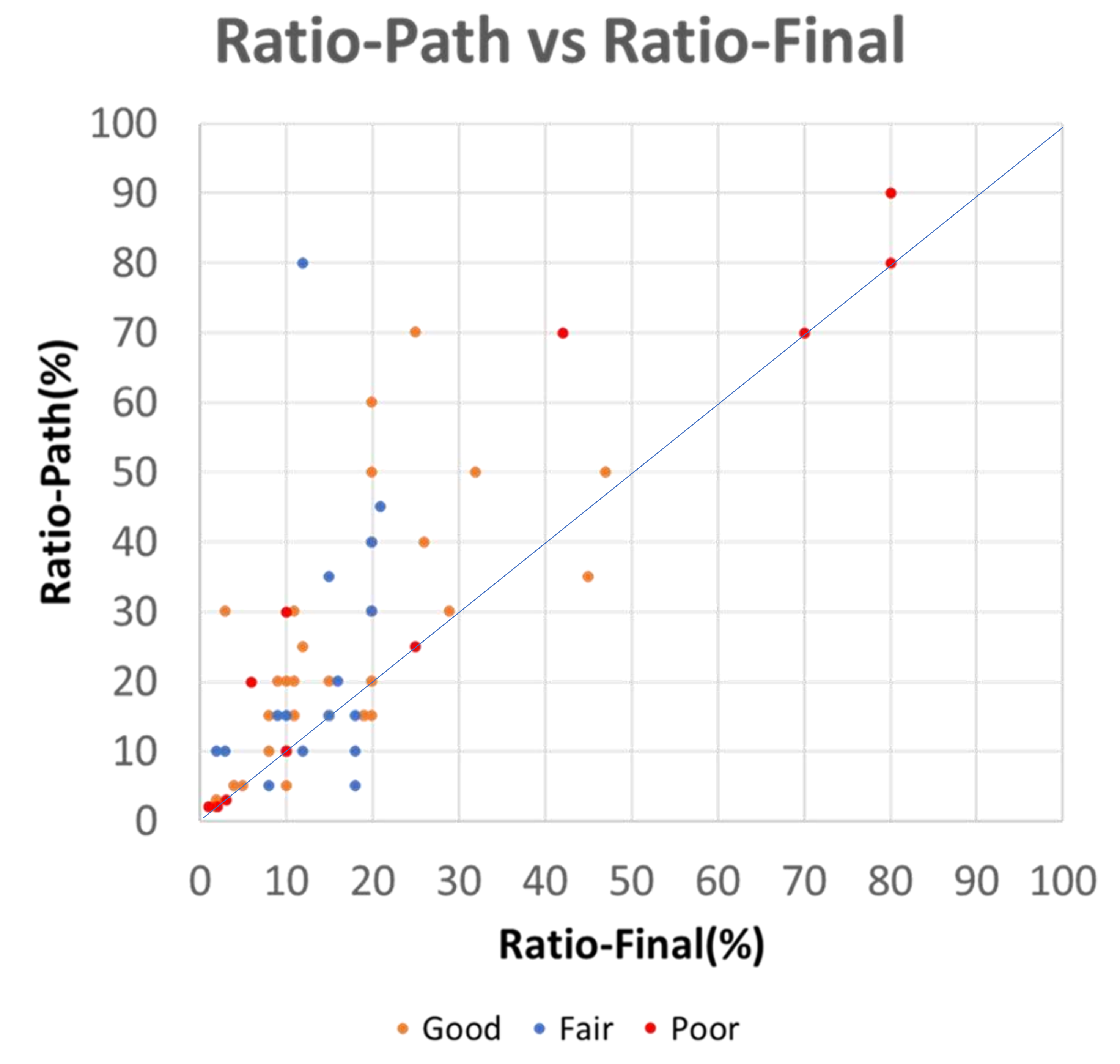
6:52
2019/09/12

Prospective Data of AI x Pathologist Tumor Cell Counts



SCIENTIFIC REPORTS

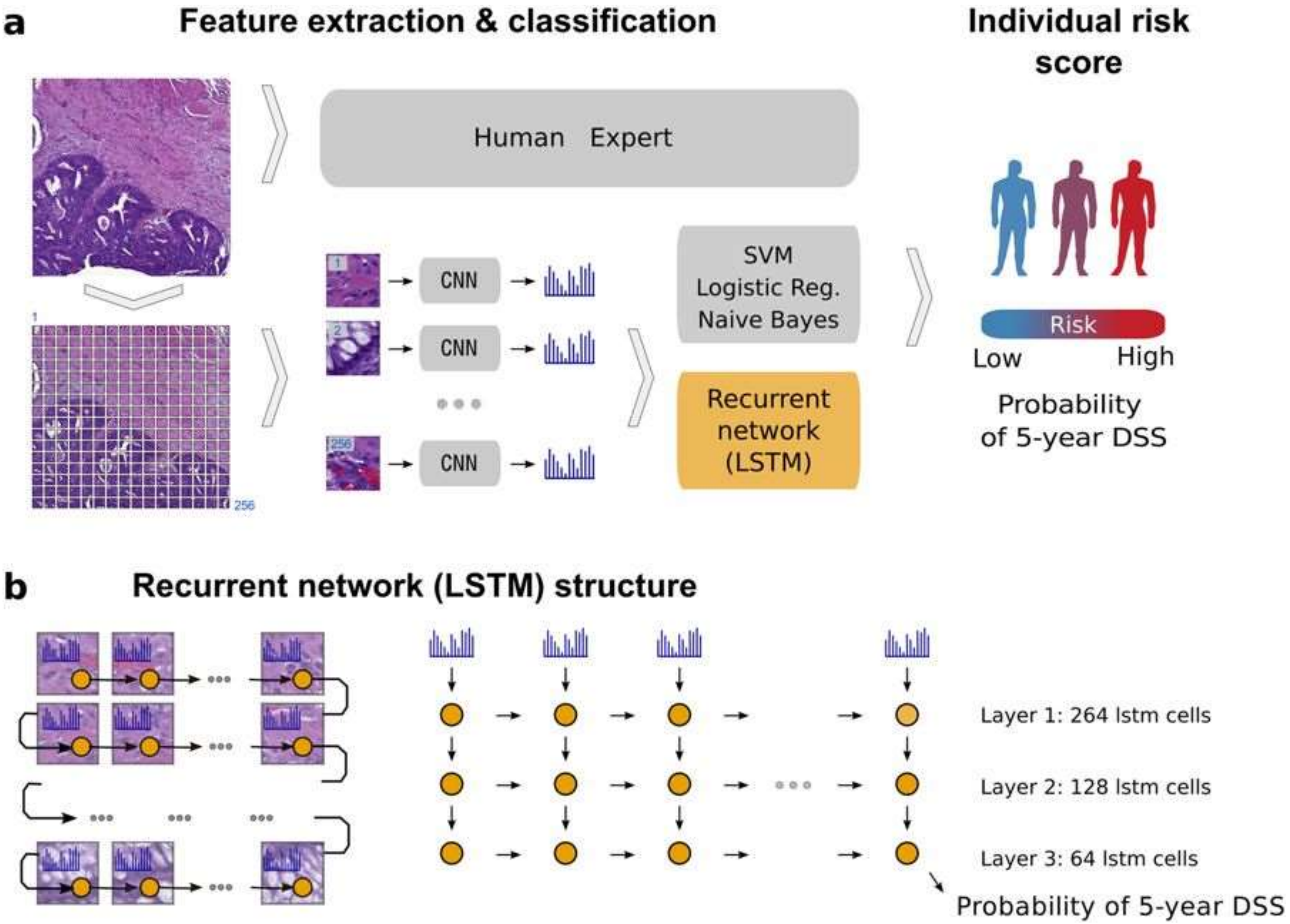
OPEN

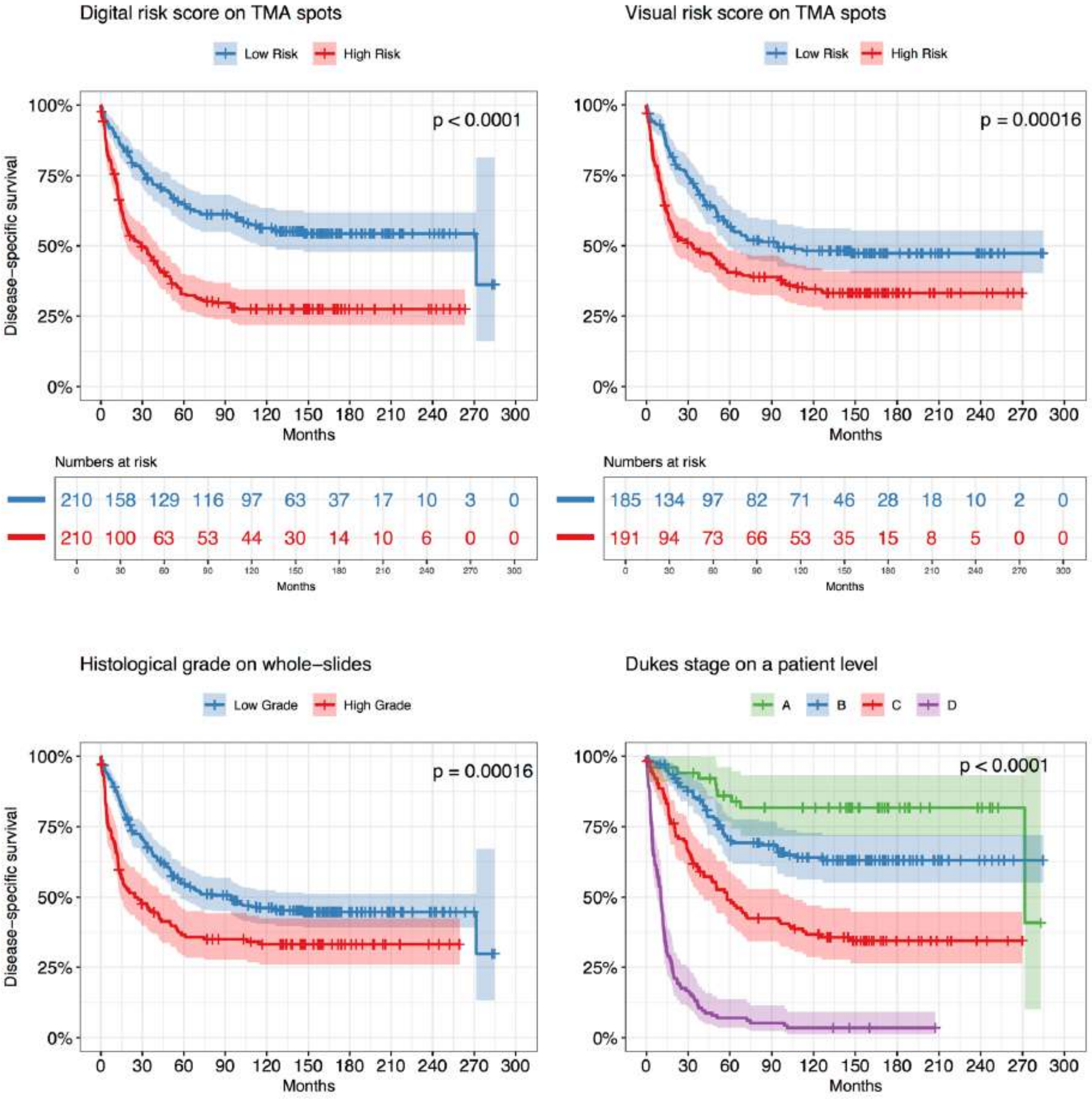
Deep learning based tissue analysis predicts outcome in colorectal cancer

Received: 16 August 2017
Accepted: 12 February 2018
Published online: 21 February 2018

Dmitrii Bychkov[1], Nina Linder[1,2], Riku Turkki[1], Stig Nordling[3], Panu E. Kovanen[4], Clare Verrill[5], Margarita Walliander[1], Mikael Lundin[1], Caj Haglund[6,7] & Johan Lundin[1,8]

Image-based machine learning and deep learning in particular has recently shown expert-level accuracy in medical image classification. In this study, we combine convolutional and recurrent architectures to train a deep network to predict colorectal cancer outcome based on images of tumour tissue samples. The novelty of our approach is that we directly predict patient outcome, without any intermediate tissue classification. We evaluate a set of digitized haematoxylin-eosin-stained tumour tissue microarray (TMA) samples from 420 colorectal cancer patients with clinicopathological and outcome data available. The results show that deep learning-based outcome prediction with only small tissue areas as input outperforms (hazard ratio 2.3; CI 95% 1.79–3.03; AUC 0.69) visual histological assessment performed by human experts on both TMA spot (HR 1.67; CI 95% 1.28–2.19; AUC 0.58) and whole-slide level (HR 1.65; CI 95% 1.30–2.15; AUC 0.57) in the stratification into low- and high-risk patients. Our results suggest that state-of-the-art deep learning techniques can extract more prognostic information from the tissue morphology of colorectal cancer than an experienced human observer.


a
Feature extraction & classification
Individual risk score
Human Expert
CNN
SVM
Logistic Reg.
Naive Bayes
Recurrent network (LSTM)
Risk
Low
High
Probability of 5-year DSS
256
b
Recurrent network (LSTM) structure
Layer 1: 264 lstm cells
Layer 2: 128 lstm cells
Layer 3: 64 lstm cells
Probability of 5-year DSS

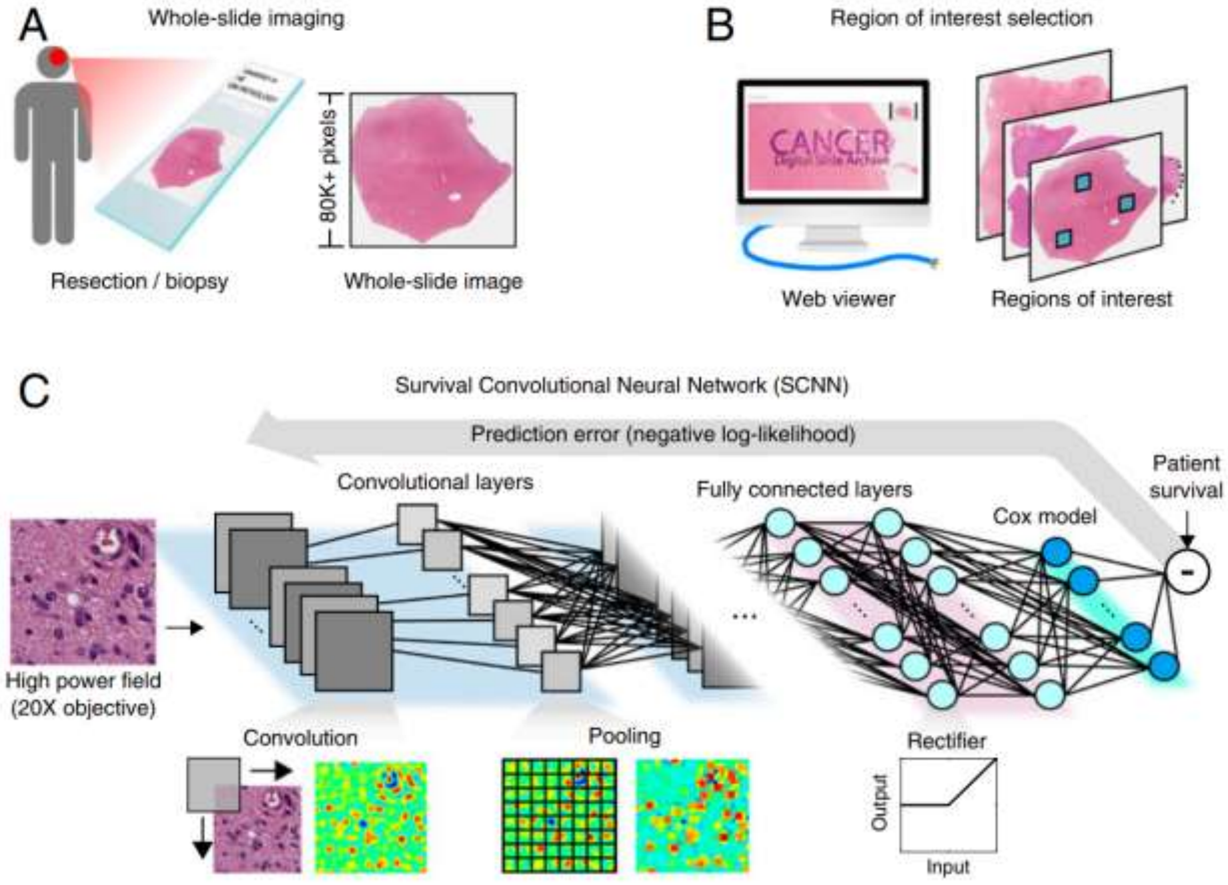

Digital risk score on TMA spots
Low Risk
High Risk
p < 0.0001
Disease-specific survival
Months
Numbers at risk
210 158 129 116 97 63 37 17 10 3 0
210 100 63 53 44 30 14 10 6 0 0
Visual risk score on TMA spots
Low Risk
High Risk
p = 0.00016
Months
Numbers at risk
185 134 97 82 71 46 28 18 10 2 0
191 94 73 66 53 35 15 8 5 0 0
Histological grade on whole-slides
Low Grade
High Grade
p = 0.00016
Disease-specific survival
Months
Dukes stage on a patient level
A
B
C
D
p < 0.0001
Months

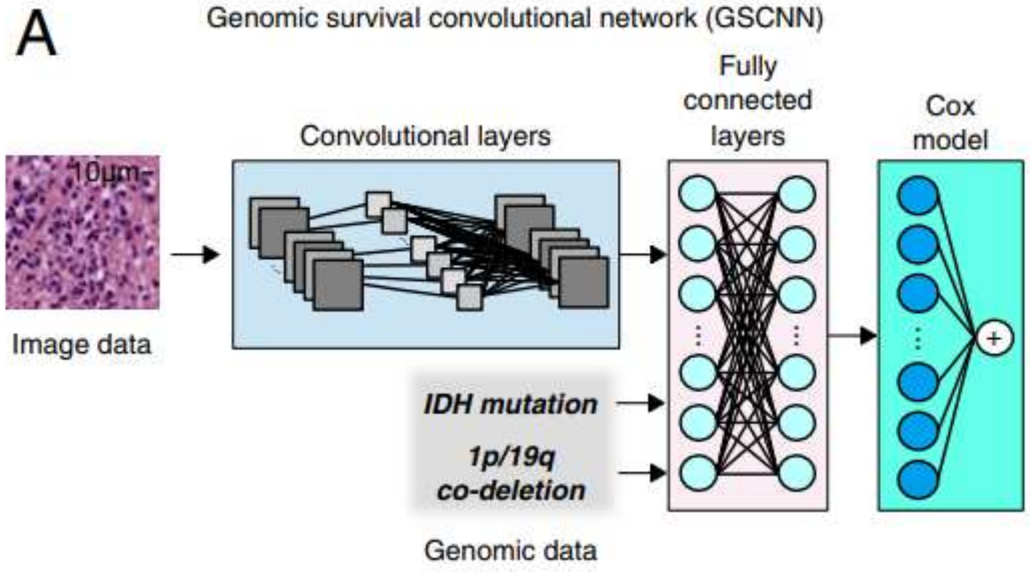
Predicting cancer outcomes from histology and genomics using convolutional networks

Pooya Mobadersany[a], Safoora Yousefi[a], Mohamed Amgad[a], David A. Gutman[b], Jill S. Barnholtz-Sloan[c], José E. Velázquez Vega[d], Daniel J. Brat[e], and Lee A. D. Cooper[a,f,g,1]

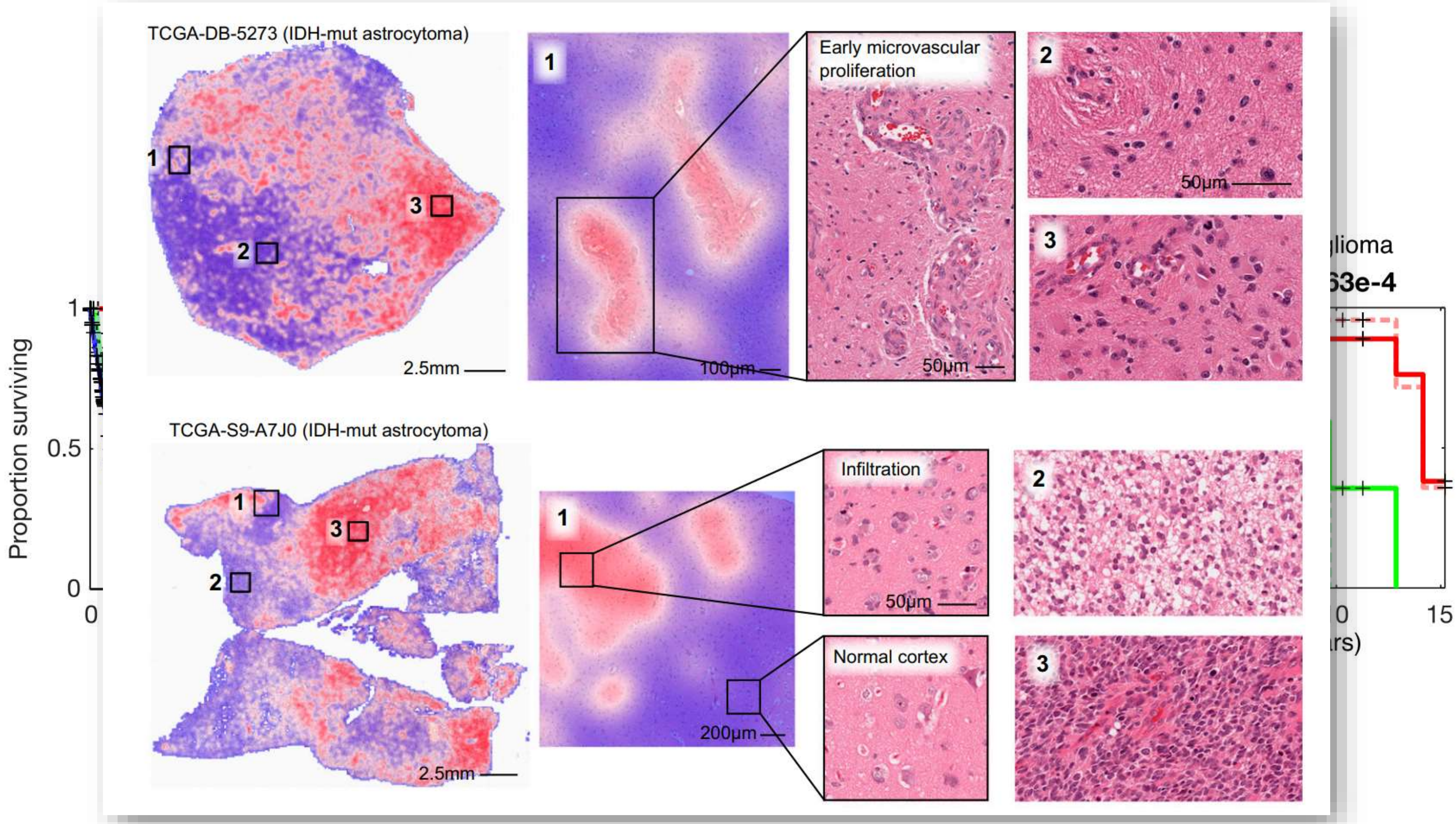
[a]Department of Biomedical Informatics, Emory University School of Medicine, Atlanta, GA 30322; [b]Department of Neurology, Emory University School of Medicine, Atlanta, GA 30322; [c]Case Comprehensive Cancer Center, Case Western Reserve University School of Medicine, Cleveland, OH 44106; [d]Department of Pathology and Laboratory Medicine, Emory University School of Medicine, Atlanta, GA 30322; [e]Department of Pathology, Northwestern University Feinberg School of Medicine, Chicago, IL 60611; [f]Winship Cancer Institute, Emory University, Atlanta, GA 30322; and [g]Department of Biomedical Engineering, Emory University and Georgia Institute of Technology, Atlanta, GA 30322

Edited by Bert Vogelstein, Johns Hopkins University, Baltimore, MD, and approved February 13, 2018 (received for review October 4, 2017)



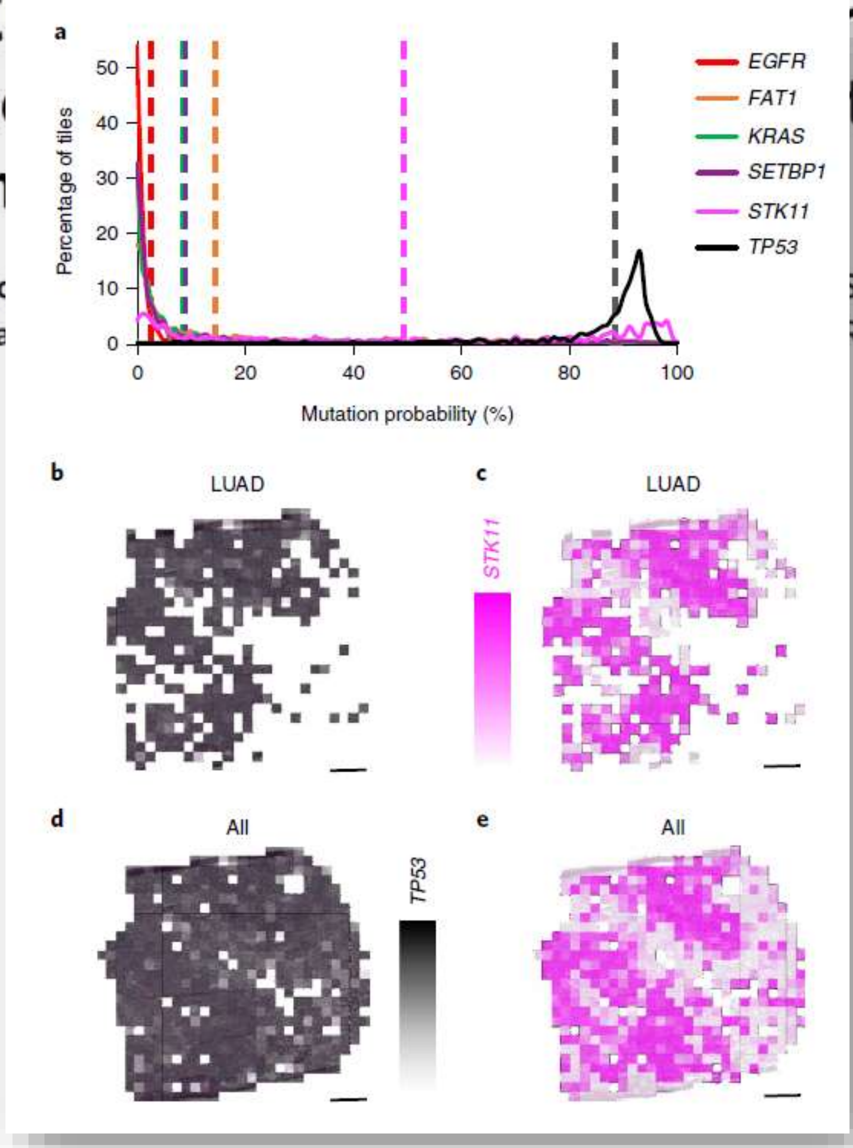


D



TCGA-DB-5273 (IDH-mut astrocytoma)
1
2
3
2.5mm
1
100μm
Early microvascular proliferation
50μm
2
50μm
3
TCGA-S9-A7J0 (IDH-mut astrocytoma)
1
2
3
2.5mm
1
200μm
Infiltration
50μm
Normal cortex
2
3
Proportion surviving
1
0.5
0
0
15

nature medicine
ARTICLES



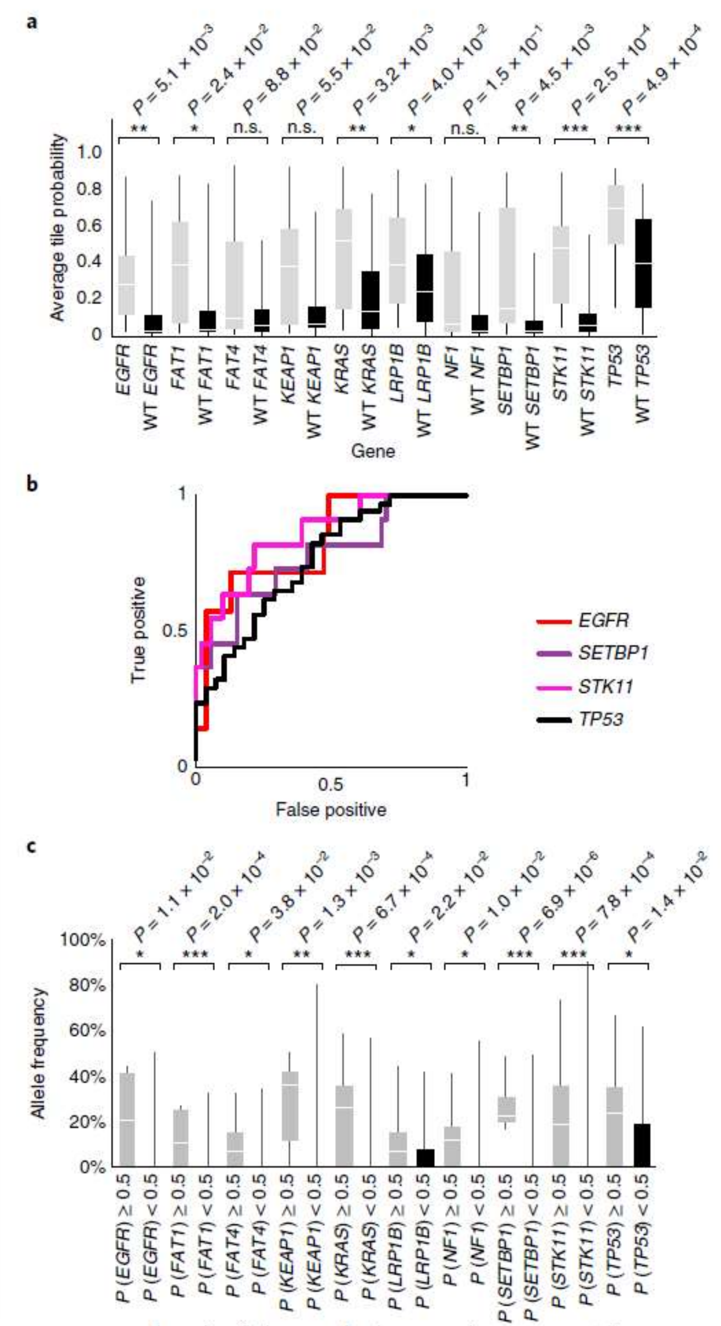
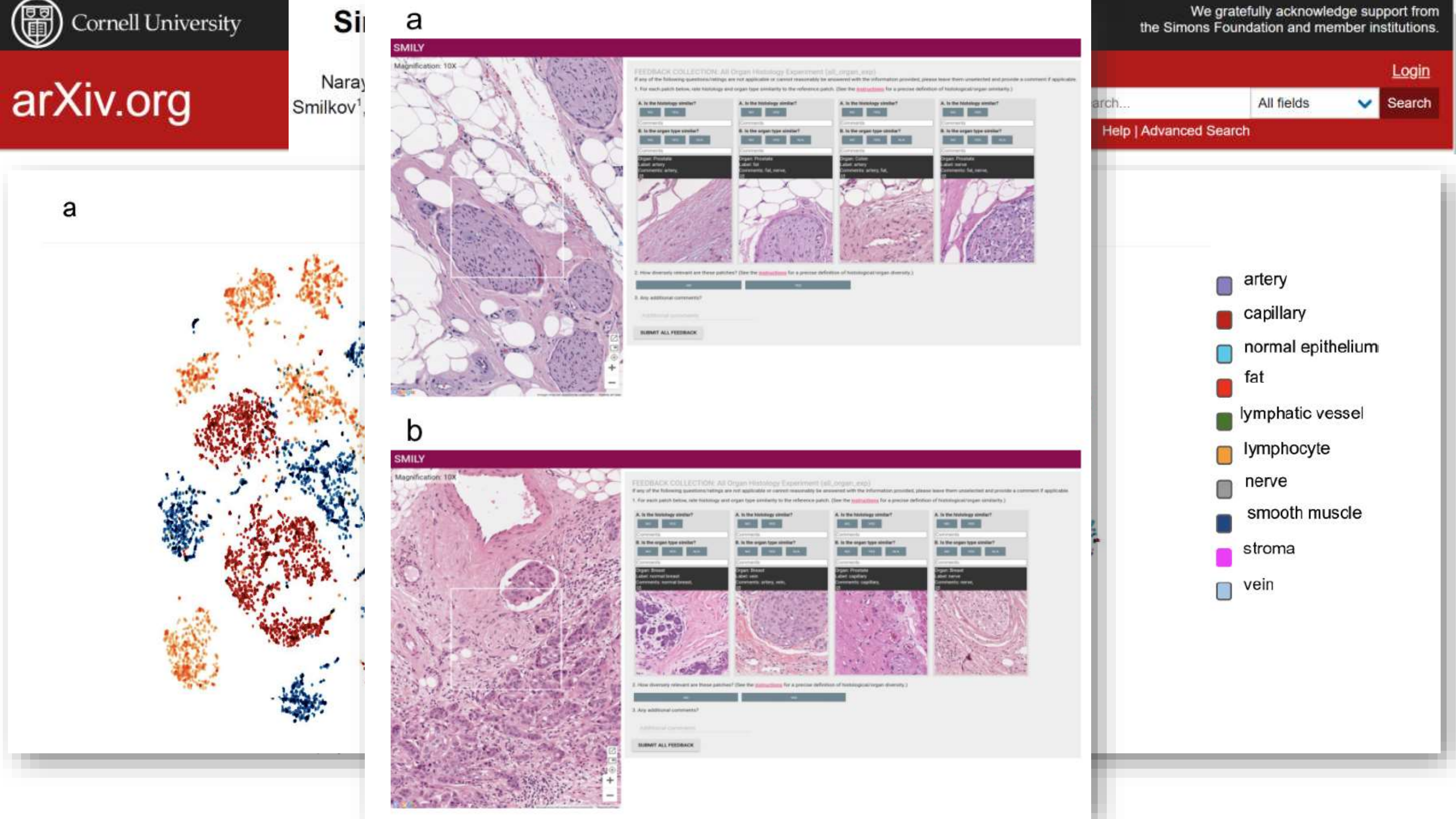


Table 1 | AUC achieved by the network trained on mutations (with 95% CIs)

Mutations	Per-tile AUC	Per-slide AUC after aggregation by…	
		… average predicted probability	… percentage of positively classified tiles
STK11	0.845 (0.838–0.852)	0.856 (0.709–0.964)	0.842 (0.683–0.967)
EGFR	0.754 (0.746–0.761)	0.826 (0.628–0.979)	0.782 (0.516–0.979)
SETBP1	0.785 (0.776–0.794)	0.775 (0.595–0.931)	0.752 (0.550–0.927)
TP53	0.674 (0.666–0.681)	0.760 (0.626–0.872)	0.754 (0.627–0.870)
FAT1	0.739 (0.732–0.746)	0.750 (0.512–0.940)	0.750 (0.491–0.946)
KRAS	0.814 (0.807–0.829)	0.733 (0.580–0.857)	0.716 (0.552–0.854)
KEAP1	0.684 (0.670–0.694)	0.675 (0.466–0.865)	0.659 (0.440–0.856)
LRP1B	0.640 (0.633–0.647)	0.656 (0.513–0.797)	0.657 (0.512–0.799)
FAT4	0.768 (0.760–0.775)	0.642 (0.470–0.799)	0.640 (0.440–0.856)
NF1	0.714 (0.704–0.723)	0.640 (0.419–0.845)	0.632 (0.405–0.845)

n = 62 slides from 59 patients.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Login
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Search
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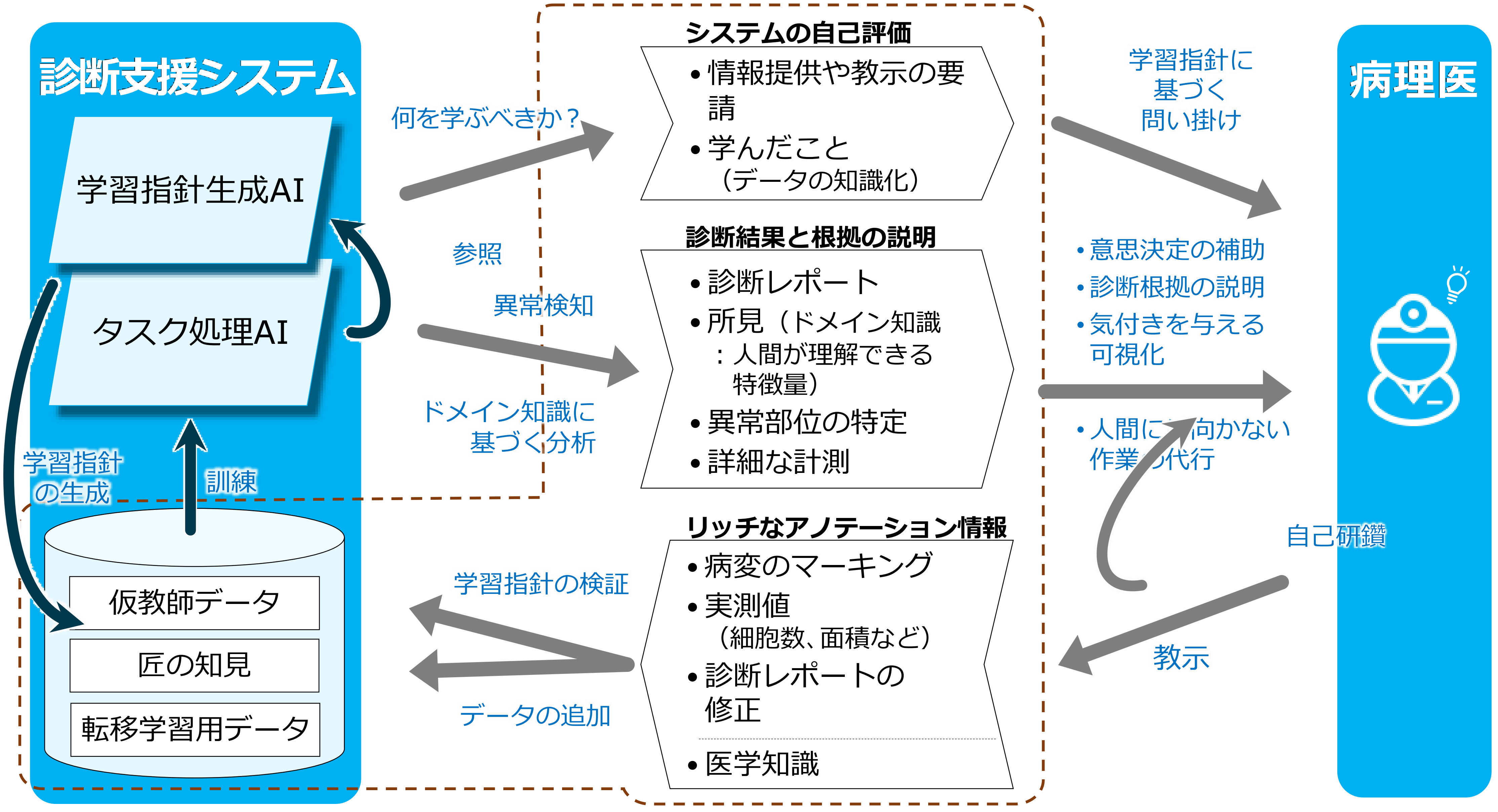
a
a
SMILY
Magnification: 10X
SUBMIT ALL FEEDBACK
b
SMILY
Magnification: 10X
SUBMIT ALL FEEDBACK
artery
capillary
normal epithelium
fat
lymphatic vessel
lymphocyte
nerve
smooth muscle
stroma
vein

X-AI (Explainable AI)

1. To understand contents of "Black Box"
2. To explain what is the "ground truth"

NEDO. Sakanashi-Fukuoka Group

～X-AI「説明可能な人工知能」～

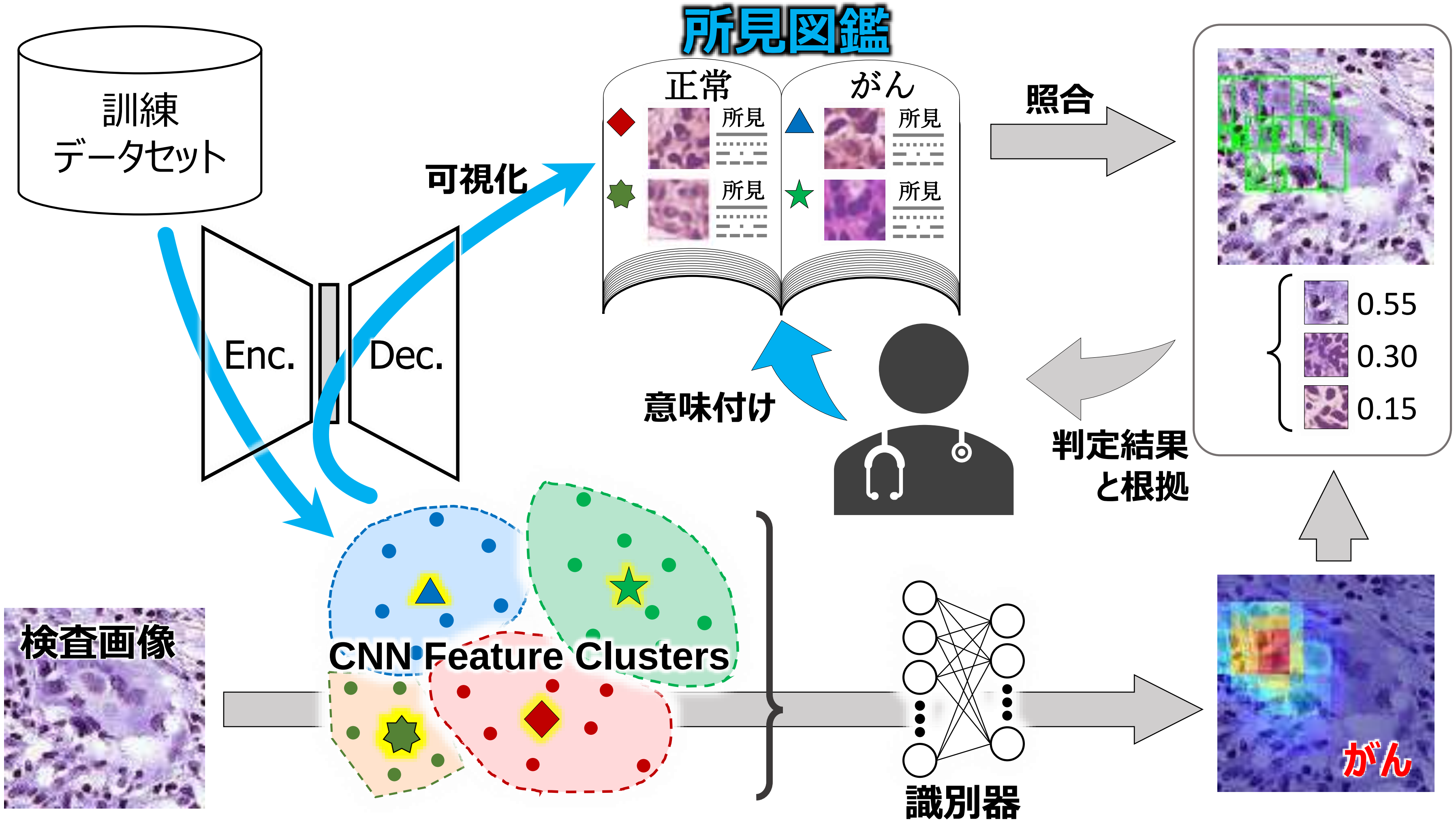


半自己学習フレームワーク　**知識を生成･蓄積する情報基盤**

①診断根拠の説明技術および半自己学習機構の研究開発
b)プロトタイプ解析

担当：産業技術総合研究所
（つくばセンター）

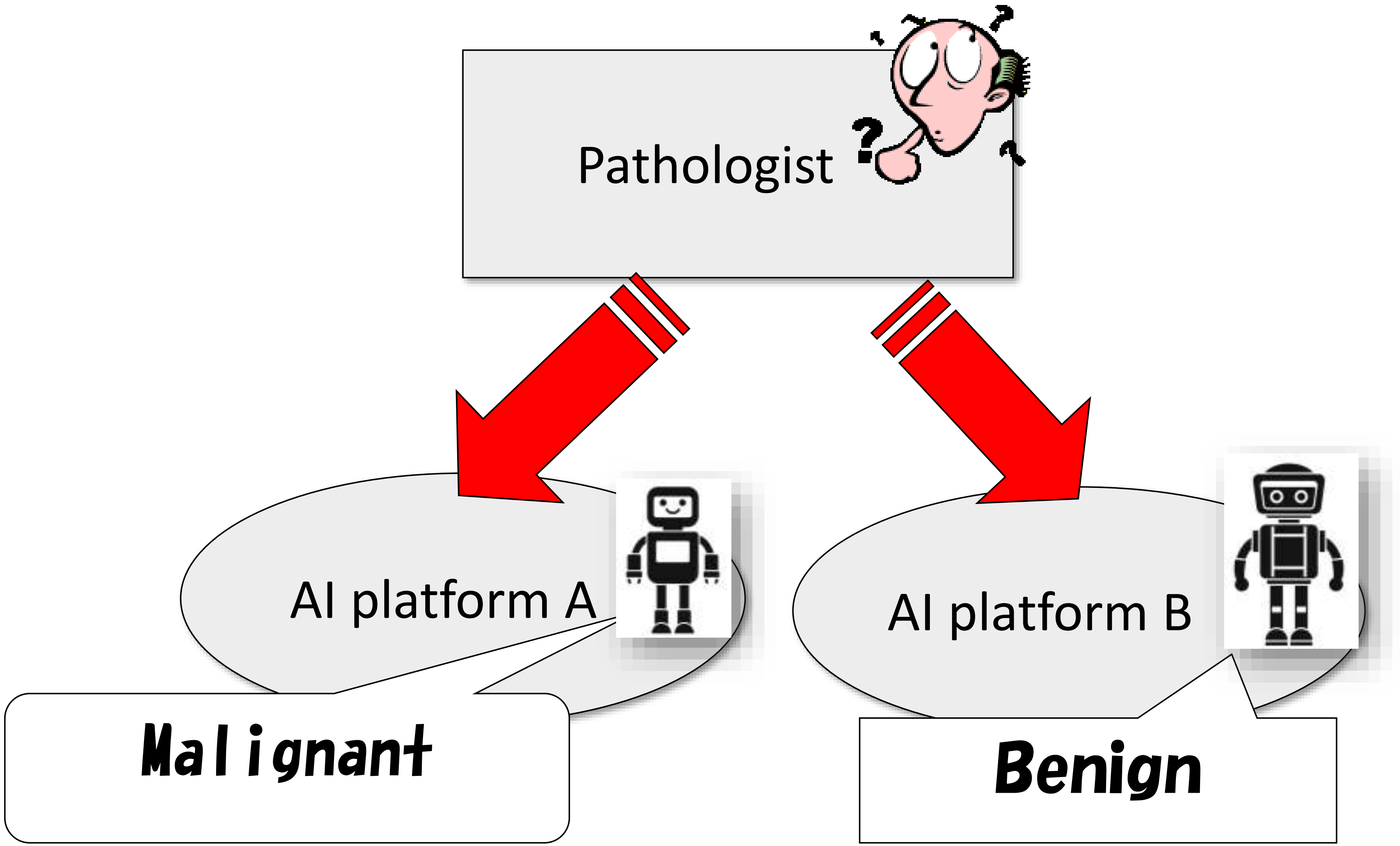
訓練済みDCNNモデルが学習データセットから生成した「所見図鑑」に基づく判定と、結果の可視化



X-AI (Explainable AI)

1. To understand contents of “Black Box”
2. To explain what is the “ground truth”

NEDO. Sakanashi-Fukuoka Group

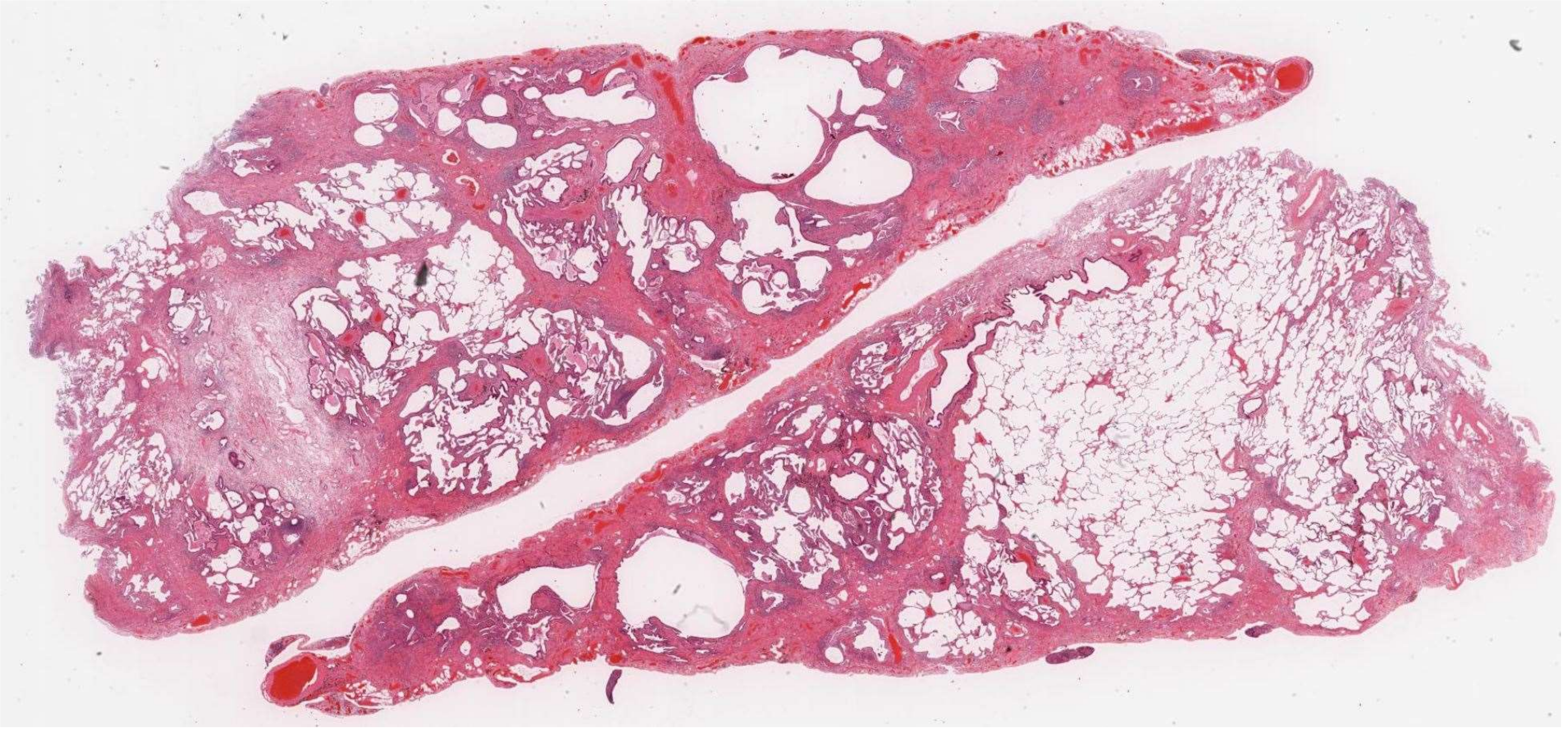

Pathologist
AI platform A
AI platform B
Malignant
Benign

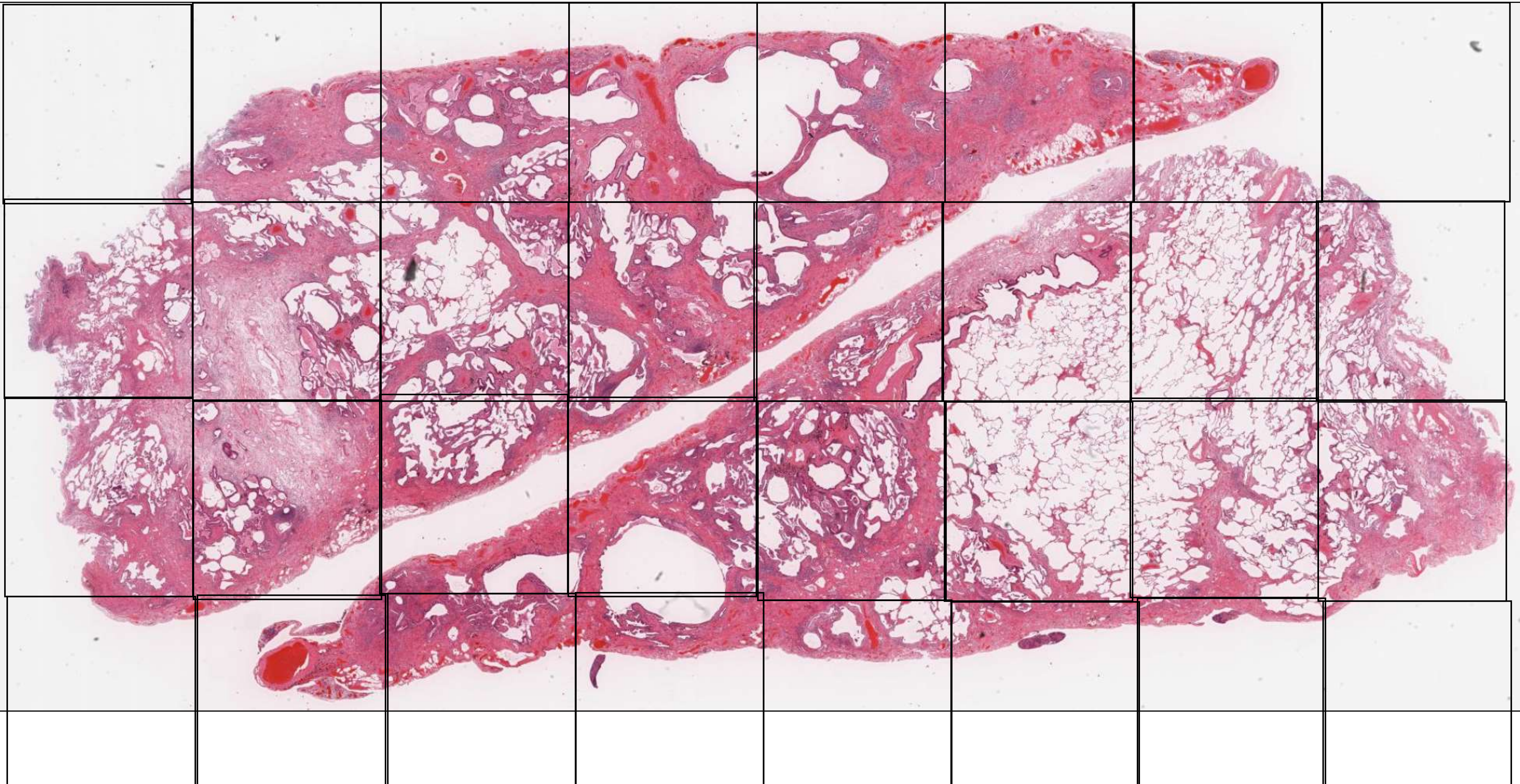
UIP vs other IIPs by 29 pathologists

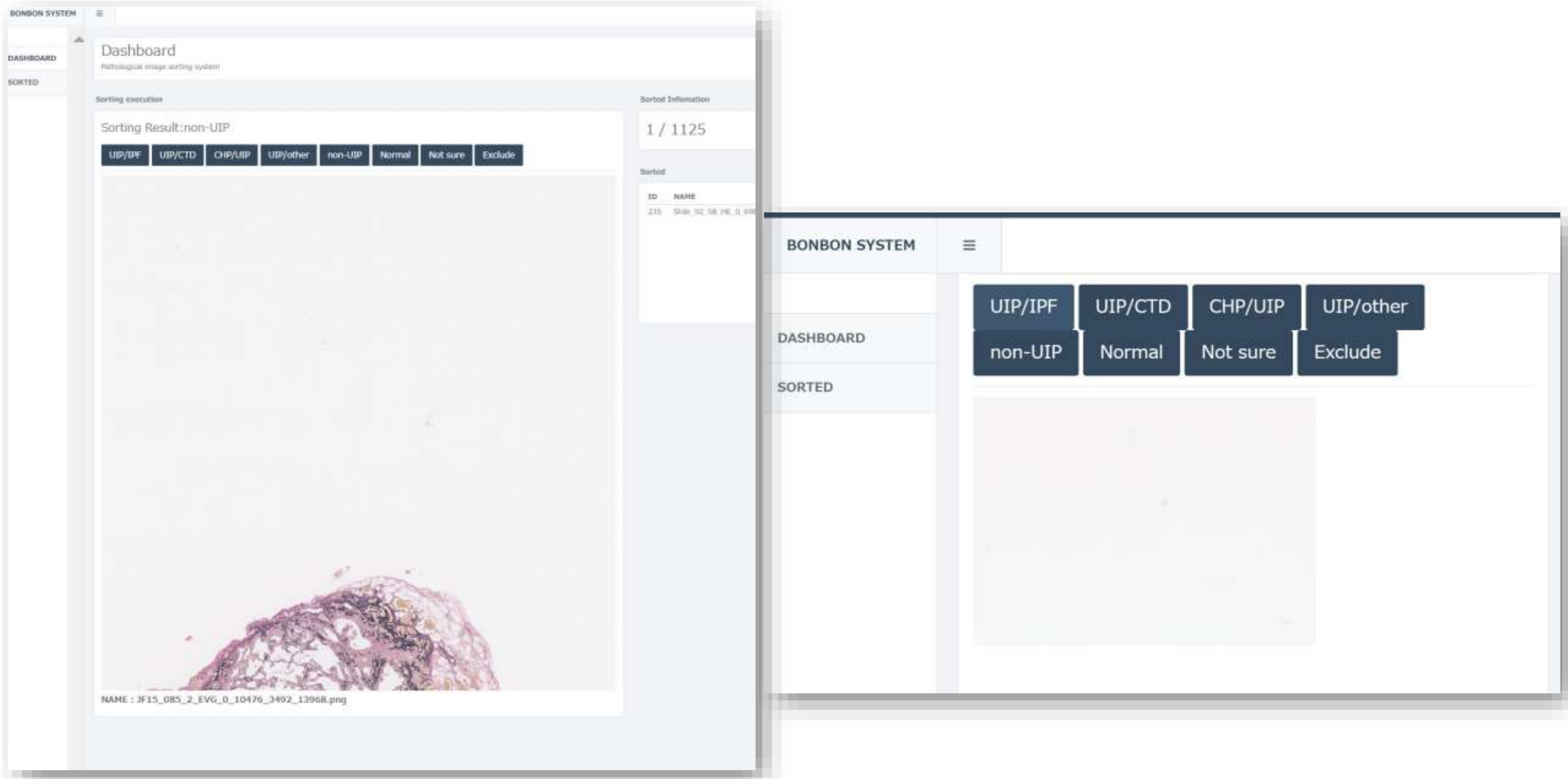
1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24	25	26	27	28	29	30
Pathologists	1	2	3	4	5	6	7	8	9	10	11	12	**13**	14	15	16	17	18	19	20	21	22	23	24	25	26	27	28	29
Category	A	A	A	A	B	B	B	B	B	B	B	B	C	C	C	C	C	C	C	C	C	C	D	D	D	D	D	D	D
Area	Ⅰ	Ⅰ	Ⅱ	Ⅲ	Ⅱ	Ⅰ	Ⅰ	Ⅱ	Ⅰ	Ⅰ	Ⅱ	Ⅱ	Ⅲ	Ⅲ	Ⅲ	Ⅲ	Ⅲ	Ⅲ	Ⅲ	Ⅲ	Ⅲ	Ⅲ							
Case1	1	0	0	1	0	1	4	4	0	1	0	0	1	1	2	4	0	0	0	2	0	1	0	4	0	3	2	1	0
Case2	1	1	1	1	1	1	3	1	1	0	1	1	1	1	2	1	1	1	0	2	2	3	1	1	3	1	5	3	1
Case3	2	2	2	1	2	1	2	0	2	2	2	2	2	2	2	2	2	0	1	2	2	1	0	2	1	2	2	2	2
Case4	1	1	1	1	0	1	1	0	0	1	1	1	1	1	1	2	1	1	1	2	1	1	0	1	1	1	1	1	2
Case5	1	1	1	1	1	1	0	0	1	1	1	1	1	1	2	2	1	1	1	2	2	1	0	1	1	5	4	5	2
Case6	1	1	1	1	1	1	1	1	1	1	1	1	1	1	2	0	1	1	1	2	2	1	1	1	1	5	6	6	1
Case7	2	2	2	1	2	1	2	2	2	1	2	2	2	2	2	2	1	1	1	2	2	1	2	2	1	5	0	2	2
Case8	1	1	1	1	1	1	2	1	0	1	1	1	1	2	2	1	1	1	1	2	1	1	0	1	1	1	1	2	2
Case9	1	1	1	1	1	1	1	1	1	1	1	1	1	1	2	1	1	1	1	2	2	1	1	1	1	1	6	1	1
Case10	1	0	2	1	0	1	0	2	0	1	0	0	1	1	2	2	2	0	0	2	2	1	1	1	1	1	0	1	2
Case11	2	2	0	0	1	2	2	0	2	0	1	2	2	2	2	2	2	0	2	2	0	2	2	5	1	5	1	1	5
Case12	1	1	1	1	1	1	1	1	1	1	1	0	1	1	2	1	1	1	1	0	1	1	1	1	1	1	1	2	1
Case13	2	2	2	2	0	2	2	0	2	2	1	2	2	2	2	2	2	0	2	2	2	2	0	5	1	5	6	1	2
Case14	2	2	2	1	2	3	2	4	2	2	1	5	2	2	2	0	2	0	0	2	2	1	2	2	1	2	1	2	2
Case15	0	1	1	1	2	0	1	4	2	0	1	1	1	1	2	2	1	1	0	1	1	1	1	4	1	1	1	0	0
Case16	2	2	2	5	5	2	0	5	2	0	0	2	2	2	2	2	2	0	2	2	2	2	0	5	1	5	6	7	5
Case17	1	1	0	1	0	0	0	0	0	0	0	1	2	1	2	2	1	0	1	1	0	1	1	7	0	7	7	4	0
Case18	0	1	1	1	0	1	0	1	1	1	1	1	1	1	1	1	1	1	0	2	0	1	1	4	1	1	2	1	1
Case19	1	1	1	2	1	1	2	1	1	1	1	1	1	1	1	1	1	1	1	2	0	1	0	1	1	1	1	1	1
Case20	1	1	1	1	1	1	1	1	1	1	1	1	1	1	2	1	1	1	1	1	0	1	1	1	1	1	1	1	2
	ATS/ERS				US/EU								JPN pulmonary path										General path						

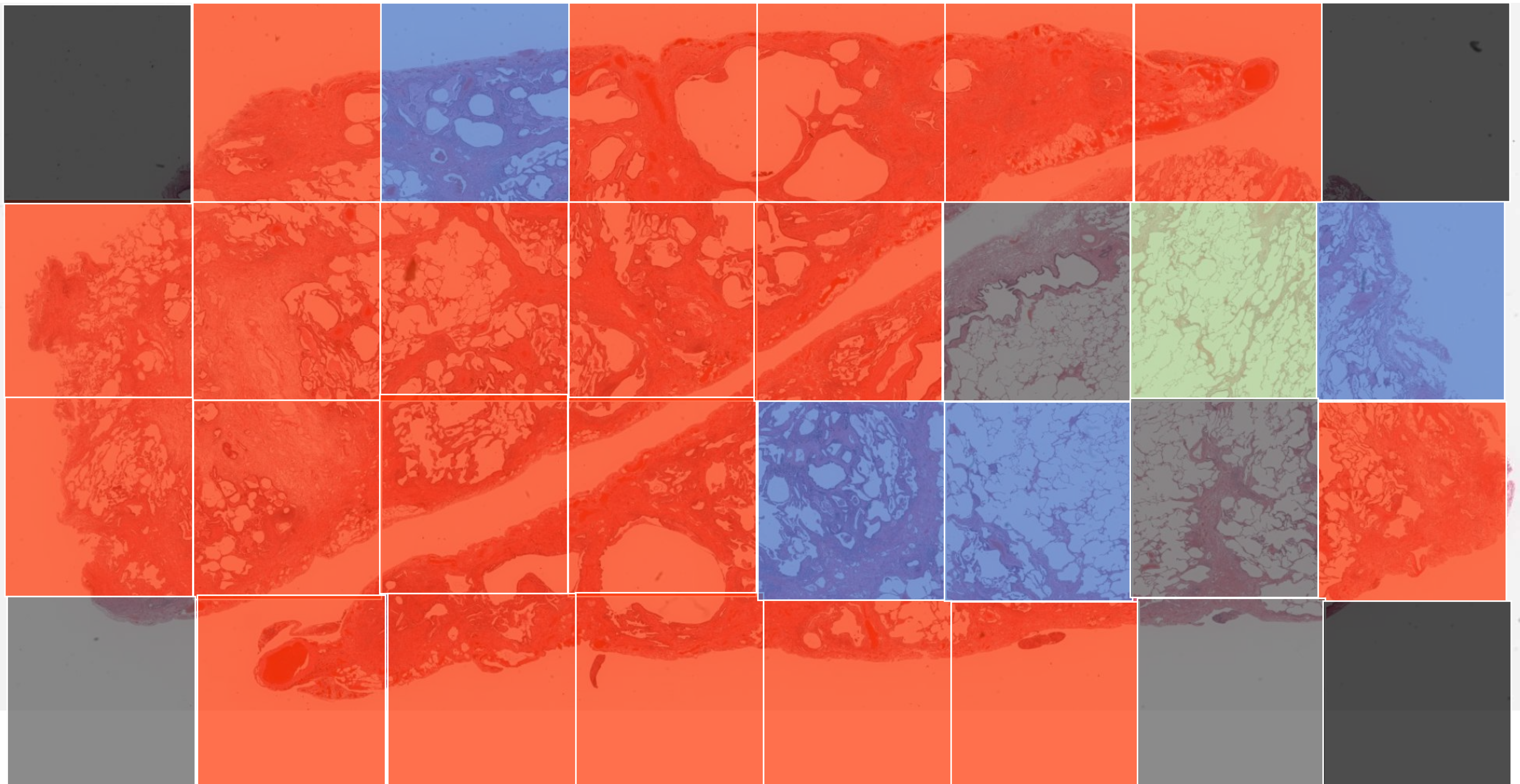
Category:		**Kappa**
EX	**(ATS/ERS)**	**0.41**
USEP	**(US/EU Pulmonary)**	**0.30**
JP	**(JPN Pulmonary)**	**0.18**
GP	**(General Pathologist)**	**0.13**

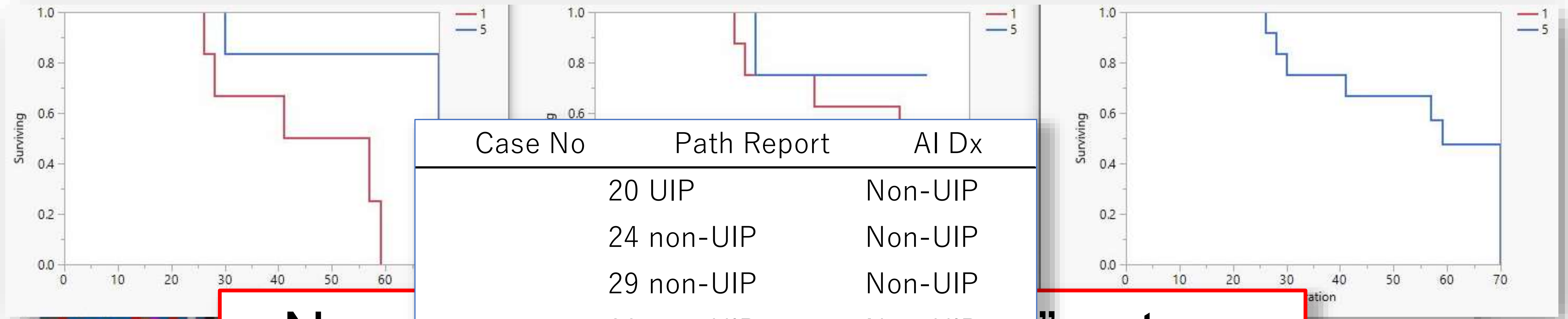
平成21年厚労省班研究報告





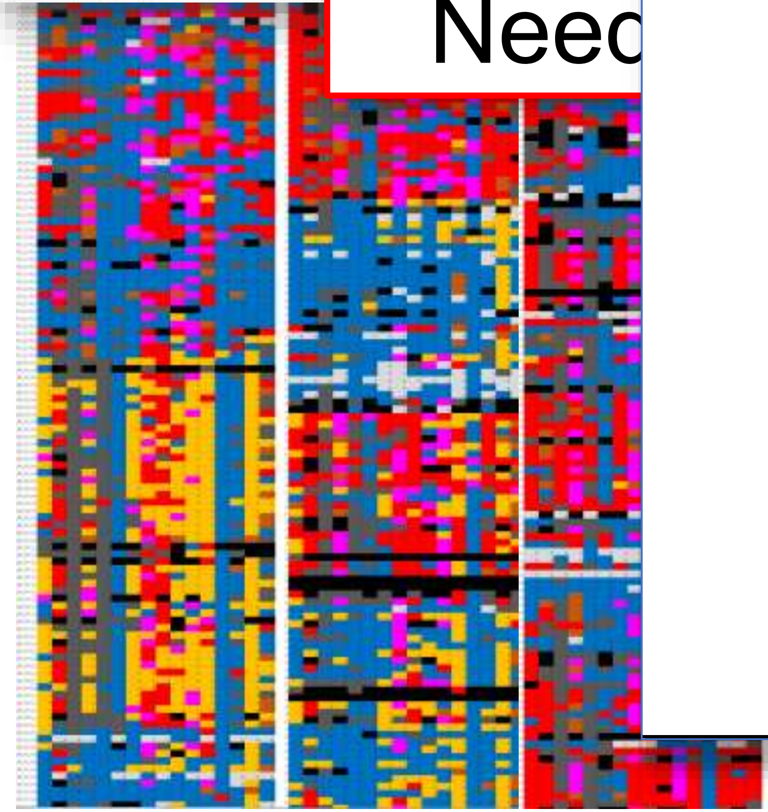

BONBON SYSTEM
DASHBOARD
SORTED
Dashboard
Pathological image sorting system
Sorting execution
Sorting Result:non-UIP
UIP/IPF
UIP/CTD
CHP/UIP
UIP/other
non-UIP
Normal
Not sure
Exclude
NAME : JF15_085_2_EVG_0_10476_3492_13968.png
Sorted Information
1 / 1125
Sorted
ID
NAME
BONBON SYSTEM
DASHBOARD
SORTED
UIP/IPF
UIP/CTD
CHP/UIP
UIP/other
non-UIP
Normal
Not sure
Exclude

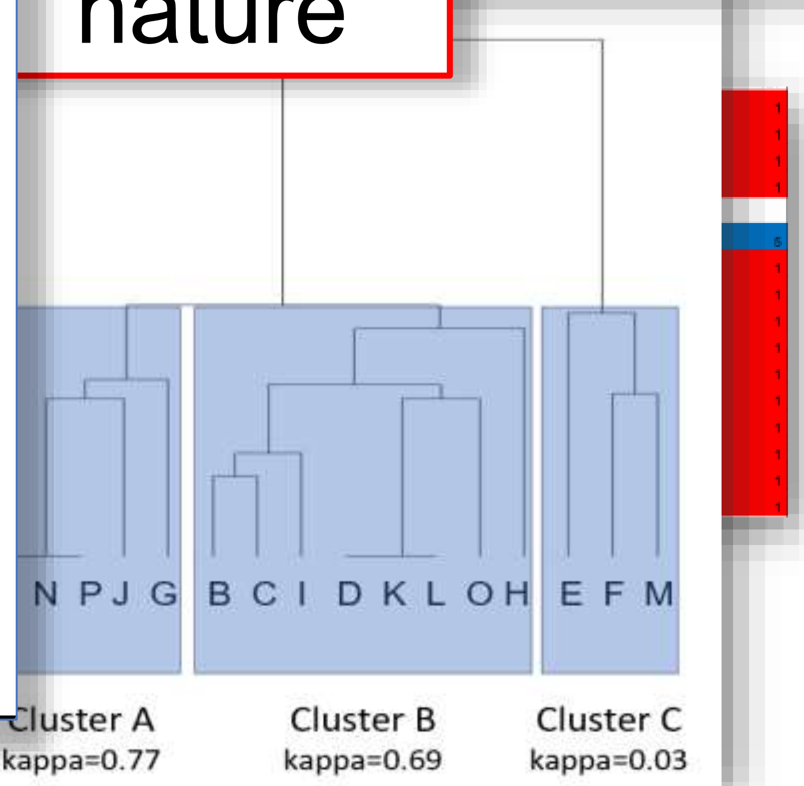




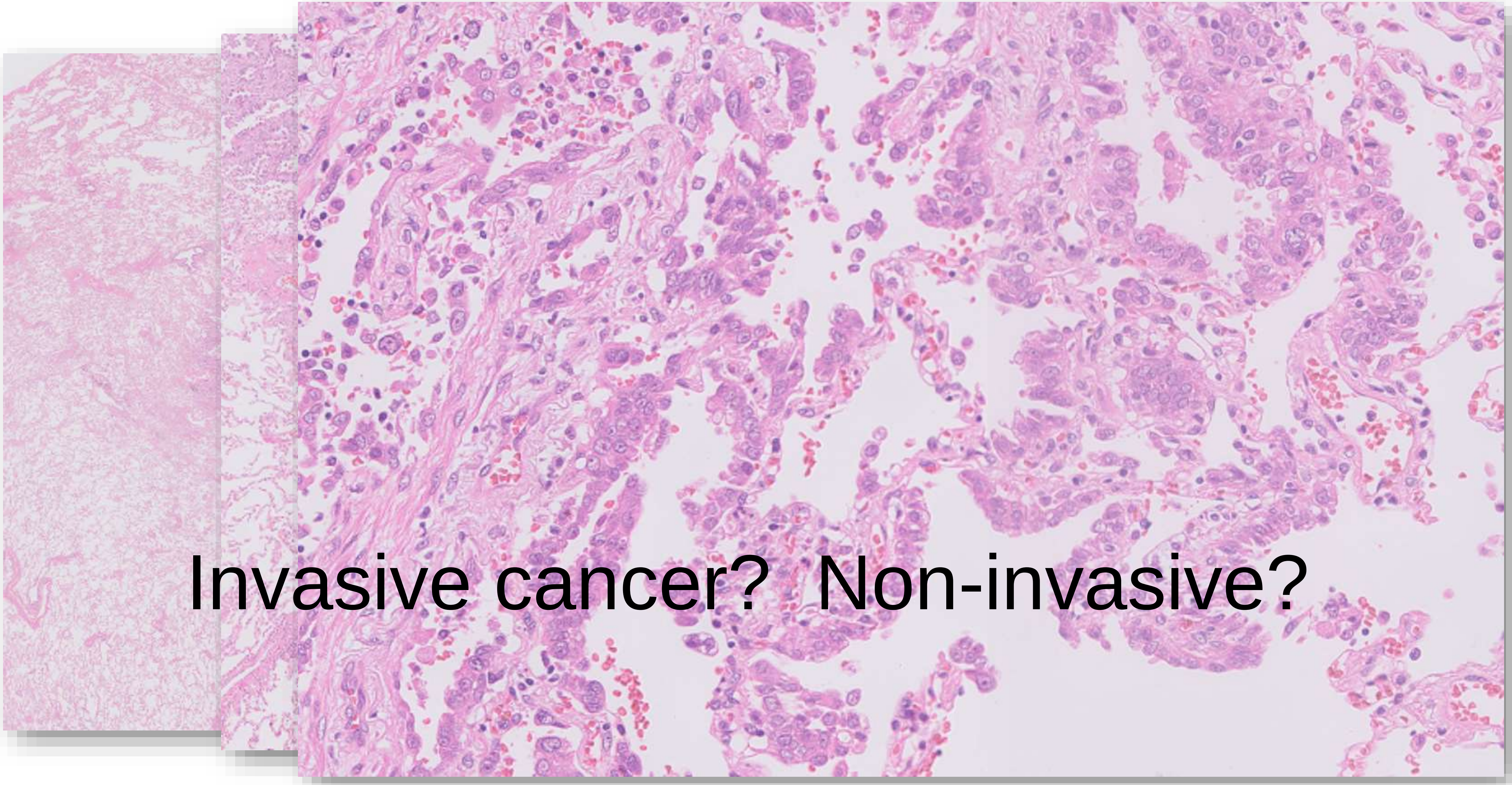
Need

” nature

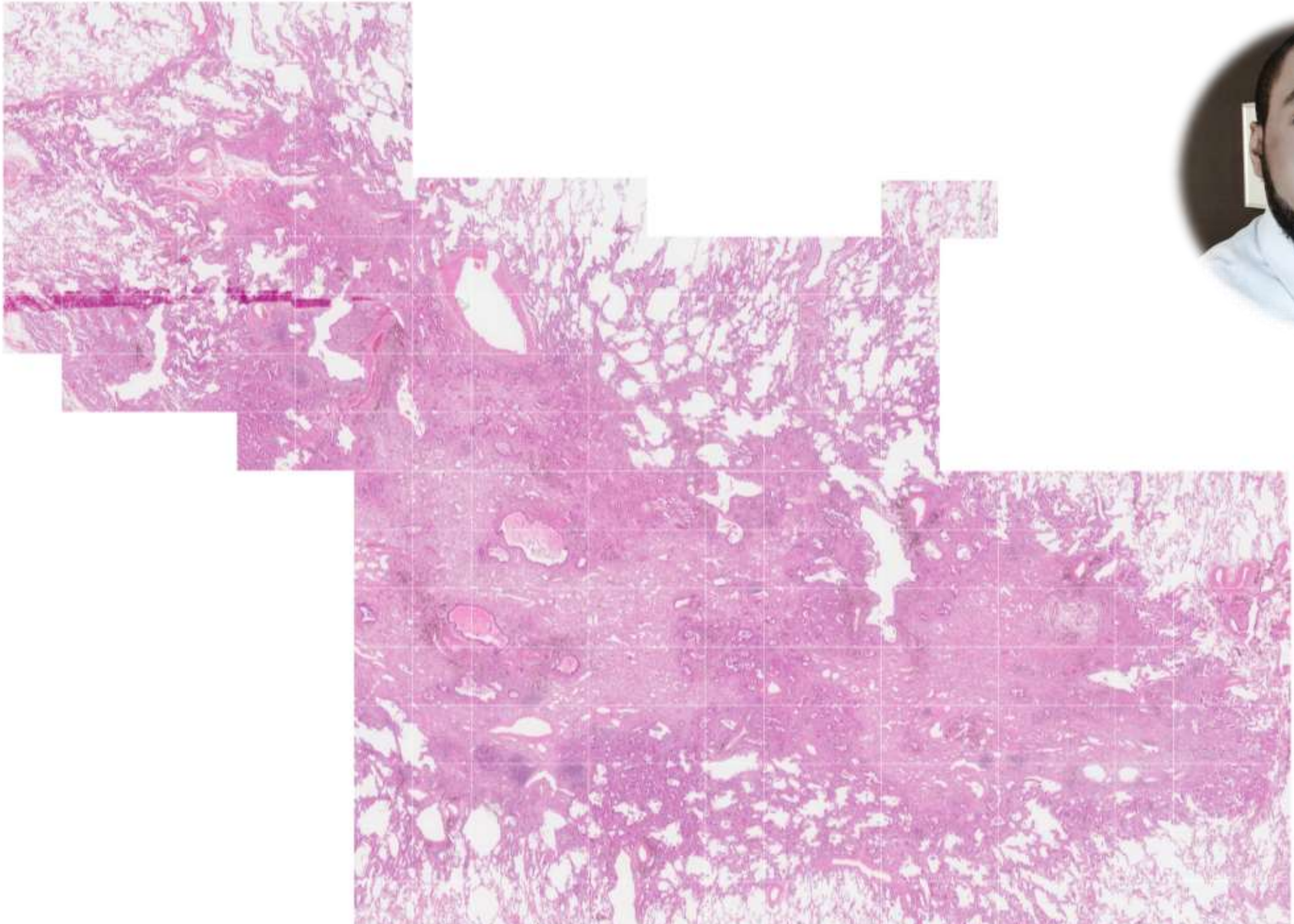




Case No	Path Report	AI Dx
20	UIP	Non-UIP
24	non-UIP	Non-UIP
29	non-UIP	Non-UIP
30	non-UIP	Non-UIP
31	non-UIP	Non-UIP
33	UIP	UIP
64	non-UIP	UIP
70	non-UIP	Non-UIP
69	non-UIP	Non-UIP
65	UIP	UIP
68	UIP	UIP
60	non-UIP	Non-UIP
71	UIP	UIP

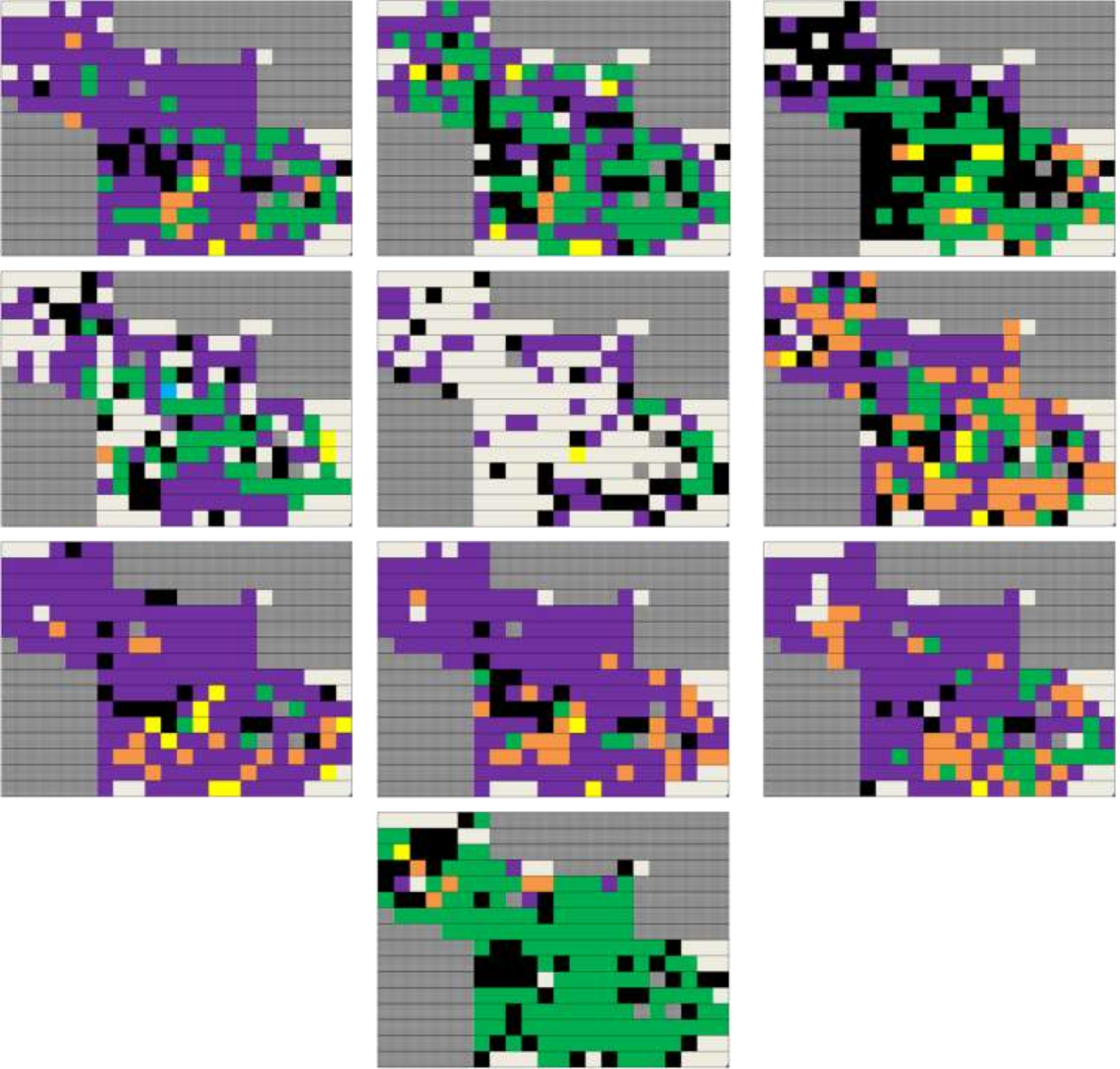


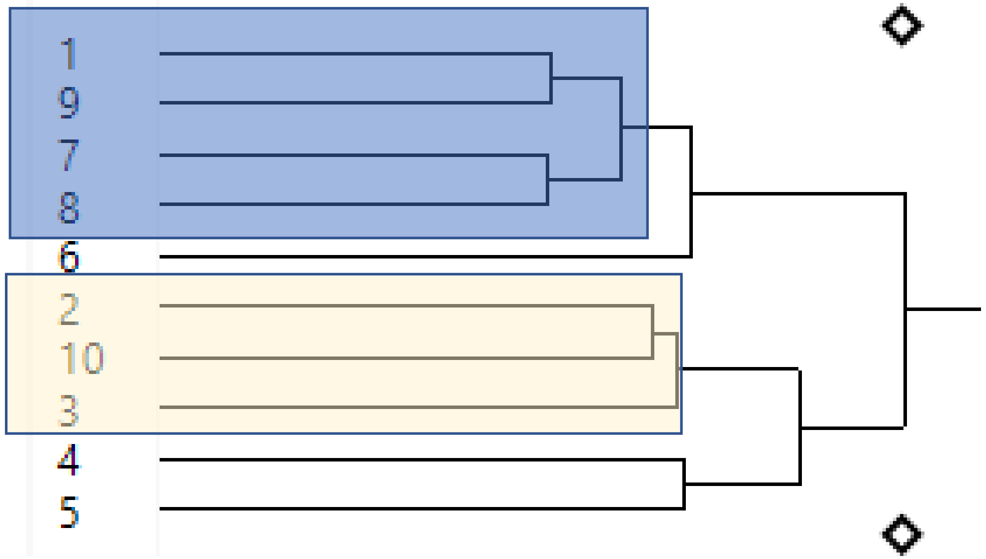
Invasive cancer? Non-invasive?




BONBON SY
PathPresente
sorting.nex.blue
BONBON SYSTEM
Sorting execution
Lepidic
pap
Acinar
Micro pap
solid
mucious
Normal
Exclude

	Path	Path:	Path:	Path·	Path·	Path(	Path'	Path:	Path!	Path1	
1	Papillary	Papillary	Papillary	Non-invasive	Papillary	Non-invasive	Papillary	Papillary	Papillary	Micropapillary	Acinar
2	Normal lung	Normal lung	Normal lung	Normal lung	Normal lung	Normal lung	Normal lung	Normal lung	Normal lung	Normal lung	Papillary
3	Normal lung	Normal lung	Normal lung	Normal lung	Normal lung	Normal lung	Normal lung	Normal lung	Normal lung	Normal lung	Micropapillary
4	Papillary	Acinar	Acinar	Acinar	Normal lung	Non-invasive	Non-invasive	Non-invasive	Papillary	Acinar	Solid
5	Normal lung	Acinar	Normal lung	Normal lung	Normal lung	Exclude	Exclude	Normal lung	Normal lung	Normal lung	Non-invasive (Lepidic)
6	Non-invasive	Non-invasive	Non-invasive	Non-invasive	Non-invasive	Non-invasive	Non-invasive	Non-invasive	Non-invasive	Papillary	Normal lung
7	Non-invasive	Acinar	Exclude	Exclude	Normal lung	Non-invasive	Non-invasive	Non-invasive	Non-invasive	Acinar	Exclude
8	Non-invasive	Acinar	Acinar	Acinar	Normal lung	Non-invasive	Non-invasive	Non-invasive	Non-invasive	Acinar	
9	Non-invasive	Papillary	Acinar	Non-invasive	Non-invasive	Non-invasive	Non-invasive	Non-invasive	Non-invasive	Papillary	
10	Non-invasive	Acinar	Acinar	Non-invasive	Papillary	Non-invasive	Non-invasive	Non-invasive	Papillary	Acinar	
11	Non-invasive	Non-invasive	Exclude	Non-invasive	Normal lung	Non-invasive	Non-invasive	Non-invasive	Non-invasive	Acinar	
12	Non-invasive	Acinar	Exclude	Solid	Solid	Solid	Solid	Solid	Solid	Exclude	
13	Non-invasive	Non-invasive	Exclude	Non-invasive	Normal lung	Non-invasive	Non-invasive	Non-invasive	Non-invasive	Acinar	
14	Normal lung	Normal lung	Normal lung	Normal lung	Normal lung	Normal lung	Exclude	Non-invasive	Normal lung	Normal lung	
15	Non-invasive	Papillary	Papillary	Non-invasive	Non-invasive	Papillary	Papillary	Papillary	Papillary	Papillary	
16	Non-invasive	Micropapillary	Exclude	Non-invasive	Exclude	Papillary	Papillary	Papillary	Papillary	Micropapillary	
17	Acinar	Acinar	Acinar	Acinar	Acinar	Papillary	Acinar	Acinar	Papillary	Acinar	
18	Non-invasive	Exclude	Exclude	Exclude	Normal lung	Papillary	Non-invasive	Non-invasive	Non-invasive	Acinar	
19	Non-invasive	Acinar	Exclude	Non-invasive	Non-invasive	Non-invasive	Non-invasive	Papillary	Non-invasive	Micropapillary	
20	Non-invasive	Normal lung	Exclude	Non-invasive	Normal lung	Non-invasive	Non-invasive	Non-invasive	Non-invasive	Acinar	
21	Exclude	Acinar	Exclude	Normal lung	Normal lung	Exclude	Non-invasive	Non-invasive	Non-invasive	Exclude	
22	Non-invasive	Acinar	Exclude	Non-invasive	Non-invasive	Non-invasive	Non-invasive	Non-invasive	Non-invasive	Micropapillary	
23	Non-invasive	Non-invasive	Exclude	Normal lung	Non-invasive	Non-invasive	Non-invasive	Non-invasive	Non-invasive	Acinar	
24	Papillary	Papillary	Papillary	Papillary	Papillary	Papillary	Micropapillary	Acinar	Papillary	Micropapillary	
25	Non-invasive	Non-invasive	Non-invasive	Non-invasive	Non-invasive	Papillary	Non-invasive	Non-invasive	Non-invasive	Papillary	
26	Non-invasive	Acinar	Acinar	Non-invasive	Acinar	Papillary	Papillary	Papillary	Acinar	Acinar	
27	Acinar	Acinar	Acinar	Acinar	Acinar	Acinar	Papillary	Acinar	Acinar	Acinar	
28	Non-invasive	Non-invasive	Exclude	Normal lung	Normal lung	Non-invasive	Non-invasive	Non-invasive	Non-invasive	Exclude	
29	Solid	Solid	Solid	Solid	Solid	Solid	Solid	Solid	Solid	Solid	
30	Exclude	Normal lung	Exclude	Exclude	Normal lung	Exclude	Exclude	Non-invasive	Non-invasive	Exclude	
31	Non-invasive	Micropapillary	Exclude	Exclude	Exclude	Non-invasive	Non-invasive	Non-invasive	Papillary	Acinar	
32	Non-invasive	Acinar	Exclude	Exclude	Normal lung	Non-invasive	Non-invasive	Non-invasive	Non-invasive	Acinar	
33	Non-invasive	Non-invasive	Exclude	Exclude	Normal lung	Papillary	Non-invasive	Non-invasive	Non-invasive	Acinar	
34	Papillary	Micropapillary	Micropapillary	Papillary	Micropapillary	Papillary	Micropapillary	Micropapillary	Papillary	Micropapillary	
35	Acinar	Papillary	Acinar	Acinar	Acinar	Papillary	Papillary	Acinar	Acinar	Acinar	
36	Exclude	Normal lung	Exclude	Exclude	Normal lung	Exclude	Exclude	Exclude	Exclude	Exclude	
37	Non-invasive	Non-invasive	Non-invasive	Non-invasive	Normal lung	Non-invasive	Non-invasive	Non-invasive	Non-invasive	Acinar	
38	Non-invasive	Normal lung	Normal lung	Normal lung	Normal lung	Normal lung	Exclude	Normal lung	Normal lung	Normal lung	
39	Micropapillary	Acinar	Acinar	Micropapillary	Micropapillary	Micropapillary	Papillary	Micropapillary	Papillary	Acinar	
40	Papillary	Papillary	Acinar	Acinar	Exclude	Micropapillary	Micropapillary	Papillary	Papillary	Acinar	




1
9
7
8
6
2
10
3
4
5

Barriers of AI installation

Negative mentality of Pathologists

- Why do you replace my lovely microscope?
- No good reason to replace microscope
- Microscope looks professional
- Digital Dx is slow
- Detail are not visible by digital slides
- Focusing is not always perfect
- AI to replace us may come afterwards
- etc

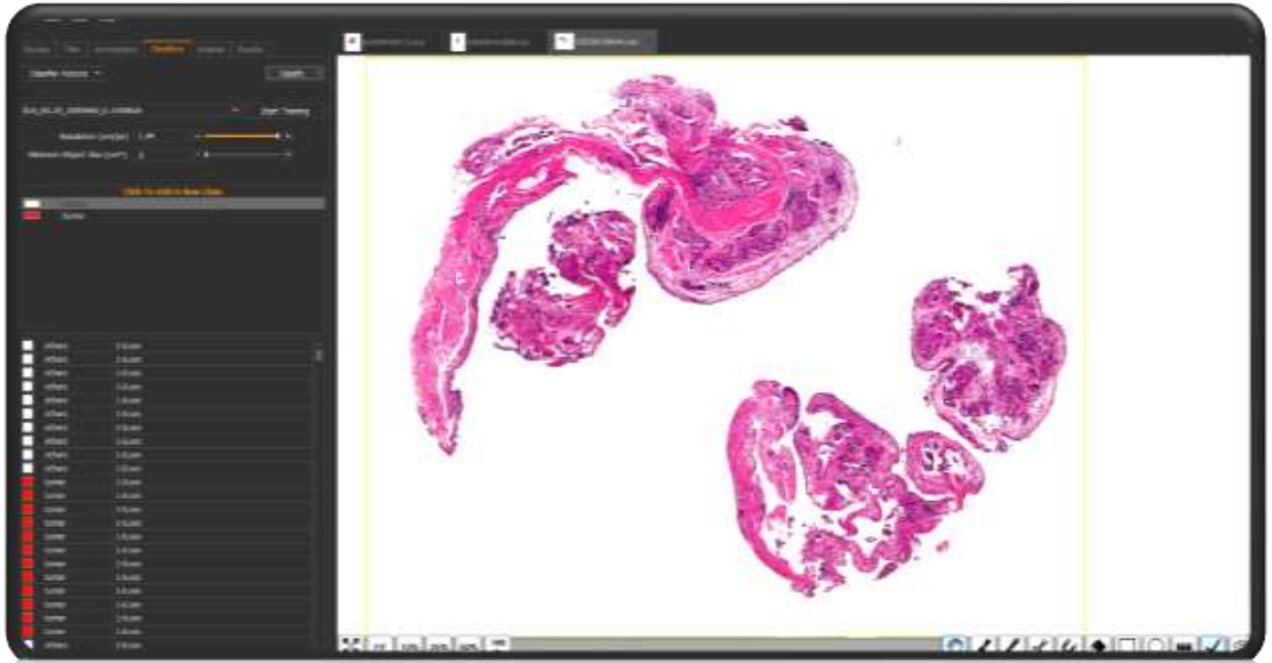
Department of Pathology, Nagasaki University Graduate School of Biomedical Sciences
Department of Pathology, Kameda Medical Center

Tissue heterogeneity

長崎大学
NAGASAKI UNIVERSITY

Kameda Medical Cent

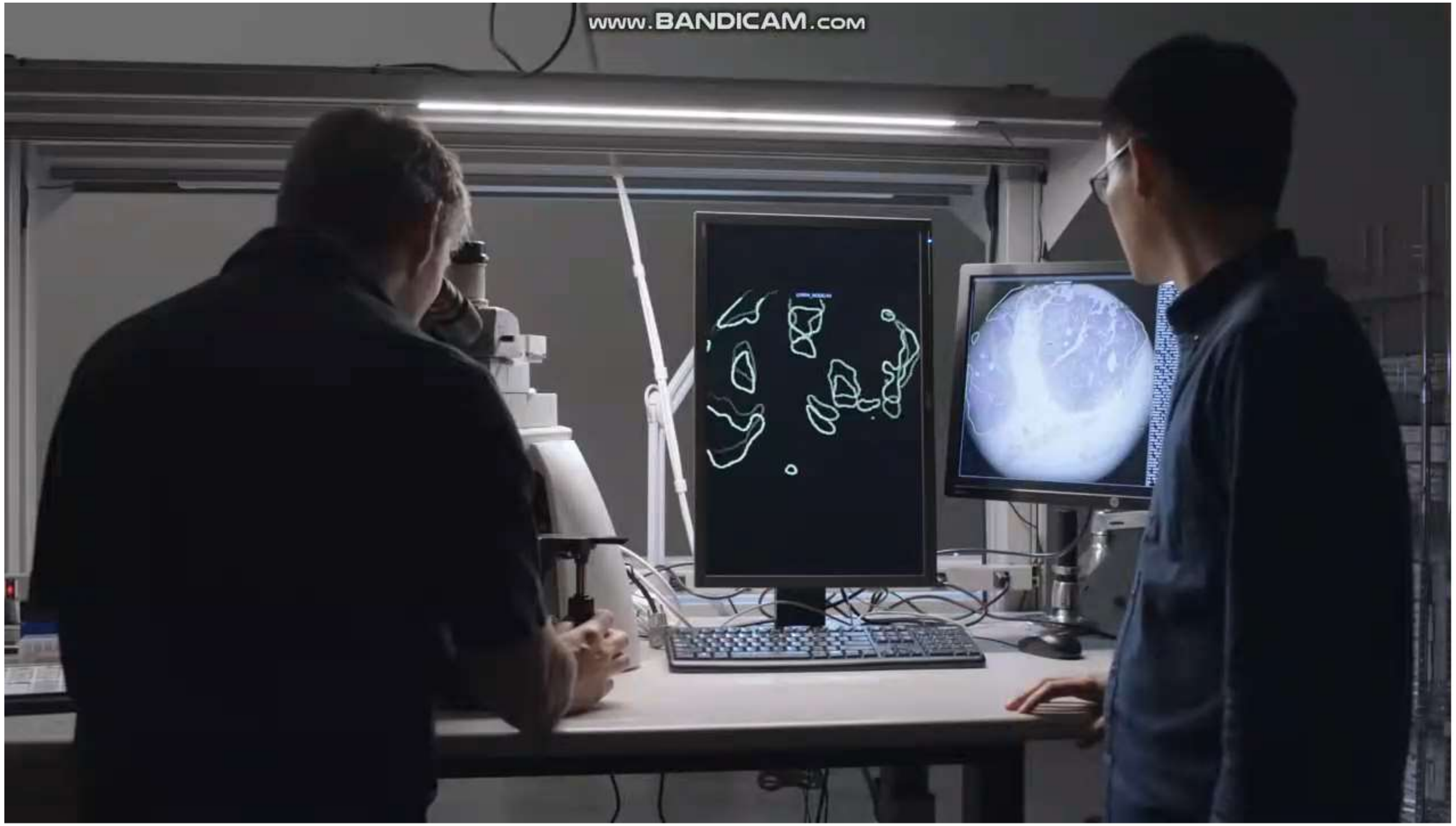
Time for image analysis matters



Segmentation by AI

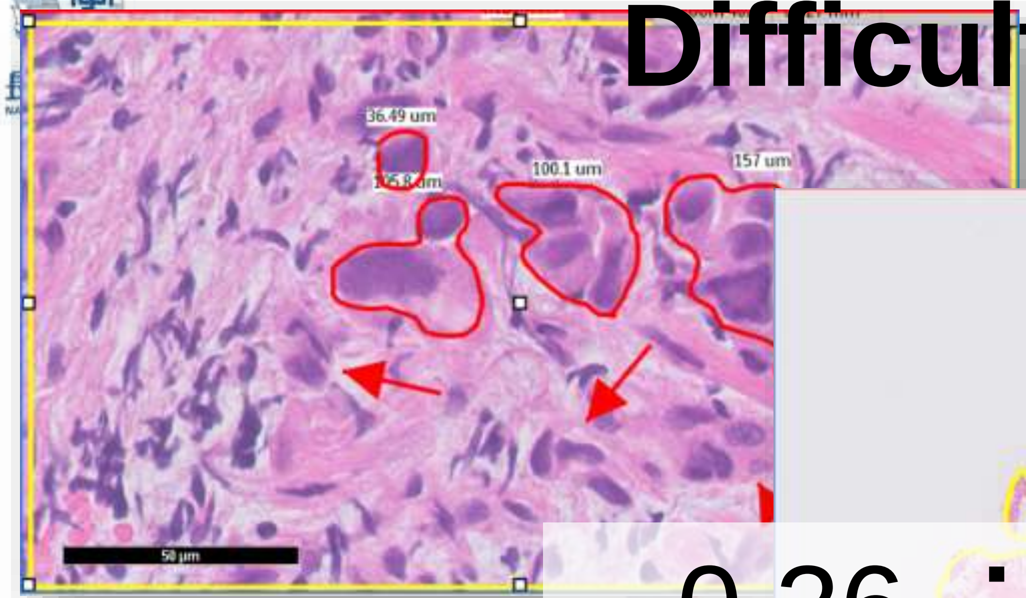
Diagnosis for 1 case

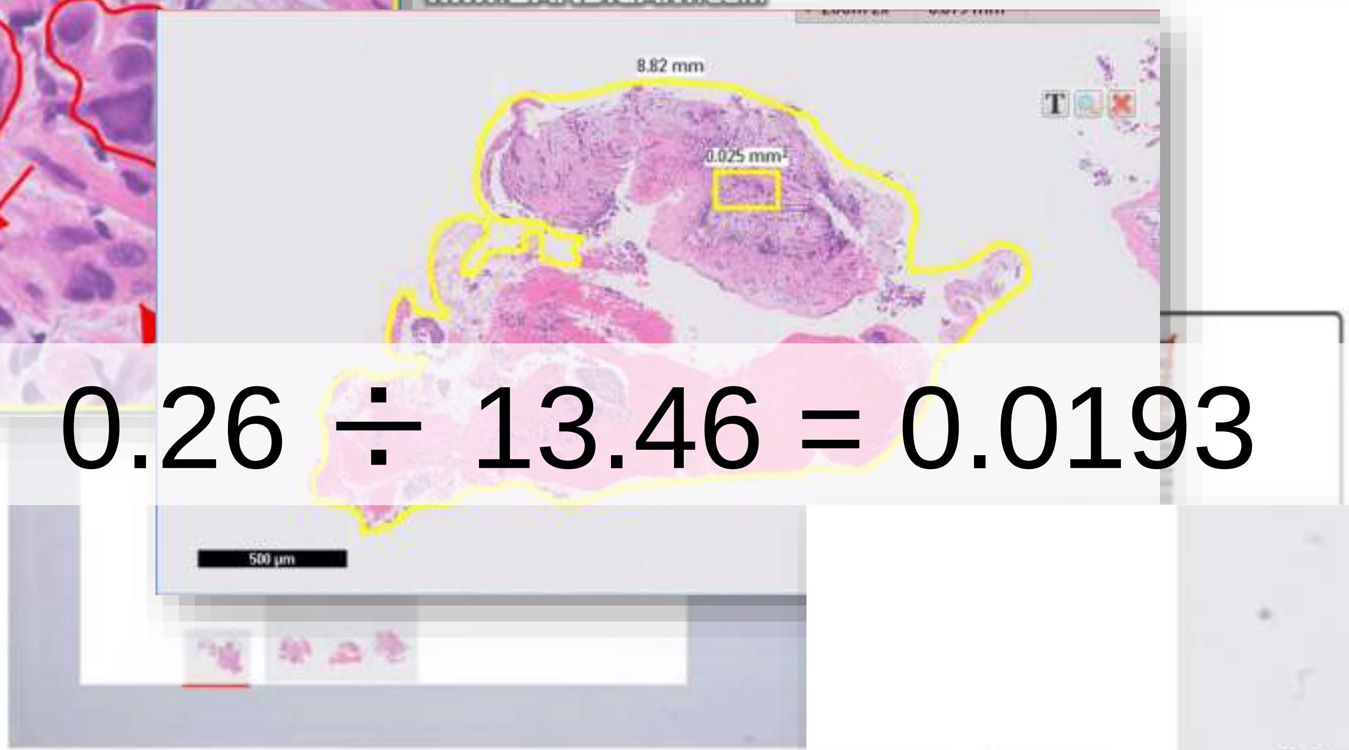
Solution may be.. Step by step



<u>But the key is User Interface!!</u>

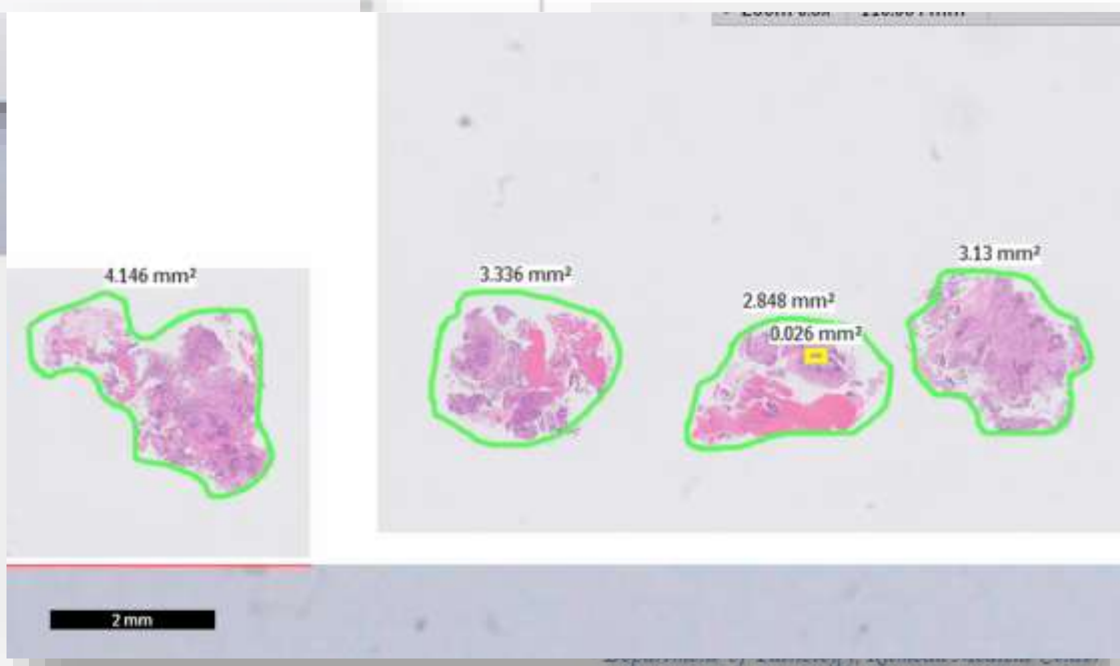
Difficulty of Annotations





$$0.26 \div 13.46 = 0.0193$$

20 mm

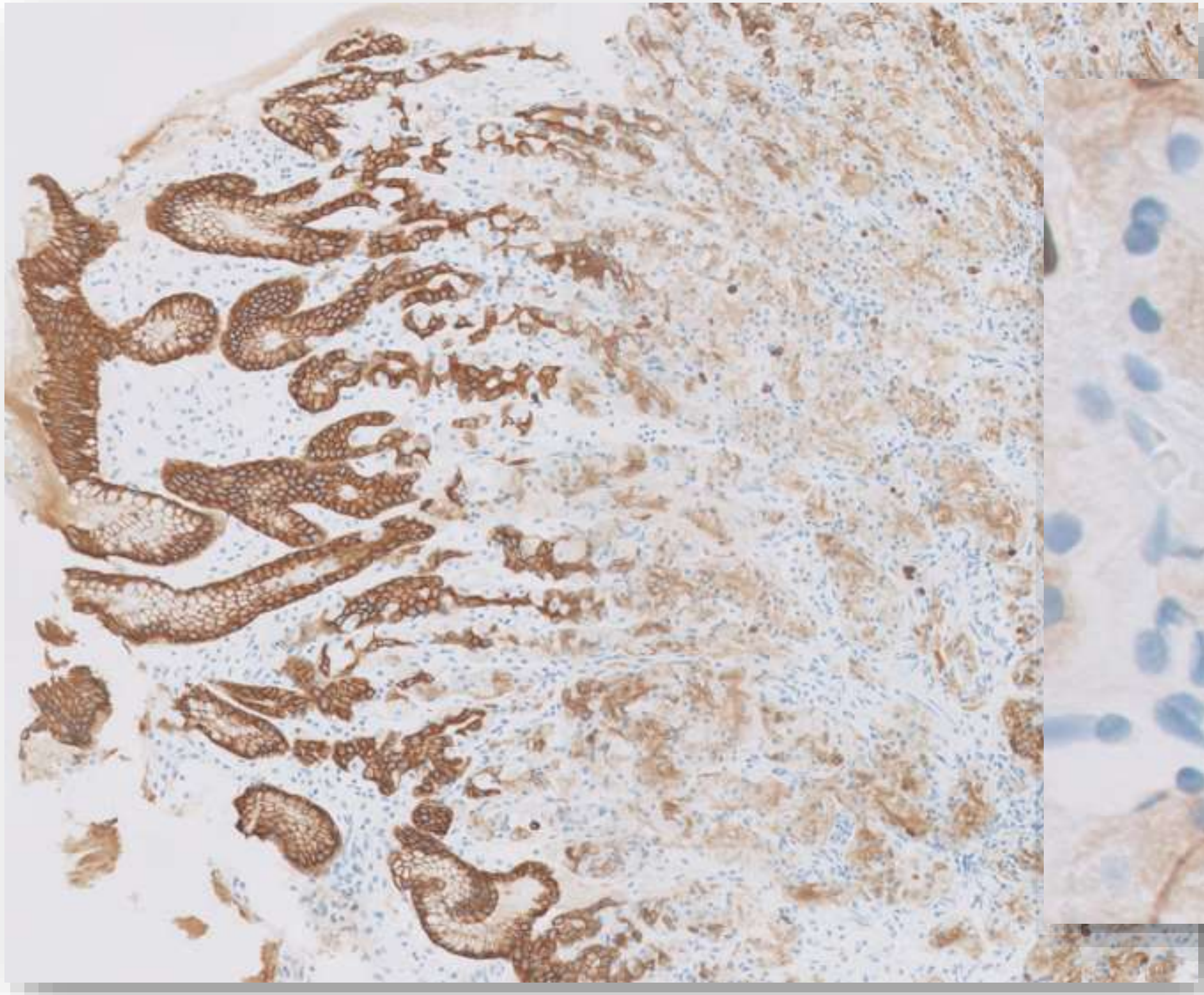


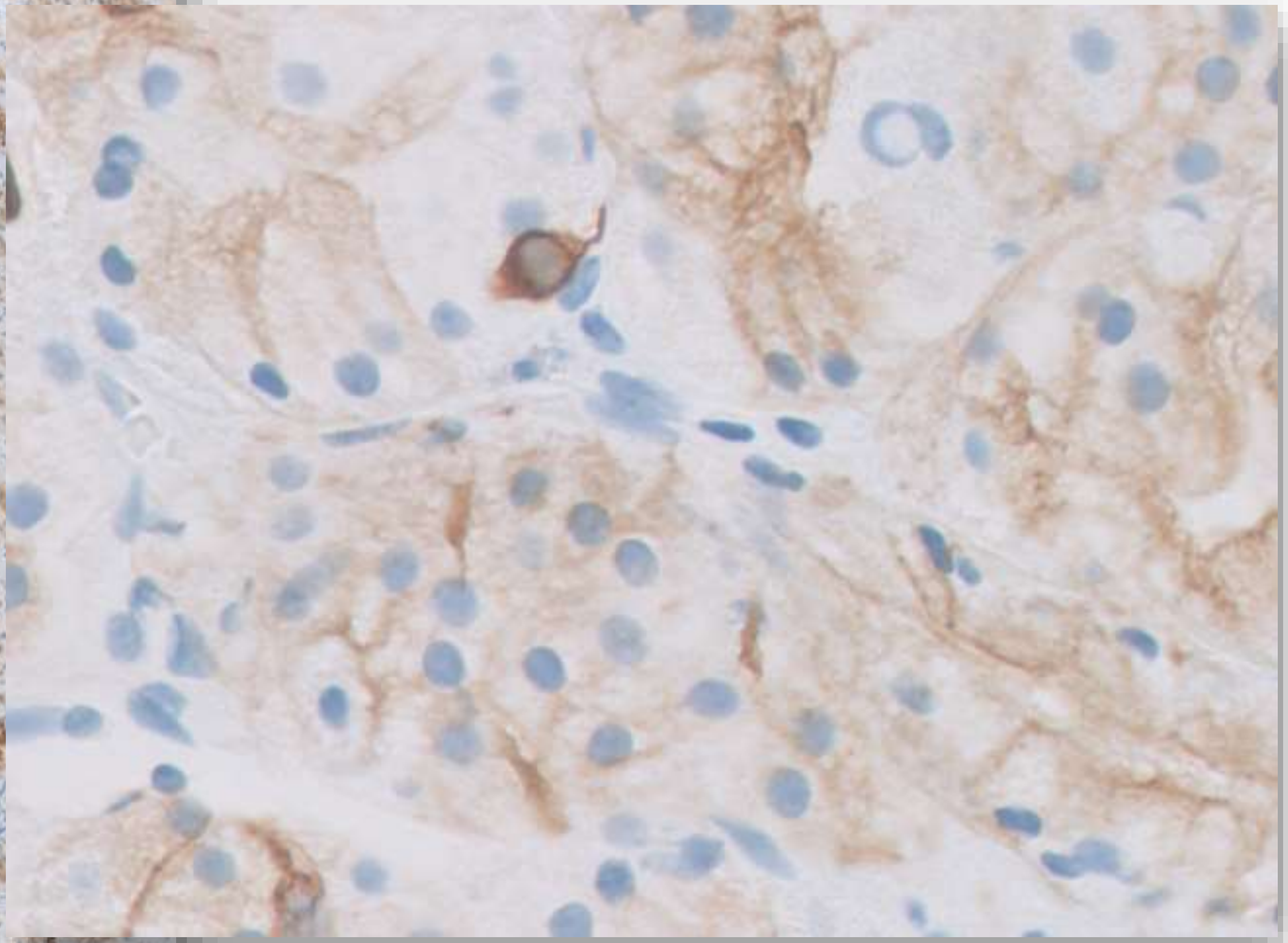
www.BANDICAM.com

Solutions:

- Correlate with objective factors:
  - Survival, Drug effects
- Annotation by multiple observers:
  - Pick up agreed images
- Use of IHC/ISH on the same (consecutive) slide

IHC is not perfect





Department of Pathology, Nagasaki University Graduate School of Biomedical Sciences
Department of Pathology, Kameda Medical Center

AI.. Friends or foe?

Pathologist has to be an AI master

DIGITAL PATHOLOGY DPA ASSOCIATION

4. Introduction of 19th JSDP 2020 in Nagasaki

Japanese Society of Digital Pathology

At

長崎大学
NAGASAKI UNIVERSITY

Invited Speakers

Joint meeting with DPA

Anil Parwani, MD, PhD, MBA
Professor, The Ohio State University, USA

Marilyn M. Bui, MD, PhD
DPA president, Professor, Moffitt Cancer Center, USA

Jeroen van der Laak, PhD
Associate Professor, Radboud UMC, Nijmegen, Netherlands
Coordinator, Camelyon 16

Yukako Yagi, PhD
Director, Digital Pathology, MSKCC, USA

Robert Osamura, MD, PhD
IAP President, Visiting Professor, Keio University, Tokyo

Shumpei Ishikawa,MD,PhD
Professor, The University of Tokyo

Fredrik Pontén, MD, PhD
Professor, Uppsala University,
Co-founder, The Human Protein Atlas, Sweeden

Rajendra Singh, MD
Professor, Mt Sinai Hospital
Founder, PathPresenter®
USA

Lee Cooper, PhD
Associate Professor, Northwestern University
USA

Representative from Asian Alliance

China, Korea, Singapore, India, Russia, Australia, Thailand, Taiwan, Myanmar, Malaysia. Major vendors of AI & scanners

Thank you for your attention