

INTELLIGENZA ARTIFICIALE IN SENOLOGIA

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RADIOLOGIA BONVICINI

BOLZANO

SOMMARIO

1 DIGITAL HEALTH

2 INTELLIGENZA ARTIFICIALE 3 INTELLIGENZA
ARTIFICIALE
IN RADIOLOGIA

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ARTIFICIALE
IN SENOLOGIA

CASI CLINICI



Intelligenza artificiale

Usi quotidiani e usi possibili

Alcuni esempi di come viene usata l'IA e delle possibilità che offre



europarl.eu

2017

Forbes

All in territories and the same

Digital Therapeutics: The Future of Health Care Will Be App-Based



A new sort of health app can do the job of drugs

MIT Technology Review

Rewriting Lite

Can "Digital Therapeutics" Be as Good as Drugs?

The New York Times Take This App and Call Me In the Morning

A new category of prescription medical treatments, what executives call digital therapeutics, comes in the form of mobile apps.

OGGI

«La Digital health è arrivata ed è destinata a rimanere»

- La disponibilità e la crescente diffusione della Digital Health e delle DTx stanno determinando un cambio di paradigma nei percorsi di cura, e anche l'atteggiamento di molti operatori sanitari nei confronti della salute digitale sta evolvendo.
- La domanda non è più «Abbiamo bisogno della Digital Health?», ma piuttosto «Come possiamo adattare il nostro sistema sanitario per integrare al meglio la Digital Health?»

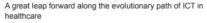
THE ERA OF **DIGITAL HEALTH** The era of digital health is upon us. It is fundamentally different from what has come before, with profound influences on health and healthcare. What has come before ICT in Health 1950s - 1960s Mainframe computers 1st WAVE Focus on corporate support functions such as accounting and payroll Applications were function driven Industry agnostic (not health specific) E-Health 2000s - 2020 Enterprise and Focus on whole system wide of health system information flows Health system centricity begin Patient following Shared health but still provider records and health information Governments as key exchanges players in and funders of e-health 3rd WAVE Healthcare as a process rather than health as an outcome Bulk of healthcare data provider-originated



THE FOURTH WAVE: **DIGITAL HEALTH (2020+)**

DIGITAL HEALTH = **HEALTH AND HEALTHCARE IN THE DIGITAL SOCIETY**

Digital Health is about HEALTH



Enabled by exponential increases in the pervasion of ICT throughout society

With service providers as participants, not controllers



Driven by citizens' demands that their health and wellbeing are controlled by them and expectations for digital service delivery embedded within their life patterns



and controlled

Data, data everywhere

Harvests data in real time from sources within and outside of traditional health settings



Generated via sophisticated analytics

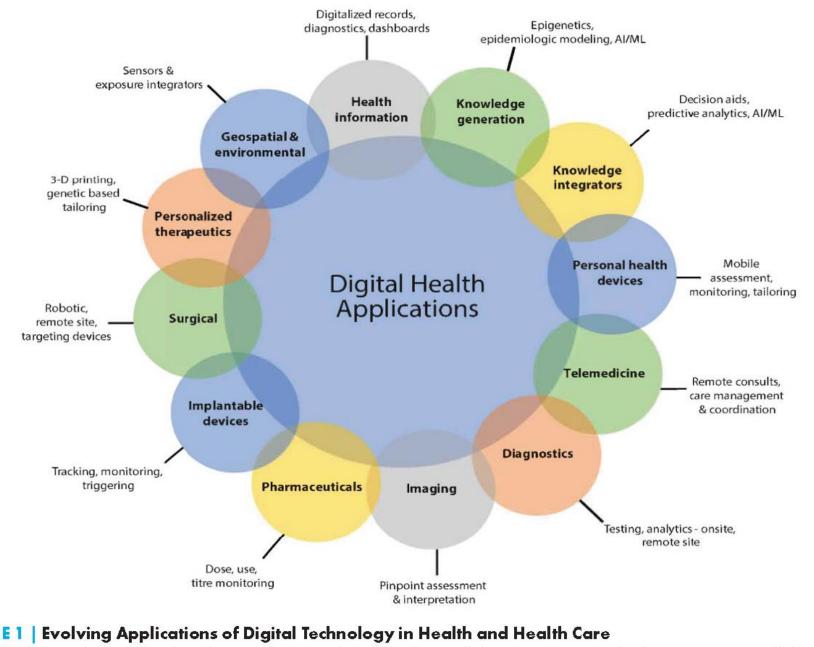


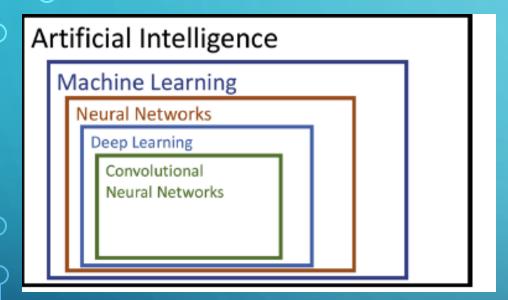
FIGURE 1 | Evolving Applications of Digital Technology in Health and Health Care

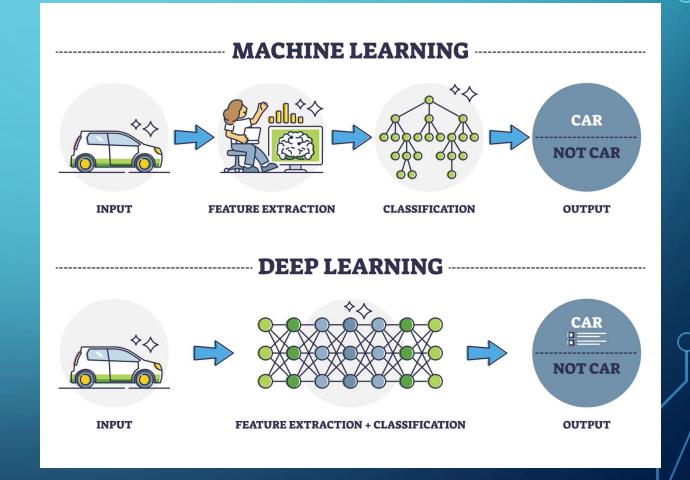
SOURCE: National Academy of Medicine. 2019. Digital Health Action Collaborative, NAM Leadership Consortium: Collaboration for a Value & Science-Driven Health System.

TRE TIPI DI INTELLIGENZA ARTIFICIALE

- Artificial Narrow Intelligence (ANI) chatbot, guida autonoma, SIRI, ALEXA...
- Artificial General Intelligence (AGI) = uomo
- Artificial Super Intelligence (ASI) superiore all'uomo

INTELLIGENZA ARTIFICIALE





PERCHÉ L'INTELLIGENZA ARTIFICIALE SPAVENTA?

facebook











1980

Luca, Manfred, Olena, Cathy, Hans











2024

Anna, Guido, Robert, Franz, Alessandro



StyleGAN2 di Nvidia

Quindi siamo spaventati dalla possibilità di essere ingannati..
 Specie se si tratti di salute

• Inoltre siamo influenzati da opinioni sui media e social che mostrano l'intelligenza artificiale come un alieno che entrerà nel nostro cervello • Il pericolo... Attualmente... è meno grave di quello che si pensa

• Si tende ad antropomorfizzare l'intelligenza artificiale che tanto intelligente poi non è. Transmission Versus Truth, Imitation Versus Innovation: What Children Can Do That Large Language and Languageand-Vision Models Cannot (Yet) Perspectives on Psychological Science 1–10 © The Author(s) 2023



Article reuse guidelines: sagepub.com/journals-permissions DOI: 10.1177/17456916231201401 www.psychologicalscience.org/PPS

S Sage

Eunice Yiuo, Eliza Kosoy, and Alison Gopnik

Department of Psychology, University of California, Berkeley

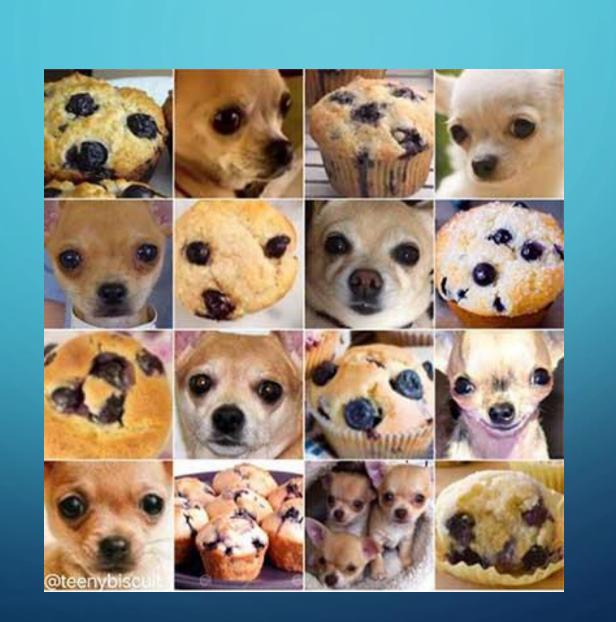
RODUTTIVA

- CHAT GPT riformula testi esistenti ... non capisce!
- Per riconoscere un gatto un bambino basta che ne veda, accarezzi, osservi 10 gatti e dopo capisce subito che è un gatto.



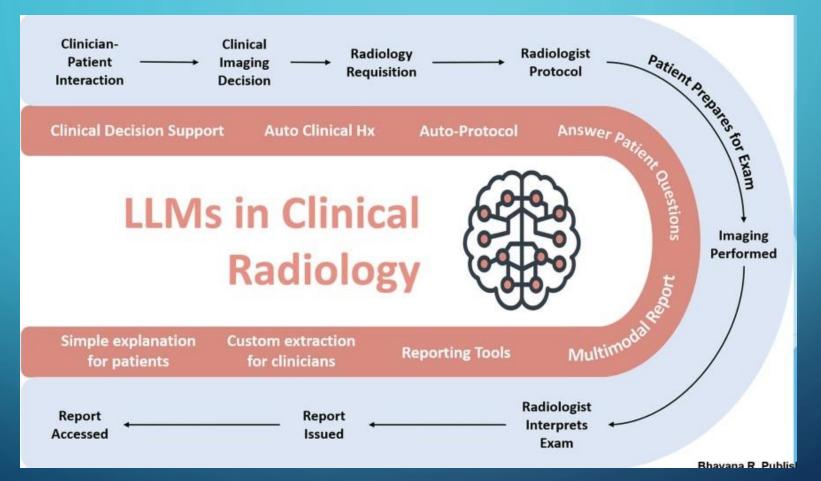


• I sistemi di intelligenza artificiali hanno bisogno di migliaia di immagini di gatto per capire che è un gatto e sbagliano se li viene mostrato uno stregatto!

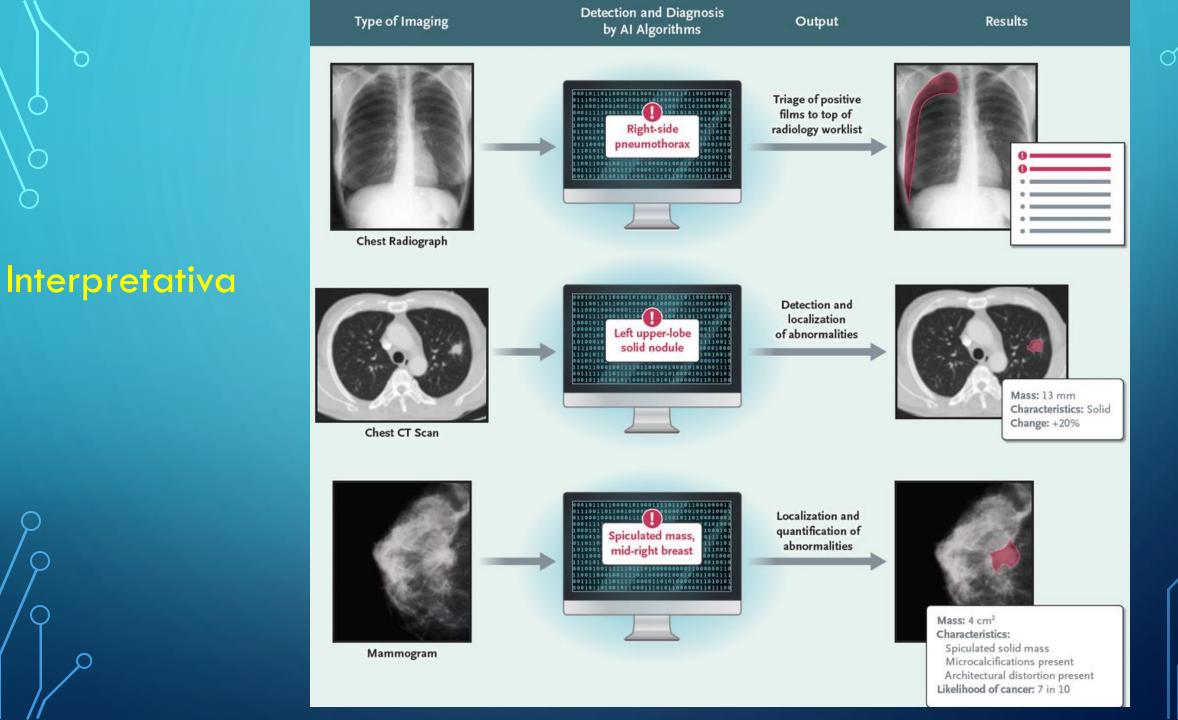


AI IN RADIOLOGIA

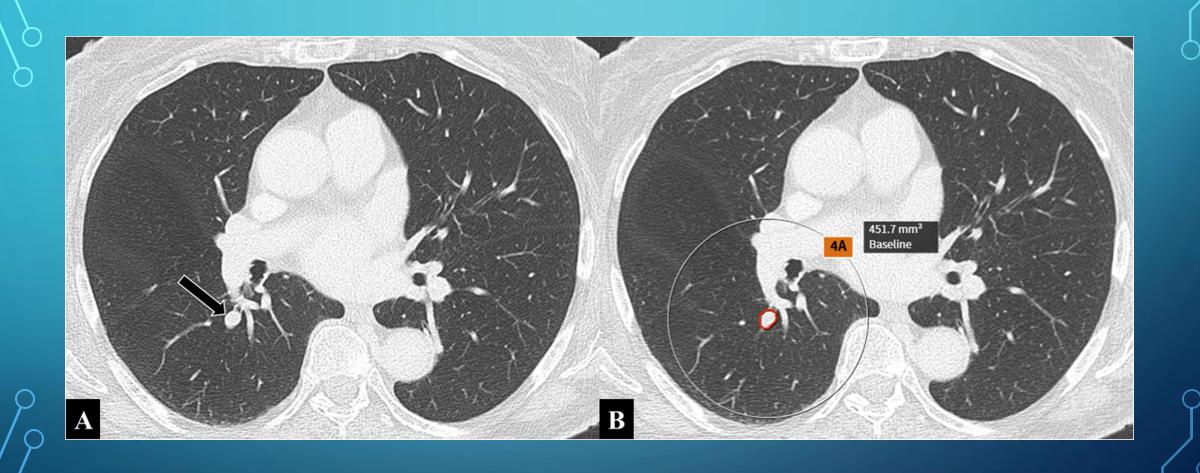
- •Interpretativa
- Non interpretativa



Bhayana et al.

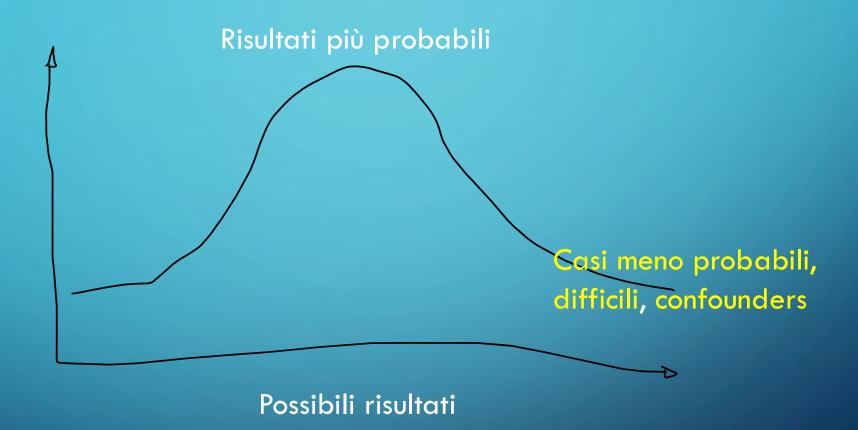






DIAGNOSI IN RADIOLOGIA

Probabilità

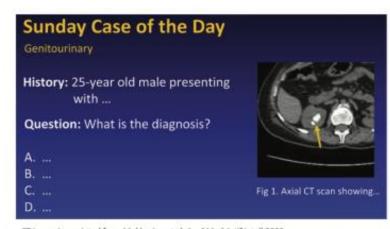


Non intepretativa



NON È TUTTO ORO QUEL CHE LUCCICA

GPT LLM Performance on RSNA 2023 Case of the Day Questions



CT image is reprinted from Mukherjee et al. Appl Med Artif Intell 2022.

- Retrospective study to evaluate GPT-4V performance compared with that of five radiologists and three junior residents.
- For 72 RSNA 2023 Case of the Day questions, median accuracy of GPT-4V was 43% (31 of 72), that of radiologists was 62% (45 of 72), and that of residents was 61% (44 of 72).
- With the GPT-4V assistance, the median accuracy of radiologists and residents was 54% (39 of 72) for both.

Mukherjee P et al. Published: October 1, 2024 https://doi.org/10.1148/radiol.240609

Radiology

 Usare solo sistemi approvati FDA o EU No Dr Goggle o Professor GPT!

AI IN SENOLOGIA

Soprattutto uso interpretativo

Fornisce una valutazione quantitativa della probabilità di malignità sulle microcalcificazioni e noduli / distorsioni

Scala 1-10 o 0-100 o altre rappresentazioni del grado di sospetto.

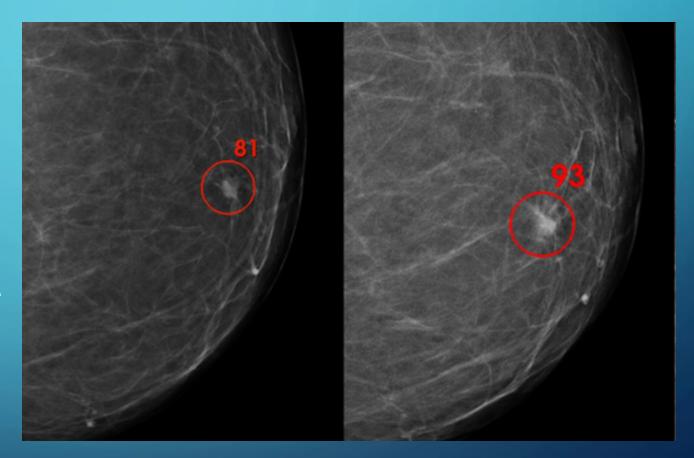


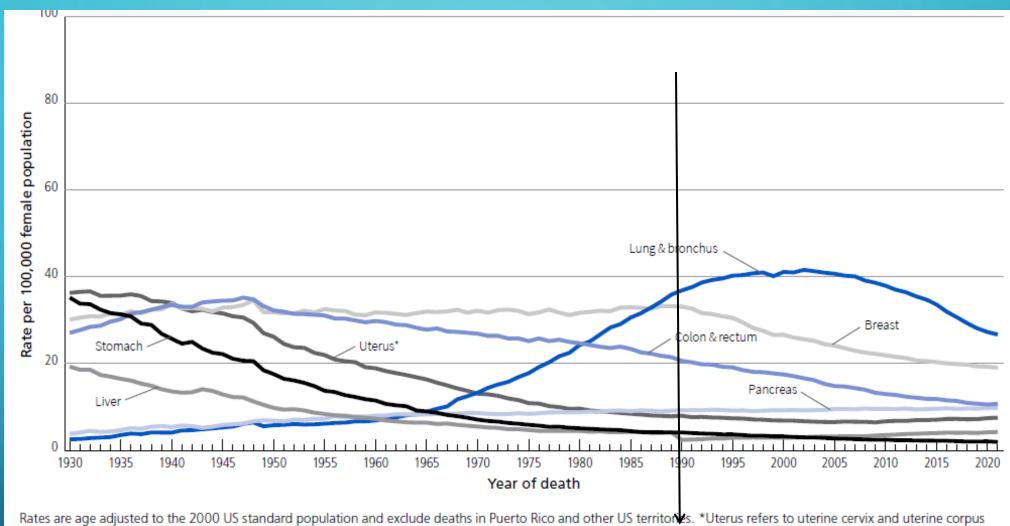
Figure 3. Leading Sites of New Cancer Cases and Deaths – 2024 Estimates

	Male				Female		
	Prostate	299,010	29%	Breast	310,720	32%	
Estimated New Cases	Lung & bronchus	116,310	11%	Lung & bronc	hus 118,270	12%	
	Colon & rectum	81,540	8%	Colon & rectu	m 71,270	7%	
	Urinary bladder	63,070	6%	Uterine corpu	is 67,880	7%	
	Melanoma of the skin	59,170	6%	Melanoma of	the skin 41,470	4%	
	Kidney & renal pelvis	52,380	5%	Non-Hodgkin	lymphoma 36,030	4%	
	Non-Hodgkin lymphoma	44,590	4%	Pancreas	31,910	3%	
	Oral cavity & pharynx	41,510	4%	Thyroid	31,520	3%	
	Leukemia	36,450	4%	Kidney & rena	l pelvis 29,230	3%	
	Pancreas	34,530	3%	Leukemia	26,320	3%	
	All sites	1,029,080		All sites	972,060		
	Male						
	Male				Female		
	Male Lung & bronchus	65,790	20%	Lung & bronc		21%	
			20% 11%	Lung & bronce		21% 15%	
	Lung & bronchus	65,790			nus 59,280		
ıths	Lung & bronchus Prostate	65,790 35,250	11%	Breast	59,280 42,250 24,480	15%	
Deaths	Lung & bronchus Prostate Colon & rectum	65,790 35,250 28,700	11% 9%	Breast Pancreas	nus 59,280 42,250 24,480 m 24,310	15% 8%	
ed Deaths	Lung & bronchus Prostate Colon & rectum Pancreas	65,790 35,250 28,700 27,270	11% 9% 8%	Breast Pancreas Colon & rectu	nus 59,280 42,250 24,480 m 24,310	15% 8% 8%	
ated Deaths	Lung & bronchus Prostate Colon & rectum Pancreas Liver & intrahepatic bile duct	65,790 35,250 28,700 27,270 19,120	11% 9% 8% 6%	Pancreas Colon & rectu Uterine corpu Ovary	m 59,280 42,250 24,480 m 24,310 s 13,250	15% 8% 8% 5%	
timated Deaths	Lung & bronchus Prostate Colon & rectum Pancreas Liver & intrahepatic bile duct Leukemia	65,790 35,250 28,700 27,270 19,120 13,640	11% 9% 8% 6% 4%	Pancreas Colon & rectu Uterine corpu Ovary	m 59,280 42,250 24,480 m 24,310 s 13,250 12,740	15% 8% 8% 5% 4%	
Estimated Deaths	Lung & bronchus Prostate Colon & rectum Pancreas Liver & intrahepatic bile duct Leukemia Esophagus	65,790 35,250 28,700 27,270 19,120 13,640 12,880	11% 9% 8% 6% 4% 4%	Pancreas Colon & rectu Uterine corpu Ovary Liver & intrah	mus 59,280 42,250 24,480 m 24,310 s 13,250 12,740 epatic bile duct 10,720 10,030	15% 8% 8% 5% 4%	
Estimated Deaths	Lung & bronchus Prostate Colon & rectum Pancreas Liver & intrahepatic bile duct Leukemia Esophagus Urinary bladder	65,790 35,250 28,700 27,270 19,120 13,640 12,880 12,290	11% 9% 8% 6% 4% 4%	Breast Pancreas Colon & rectu Uterine corpu Ovary Liver & intrahe Leukemia Non-Hodgkin	mus 59,280 42,250 24,480 m 24,310 s 13,250 12,740 epatic bile duct 10,720 10,030	15% 8% 8% 5% 4% 4% 3%	

Estimates are rounded to the nearest 10, and cases exclude basal cell and squamous cell skin cancers and in situ carcinoma except urinary bladder. Estimates do not include Puerto Rico or other US territories. Ranking is based on modeled projections and may differ from the most recent observed data.

©2024, American Cancer Society, Inc., Surveillance and Health Equity Science

Ancora piu' difficile quando parliamo di screening



Rates are age adjusted to the 2000 US standard population and exclude deaths in Puerto Rico and other US territories. *Uterus refers to uterine cervix and uterine corpus combined. Note: Due to changes in ICD coding, numerator information differs from contemporary data for cancers of the liver, lung and bronchus, colon and rectum, and uterus.

Source: US Mortality Volumes 1930 to 1959, US Mortality Data 1960 to 2020, National Center for Health Statistics, Centers for Disease Control and Prevention.

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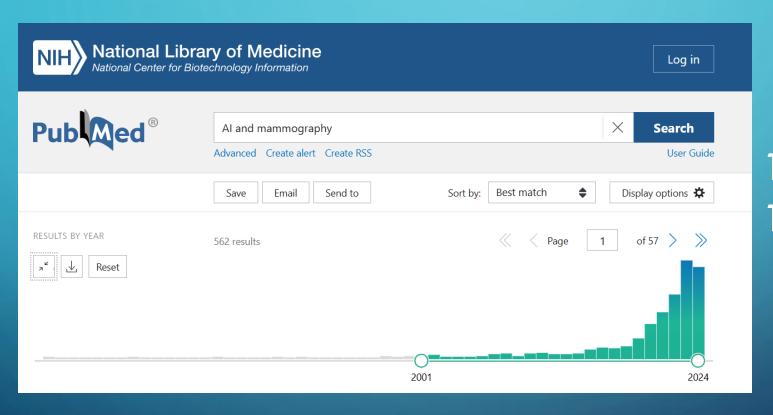




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DATI IN LETTERATURA AI IN SENOLOGIA



148 articoli 2023138 articoli 1.9.2024

•Cosa dice la letteratura?

DATI IN LETTERATURA AI IN SENOLOGIA



Artificial intelligence-supported screen reading versus standard double reading in the Mammography Screening with Artificial Intelligence trial (MASAI): a clinical safety analysis of a randomised, controlled, non-inferiority, single-blinded, screening accuracy study

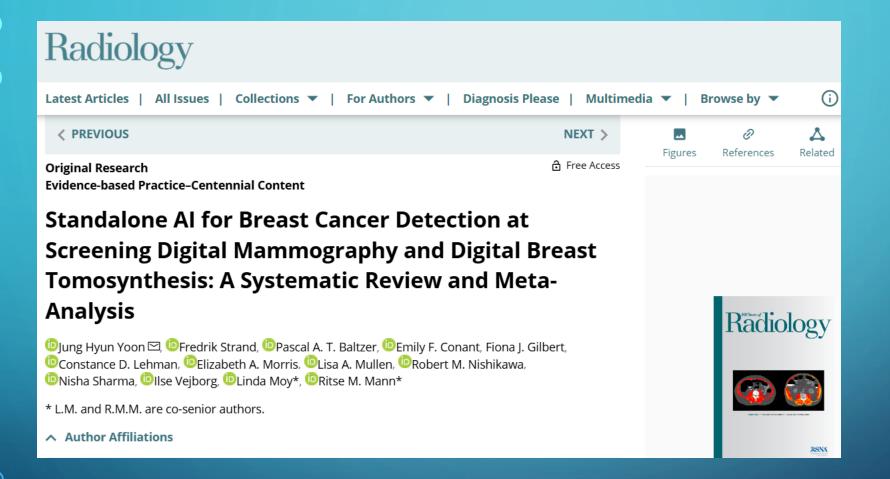
Kristina Lång, Viktoria Josefsson, Anna-Maria Larsson, Stefan Larsson, Charlotte Högberg, Hanna Sartor, Solveig Hofvind, Ingvar Andersson, Aldana Rosso

Lang et al; Lancet Oncol.2023

MASAI STUDY

- 80000 pazienti di screening in Svezia
- Al-supported mammography screening resulted in a similar cancer detection rate compared with standard double reading, with a substantially lower screen-reading workload, indicating that the use of Al in mammography screening is safe.

Lang et al; Lancet Oncol.2023



Standalone Al for screening digital mammography performed as well as or better than radiologists.

Compared with digital mammography,

Radiology

Early Indicators of the Impact of Using AI in Mammography Screening for Breast Cancer

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Supported in part by Eurostars (grant E9714 IBSCREEN). Supported in part by the Pioneer Centre for Artificial Intelligence (Danmarks Grundforskningsfond, grant P1).

Conflicts of interest are listed at the end of this article.

See also the editorial by Lee and Friedewald in this issue.

Radiology 2024; 311(3):e232479 • https://doi.org/10.1148/radiol.232479 • Content codes: BR AI

Lauritzen AD et al JUNE2024

RSNA

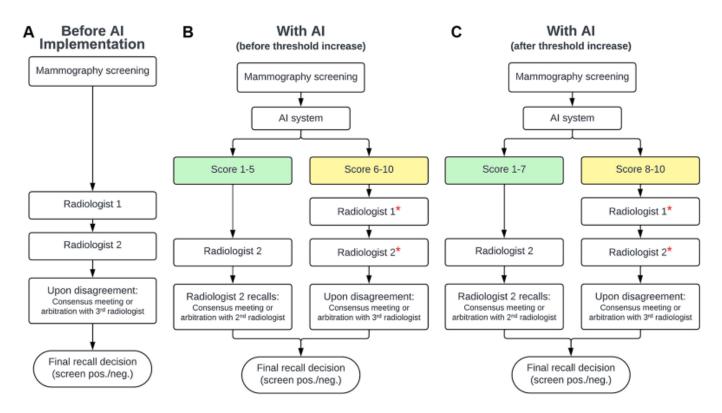


Figure 2: Flow diagram depicts mammography reading protocols (A) before an artificial intelligence (AI) system was implemented in screening and (B, C) after the AI system was implemented with (B) the original (before May 3, 2022) or (C) a higher (on or after May 3, 2022) AI examination score threshold for selecting screenings for single reading. Green boxes indicate likely normal screenings selected for single reading; yellow boxes indicate screenings selected for AI-assisted double reading, in which case radiologists (*) had access to decision support in the form of highlighted lesions provided by the AI system. neg. = negative, pos. = positive.

Results

...After Al system implementation,

The recall rate decreased by 20.5% (3.09% before Al...vs 2.46% with Al...; P < .001),

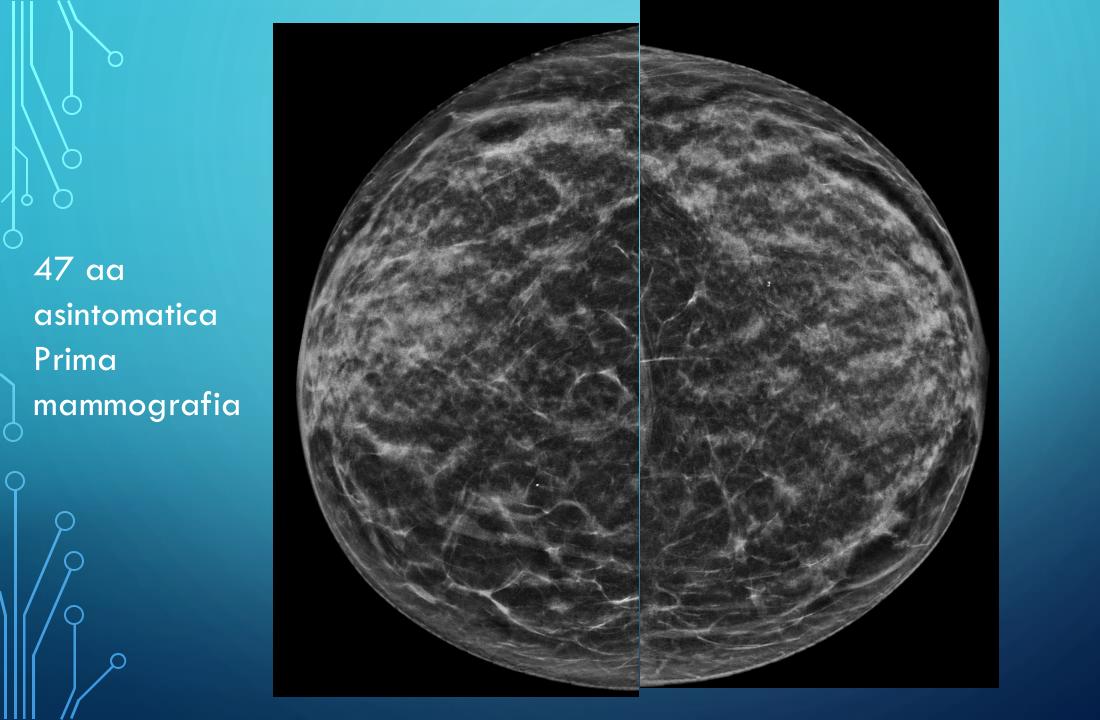
the cancer detection rate increased (0.70% ...vs 0.82% ... P = .01), the false-positive rate decreased (2.39% ...vs 1.63% ...P < .001), the positive predictive value increased (22.6% [423 of 1875] vs 33.6% ...P < .001),

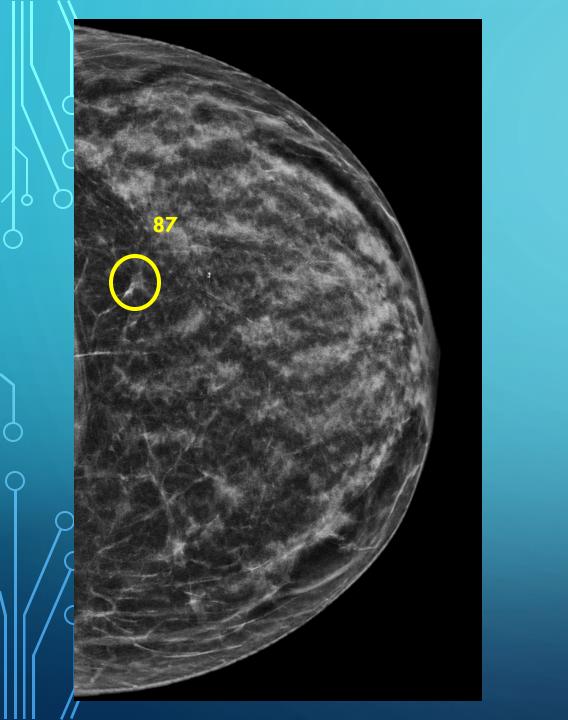
the rate of small cancers (≤1 cm) increased (36.6% ...vs 44.9% ...
The reading workload was reduced by 33.5% (38 977 of 116 492 reads).

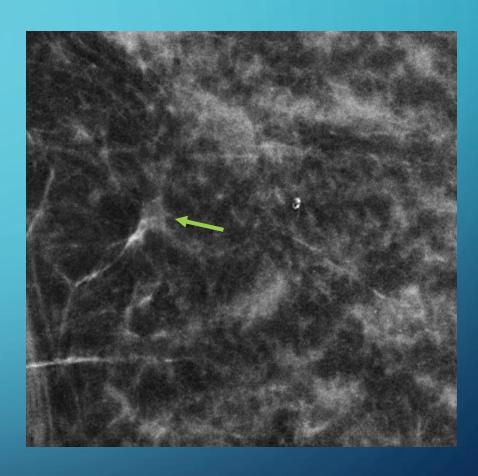
Conclusion

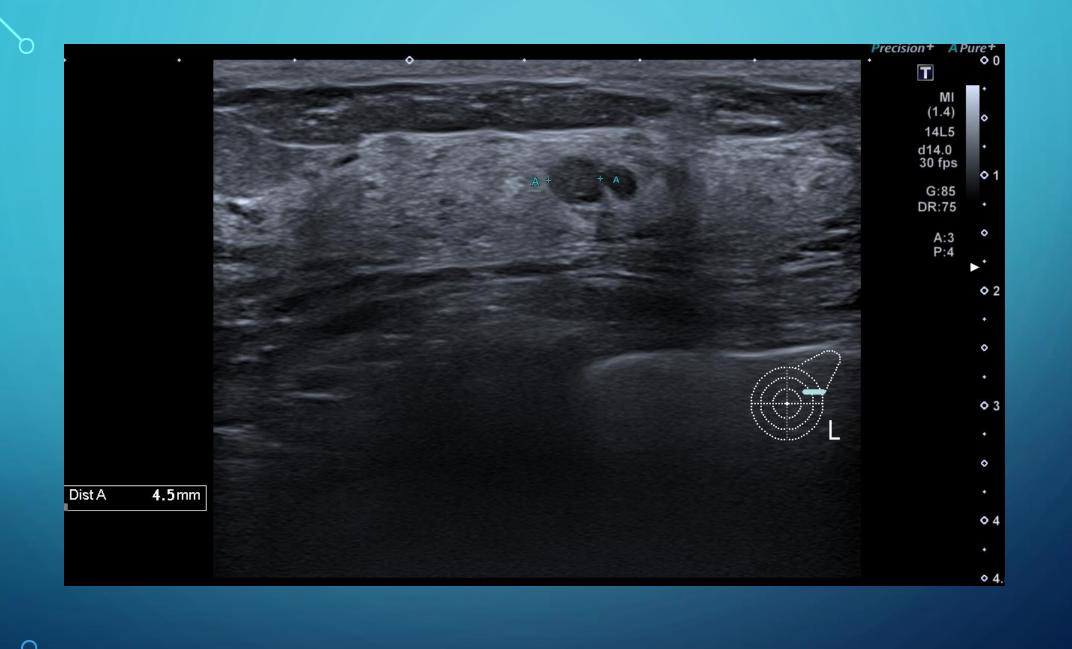
In a population-based mammography screening program, using Al reduced the overall workload of breast radiologists while improving screening performance.

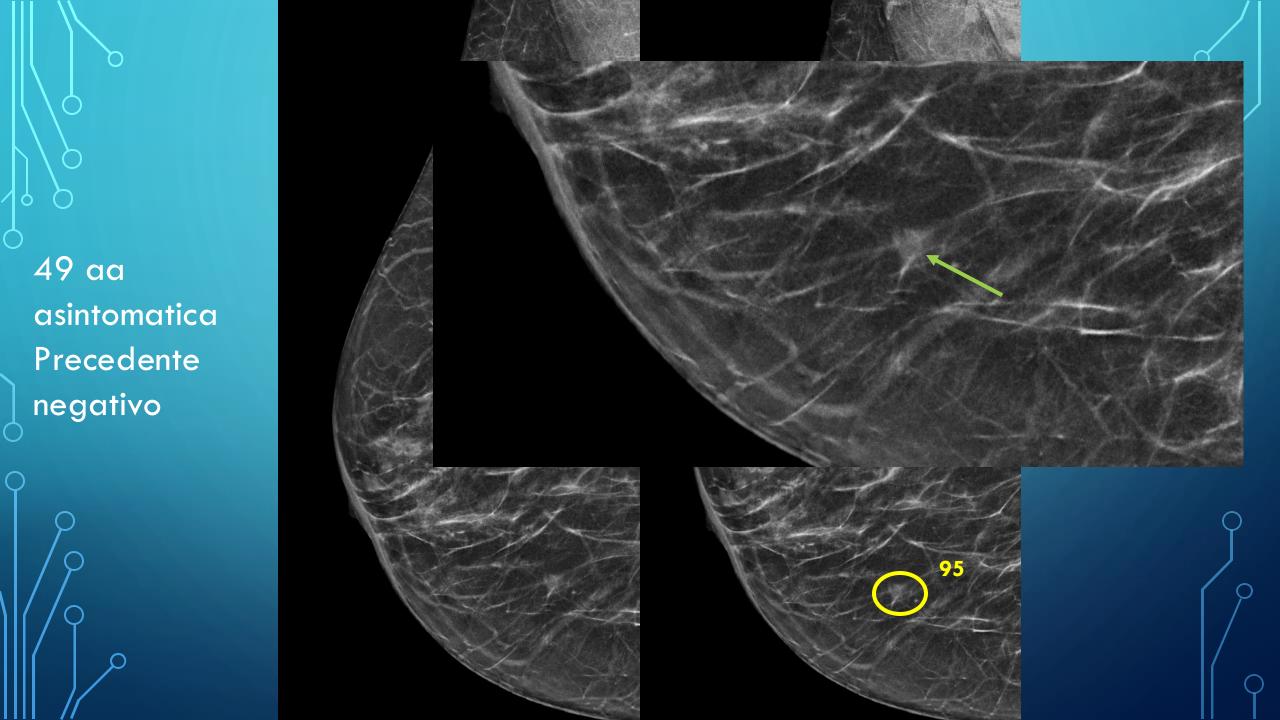
•Ma solo nello screening?

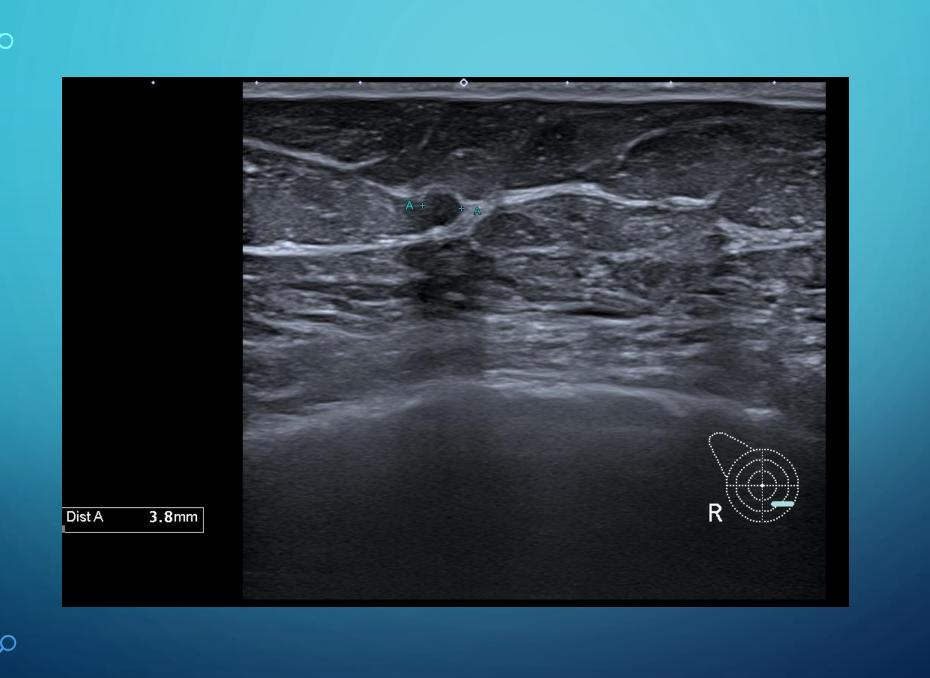


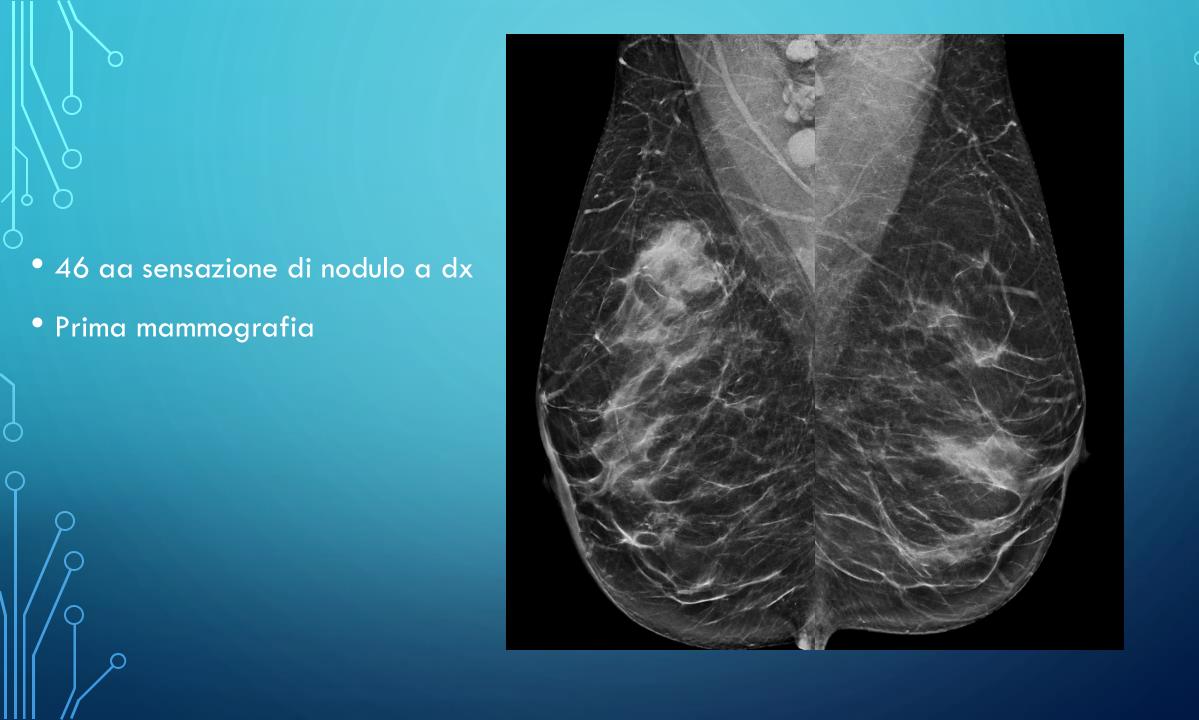


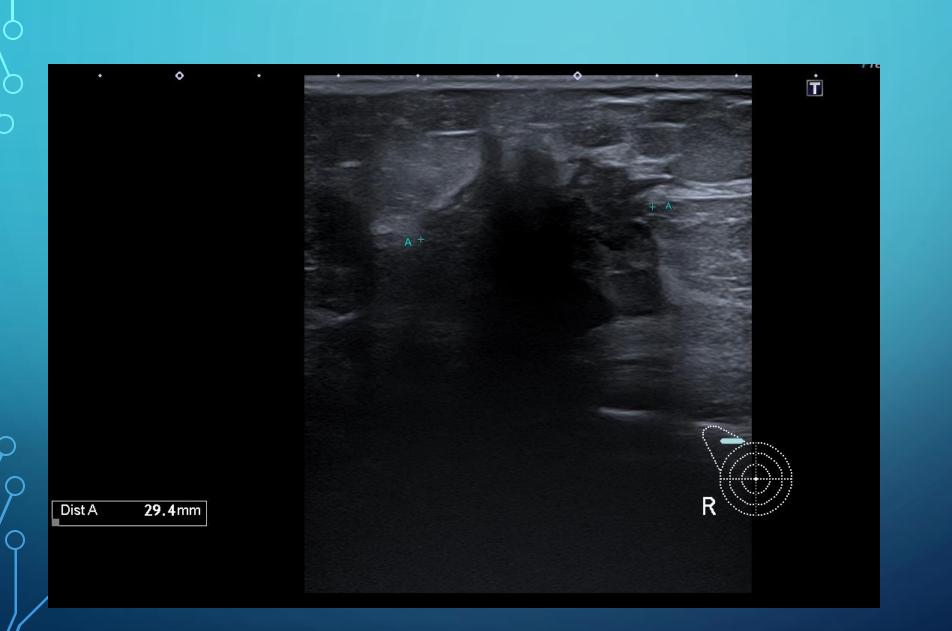




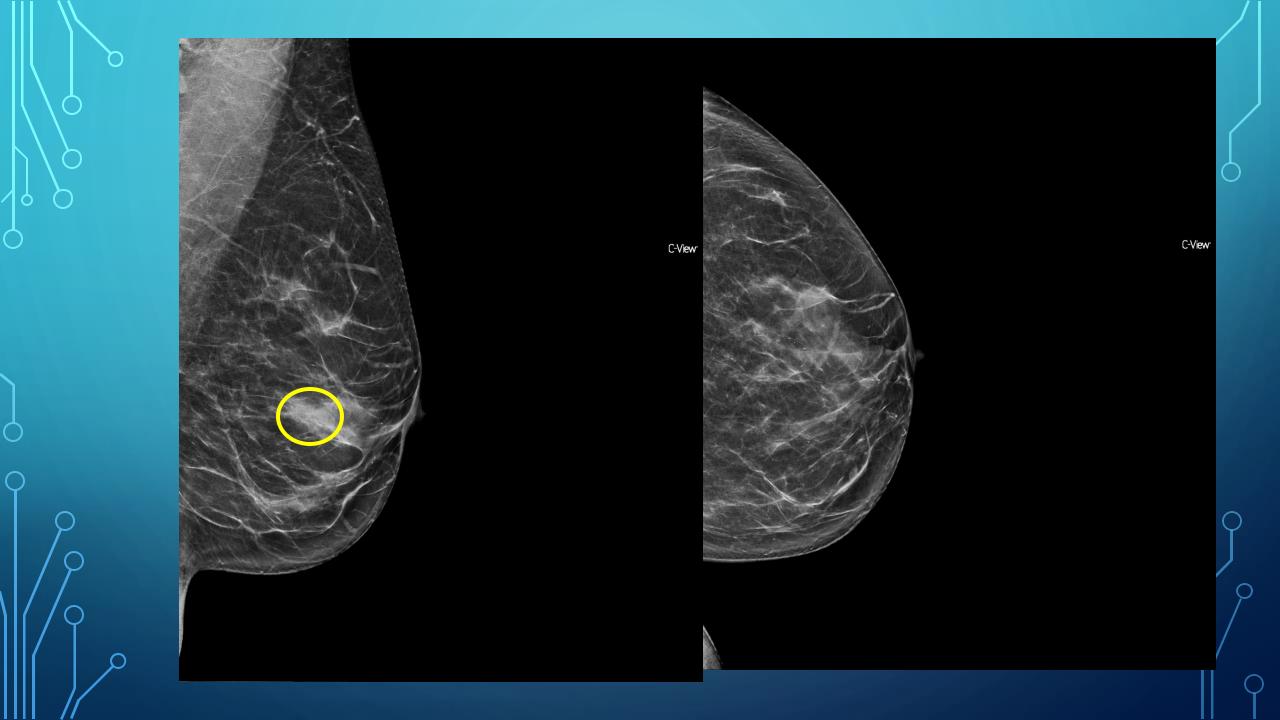


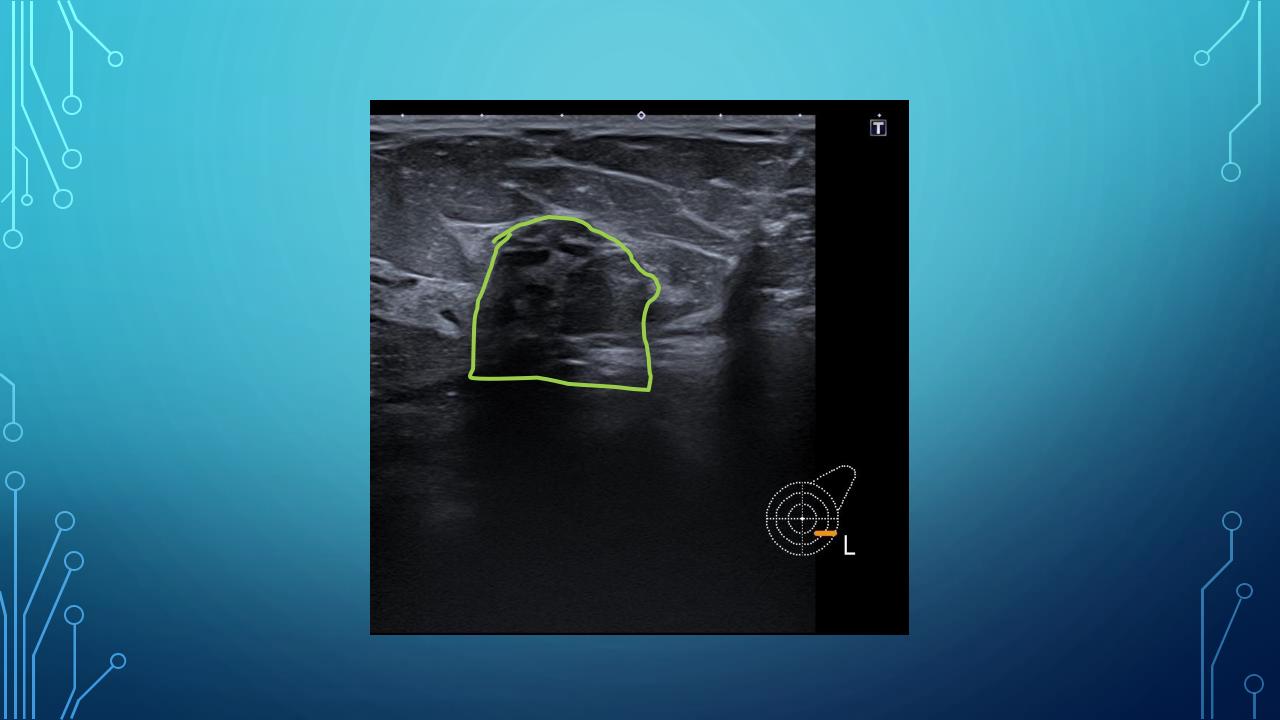


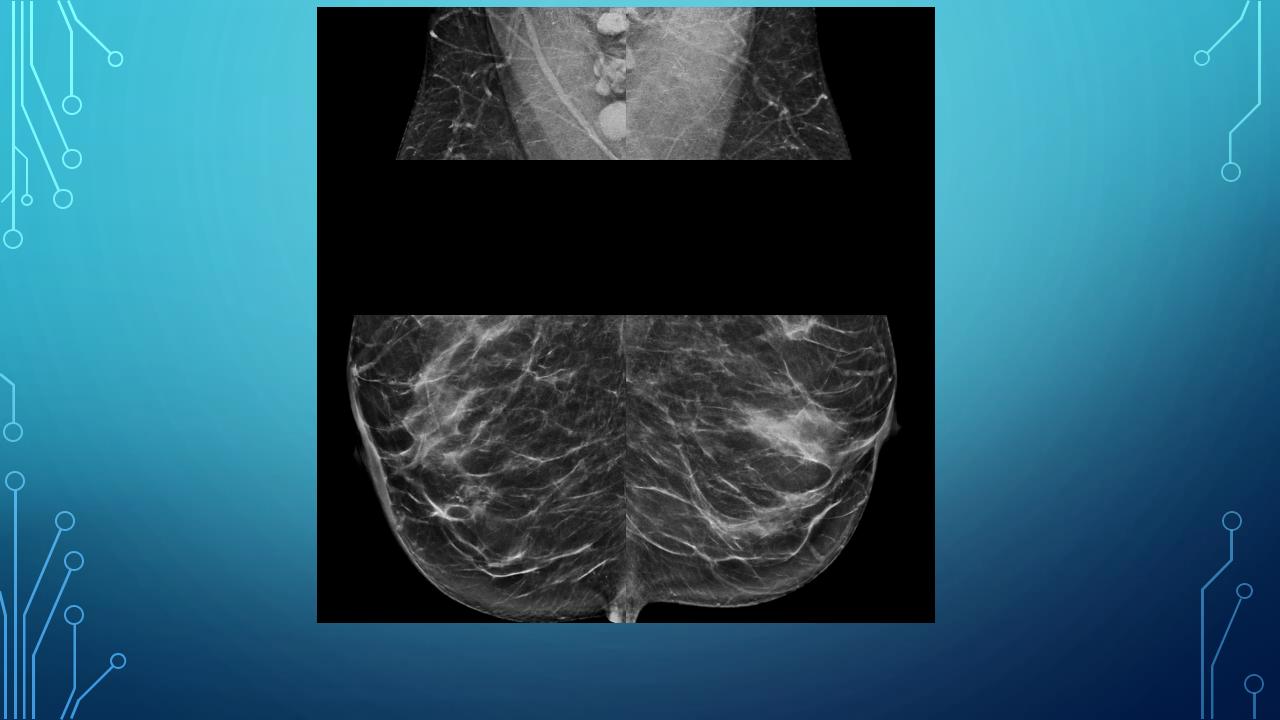












LIMITI DELL'INTELLIGENZA ARTIFICIALE

- Sistemi alcuni non completi.
- Alcuni falsi positivi banali: se istruiti all'errore possono migliorare e non lo ripetono più!
- Costi(?)
- Protezione dei dati e sicurezza in generale sulla provenienza, costruzione, inattaccabilità del software

CONCLUSIONI

- L'intelligenza artificiale è già qui... anche se non è ancora una intelligenza!
- Sta a noi sfruttarla al meglio sempre nel rispetto della sicurezza e della etica
- In senologia aiuta il radiologo se ne conosce bene le potenzialità ed i limiti

IL FUTURO

Si arriverà ad una superintelligenza delle macchine? In medicina e senolgia quanto cambierà il lavoro?

« Il futuro appartiene a quelli che si preparano per esso oggi» Malcom X Grazie per l'attenzione! paolocab@libero.it

