

1. Se dovesse scegliere un unico punto da inserire nel manifesto, quale riterrebbe fondamentale e perché

Risposta: 11. Decision support: fornire strumenti per aiutare i medici nelle decisioni cliniche (revisione dei casi per second opinion e controllo di qualità; esempio rivedere tutte le biopsie prostatiche negative del giorno precedente e con possibilità di rileggere i punti segnalati come dubbi o sospetti prima della firma)

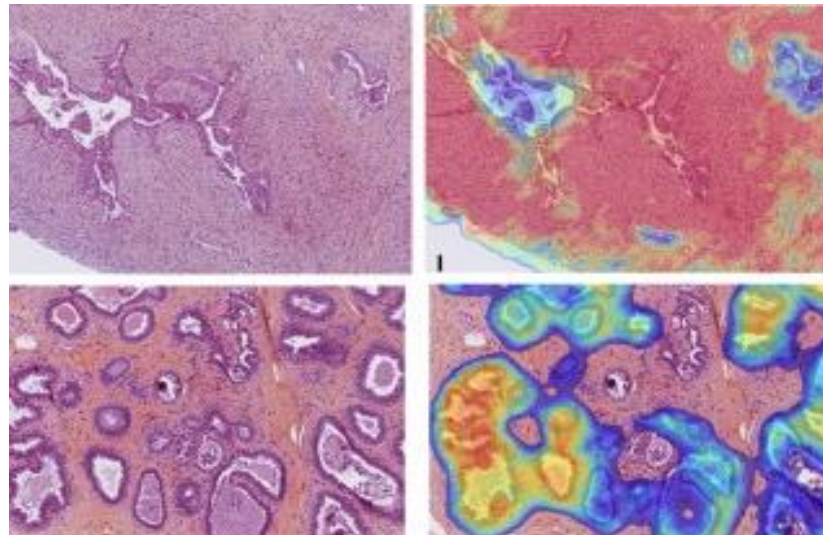
2. Selezionare in una lista di 15 punti 3 che ritiene più rilevanti per il futuro dell'AI in sanità

Risposta:

- 8. Riduzione errori medici: sfruttare l'AI per migliorare la sicurezza dei pazienti
- 9. Sostenibilità: Rendere i sistemi sanitari più efficienti e sostenibili
- 12. Telemedicina ampliare l'uso delle tecnologie AI per assistenza a Distanza

DA VILLA MANIN 2024 A VILLA MANIN 2025

DAL VETRINO DIGITALE ALL'INTELLIGENZA ARTIFICIALE



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Ruolo dell'AnatomoPatologo

Osservare al microscopio una sezione di tessuto, colorata artificialmente in modo da separare visivamente le varie componenti.

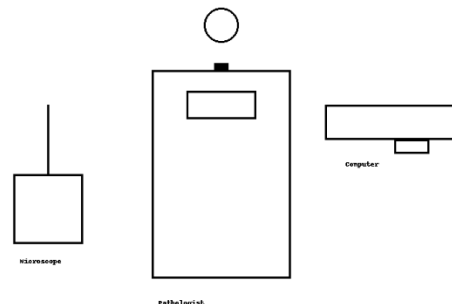
Riconoscere se un determinato quadro sia normale o patologico.

Analizzare vari fattori e anomalie fino a trovare quelle che corrispondono ad un determinato quadro diagnostico.



Realizzare un'analisi associativa di vari elementi che poi portano, grazie alla sua esperienza ed alle sue conoscenze, alla refertazione di una certa patologia.

L'evoluzione tecnologica ha permesso la digitalizzazione delle immagini istologiche e quindi la possibilità di sviluppo di algoritmi di intelligenza artificiale

Chiesto a ChatGPT:
crea l'immagine di un patologo



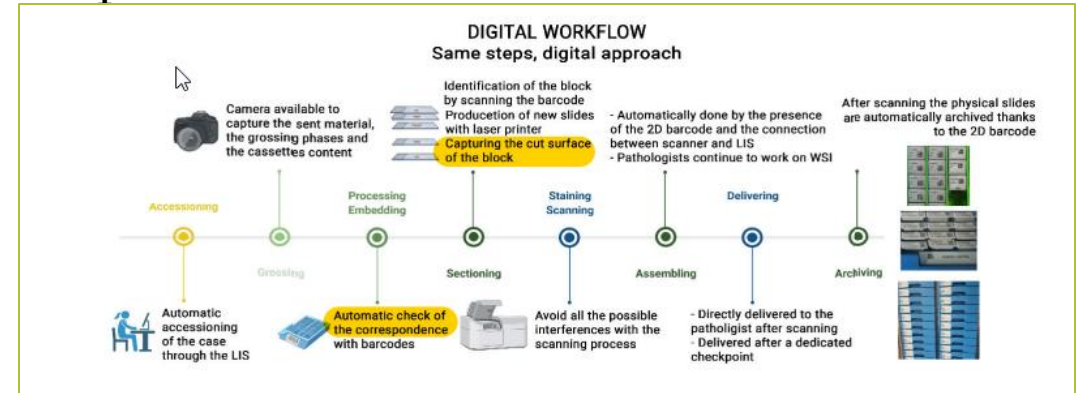
Il numero di patologi è in costante calo con evidente difficoltà di ricambio generazionale a fronte di un aumento delle richieste per soddisfare le esigenze legate all'aumento di patologie neoplastiche e delle specifiche necessità della medicina personalizzata: **AUTOMAZIONE**

Guidelines

Best Practice Recommendations for the Implementation of a Digital Pathology Workflow in the Anatomic Pathology Laboratory by the European Society of Digital and Integrative Pathology (ESDIP)

Filippo Fraggetta ^{1,2}, Vincenzo L'Imperio ^{1,3}, David Ameisen ^{1,4}, Rita Carvalho ^{1,5}, Sabine Leh ^{1,6,7},



+42%

Aumento del numero di casi per patologo registrato dal 2007 al 2017 in USA*

+26%

Aumento del numero complessivo di casi di cancro

-18%

Riduzione del numero di patologi

* Between 2010 and 2020 | Source: Jama Network Open, May 2019, HEALTH AFFAIRS, VOL. 34, no. 4: cost & quality of cancer care

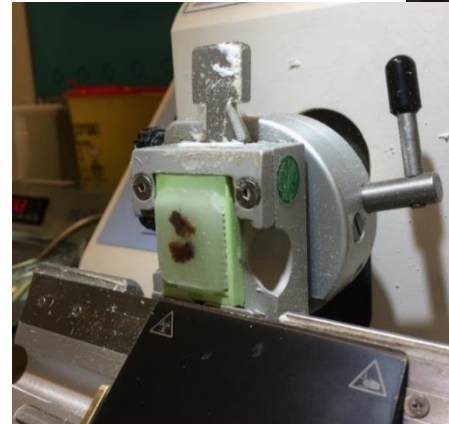
Qualità analogica del vetrino e digitalizzazione

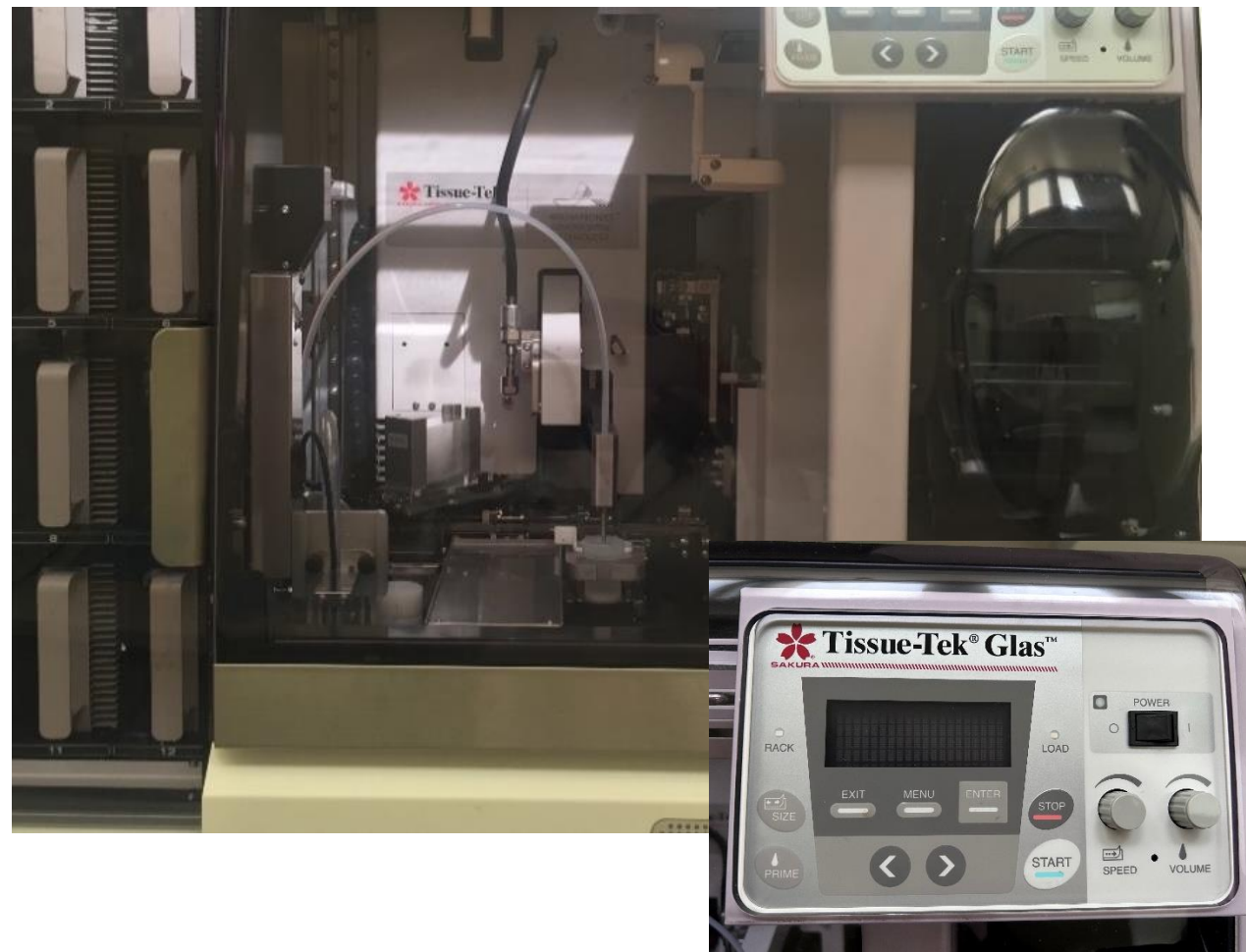
- La **qualità tecnica del vetrino fisico è un fattore imprescindibile** per ottenere un vetrino digitale realmente utilizzabile.
- **Innalzamento della qualità dei preparati istologici che talvolta nella routine “analogica” vengono tollerati anche se «insoddisfacenti»**
- Necessari **adeguati investimenti** in quanto, **nella fase di avvio NON c'è economicità immediata nella conversione digitale poiché l'allestimento e la conservazione in archivio del blocchetto in paraffina e del vetrino istologico sono comunque necessari**



Innovazione e automazione del laboratorio e le criticità del pre imaging









DIGITAL SCANNER

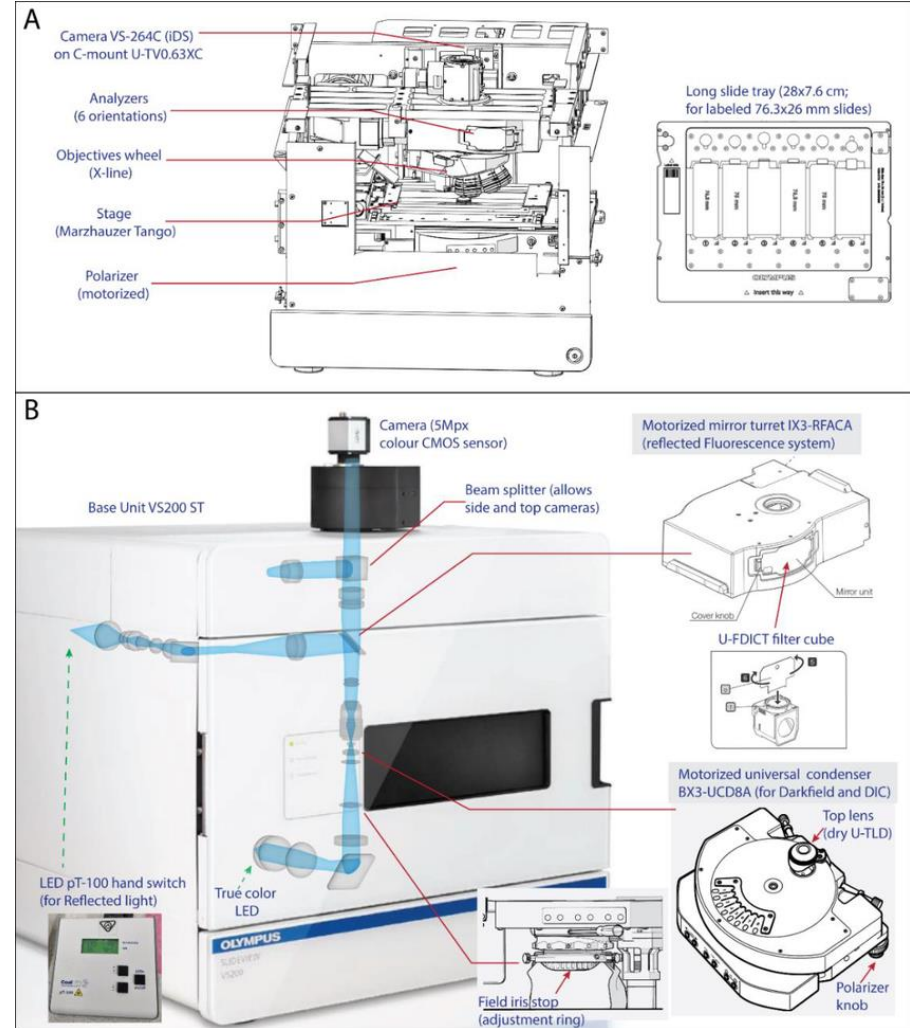
Hardware: SCANNER (è essenzialmente un microscopio)

Obiettivo/i con lenti

Sorgente di luce

Meccanismi per il movimento del vetrino

Camera/e digitali per catturare le immagini



Software per acquisire e visualizzare immagini digitali

Velocità di scansione 1 – 3 minuti/vetrino (con opzione di scansioni parziali o acquisizioni su più piani (Z stack))

Scansione su riquadri o a mosaico

Scansione su striscie con maggior facilità di formattazione per diminuire le dimensioni (4,6 GB di memoria) da cui creare una immagine nel formato desiderato



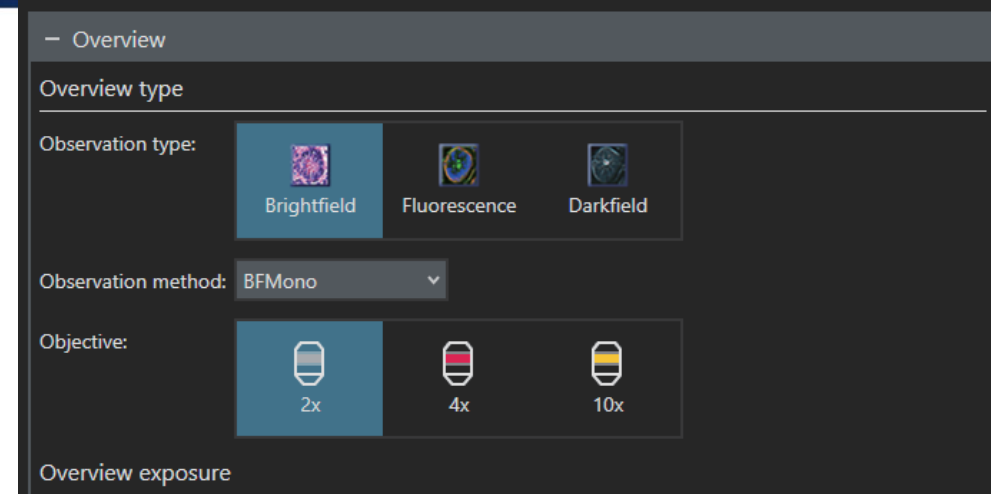
Elementi di riferimento in tema di risoluzione digitale
utili per applicazioni di AI

Acquisizioni con:

Obiettivo 20x: 0,24 – 0,5 μm /pixel

Obiettivo 40x: 0,1375 - 0,25 μm /pixel

Equivale ad un range compreso tra 4,4 milioni – 16 milioni di pixel/mm²



Definizione apertura numerica (AN) elevata: misura critica della capacità del microscopio di raccogliere la luce e risolvere dettagli fini:

AN elevato: miglior risoluzione e maggior qualità ma riduce la profondità di campo e richiede una messa a fuoco più precisa ES: AN (0,65) vs AN (1,40)

Caratteristiche dei Display

Non esistono linee guida internazionali armonizzate e in particolare **in Italia non vi è alcun riferimento formale ma solo indicazioni dettate dall'uso comune**



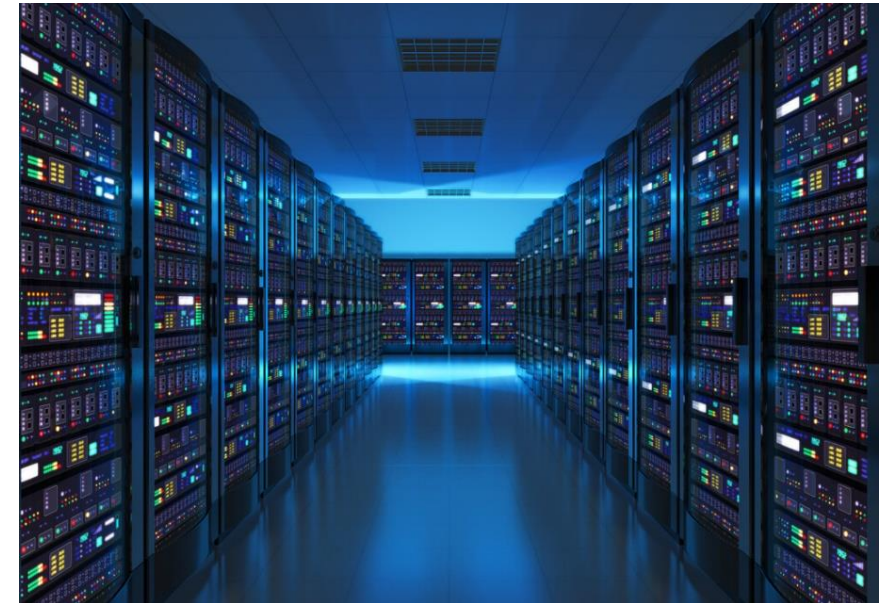
1. Contrasto superiore al più uguale a 1000:1
2. Risoluzione superiore a 2560×1600 (coerente con la sorgente: 8 MP (3840 x 2160))
3. Aspect Ratio di 16:10
4. Diagonale 27" (fino a 32")
5. Luminanza massima pari a 300 cd/mq
6. Color gamut: NTSC, sRGB e DCI-P3

I requisiti minimi dei monitor DP sono ancora dibattuti e non esiste un consenso su come valutarne la qualità. Le fonti esterne di variabilità complicano ulteriormente la questione, come la distanza dal monitor e le condizioni di illuminazione della stanza, rendendo più difficile un confronto imparziale tra i diversi dispositivi disponibili.

Acquisizione delle immagini

Attuale limite: impossibilità di acquisizione diretta (come invece è possibile in radiologia) ma solo copia digitale fedele di un vetrino analogico e quindi

ai costi noti si sommano i costi per gli SLIDE SCANNER, quelli per i monitor dedicati e per acquisire spazi di memoria per archiviazione necessari a supportare la trasformazione della diagnostica microscopica in microscopia digitale.



Dove sta il guadagno?

Qualità diagnostica

Possibilità di tele-consulto

Sicurezza nell'attribuzione del referto

Ottimizzazione dei tempi

Rivalutazione rapida di precedenti diagnosi

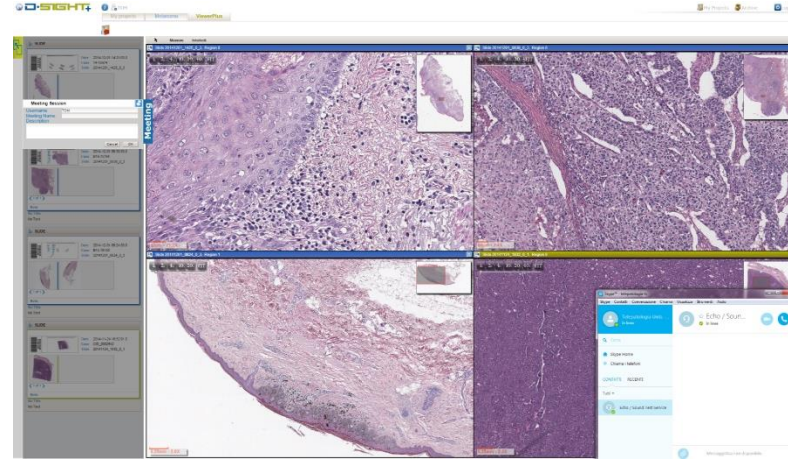
Formazione e ricerca

Applicazione di analisi d'immagine e di algoritmi di intelligenza artificiale

Quali gli ostacoli da superare?

Reticenze dei Patologi sull'abbandono del microscopio ottico

Amministrazioni spesso **"in rosso"** per completare tutte le fasi del processo



Machine Learning (ML)

Disciplina dell'Intelligenza Artificiale che si occupa di creare sistemi che apprendono o migliorano le proprie performance in base ai dati forniti.

« Definizione : “Si dice che un programma apprende dall'esperienza E , con riferimento ad alcune classi di compiti T e con misurazione della performance P , se le sue performance nel compito T , come misurato da P , migliorano con l'esperienza E' . (Tom Michel Mitchell)

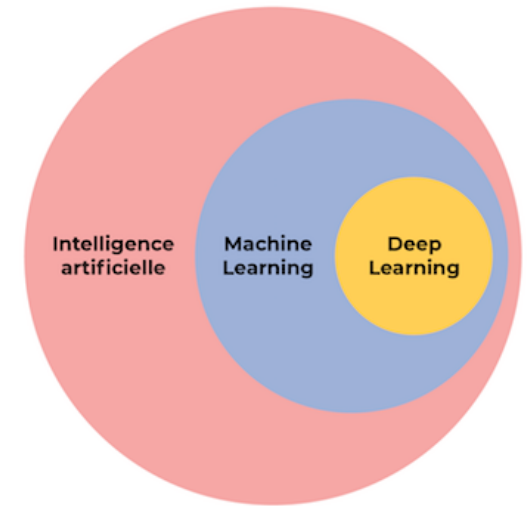
Le macchine **hanno bisogno di un utente esterno che fornisca loro degli esempi da cui apprendere.**

Apprendimento supervisionato: alla macchina vengono forniti come input sia i set di dati (per esempio un set di validazione) sia le informazioni relative ai risultati desiderati (output che coincide con le diagnosi relative ai singoli casi del set di validazione). In questo modo la macchina, analizzando i dati **realizza delle associazioni tra di essi, identifica una regola generale che colleghi dati in ingresso e dati in uscita**

Machine Learning (ML) e Deep Learning

Successivamente assume un comportamento adattivo: impara dall'esperienza fornita dal set di dati e migliora autonomamente le proprie prestazioni sfruttando i dati strutturati e già etichettati per creare degli algoritmi di apprendimento automatico per fare delle previsioni. Gli algoritmi di Deep Learning riescono ad elaborare **dati non etichettati e autonomamente riescono ad estrarre le informazioni necessarie:** alla macchina vengono fornite solamente immagini di vetrini senza informazioni aggiuntive: la macchina riuscirà autonomamente a raggruppare le varie immagini in base a caratteristiche distintive, attribuendole alle relative patologie.

In questo modo il sistema potrà essere integrato all'interno del flusso di lavoro dei reparti di Anatomia Patologica come supporto per la refertazione di determinate patologie



PROBLEMATICA DEL MANTENIMENTO DEI TEMPI DI REFERTAZIONE

Gestione degli Arretrati

Momenti di criticità per incremento dell'attività
(picco prenatalizio e picco prima delle ferie estive)
o per riduzione non programmata dei Patologi



Dare la priorità'
ai CASI POSITIVI



Filter by Case ID, Tissue or Assignee

Case ID	Date ↓	Tissue	No. of Slides	Findings	Assigned to
MC-014967	2022-08-16	gastric	2	H. pylori-related Gastritis	Pathologist
MC-014444	2022-08-16	prostate	1		Pathologist
MC-045262	2022-08-16	breast	1	Cancer Invasive Cancer	Pathologist
MP-003300	2022-06-08	prostate	6		Pathologist
UP-000524	2022-06-08	prostate	18	Cancer	Pathologist
CP-009005	2022-06-08	prostate	5	Cancer	Pathologist
MC-032851	2022-06-07	breast	2	Cancer Invasive Cancer ADH/DCIS	Pathologist
IC-000129	2022-06-07	breast	1	Cancer Invasive Cancer	Pathologist
KM-000040	2022-06-07	breast	9	Cancer Invasive Cancer	Pathologist
CP-000098	2022-06-07	breast	17	Cancer Invasive Cancer	Pathologist
MC-051522	2022-06-06	gastric	16	Cancer H. pylori-related Gastritis	Pathologist
MP-015049	2022-06-06	gastric	2	Cancer	Pathologist
CP-001067	2022-06-06	gastric	2	H. pylori-related Gastritis	Pathologist
CP-001083	2022-06-06	gastric	2		Pathologist
MC-033320	2022-06-05	gastric	2		Pathologist
KG-000001	2022-06-03	prostate	7	Cancer	Pathologist
MP-013130	2022-06-03	prostate	16	Cancer	Pathologist
MP-013135	2022-06-03	prostate	15	Cancer	Pathologist
MC-037797	2022-06-01	gastric	12		Pathologist

1 - 20 of 58 items

Possibilità di ricerca casi per ottimizzare il flusso di lavoro dando le assegnazioni e le priorità sulla base dell'expertise

Permette al Patologo di identificare con facilità i casi che presentano criteri di urgenza.

Identificazione di casi complessi da approfondire con IHC e quindi ottimizzare i Tempi di refertazione (TAT)

Ottimizzazione delle priorità

Problematica dei formati e della compatibilità con di diversi Viewer e software di IA

I formati più comuni sono: JPEG2000
TIFF/SVS
MRXS/VSI/iSyntax
NDPI/BIFF/MIRAX)

Viewer

Image Scope
Web Scope → Leika

NDP → Hammamatsu

Panoramic Viewer : → 3D Histec

Intellisite: → Philips

WSI: → Olympus

**I formati devono essere compatibili con i viewer e con i sistemi di analisi
e/o di IA che si intende utilizzare (es. Open Slide)**



<https://doi.org/10.1038/s41746-024-01106-8>

Artificial intelligence in digital pathology: a systematic review and meta-analysis of diagnostic test accuracy

 Check for updates

Clare McGenity^{1,2}✉, Emily L. Clarke^{1,2}, Charlotte Jennings^{1,2}, Gillian Matthews²,
 Caroline Cartlidge¹, Henschel Freduah-Agyemang¹, Deborah D. Stocken¹ & Darren Treanor^{1,2,3,4}

<https://doi.org/10.1038/s41746-024-01106-8>

Table 8 | Mean performance across studies by pathological subspecialty

Pathological subspecialty	No. AI models	Mean sensitivity	Mean specificity
Gastrointestinal pathology	14	93%	94%
Breast pathology	8	83%	88%
Uropathology	8	95%	96%
Hepatobiliary pathology	5	90%	87%
Dermatopathology	4	89%	81%
Cardiothoracic pathology	3	98%	76%
Haematopathology	3	95%	86%
Gynaecological pathology	2	87%	83%
Soft tissue & bone pathology	1	98%	94%
Head & neck pathology	1	98%	72%
Neuropathology	1	100%	95%

Patologia Mammaria

Table 1 | Characteristics of breast pathology studies

First author, year & reference	Location	Index test	Disease studied	Reference standard	Data sources	Training set details	Validation set details	Test set details	External validation	U
Cengiz ⁹⁷	Turkey	CNN	Breast cancer	Not stated	Not stated	296,675 patches		101,706 patches	Unclear	P
Choudhary ⁹⁸	India, USA	CNN (VGG19, ResNet54, ResNet50)	Breast cancer	Pathologist annotations, slide diagnoses	IDC dataset	194,266 patches		83,258 patches	No	P
Cruz-Roa ⁹⁹	Colombia, USA	FCN (HASH)	Breast cancer	Pathologist annotations	Hospital of the University of Pennsylvania; University Hospitals Case Medical Centre/ Case Western Reserve University; Cancer Institute of New Jersey; TCGA	698 cases	52 cases	195 cases	Yes	P
Cruz-Roa ¹⁰⁰	Colombia, USA	CNN (ConvNet)	Breast cancer	Pathologist annotations	University of Pennsylvania Hospital; University Hospitals Case Medical Centre/ Case Western Reserve University; Cancer Institute of New Jersey; TCGA	349 patients	40 patients	216 patients	Yes	P
Hameed ¹⁰¹	Spain, Columbia	CNN (ensemble of fine-tuned VGG16 & fine-tuned VGG19)	Breast cancer	Pathologist labels & annotations	Colsanitas Colombia University	540 images/ patches	135 images/ patches	170 images/ patches	No	P
Jin ⁹⁴	Canada	U-net CNN (ConcatNet)	Breast cancer	Labels	PatchCamelyon dataset; Open-source dataset from PMID 27563488; Warwick dataset	262,144 patches + 538 images	32,768 patches	32,768 patches	No	P
Johny ⁹⁵	India	Custom deep CNN	Breast cancer	Pathologist patch labels	PatchCamelyon Dataset	262,144 patches		65,536 patches	No	P
Kanavati ¹⁰²	Japan	CNN tile classifier (EfficientNetB1) + RNN tile aggregator	Breast cancer	Diagnostic review by pathologists	International University of Health and Welfare, Mita Hospital; Sapporo-Kosei General Hospital	1652 WSIs	90 WSIs	1930 WSIs	Yes	Si
Khalil ⁹⁷	Taiwan	Modified FCN	Breast cancer	Pathologist annotations, IHC	National Taiwan University Hospital dataset	68 WSIs		26 WSIs	No	Si
Lin ¹⁰³	Hong Kong, China, UK	Modified FCN	Breast cancer	Slide level labels, pathologist annotations	Camelyon dataset	202 WSIs	68 WSIs	130 WSIs	No	Si
Roy ⁹⁹	India, Germany	Multiple machine learning classifiers (CatBoost & others)	Breast cancer	Unclear	IDC Breast Histopathology Image Dataset	Unclear	Unclear	Unclear	No	P
Sadeghi ¹⁰⁰	Germany, Austria	CNN	Breast cancer	Pathologist supervised annotations, IHC	Camelyon17 dataset; Camelyon16 dataset	400 WSIs	100 WSIs	20,000 patches	No	P
Steiner ¹⁰¹	USA	CNN (LYNA - Inception framework)	Breast cancer	Pathologist review, IHC	Camelyon; Expired clinical archive blocks from 2 sources	215 WSIs	54 WSIs	70 WSIs	Yes	Si
Valkonen ¹⁰²	Finland	Random forest	Breast cancer	Pathologist WSI annotations	Camelyon16 dataset	1,000,000 patches	270 WSIs leave-one-out cross validation		Yes	P
Wang Q ⁹²	China	SoMIL + adaptive aggregator + RNN	Breast cancer	WSI labels, pixel level annotations of metastases	Camelyon16; MSK breast cancer metastases dataset	289 WSIs		240 WSIs	Yes	Si
Wu ⁹¹	USA	ROI classifier + Tissue segmentation CNN +;Diagnosis classifier SVM	Breast cancer	Pathologist pixel labels	Breast Cancer Surveillance Consortium-associated tumour registries in New Hampshire and Vermont	58 ROIs		Cross validation 428 ROIs	Unclear	O (F



Patologia urologica

Medicine | 2024 | 7:114

Table 6 | Characteristics of urological pathology studies

First author, year & reference	Location	Index test	Disease studied	Reference standard	Data sources	Training set details	Validation set details	Test set details	External validation
da Silva ²⁴	Brazil, USA	CNN (Paige Prostate 1.0)	Prostate cancer	Pathologist consensus, IHC	Instituto Mario Penna, Brazil	Prior study: trained on 2000 WSIs		661 WSIs (579 part specimens)	Yes
Duran-Lopez ¹²⁰	Spain	CNN (PROMETEO) + Wide and deep neural network	Prostate cancer	Pathologist pixel annotations	Pathological Anatomy Unit of Virgen de Valme Hospital, Spain		5 fold cross validation	332 WSIs	No
Esteban ²³	Spain	Optical density granulometry-based descriptor + Gaussian processes	Prostate cancer	Pathologist pixel annotations	SICAPv1 database; Prostate cancer database by Gertych et al.		60 WSIs 5 fold cross validation	19 WSIs + 593 patches	Yes
Han ¹²⁰	Canada	Multiple ML approaches (Transfer learning with TCMs & others)	Prostate cancer	Pathologist annotations & supervision	Western University		286 WSIs cross validation for train/test (leave one out)	13 WSIs	No
Han ²¹	Canada	Traditional ML and 14 texture features extracted from TCMs; Transfer learning with pretrained AlexNet fine-tuned by TCM ROIs; Transfer learning with pretrained AlexNet fine-tuned with raw image ROIs	Prostate cancer	Pathologist annotations & supervision	Western University		286 WSIs cross validation for train/test (leave one out)	13 WSIs	No
Huang ¹³⁰	USA	CNN (U-Net gland segmenter) + CNN feature extractor & classifier	Prostate cancer	Pathologist review, patch annotations using ISUP criteria.	University of Wisconsin Health System	838 WSIs		162 WSIs	No
Swiderska-Chadaj ⁵⁰	Netherlands, Sweden	CNN (U-Net, DenseNetFCN, EfficientNet)	Prostate cancer	Slide level labels, pathologist annotations	The Penn State Health Department of Pathology; PAMM Laboratorium voor Pathologie; Radboud University Medical Centre.	264 WSIs	60 WSIs	297 WSIs	Yes
Tsuneki ²⁹	Japan	Transfer learning (TL-colon poorly ADC-2 (20x, 512)); CNN (EfficientNetB1 20x, 512); CNN (EfficientNetB1 (10x, 224)	Prostate cancer	Pathologist diagnosis & consensus	Wajiro, Shimizumaki, Shin-komonji, and Shinyukhashi hospitals, Fukuoka; TGCA	1122 WSIs	60 WSIs	2512 WSIs	Yes
Abdeltawab ²¹	USA, UAE	CNN (pyramidal)	Renal cancer	Pathologist review & annotations	Indiana University, USA	38 WSIs	6 WSIs	20 WSIs	No
Fenstermaker ²²	USA	CNN	Renal cancer	Pathology report	TCGA		15,168 patches train/validate	4286 patches	No
Tabibu ¹³²	India	CNNs (ResNet18 & 34) + SVM (DAG-SVM)	Renal cancer	Clinical information including pathology reports	TCGA	1474 WSIs	317 WSIs	314 WSIs	Yes
Zhu ²⁵	USA	CNN (ResNet-18) + Decision Tree	Renal cancer	Pathologist annotations	Dartmouth-Hitchcock Medical Centre (DHMC); TCGA	385 WSIs	23 WSIs	1074 WSIs	Yes

Table 5 | Characteristics of gastrointestinal studies

First author, year & reference	Location	Index test	Disease studied	Reference standard	Data sources	Training set details	Validation set details	Test set details	External validation	Unit analysis
Sali ¹¹⁷	USA	CNN & Random forest; SVM; k-means; GMM	Barrett's Oesophagus	Pathologist consensus, pixel-wise annotations	Hunter Holmes McGuire Veterans Affairs Medical Centre	115 WSIs	535 WSIs 10 fold cross validation		No	Slide
Syed ¹¹⁸	USA, Pakistan, Zambia, UK	CNN (ResNet50; ResNet50 multi-zoom; shallow CNN; ensemble).	Coeliac & Environmental Enteropathathy	Slide level diagnosis, IHC, patch labels.	Aga Khan University; University of Zambia & University Teaching Hospital Zambia; University of Virginia, USA	231 WSIs	115 WSIs	115 WSIs	Unclear	Slide
Nasir-Moin ¹¹⁹	USA	CNN (ResNet18)	Colorectal adenoma/polyps	Pathologist consensus	Dartmouth-Hitchcock Medical Centre (DHMC). Prior validation on 24 US institutions	508 WSIs		100 WSIs + Previous validation 238 WSIs	Yes	Slide
Song ⁸⁰	China	CNN (DeepLab v2 + ResNet34)	Colorectal adenoma/polyps	Pathologist labels	Chinese People's Liberation Army General Hospital (PLAGH); China-Japan Friendship Hospital (CJFH); Cancer Hospital, Chinese Academy of Medical Science (CH).	177 WSIs	40 WSIs	362 WSIs	Yes	Slide
Wei ¹²⁰	USA	CNN (ResNet)	Colorectal adenoma/polyps	Pathologist annotations	Dartmouth-Hitchcock Medical Centre (DHMC); External set multiple institutions	326 WSIs	25 WSIs	395 WSIs	Yes	Slide
Feng ¹²¹	China, USA, South Korea	CNN (ensemble of 8 networks+modified U-Net + VGG-16 or VGG-19)	Colorectal cancer	Pixel annotations, pathologist labels	DigestPath 2019 Challenge (task 2)	750 WSIs				
Haryanto ¹²²	Indonesia	Conditional Sliding Window (CSW) algorithm used to generate images for CNN 7-5-7	Colorectal cancer	Pathologist labels & annotations	Warwick dataset; University of Indonesia	Unclear				
Sabol ¹²³	Slovakia, Japan	CNN + X-CFCMC	Colorectal cancer	Annotations	Publicly available dataset from Kather et al.					
Schrammen ¹²⁴	Germany, Netherlands, UK	Single neural network (SLAM - based on ShuffleNet)	Colorectal cancer	Patient/slide level labels	DACHS study, YCR-BCIP	2448 cases				
Tsuneki ¹²⁵	Japan	CNN (EfficientNetB1)	Colorectal cancer	Pathologist diagnosis & annotations	Wajiro, Shinmizumaki, Shin-komogji, & Shinyukuhashi hospitals, Fukuoka; Mita Hospital, Tokyo	680 WSIs				
Wang KS ¹²⁶	China, USA	CNN (Inception V3)	Colorectal cancer	Pathologist consensus & labels	14 hospitals/sources	559 WSIs				
Wang C ¹²⁷	China	CNN (bilinear)	Colorectal cancer	Annotations	University Medical Centre Mannheim, Heidelberg					
Xu ¹²⁸	China	Dual resolution deep learning network with self-attention mechanism (DRSANet)	Colorectal cancer	Pathologist annotations, Patch labels, Pathologist pixel annotations.	TCGA; Affiliated Cancer Hospital and Institute of Guangzhou Medical University (ACHIGMU)	100,000 patches				

Patologia gastrointestinale

Table 5 (continued) | Characteristics of gastrointestinal studies

First author, year & reference	Location	Index test	Disease studied	Reference standard	Data sources	Training set details	Validation set details	Test set details	External validation
Zhou ¹²⁹	China, Singapore	CNN (ResNet) + Random Forest	Colorectal cancer	Pathologist slide labels, reports, annotations & consensus	TGCA; Hospital of Zhejiang University; Hospital of Soochow University; Nanjing First Hospital	950 WSIs		446 WSIs	Yes
Ashraf ¹³⁰	South Korea	CNN (DenseNet-201)	Gastric cancer	Pathologist review & annotations	Seegene Medical Foundation in South Korea; Camelyon	Primary model: 723 WSIs; LN model: 262,11 patches	Primary model: 91 WSIs; LN model: 32,768 patches	Primary model: 91 WSIs; LN model: 32,768 patches	No
Cho ¹³¹	South Korea	CNN (AlexNet; ResNet50; Inception-v3)	Gastric cancer	Labels	TCGA-STAD; SSMH Seoul St. Mary's Hospital dataset		10 fold cross validation		Yes
Ma ¹³²	China	CNN (modified InceptionV3) + random forest classifier	Gastric cancer	Pathologist annotations	Ruijin Hospital	534 WSIs	76 WSIs	153 WSIs	No
Rasmussen ¹³³	Canada	CNN (DenseNet169)	Gastric cancer	Pathologist annotations	Queen Elizabeth II Health Sciences Centre & Dalhousie University; Sunnybrook Health Science Centre, University of Toronto	14,266 patches	1585 patches	1785 patches	Yes
Song ⁸⁶	China, USA	CNN (Multiple models); random forest	Gastric cancer	Pathologist pixel level annotations	PLAGH dataset; Multicentre dataset (PUMCH, CHCAMC & Peking Union Medical College)	2860 WSIs	300 WSIs	4993 WSIs	Yes
Tung ¹³⁴	Taiwan	CNN (YOLOv4)	Gastric cancer	Pathologist annotations	Taiwan Cancer Registry Database	2200 image tiles		550 image tiles	No
Wang S ¹³⁵	China	Recalibrated multi-instance deep learning method (RMIL)	Gastric cancer	Pathologist pixel annotations	Sun Yat-sen University	408 WSIs		200 WSIs	No
Ba ¹³⁷	China	CNN (ResNet50)	Gastritis	Pathologist review & pixel annotations	Chinese People's Liberation Army General Hospital	1008 WSIs	100 WSIs	142 WSIs	No
Steinbusch ¹³⁶	Germany	CNN (Xception)	Gastritis	Diagnoses - modified Sydney Classification, pathologist annotations	Institute of Pathology, University Clinic Heidelberg	825 patches	196 patches	209 patches	No
Iizuka ¹³⁸	Japan	CNN (InceptionV3 + max-pooling or RNN aggregator)	Multiple (Colorectal cancer & Gastric tumours)	Pathologist annotations	Hiroshima University Hospital dataset; Haradai Hospital dataset; TCGA dataset	Stomach: 3628 WSIs; Colon: 3536 WSIs		Stomach: 1475 WSIs; Colon: 1574 WSIs	Yes

Table 3 | Characteristics of dermatopathology studies

First author, year & reference	Location	Index test	Disease studied	Reference standard	Data sources	Training set details	Validation set details	Test set details	External validation
Kimeswenger ¹¹¹	Austria, Switzerland	CNN + ANN (Feature constructor ImageNet CNN + classification ANN)	Basal cell carcinoma	Categorised by pathologist	Kepler University Hospital; Medical University of Vienna.	688 WSIs		132 WSIs	No
Alheejaw ¹¹²	Canada, India	CNN	Melanoma	MART-1 stained images	University of Alberta, Canada	70,960 × 960 pixel images	15,960 × 960 pixel images	15,960 × 960 pixel images	No
De Logu ¹¹³	Italy	CNN (Inception ResNet v2)	Melanoma	Pathologist review	University of Florence; University Hospital of Siena; Institute of Biomolecular Chemistry, National research Council	45 WSIs	15 WSIs	40 WSIs	No
Hekler ¹¹⁴	Germany	CNN (ResNet50)	Melanoma	Image labels	Dr Dieter Krahl institute, Heidelberg	595 cropped images		100 cropped images	No
Hahn ¹¹⁵	Germany	CNN (ResNeXt150)	Melanoma	Pathologist diagnosis	Two laboratories unspecified	232 WSIs	67 WSIs	132 WSIs	No
Li ¹¹⁶	China	CNN (ResNet50)	Melanoma	Pathologist WSI annotations	Central South University Xiangya Hospital; TCGA	491 WSIs	105 WSIs	105 WSIs	No
Wang L ¹¹⁷	China	CNN for patch-level classification (VGG16) & random forest for WSI-level classification	Melanoma	Pathologist diagnosis, consensus, IHC, annotations.	Zhejiang University School of Medicine; Ninth People's Hospital of Shanghai	105,415 patches	1962 patches	118,123 patches	Yes
del Amor ¹¹⁸	Spain	CNN (VGG16, ResNet50, InceptionV3, MobileNetV2)	Spitzoid skin tumours	Pathologist annotations	CLARIFYV1	36 WSIs	5 fold cross validation of training set	15 WSIs	No

Table 4 | Characteristics of hepatobiliary pathology studies

First author, year & reference	Location	Index test	Disease studied	Reference standard	Data sources	Training set details	Validation set details	Test set details	External validation
Aatresh ¹¹⁹	India	CNN (LiverNet)	Liver cancer	Pathologist annotations	Kasturba Medical College (KMC); TCGA	5 fold cross-validation	5450 samples		No
Chen ¹¹⁴	China	CNN (Inception V3)	Liver cancer	Labels	TCGA, Sir Run-Run Shaw Hospital	278 WSIs	56 WSIs	258 WSIs	Yes
Kiani ¹¹⁵	USA	CNN (Densenet)	Liver cancer	Pathologist diagnosis, consensus, IHC, special stains	TCGA; Stanford whole-slide image dataset	20 WSIs	50 WSIs	106 WSIs	Yes
Yang ¹¹⁶	Taiwan	Feature Aligned Multi-Scale Convolutional Network (FA-MSCN)	Liver cancer	Pathologist labels and ROIs	Unclear	20 WSIs		26 WSIs	Unclear
Schau ¹¹⁷	USA, Thailand	CNNs (Inception v4)	Liver metastases	Pathologist labels, annotations	OHSU Knight BioLibrary	200 WSIs		85 WSIs	No
Fu ¹¹⁸	China	CNN (InceptionV3 patch-level classification), lightGBM model (WSI-level classification) & U-Net CNN (patch-level segmentation)	Pancreatic cancer	Pathologist annotations, labels	Peking Union Medical College Hospital (PUMCH); TCGA	79,588 patches	9952 patches	9948 patches + 52 WSIs	Yes
Naito ¹¹⁹	Japan	CNN (EfficientNetB1)	Pancreatic cancer	Pathologist review, pathologist annotations	Kurume University	372 WSIs	40 WSIs	120 WSIs	No
Song ¹²⁰	South Korea	Bayesian classifier; k-NN; SVM; ANN.	Pancreatic neoplasms	Unclear	Pathology department of Yeongnam University	240 patches		160 patches	No

Patologia Dermatologica

Patologia Epatobiliare



<https://doi.org/10.1038/s41746-024-01106-8>

Review article

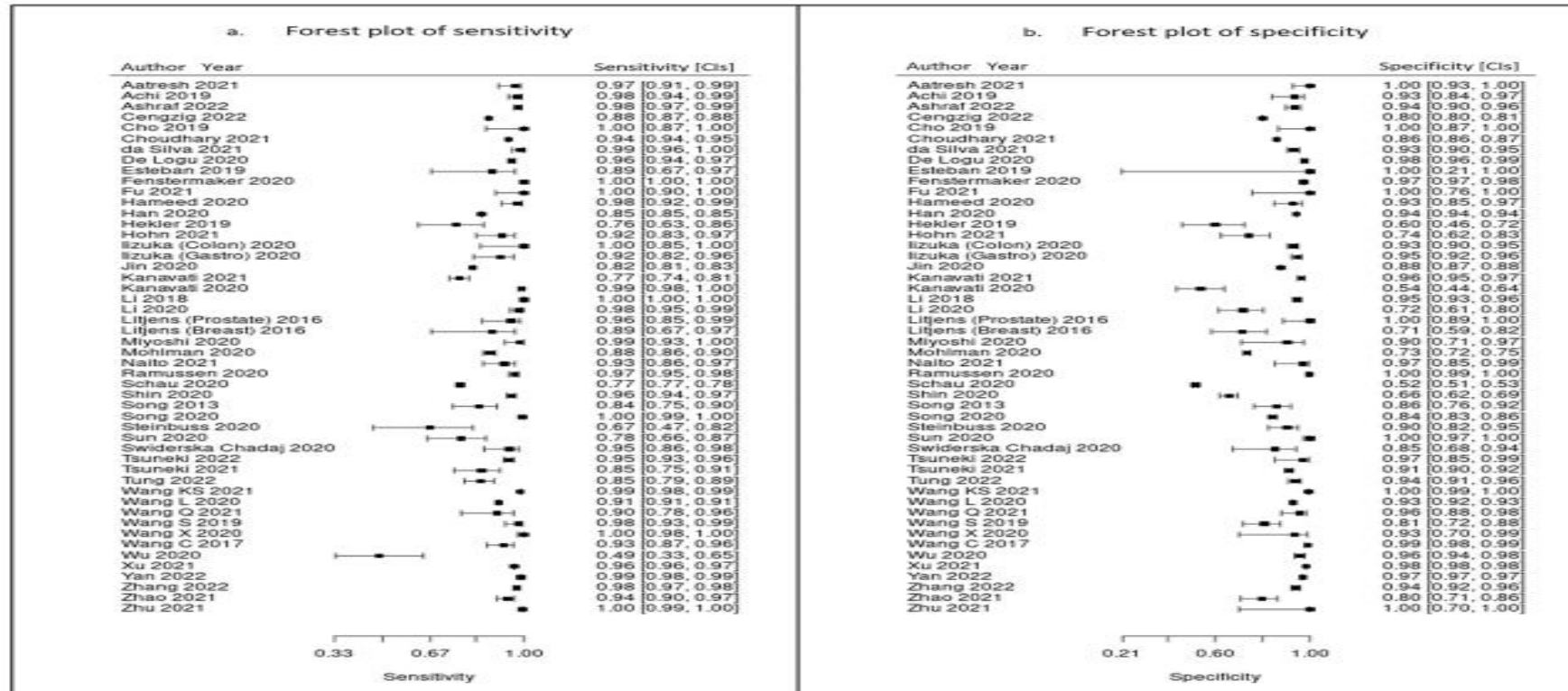


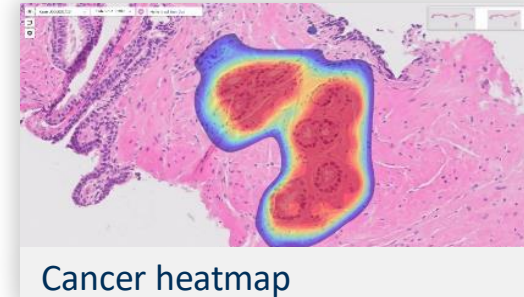
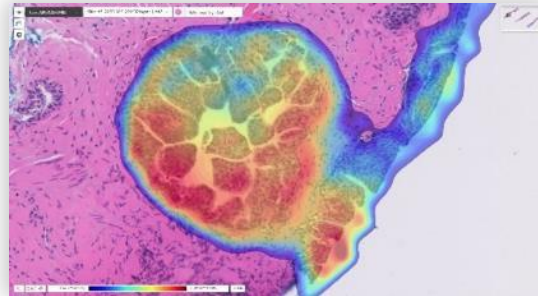
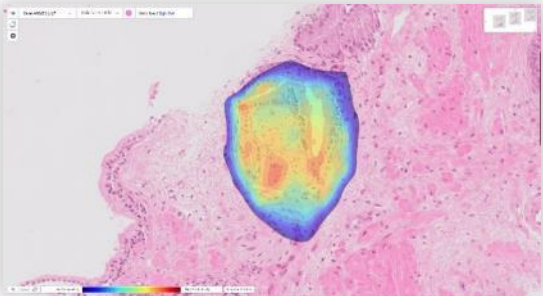
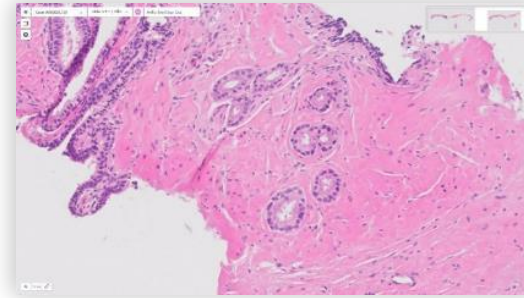
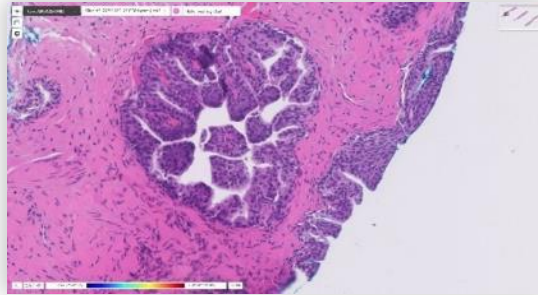
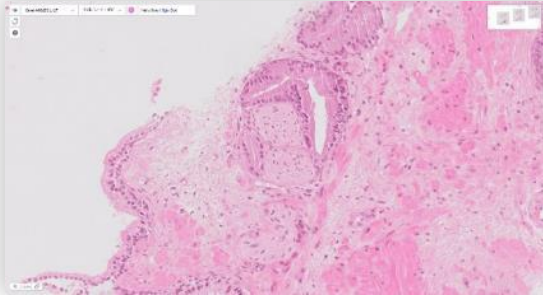
Fig. 4 | Forest plots of performance across studies included in the meta-analysis. These show sensitivity (a) and specificity (b) in studies of all pathologies with 95% confidence intervals. These plots were generated by MetaDTA: Diagnostic Test Accuracy Meta-Analysis v2.01 Shiny App <https://crsu.shinyapps.io/MetaDTA/> and the raw data can be found in Supplementary Table 4^{30,31}.

Conclusions

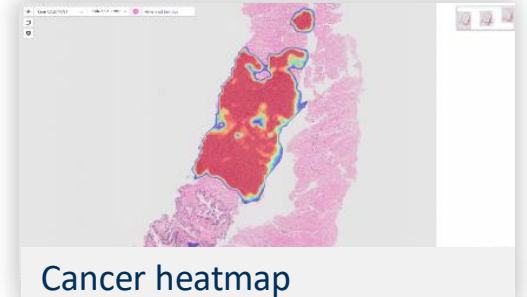
There are **many promising applications for AI models in WSIs to assist the pathologist**. This systematic review has outlined a high diagnostic accuracy for AI across multiple disease types. **A larger body of evidence is available for gastrointestinal pathology, urological pathology and breast pathology**. Many other disease areas are underrepresented and should be explored further in future. To improve the quality of future studies, reporting of sensitivity, specificity and raw data (true positives, false positives, false negatives, true negatives) for pathology AI models would help with transparency in comparing diagnostic performance between studies. Providing a clear outline of the breakdown of data and the data sources used in model development and testing would improve interpretation of results and transparency. Performing an external validation on data from an alternative source to that on which an AI model was trained, providing details on the process for case selection and using large, diverse datasets would help to reduce the risk of bias of these studies. Overall, **better quality study design, transparency, reporting quality and addressing substantial areas of bias is needed to improve the evidence quality in pathology AI** and to therefore harness the benefits of AI for patients and clinicians.

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<https://doi.org/10.1038/s41746-024-01106-8>

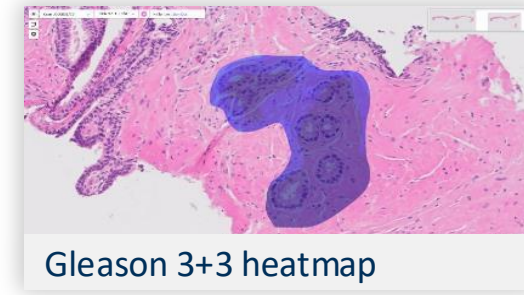
Il futuro è già ora



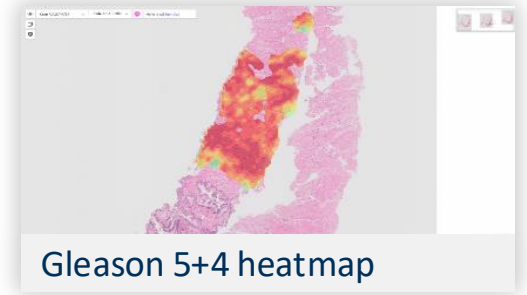
Cancer heatmap



Cancer heatmap



Gleason 3+3 heatmap



Gleason 5+4 heatmap

IA riconosce in maniera accurata il carcinoma Prostatico, Grading corretto e altre rilevanti caratteristiche

THE LANCET
Digital Health

Articles

An artificial intelligence algorithm for prostate cancer diagnosis in whole slide images of core needle biopsies: a blinded clinical validation and deployment study

Shih-Peng Wang, Deborah M. Zeigler, George M. Veltri, David S. Klimov, Clayton R. Kujawa, J. Robert Anderson, Justin S. Madigan, Steven M. Gorewitz, Michael S. Broderick, Richard M. Lesh, Robert M. Lesh, and Charles R. Haines



Summary
Background: There is high demand to develop computer-aided diagnostic tools to evaluate prostate core needle biopsies (CNBs). We have clinical validation and a lack of clinical deployment of such tools. We report here on a blinded clinical validation study and deployment of an artificial intelligence (AI)-based algorithm in a pathology laboratory for routine clinical use in prostate diagnosis.

Methods: An AI-based algorithm was developed using haematoxylin and eosin (H&E)-stained slides of prostate CNBs digitised with a Philips scanner, which were divided into training (1 017 439 image patches from 143 H&E-stained slides) and test sets (10 381 H&E-stained slides). The algorithm provided slide-level scores for the probability of cancer, Gleason score (GS) (ie, Gleason score 6 or cryptic and/or acinar proliferation (CAPAP), Gleason pattern 5, and perineural invasion) and calculation of cancer percentage present in CNB needles. The algorithm was subsequently validated on an external dataset of 100 consecutive cases (1007 H&E-stained slides) digitised as an Aperio A22 scanner. In addition, the AI tool was implemented in a pathology laboratory while routine clinical workflow as a second reader to assess all prostate CNBs. Algorithm performance was assessed externally under the receiver operating characteristic curve (AUC), specificity, and sensitivity, as well as Pearson's correlation coefficient (Pearson's r) for cancer percentage.

Findings: The algorithm achieved an AUC of 0.991 (95% CI 0.985 to 0.997) for cancer detection in the external test set and 0.993 (0.987 to 0.998) in the overall validation set. The AUC for distinguishing between a low-grade (Gleason score 6 or CAPAP) and high-grade (Gleason score 7-10) cancer diagnosis was 0.941 (0.935 to 0.947) and the AUC for detecting Gleason pattern 5 was 0.971 (0.964 to 0.978) in the external validation set. Cancer percentage calculated by pathologists and the algorithm showed good agreement (p=0.133, Cohen's K=0.824 to 0.931 (p<0.0001) with a mean bias of -4.34% (p<0.0001, -1.31). The algorithm achieved an AUC of 0.937 (0.930 to 0.943) for perineural invasion. In routine practice, the algorithm was used to assess 11 413 H&E-stained slides pertaining to 541 cases leading to 90 Gleason score 7-10 cases and 563 cancer alerts. Of 683 cases alerted as additional cases or alerts being ordered, 485 (71%) of which led to a third opinion request. We report on the first case of retained cancer that was detected by the algorithm.

Interpretation: This study reports the successful development, external clinical validation, and deployment in clinical practice of an AI-based algorithm to accurately detect, grade, and evaluate clinically relevant findings in digital slides of prostate CNBs.

Funding: See Medical Analysis.

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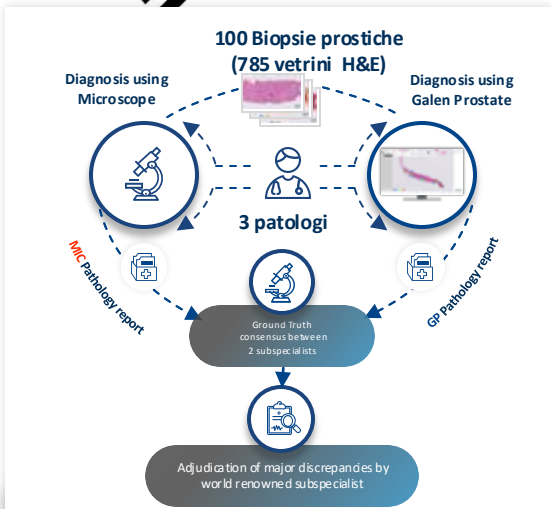
Introduction
Advancements of the prostate in the recent years increase cancer diagnosed in men with more than 1 million newly diagnosed cases of prostate cancer annually. These prostate cancers are heterogeneously characterised as cryptic pathology patterns. Thus, the histopathological assessment of biopsy cores in the context of diagnostic prostate cancer, which includes Gleason score (GS) and Gleason pattern (GP), is a challenging task. In some pathology laboratories, the conventional workflow for prostate cancer diagnosis involves high interobserver

variation of haematoxylin and eosin (H&E)-stained core needles. Due to changing guidelines, there has been a shift towards the detection of the retained prostate cancer features and grading changes of pathology with the use of deep learning and computer-aided diagnostic (CAD) tools. AI-based tools can support pathologists in the diagnosis of prostate cancer and identify grading patterns. The aim of this study was to evaluate the performance of an AI-based algorithm for prostate cancer diagnosis in digital slides of prostate CNBs.

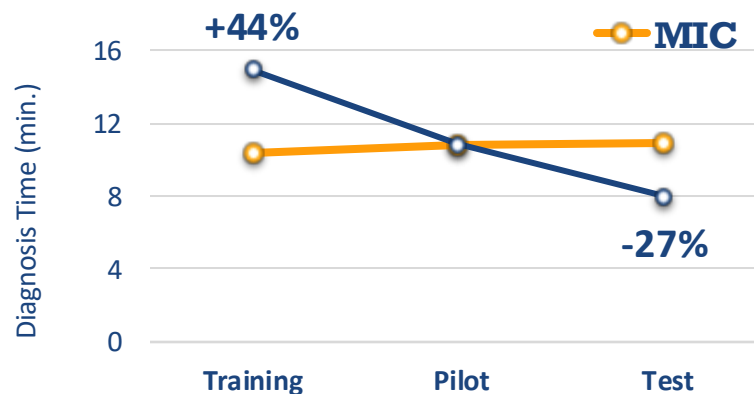
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Cancer detection	AUC = 0.991
G7+	AUC = 0.941
G5	AUC = 0.971
PNI (perineural invasion)	AUC = 0.957
Cancer Size	Correlation = 0.88

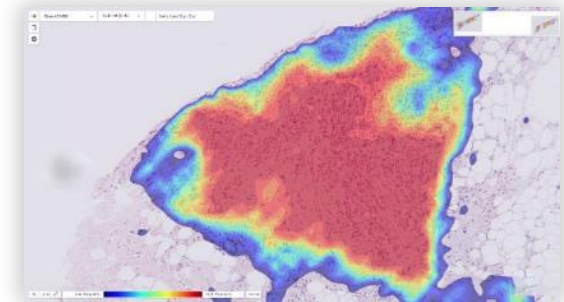
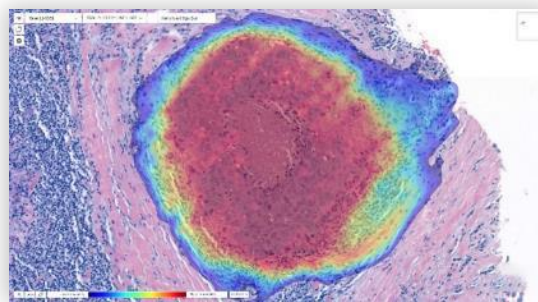
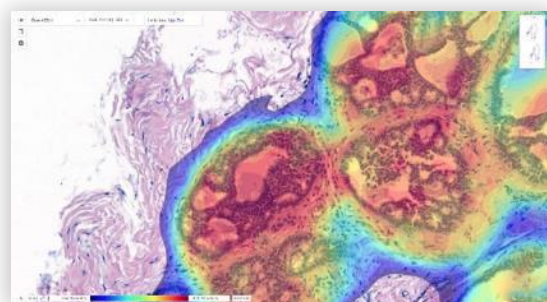
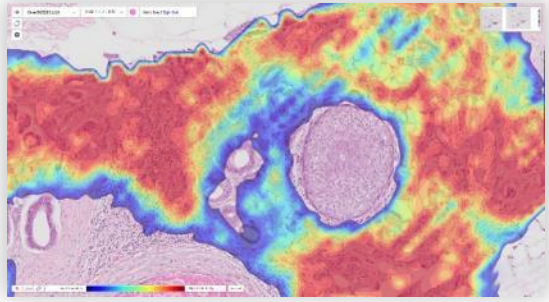
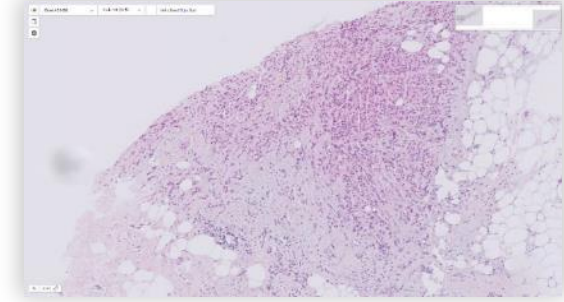
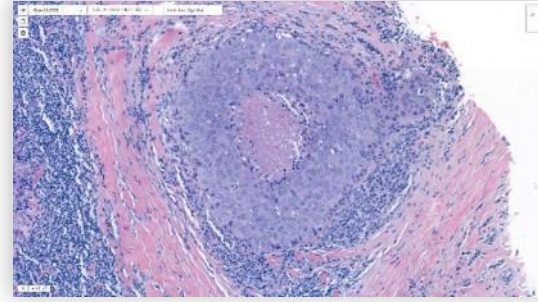
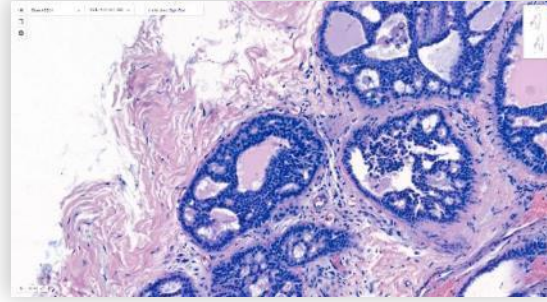
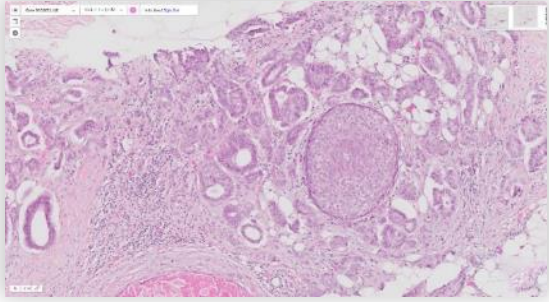
- Clinical study of Galen Prostate at the University of Pittsburgh Medical Center¹
- 100 prostate CNB cases
- Multiple pathologists. Rigorous, blinded design
- The study **successfully validated** the performance of Galen Prostate, with very high performance in cancer detection and grading
- First study to go **beyond cancer** (Gleason, PNI & sizing)
- AI detected misdiagnosis on 17 parts
- The **first study to report deployment** and benefits of AI solution in routine clinical practice (at Maccabi Healthcare Services)



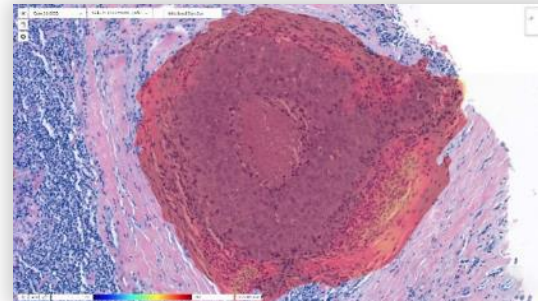
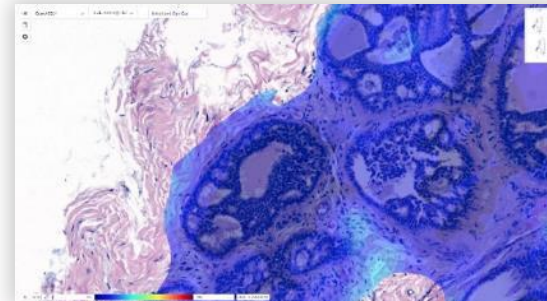
Arm	Agreement Rate	Major Discrepancy Rate	Sensitivity
Galen Prostate	95.16%	4.84%	94.91%
Microscope	92.87%	7.13%	91.64%
Difference		-32%	

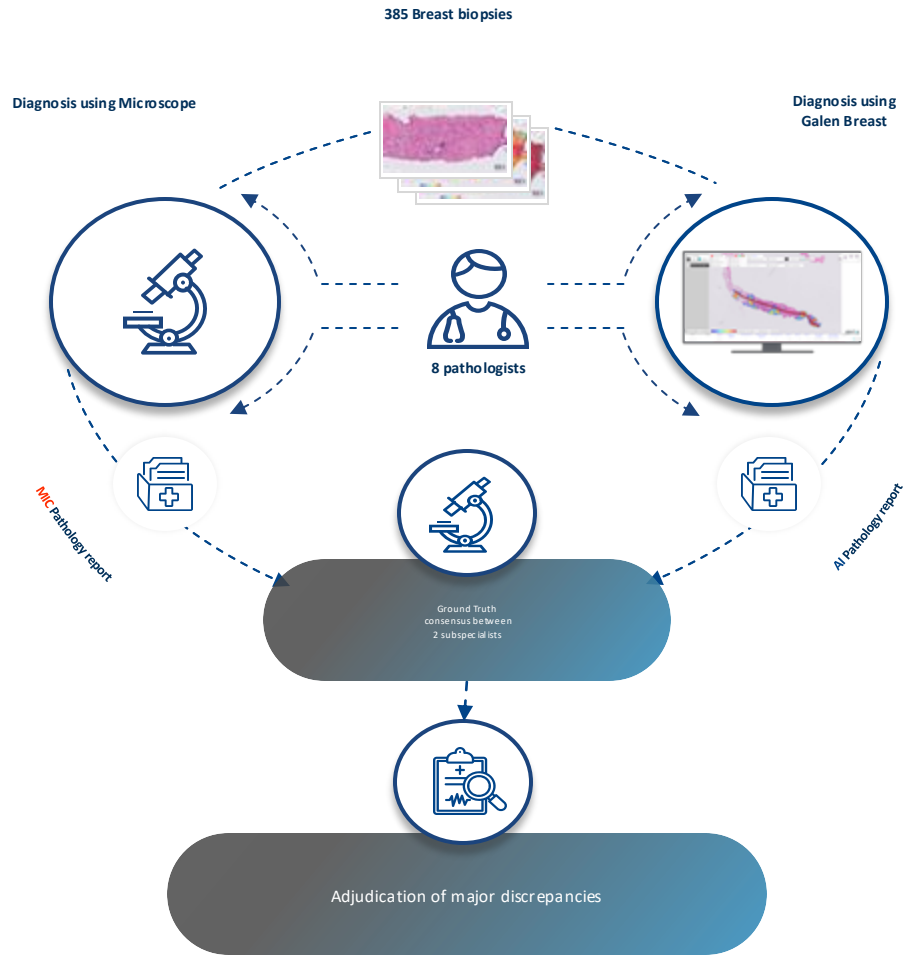


- Casistica di studi con “AI Galen Prostate” nella diagnosi primaria (420 casi complessivi)
- Braccio parallelo che confronta Patologi con AI vs Patologi con microscopio
- AI “Galen Prostate” si è dimostrato in grado di supportare i Patologi per fornire prestazioni significativamente migliori:
 - Miglioramento dell’accuratezza (+ 32%)¹
 - Incremento della produttività (+ 37%)²
 - Tempo di refertazione piu’ rapido (1.8 > 9min)²



IA riconosce in maniera accurata il carcinoma mammario ed il grading corretto





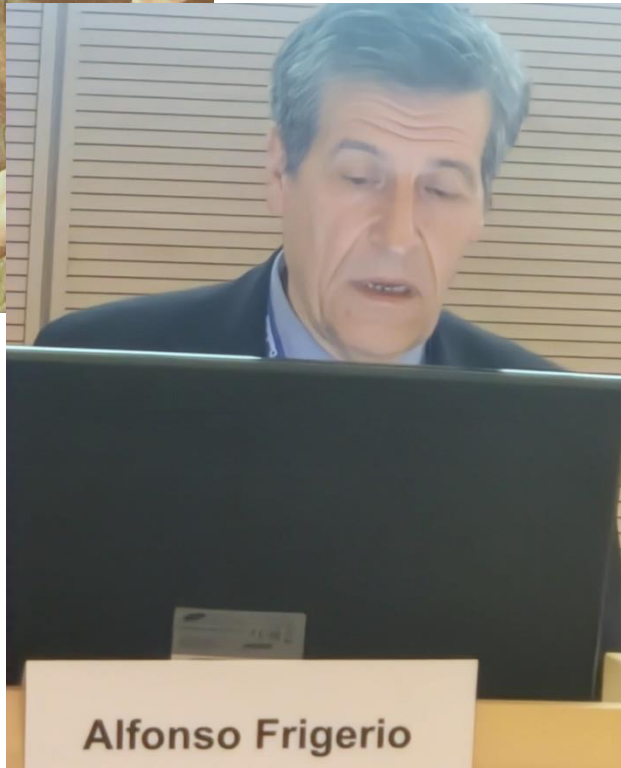
	Tasso di concordanza	% di discordanze maggiori	Sensitivity
Galen Breast	96.9%	3.12%	100.00%
Microscope	95.6%	4.42%	93.2%
Difference		-29%	

AI aiuta il patologo che è in grado di fornire prestazioni migliori che al microscopio con aumento del 29% di accuratezza

Salomon V et al. Eur. Congress of Pathol. 2022



Google Lens Inserisce foto cerca



Raffaello (a.1507): Deposizione di Gesù (galleria Borghese)

La sfida è già iniziata ALZIAMO LO SGUARDO



1. Se dovesse scegliere un unico punto da inserire nel manifesto, quale riterrebbe fondamentale e perché

Risposta: 11. Decision support: fornire strumenti per aiutare i medici nelle decisioni cliniche (revisione dei casi per second opinion e controllo di qualità; esempio rivedere tutte le biopsie prostatiche negative del giorno precedente e con possibilità di rileggere i punti segnalati come dubbi o sospetti prima della firma)

2. Selezionare in una lista di 15 punti 3 che ritiene più rilevanti per il futuro dell'AI in sanità

Risposta:

- 8. Riduzione errori medici: sfruttare l'AI per migliorare la sicurezza dei pazienti
- 9. Sostenibilità: Rendere i sistemi sanitari più efficienti e sostenibili
- 12. Telemedicina ampliare l'uso delle tecnologie AI per assistenza a Distanza