Associazione Italiana Tecnici di Radiologia Tomografia Computerizzata

SISTEMA SANITARIO REGIONALE
ASL ROMA 1

SAPIENZA UNIVERSITÀ DI ROMA

Applicazioni avanzate dell'I.A. in TC

M. Iacono - R. Cicchetti

Formazione per l'eccellenza

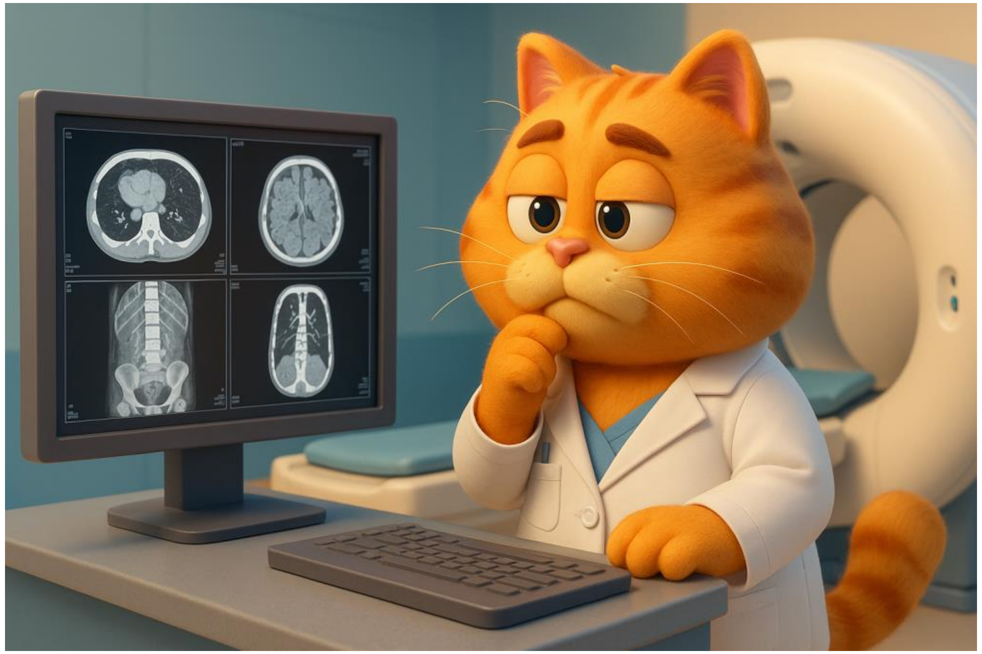
Ordine dei tecnici sanitari di radiologia medica e delle professioni sanitarie tecniche, della riabilitazione e della prevenzione Viterbo.

Rivista.AI

Perché oggi parliamo di IA in TC?

“La domanda non è se l’IA sostituirà i radiologi o i TSRM, ma se chi adotterà l’IA sostituirà chi non lo farà”

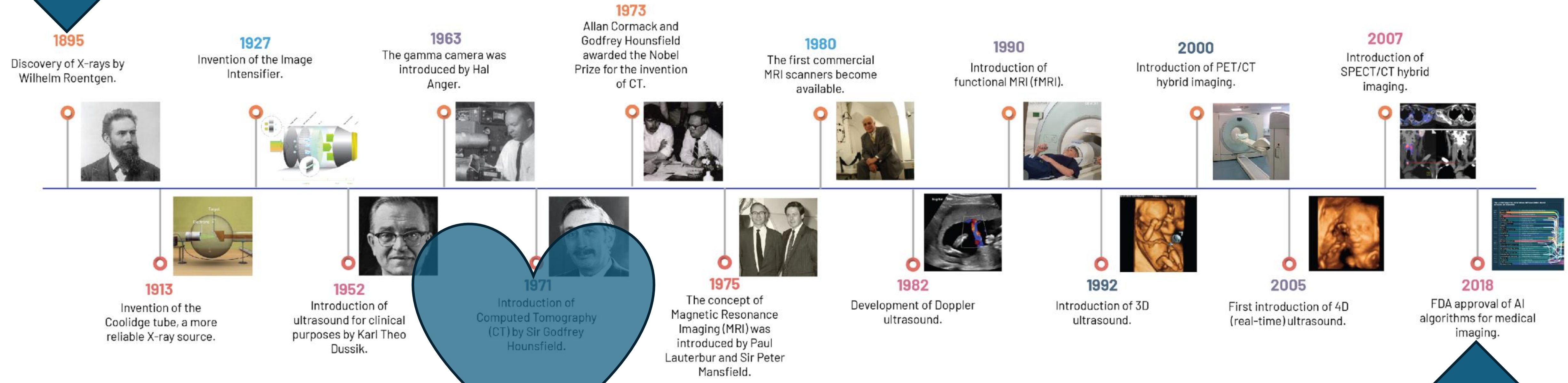
Curtis Langlotz, Professor of Radiology, Medicine, and Biomedical Data Science
Director of the Center for AI in Medicine and Imaging Stanford University



KEY-POINTS

1.0 Introduzione — 2.0 IA nel pre-scan — 3.0 Algoritmo DLR — 4.0 Post-scan e Radiomica

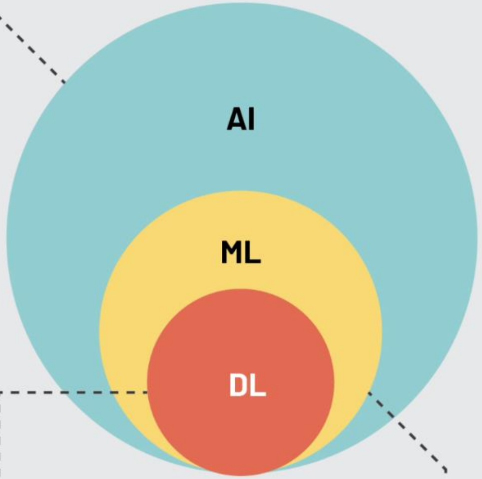
Cronologia delle scoperte più importanti nell'imaging medico



Hierarchy of AI, ML, and DL

Artificial Intelligence (AI)

The development of intelligent machines capable of performing tasks that typically require human intelligence.



Machine Learning (ML)

Algorithms that enable computers to learn and improve from experience without explicit programming.

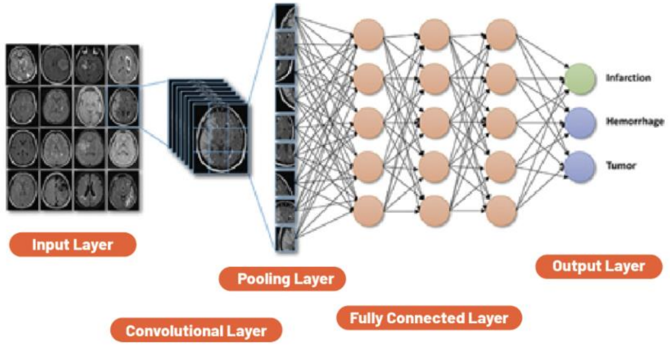
Deep Learning (DL)

A subset of machine learning that utilises neural networks with multiple layers to automatically learn and extract intricate patterns and features from data.

Types of ML

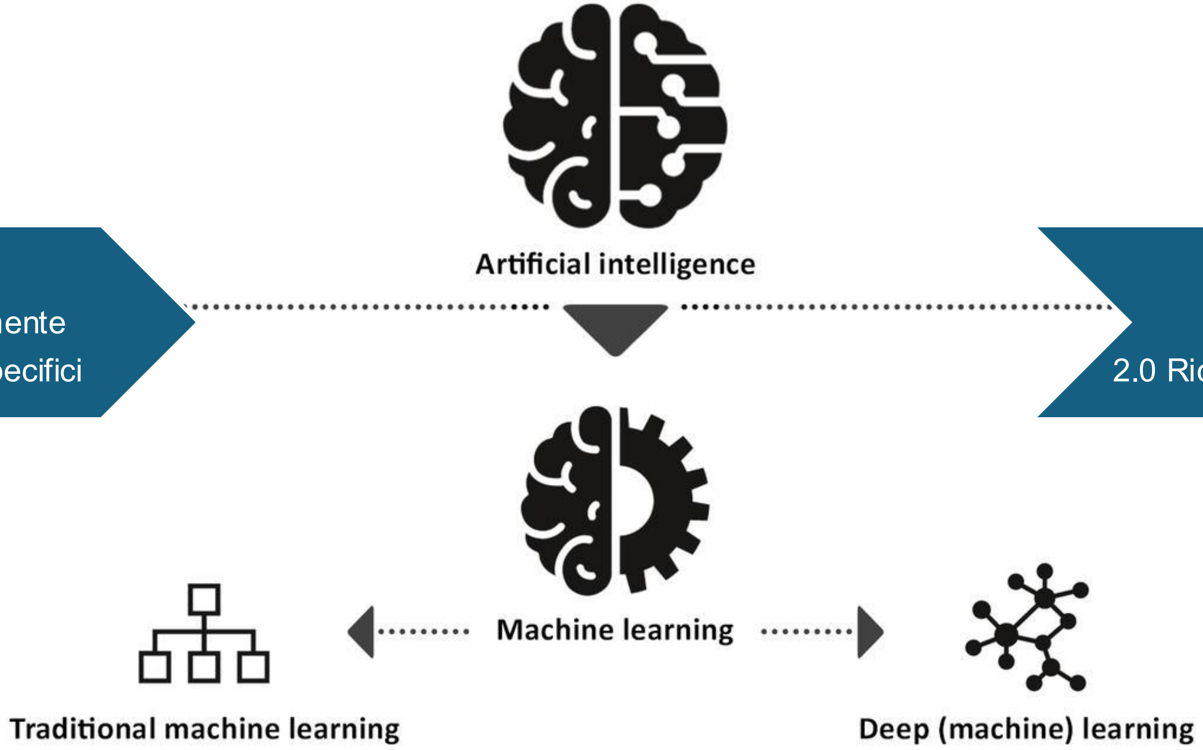
- **Supervised Learning:** ML algorithm learns from labeled data with known input-output pairs.
- **Unsupervised Learning:** ML algorithm learns patterns and structures from unlabeled data without predefined outputs.

Neural Network Layers



Il ML permette alla macchina di adattarsi a nuove situazioni, riconoscere ed estrapolare pattern nei dati

Il ***ML*** tradizionale:
1.0 Usa algoritmi progettati manualmente
2.0 Metodi specializzati per compiti specifici



*Il **DL**:*
1.0 Utilizza le reti neurali
2.0 Riconosce pattern non riconoscibili con ML

Rivista.AI

Gli algoritmi IA abbracciano l'intero workflow TC

FASE	*FUNZIONE*
PRE ACQUISIZIONE	• *Centraggio automatico* • *Protocollo e volume di scansione*
ACQUISIZIONE	• *Algoritmo di ricostruzione dell'immagine* • *Dose e qualità dell'immagine*
POST ACQUISIZIONE	• *Applicazioni cliniche avanzate* • *Radiomica*

IA NEL PRE SCAN TC

Radiation dose reduction, improved isocenter accuracy and CT scan time savings with automatic patient positioning by a 3D camera

Bari Dane [1], Thomas O'Donnell [2], Shu Liu [3], Emilio Vega [4], Sharon Mohammed [5], Vivek Singh [6], Ankur Kapoor [7], Alec Megibow [8]

Affiliations + expand

PMID: 33454459 DOI: 10.1016/j.ejrad.2021.109537

- OBIETTIVO DELLO STUDIO (Dane et al.)

Confrontare **accuratezza dell'isocentro**, **dose radiante** e **tempi di scansione** tra TC effettuate con e senza l'uso di una camera 3D per il posizionamento del paziente

Fig. 3. Left: Color image of a patient laying supine on the CT scan table anonymized by the black oval covering their face. Right: Depth image of the same patient from the 3D camera. The whiter the pixel, the closer that part of the body is to the camera.

Fig. 2. 3D camera. The 3D camera is positioned on the ceiling above the CT scanner. It uses infrared imaging to measure how far away the patient is from the camera and automatically adjusts the table height so the patient should be isocentered when the patient table moves into the CT gantry.

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VANTAGGI

➢ **Maggiore accuratezza nel posizionamento**

Scostamento medio dall'isocentro reale:

- **6.8 mm** con camera 3D
- **16.3** mm senza camera

Il 93% dei TSRM ha accettato la posizione suggerita dalla camera senza modificarla

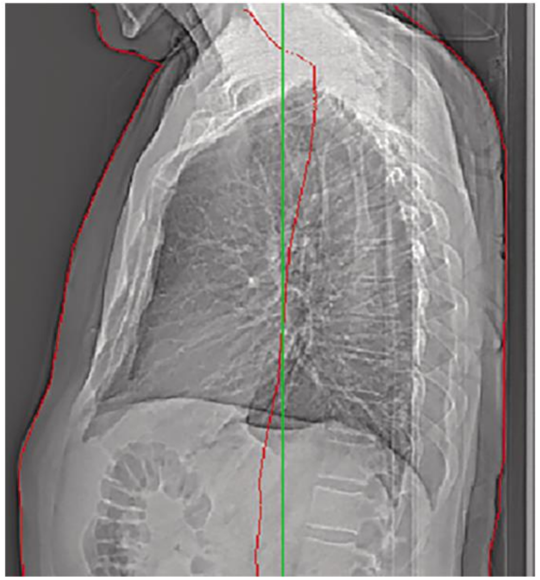

Fig. 5. True AP isocenter determination schematic. The red line indicates the AP isocenter along each point of the CT scan volume. The average isocenter along the CT scan volume z-axis indicated by the green line is used to determine true isocenter.

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VANTAGGI

➢ **Riduzione di dose con la camera 3D per i protocolli principali di acquisizione:**

da -1.0 a -2.4 mGy, pari a un risparmio di dose dal 17% al 31%

- TC torace (paziente sesso femminile): **−1.4 mGy**
- Entero TC: **−2.1 mGy**
- Uro TC: **−2.4 mGy**

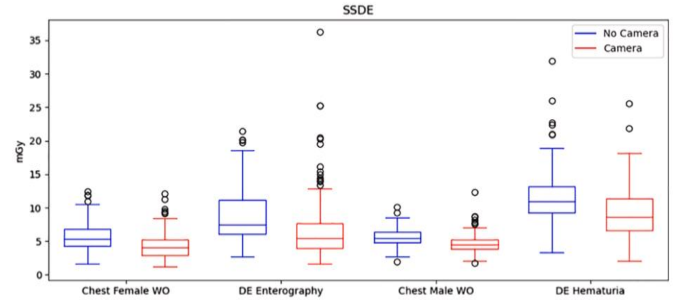

Fig. 6. Box plot showing SSDE for the 4 most common CT examination protocols with (red) and without (blue) the 3D camera.

Table 4
Patient size comparison with and without 3D camera for the 4 most common CT protocols.

Protocol	Cohort	AP thickness (cm)	Weight (kg)	Height (m)	BMI (kg/m^2)
Reduced Dose Chest CT without contrast (Female)	Camera	405.7	68.3	1.61	26.4
	No camera	366.9	67.0	1.61	25.8
	p	<0.01	0.48	0.98	0.39
Abdominopelvic CT Enterography	Camera	420.6	73.6	1.67	26.4
	No camera	408.4	78.6	1.69	27.5
	p	0.13	0.02	0.04	0.11
Reduced Dose Chest CT without contrast (Male)	Camera	409.7	87.0	1.77	27.9
	No camera	392.4	82.8	1.76	26.6
	p	<0.01	0.13	0.99	0.09
Hematuria Protocol Abdominopelvic CT	Camera	402.8	75.6	1.7	26.0
	No camera	397.1	81.6	1.7	28.0
	p	0.32	<0.01	0.97	<0.01

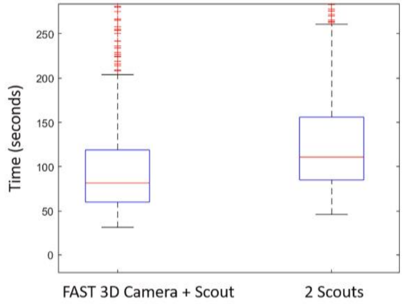

Fig. 8. Box plot comparing scout time of Camera Cohort (left) with No Camera Cohort (right). Scout time is shorter for Camera Cohort (left) compared with No Camera Cohort (right).

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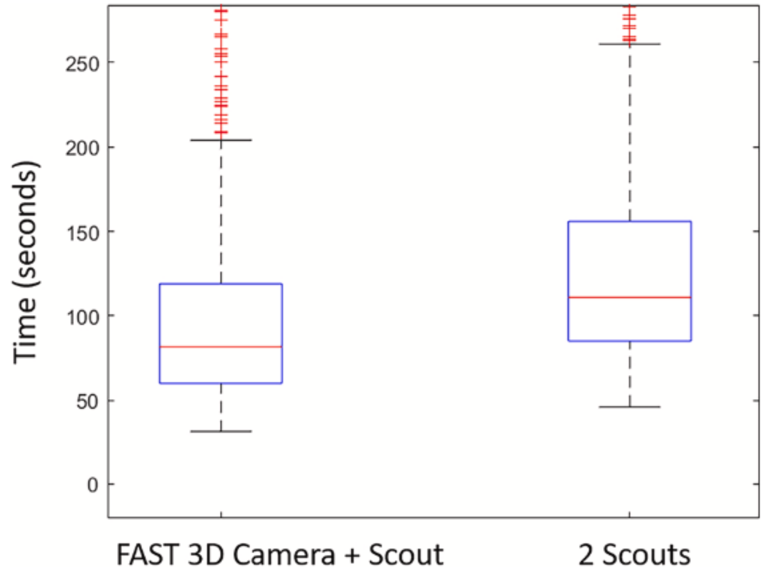
VANTAGGI

➢ **Risparmio di tempo**

- Tempo di acquisizione del topogramma ridotto di 32 secondi (1 solo scanogramma)
- Tempo totale scansione: risparmiati 17–19 secondi in media a paziente



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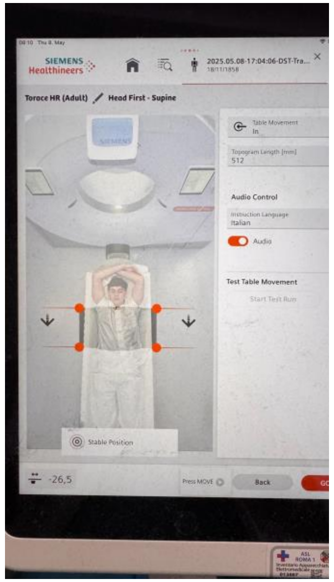
➢ VANTAGGI PER IL TSRM

- Riduzione degli errori di posizionamento
- Possibilità di gestire tutto da tablet, anche fuori dalla sala TC
- Contribuisce a ridurre il carico operativo e aumenta la produttività



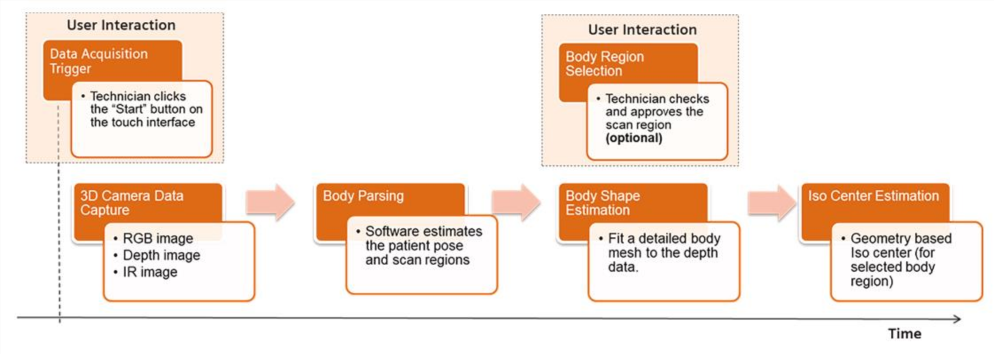


Fig. 4. 3D Camera algorithm for human body surface geometry estimation.

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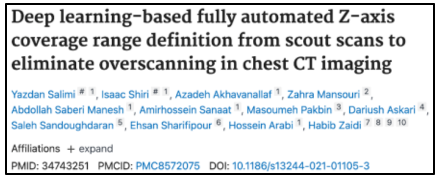
IA NEL PRE SCAN TC


Deep learning-based fully automated Z-axis coverage range definition from scout scans to eliminate overscanning in chest CT imaging

Yazdan Salimi # 1, Isaac Shiri # 1, Azadeh Akhavanallaf 1, Zahra Mansouri 2, Abdollah Saberi Manesh 1, Amirhossein Sanaat 1, Masoumeh Pakbin 3, Dariush Askari 4, Saleh Sandoughdaran 5, Ehsan Sharifipour 6, Hossein Arabi 1, Habib Zaidi 7 8 9 10

Affiliations + expand

PMID: 34743251 PMCID: PMC8572075 DOI: 10.1186/s13244-021-01105-3

➢ OBIETTIVO DELLO STUDIO (Salimi et al.)

Sviluppare un algoritmo DL per definire automaticamente il range lungo l'asse Z da scout AP e LL

TRICKS: overscanning presente nel 95-99% dei casi, soprattutto in senso caudale → Aumenta la dose agli organi

Confrontare:

- ***Range definito dal TSRM***
- ***Range automatico ottenuto da segmentazione 3D***

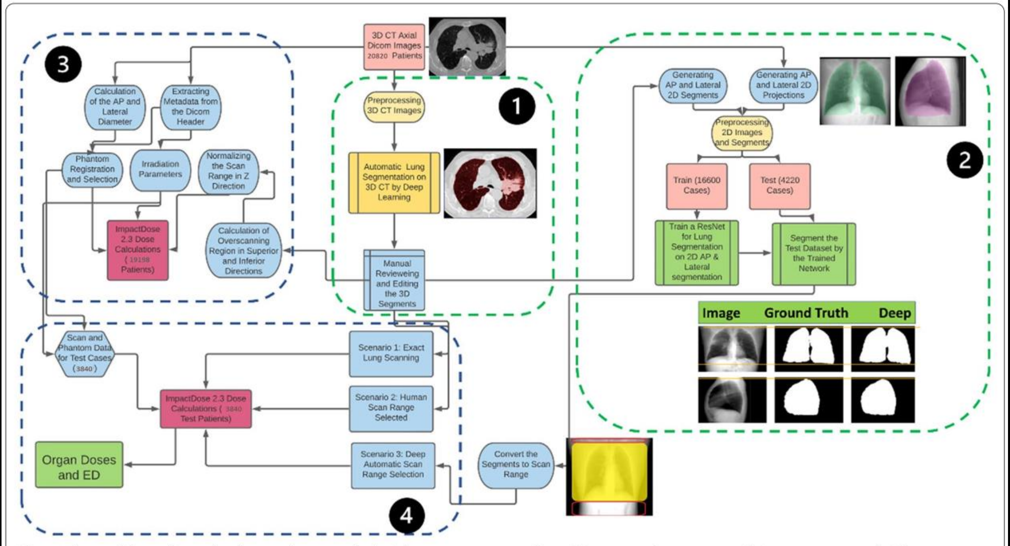


Fig. 1 The workflow adopted in this study protocol. 1) 3D lung segmentation from CT images, 2) generation of 2D projections and 2D lung segments from 3D images and training the deep learning network for semantic segmentation, 3) extracting the metadata and estimating the dosimetric impact of overscanning for all 20,820 patients. 4) Calculation of the ED and organ doses based on three scenarios described in the text

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➢ **Risultati principali**

- Errore medio DL:

Superiore +0.08 mm
Inferiore: –1.5 mm

- DL più accurato del TSRM (p < 0.001)
- Dose efficace totale ridotta del 21% (~1.3 mSv)
- Dose alla tiroide: –67%

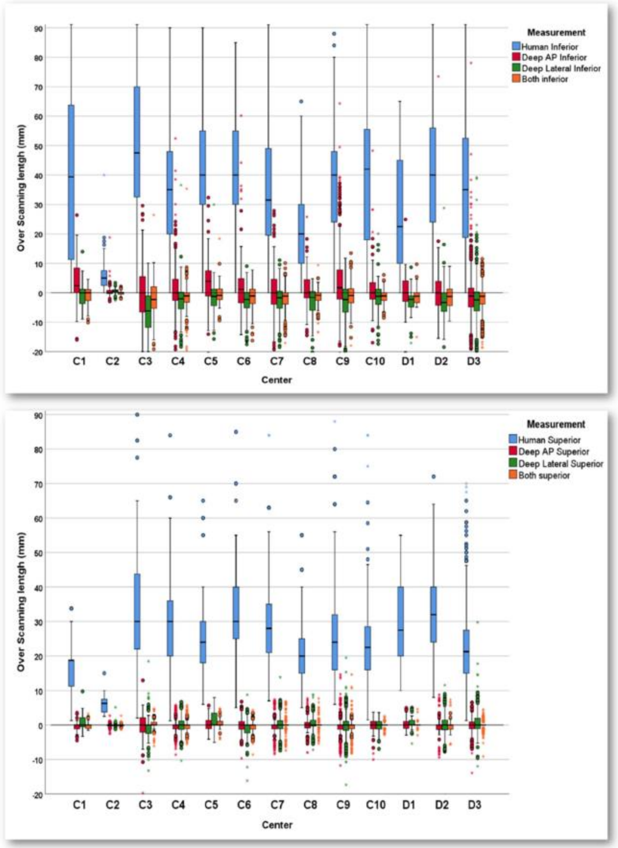

Fig. 4 Error from the desired exact lung coverage in the superior (bottom) and inferior (top) directions according to the technologist (Human) performance and DL approach based on AP, lateral, and both projections for different categories of datasets

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Affiliations + expand

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- **Vantaggi per il TSRM**

- Riduzione dose paziente (tiroide, fegato)
- Supporto decisionale automatizzato
- Accuratezza anche in scarse condizioni cliniche (es. pneumotorace, pz obeso)
- Tempo di scansione ottimizzato

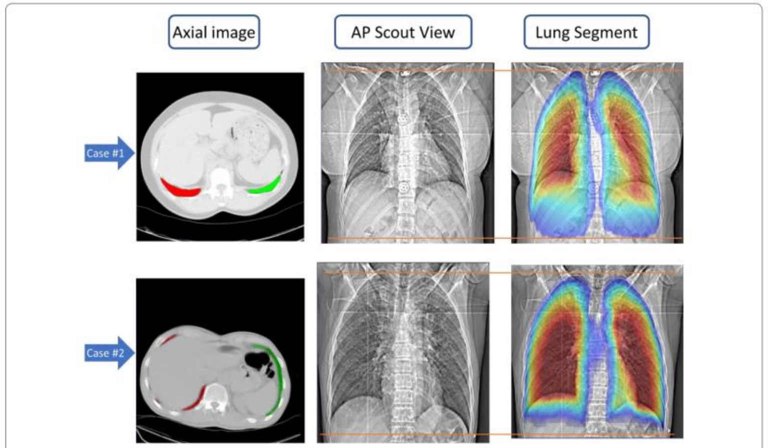

Fig. 7 Display of the axial CT image and the segmented lungs (left), AP scout view (middle) and the segmented lung overlaid on the AP scout view (right) for two clinical studies. The red line indicates the desired scan limit in the inferior direction. The colored segments show the thickness of the lung segment in any region, where the red and blue colors stand for the thicker and narrower lung segments, respectively

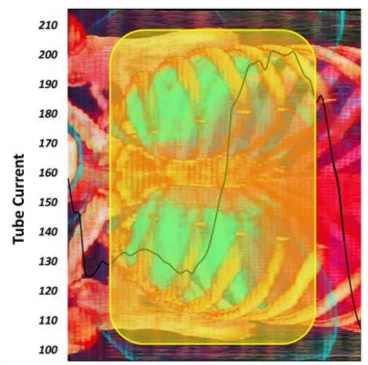

Fig. 6 Tube current pattern (black line—mA) in the craniocaudal (left to right) direction. The yellow box indicates the lung segment boundaries

Algoritmo DLR in TC

- **CHE COSA E’ L’ALGORITMO DLR**

- Tecnica di ricostruzione delle immagini basata su reti neurali
- Supera i limiti di FBP e IR
- Apprende da grandi dataset per ricostruire le immagini TC

SI BASA SU
PROGETTAZIONE, ADDESTRAMENTO, VERIFICA

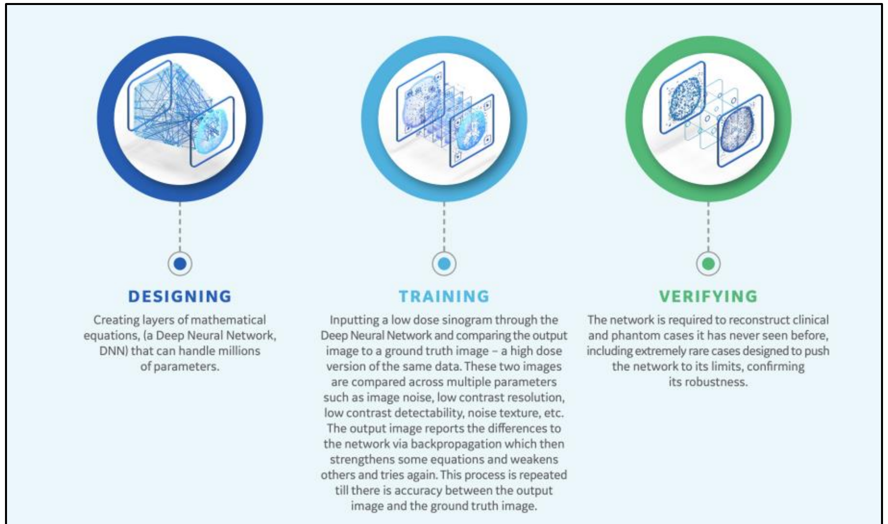

Figure 5: Key phases of designing the deep learning image reconstruction engine.

Review > Radiology. 2023 Mar;306(3):e221257. doi: 10.1148/radiol.221257. Epub 2023 Jan 31.

Deep Learning Image Reconstruction for CT: Technical Principles and Clinical Prospects

Lennart R Koetzier [#] [1], Domenico Mastrodicasa [#] [1], Timothy P Szczykutowicz [1], Niels R van der Werf [1], Adam S Wang [1], Veit Sandfort [1], Aart J van der Molen [1], Dominik Fleischmann [1], Martin J Willemink [1]

Affiliations + expand

PMID: 36719287 PMCID: PMC9968777 DOI: 10.1148/radiol.221257

➢ RICORDA CHE

- *FBP è veloce, ma comporta rumore a basse dosi*

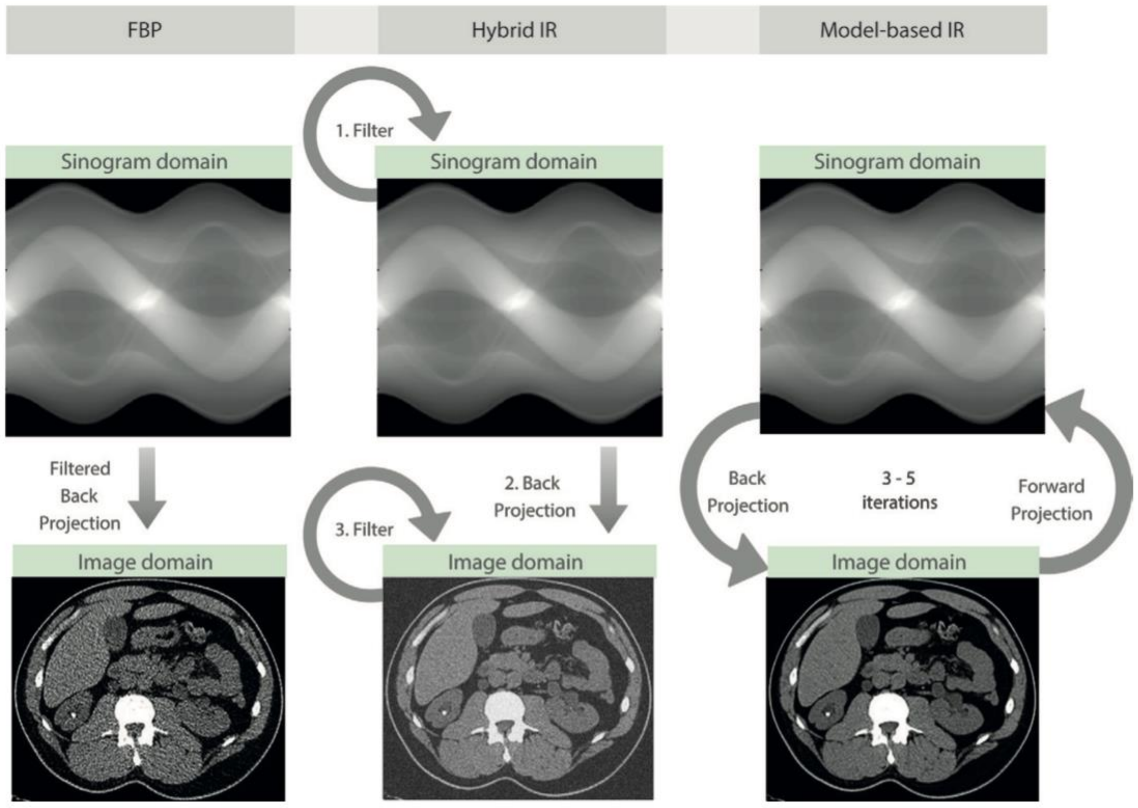

Figure 1: Overview of filtered back projection (FBP), hybrid iterative reconstruction (IR), and model-based IR. With FBP, projection data (sinograms) are filtered by a high-pass filter and subsequently backward-projected into the image … ms are iteratively filtered to reduce artifacts and backward-projected into the image domain; then, images are iteratively filtered … model-based IR, sinograms are backward-projected into the image domain. Subsequently, with use of models of the acquisitio… the sinogram domain to generate artificial sinograms. The artificial sinograms are compared with the true sinograms to thereup… This process usually takes three to five iterations (right column).

Review > Radiographics. 2021 Sep-Oct;41(5):1493-1508. doi: 10.1148/rg.2021200196.

CT Noise-Reduction Methods for Lower-Dose Scanning: Strengths and Weaknesses of Iterative Reconstruction Algorithms and New Techniques

Payam Mohammadinejad [1], Achille Mileto [1], Lifeng Yu [1], Shuai Leng [1], Luis S Guimaraes [1], Andrew D Missert [1], Corey T Jensen [1], Hao Gong [1], Cynthia H McCollough [1], Joel G Fletcher [1]

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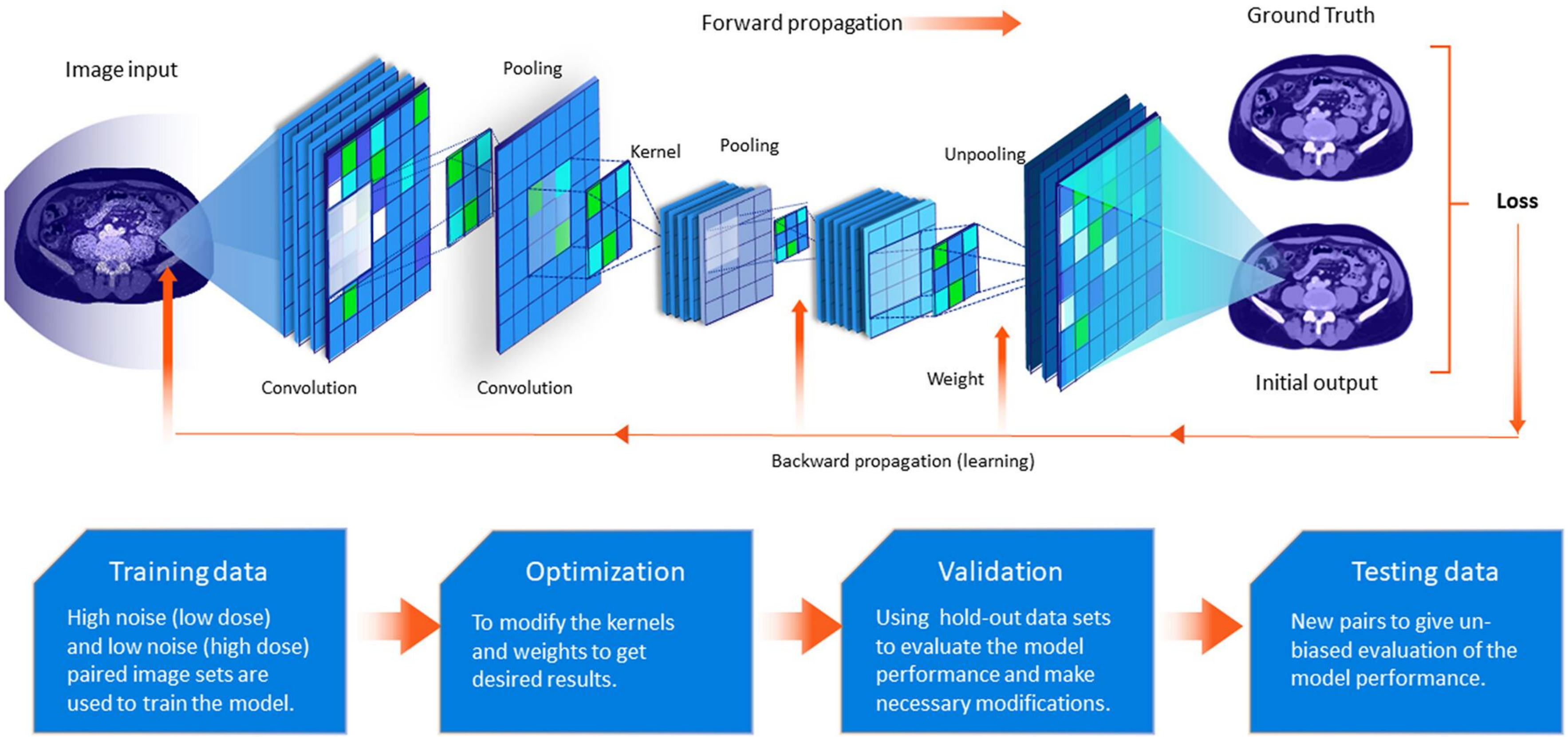

Layout of key steps in the training of a CNN. The network compares output and ground truth images using detected loss of information to iteratively learn and adjust through backward propagation.

Mileto A. Published Online: November 29, 2024
https://doi.org/10.1148/rg.240095

L'IA IN FASE DI ACQUISIZIONE

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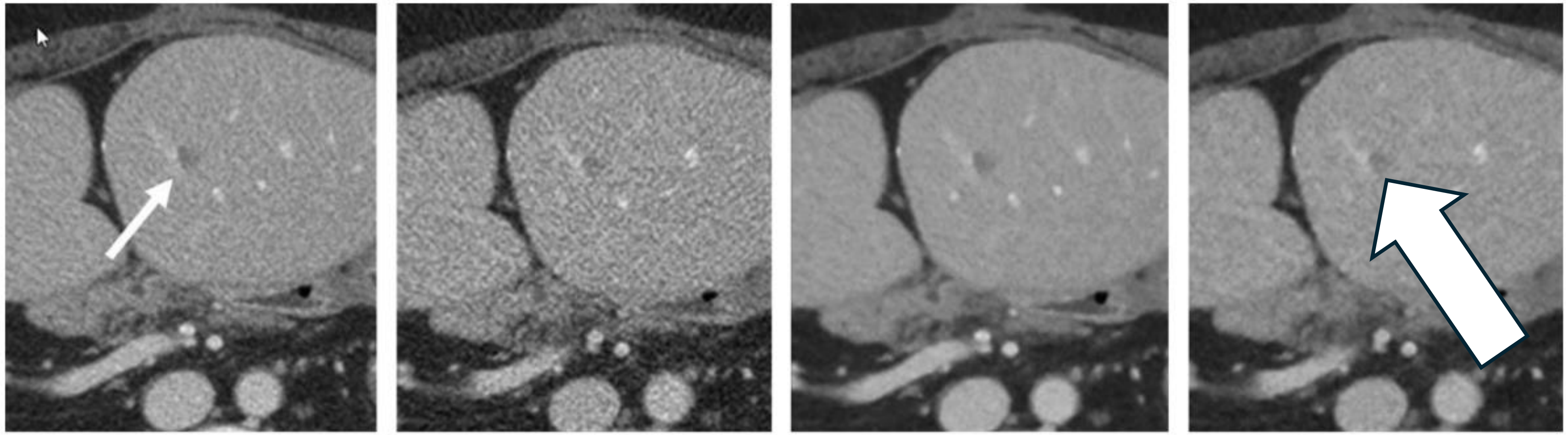
- o *IR riduce dose e rumore ma le immagini possono risultare meno naturali ('plastic look')*

- ➢ **TSRM TRICK:** *IR* ***modifica la texture e la risoluzione spaziale****, rendendo* ***meno affidabili parametri oggettivi*** *come CNR e MTF*



a. **b.** **c.** **d.**

Figure 8. FBP **(a, b)** and ASiR-V 60% **(c, d)** images from contrast-enhanced CT with a standard $CTDI_{vol}$ of 25 mGy **(a, c)** and a $CTDI_{vol}$ of 11 mGy **(b, d)** obtained in the same breath hold show a colorectal hepatic metastasis (arrow in **a**). The metastasis was not identified by one reader during evaluation of the reduced-dose ASiR-V 60% image **(d)**, and its identification was rated with lower confidence by the other two readers compared with on the standard-dose FBP image **(a)**, where the lesion was seen by all readers. These results demonstrate that IR algorithms are not able to preserve observer performance for detection of low-contrast liver lesions.

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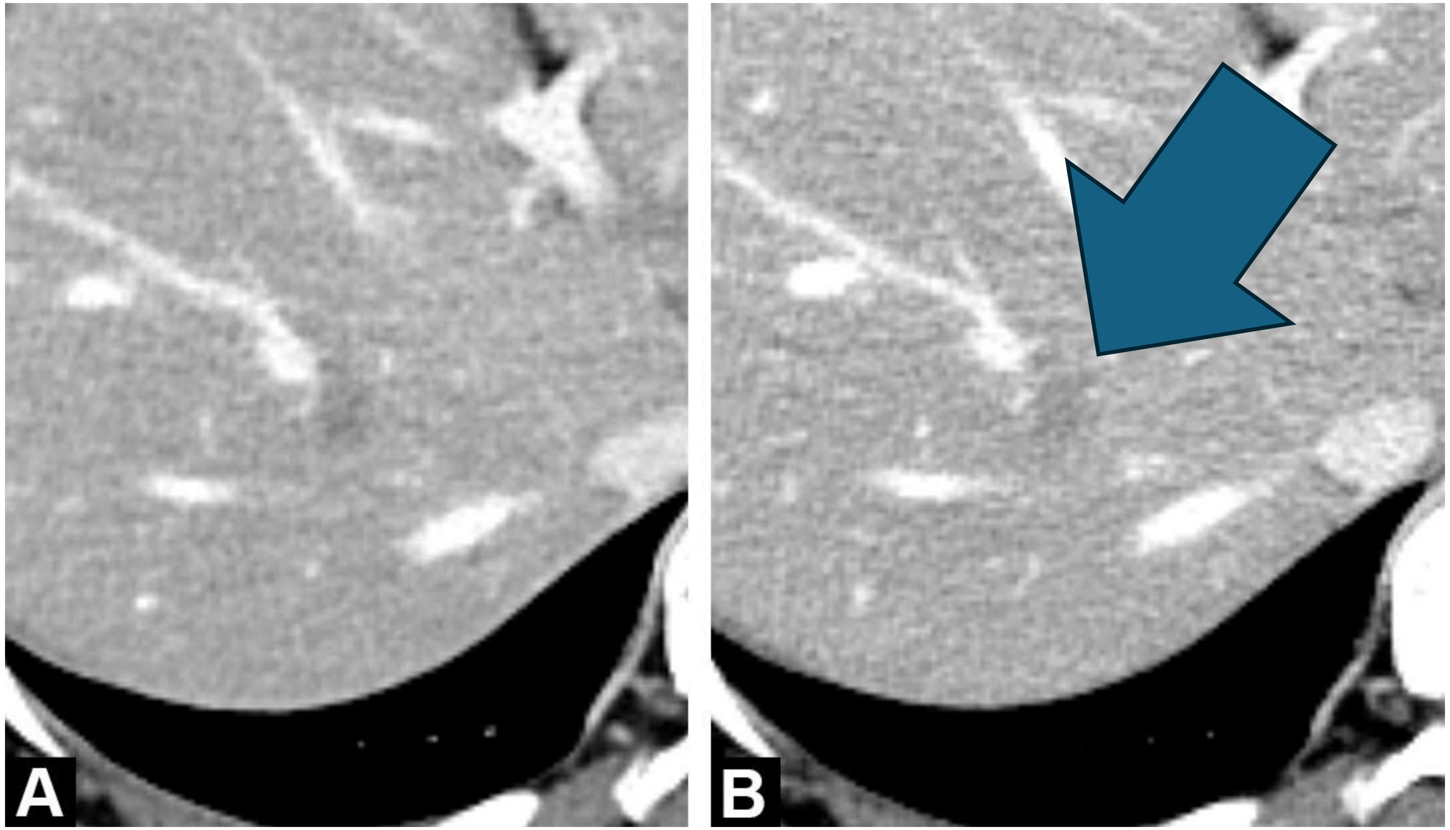

TrueFidelity DLR. Axial contrast-enhanced CT images show a colorectal adenocarcinoma metastasis (arrow in **B**) in the liver of a research participant. The image DLR with TrueFidelity at medium strength **(A)** shows slightly improved lesion conspicuity even at a 66% radiation dose reduction compared with that on the standard-dose FBP image **(B)** obtained in the same breath hold. Interestingly, this lesion was missed by a study reader using the standard-dose FBP images but identified by the same reader using the DLR technique.

Mileto A. Published Online: November 29, 2024
https://doi.org/10.1148/rg.240095

RadioGraphics

L'IA IN FASE DI ACQUISIZIONE

- **L'algoritmo DLR può agire:**

- ***Direttamente*** *al posto di FBP/IR*
- ***Indirettamente*** *prima o dopo di FBP/IR*

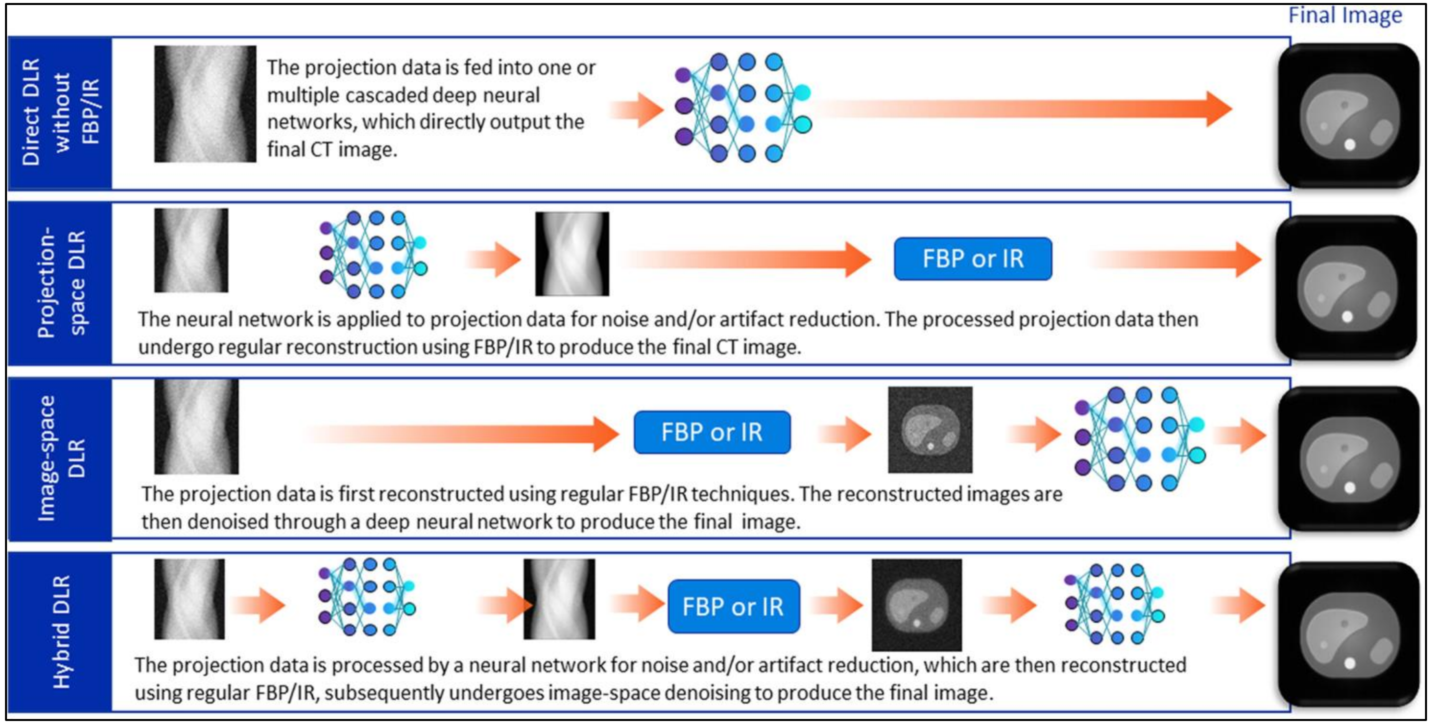

Figure ... ds.

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- ***Direttamente*** *al posto di FBP/IR*
- ***Indirettamente*** *prima o dopo di FBP/IR*

- **TSRM TIP: Studia le caratteristiche del tuo DLR (es. TrueFidelity, AiCE, Precise Image)!**

Table 1: Currently Commercially Available Deep Learning Algorithms

Algorithm Name	Algorithm Developer	Algorithm Class	Algorithm Type	Ground Truth Images
TrueFidelity	GE Healthcare	DLR	Direct	FBP
AiCE	Canon Medical Systems	DLR	Indirect, image-based	MBIR
Precise Image	Philips Healthcare	DLR	Direct	FBP
PixelShine	AlgoMedica	DLD	Image denoiser	FBP, HIR, MBIR
ClariCT.AI	ClariPi	DLD	Image denoiser	FBP

Note.—AiCE = Advanced Intelligent Clear-IQ Engine, DLR = deep learning reconstruction, DLD = deep learning–based denoiser, FBP = filtered back projection, HIR = hybrid iterative reconstruction, MBIR = model-based iterative reconstruction.

Review > Radiology. 2023 Mar;306(3):e221257. doi: 10.1148/radiol.221257. Epub 2023 Jan 31.

Deep Learning Image Reconstruction for CT: Technical Principles and Clinical Prospects

Lennart R Koetzier [#, 1], Domenico Mastrodicasa [#, 1], Timothy P Szczykutowicz [1], Niels R van der Werf [1], Adam S Wang [1], Veit Sandfort [1], Aart J van der Molen [1], Dominik Fleischmann [1], Martin J Willemink [1]

Affiliations + expand

PMID: 36719287 PMCID: PMC9968777 DOI: 10.1148/radiol.221257

LA SFIDA DEL RUMORE A BASSA DOSE

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➢ TSRM TIPS

- *DLR riduce la dipendenza del rumore dalla dose*
- *Migliore SNR, CNR e minor SD anche in spessori sottili*
- *Texture più naturale rispetto a MBIR, meno "plasticosa"*

Essentials

- Deep learning reconstruction (DLR) algorithms can be applied in the raw data domain, image domain, or both.
- Compared with filtered back projection and hybrid iterative reconstruction (HIR), DLR provides improved image quality.
- DLR potentially allows for radiation dose reductions between 30% and 71% compared with HIR while maintaining diagnostic image quality due to improved noise reduction.
- Deep learning–based metal artifact reduction (MAR) has the potential to remove metal artifacts more accurately than current state-of-the-art MAR methods.

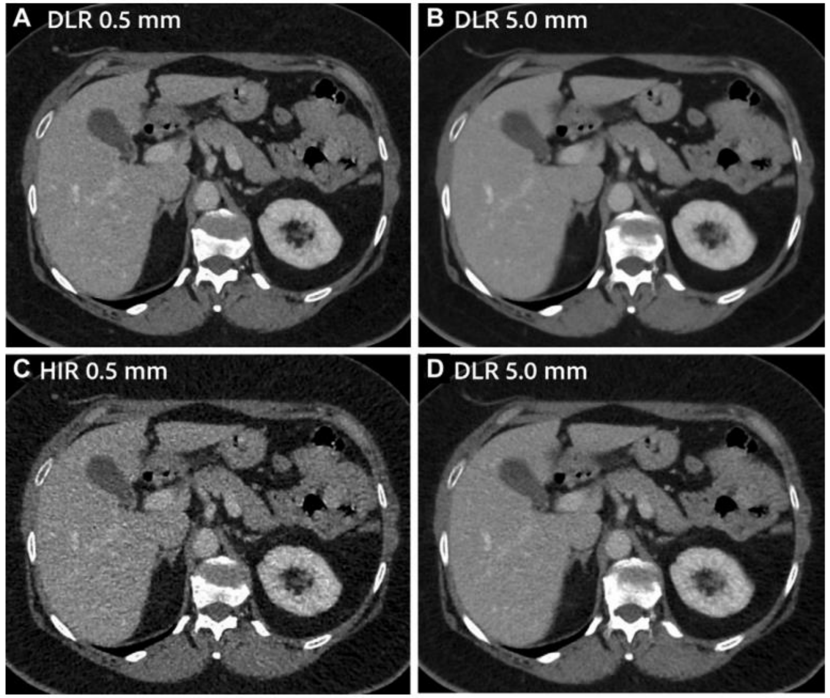

Figure 10: Contrast-enhanced axial abdominal CT images in a 63-year-old woman with recurrent endometrial carcinoma. Images were acquired at 120 kVp and 343 mA and reconstructed with **(A)** 0.5-mm Advanced Intelligent Clear-IQ Engine (AiCE), **(B)** 5.0-mm AiCE, **(C)** 0.5-mm hybrid iterative reconstruction (HIR), and **(D)** 5.0-mm HIR. AiCE is an indirect image-based deep learning reconstruction (DLR) algorithm. Thin sections in reconstructions **A** and **C** preserved spatial resolution but had more image noise compared with thick sections in reconstructions **B** and **D**. AiCE keeps image noise low in thin sections, whereas HIR leads to unacceptable higher levels of noise in 0.5-mm images.

TRICKS TECNICI

- ***Attenzione alla texture del rumore***

Se il radiologo dice: “immagine plasticosa”, probabilmente è un MBIR spinto

DLR mantiene texture simile a FBP → + confidenza diagnostica

- ***Se puoi, spingi su protocolli a bassa dose***

DLR consente riduzioni di dose dal 30% al 71%

Provalo in addome o torace nei follow-up!

AJR Am J Roentgenol. 2020 Jul;215(1):50-57. doi: 10.2214/AJR.19.22332. Epub 2020 Apr 14.

Image Quality Assessment of Abdominal CT by Use of New Deep Learning Image Reconstruction: Initial Experience

Corey T Jensen [1], Xinming Liu [2], Eric P Tamm [1], Adam G Chandler [2], Jia Sun [3], Ajaykumar C Morani [1], Saeed Javadi [1], Nicolaus A Wagner-Bartak [1]

Affiliations + expand

PMID: 32286872 DOI: 10.2214/AJR.19.22332

TRICKS TECNICI

➢ *"ATTENZIONE ALLA FORZA DEL DLR"*

DLIR e lesioni < 5 mm (Jensen et al., AJR 2020)

- *Con DLR-H si può osservare **blurring** di **lesioni puntiformi ipodense** (< 5 mm) e di **piccoli vasi iperdensi** (post mdc), con valutazioni talora inferiori rispetto a DLIR-M o ASIR-V*
- *DLR-M rappresenta spesso il **miglior compromesso tra qualità d'immagine** e **CNR***
- ***L'ottimizzazione di Window e Level** può migliorare la visualizzazione di strutture sfocate con DLIR-H*

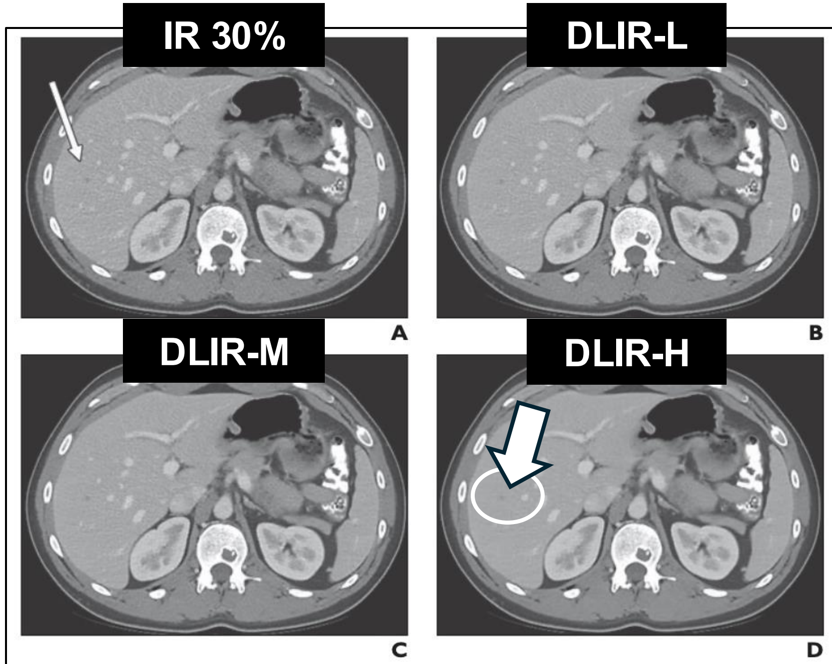

Fig. 3—26-year-old man with testicular germ cell tumor.
A–D, Axial contrast-enhanced CT images of same anatomic location show image quality comparison between standard 30% adaptive statistical iterative reconstruction V (30% ASIR-V) (**A**) and low-strength (**B**), medium-strength (**C**), and high-strength (**D**) deep learning image reconstruction (DLIR). Hepatic metastasis (*arrow*, **A**) measuring 0.5 cm is present in right liver. Readers rated overall image quality, lesion diagnostic confidence, and lesion conspicuity higher with progressively stronger levels of DLIR compared with 30% ASIR-V. Readers reported that benefit of image noise reduction generally outweighed concerns about small lesion or vessel blurring but that use of lower denoising strengths (low- or medium-strength DLIR) mitigated this concern.

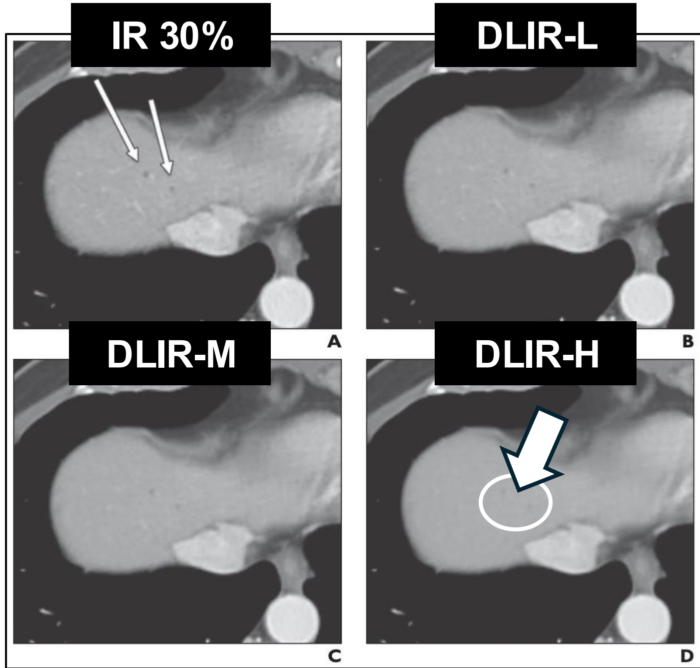

Fig. 5—65-year-old woman with bladder cancer.
A, Axial contrast-enhanced CT image reconstructed with 30% adaptive statistical iterative reconstruction V shows two punctate long-term stable presumed hepatic cysts (*arrows*).
B–D, Axial contrast-enhanced CT images reconstructed with low-strength (**B**), medium-strength (**C**), and high-strength (**D**) deep learning image reconstruction (DLIR) show that cysts in **A** become blurred with increasing strengths of DLIR, resulting in lower reader scores for lesion confidence and conspicuity on high-strength DLIR image.


Review > Radiology. 2023 Mar;306(3):e221257. doi: 10.1148/radiol.221257. Epub 2023 Jan 31.

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Affiliations + expand

PMID: 36719287 PMCID: PMC9968777 DOI: 10.1148/radiol.221257

TRICKS TECNICI

- ***DLR e artefatti metallici: sì, ma con criterio***

La DLR è efficace sui metal artifacts, ma va usata in sinergia con MAR

Le migliori riduzioni si ottengono con pipeline: MAR → DLR

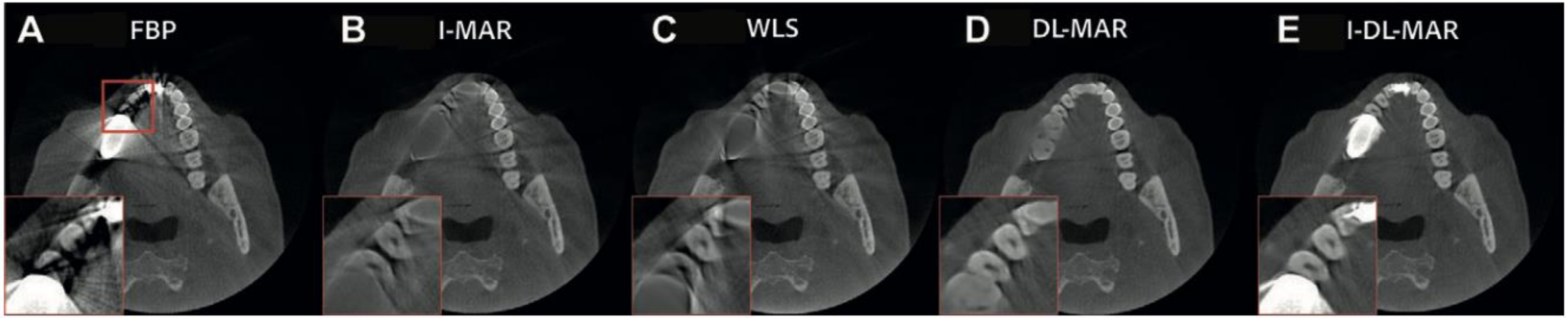

Figure 7: Images in a patient with a metal dental implant. Images were reconstructed with **(A)** filtered back projection (FBP), **(B)** interpolation metal artifact reduction (I-MAR), **(C)** weighted least square (WLS) iterative reconstruction, **(D)** deep learning metal artifact reduction (DL-MAR), and **(E)** sequential combination of I-MAR and DL-MAR (I-DL-MAR). The zoomed-in inset from the upper red box in image **A** shows shading and streak artifacts. The red boxes in images **B**, **C**, **D**, and **E** show the restoration of metal artifacts. Note the clear restoration quality of I-DL-MAR in image **E**. Reprinted, with permission, from reference 56.

Formazione per l'eccellenza

Ordine dei tecnici sanitari di radiologia medica e delle professioni sanitarie tecniche, della riabilitazione e della prevenzione Viterbo

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Review > Radiology. 2023 Mar;306(3):e221257. doi: 10.1148/radiol.221257. Epub 2023 Jan 31.

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PMID: 36719287 PMCID: PMC9968777 DOI: 10.1148/radiol.221257

TRICKS TECNICI

- TSRM TIPS:

- ***DLR riduce gli artefatti metallici meglio dei metodi classici***
- ***Occhio alle "hallucinations": falsi positivi/negativi se la rete non è addestrata correttamente!***

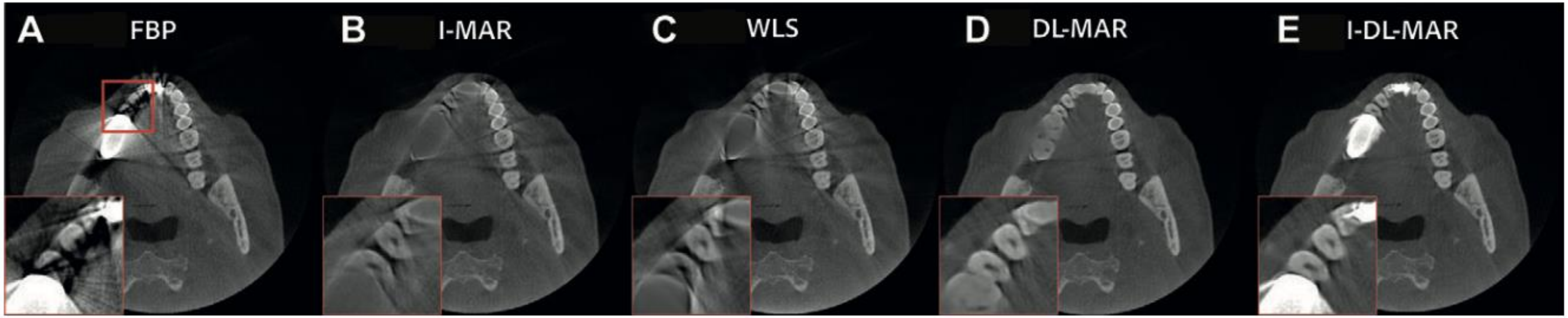

Figure 7: Images in a patient with a metal dental implant. Images were reconstructed with **(A)** filtered back projection (FBP), **(B)** interpolation metal artifact reduction (I-MAR), **(C)** weighted least square (WLS) iterative reconstruction, **(D)** deep learning metal artifact reduction (DL-MAR), and **(E)** sequential combination of I-MAR and DL-MAR (I-DL-MAR). The zoomed-in inset from the upper red box in image **A** shows shading and streak artifacts. The red boxes in images **B**, **C**, **D**, and **E** show the restoration of metal artifacts. Note the clear restoration quality of I-DL-MAR in image **E**. Reprinted, with permission, from reference 56.

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TSRM TIPS

➢ ***DLR è un game-changer nei bambini***

Alta qualità anche a dosi molto basse.

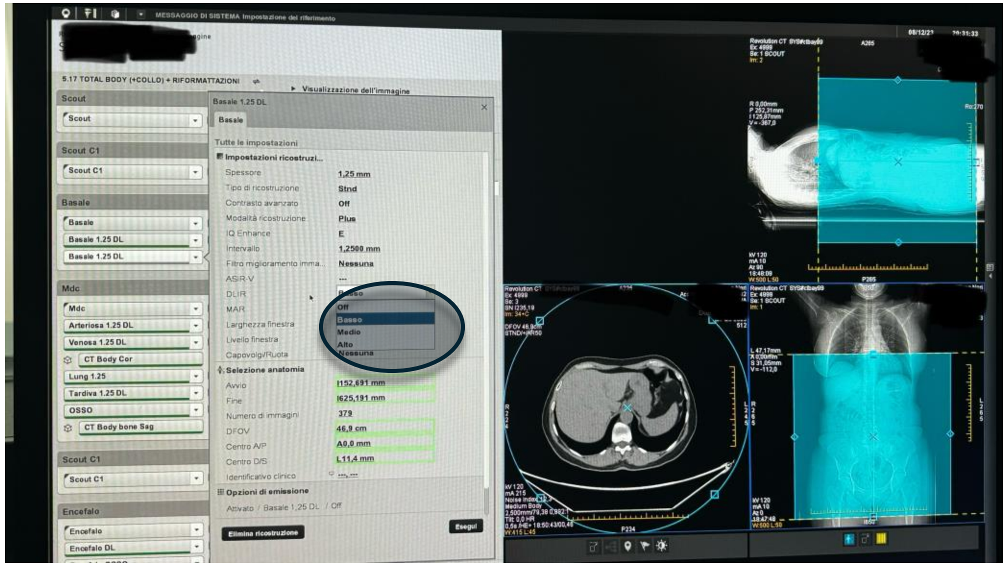
Usalo sempre se disponibile!

Figure 11: Contrast-enhanced axial abdominal CT images in a 2-year-old boy after chemotherapy for hepatoblastoma show multiple areas of necrosis within the hepatic tumor. Images were acquired at 80 kVp with a volumetric CT dose index of 1.79 mGy and reconstructed with **(A)** 3.75-mm hybrid iterative reconstruction (HIR) standard kernel, **(B)** 1.25-mm HIR standard kernel, and **(C)** 1.25-mm TrueFidelity deep learning reconstruction (DLR)–high weight standard kernel. TrueFidelity is a direct DLR algorithm. Thin-section HIR in image **B** shows reduced low-contrast detectability and lesion delineation due to elevated image noise and deteriorated noise texture. Thin-section DLR in image **C** mimics the thicker-section HIR in image **A** in terms of image noise but shows improved spatial resolution.

L'IA IN FASE DI ACQUISIZIONE

- DLR consente protocolli ***ultra-low dose***
- Il TSRM deve conoscere ***la forza del DLR*** (basso – medio – alto)
- Attenzione alla ***selezione del protocollo***: DLR non sostituisce l'esperienza

L'obiettivo è ottimizzare la dose senza compromettere la diagnosi!



DLR in Dual Energy TC

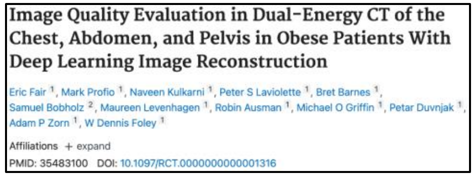


Image Quality Evaluation in Dual-Energy CT of the Chest, Abdomen, and Pelvis in Obese Patients With Deep Learning Image Reconstruction

Eric Fair [1], Mark Profio [1], Naveen Kulkarni [1], Peter S Laviolette [1], Bret Barnes [1], Samuel Bobholz [2], Maureen Levenhagen [1], Robin Ausman [1], Michael O Griffin [1], Petar Duvnjak [1], Adam P Zorn [1], W Dennis Foley [1]

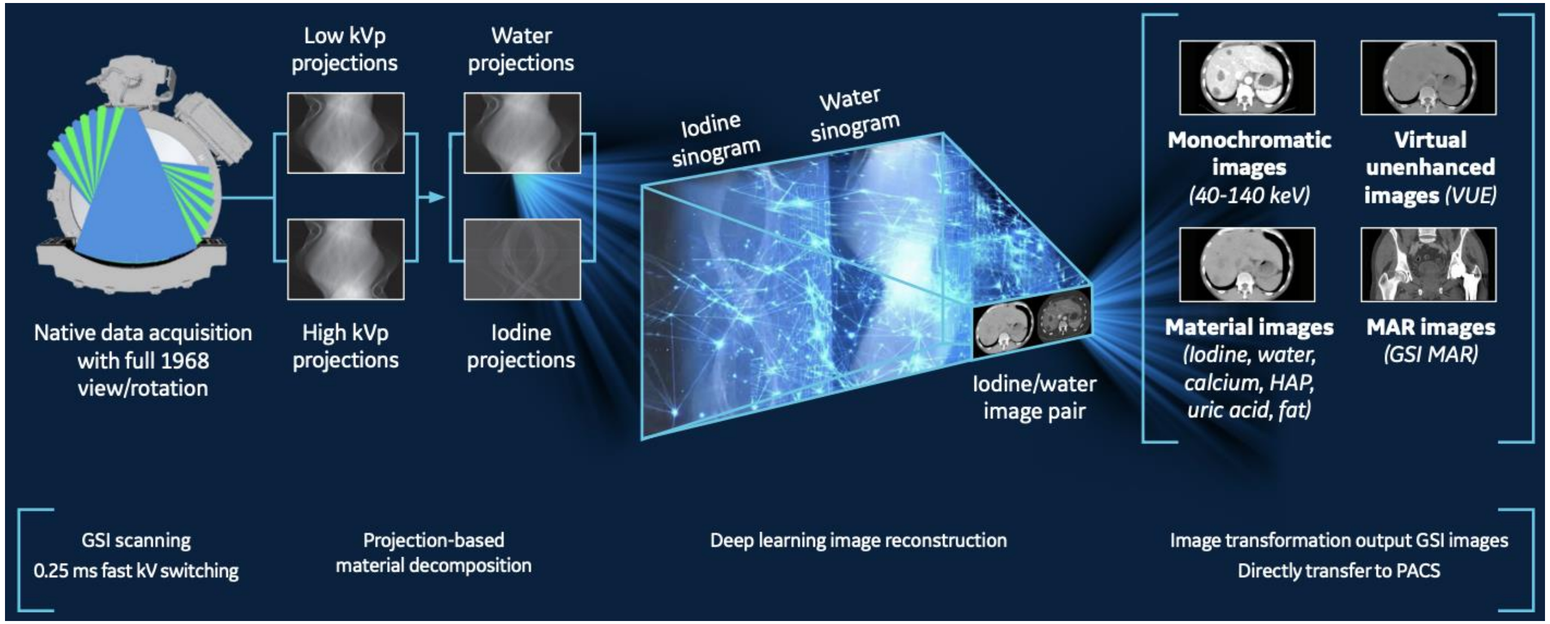
Affiliations + expand

PMID: 35483100 DOI: 10.1097/RCT.0000000000001316

➢ OBIETTIVO DELLO STUDIO (Fair et al.)

Valutare qualità dell'immagine DECT del torace, addome e pelvi in pazienti obesi, usando algoritmi di ricostruzione:

- ***ASIR-V (standard IR)***
- ***TrueFidelity DL (media e alta intensità)***



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DLR in Dual Energy TC

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Affiliations + expand

PMID: 35483100 DOI: 10.1097/RCT.0000000000001316

- ➢ Maggiore qualità soggettiva dell'immagine e migliore SNR-CNR
- **CNR AORTA: da 21.3 (ASiR-V) a 27.8 (DL-High)**
- **SNR FEGATO: da 6.5 (ASiR-V) a 8.6 (DL-High)**

TABLE 5. Estimated Marginal Means With CIs for CNR and SNR Values for ASiR-V, TrueFidelity-Medium, and True-Fidelity-High Reconstruction Methods for Aorta and Liver Parenchyma

Variable	ASiR-V	TrueFidelity-Medium	TrueFidelity-High
Aorta CNR	21.285 (16.686–25.884)	23.024 (18.425–27.624)	27.780 (23.179–32.381)
Liver CNR	3.53 (2.482–4.578)	3.847 (2.799–4.895)	4.662 (3.613–5.711)
Aorta SNR	24.309 (19.697–28.921)	26.273 (21.659–30.886)	31.701 (27.087–36.316)
Liver SNR	6.554 (5.373–7.736)	7.095 (5.913–8.277)	8.583 (7.401–9.765)

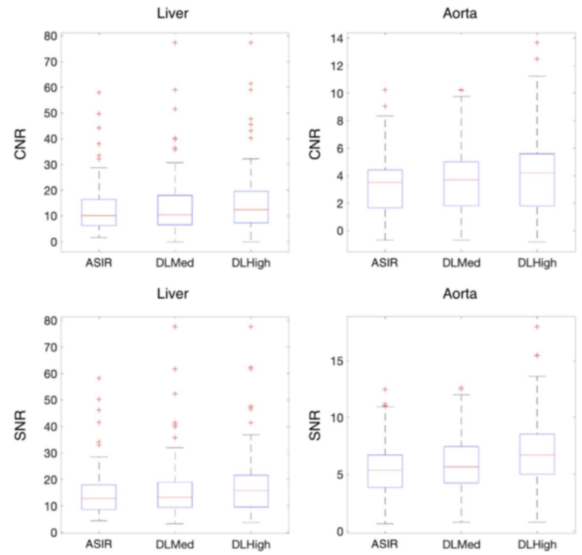

FIGURE 5. Boxplot showing the distribution of CNR and SNR values with ASiR-V, TrueFidelity-Medium (DLMed), and TrueFidelity-High (DLHigh) image reconstructions for liver parenchyma measured on portal venous phase images and aorta measured on arterial phase images using pooled data from all different DECT image types obtained for each case, including MC, MD, and VUE images. Figure 5 can be viewed online in color at www.jcat.org.

DLR in Dual Energy TC

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Eric Fair [1], Mark Profio [1], Naveen Kulkarni [1], Peter S Laviolette [1], Bret Barnes [1], Samuel Bobholz [2], Maureen Levenhagen [1], Robin Ausman [1], Michael O Griffin [1], Petar Duvnjak [1], Adam P Zorn [1], W Dennis Foley [1]

Affiliations + expand

PMID: 35483100 DOI: 10.1097/RCT.0000000000001316

- **L’algoritmo DL mantiene texture omogenee e dettagli anatomici ben delineati rispetto a IR**

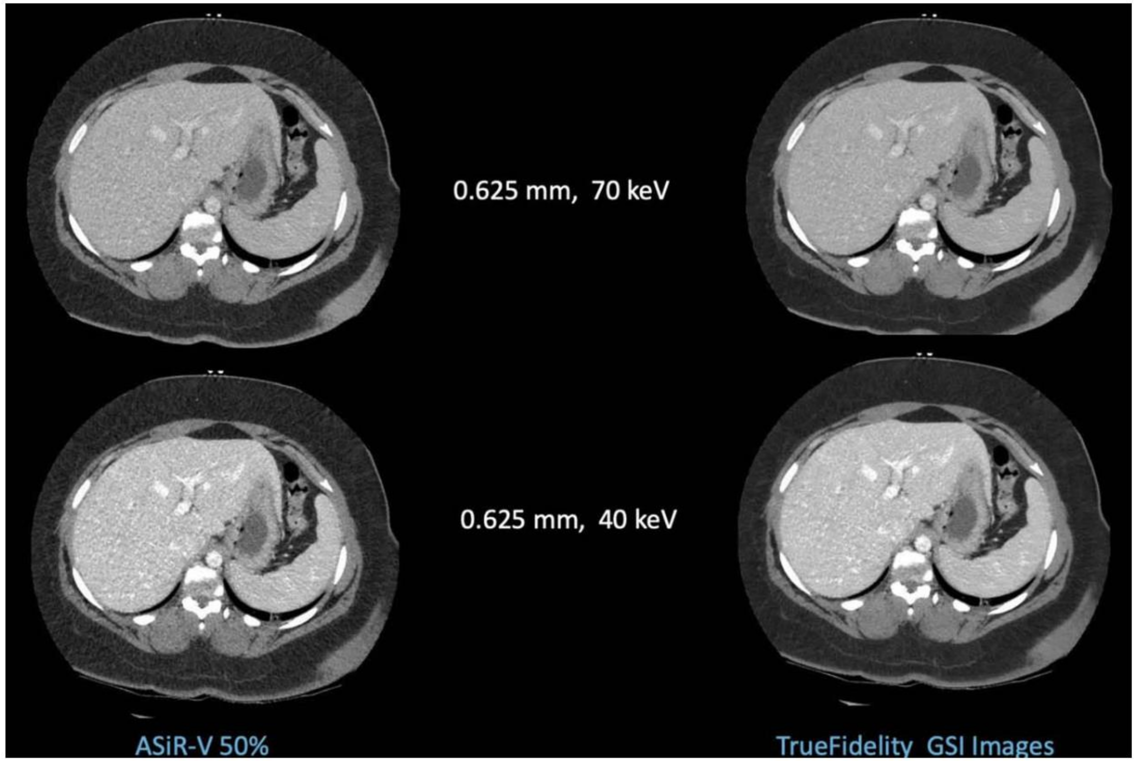

FIGURE 4. Example dual-energy CT images reconstructed with ASiR-V 50% and TrueFidelity-High in a patient with a BMI of 55. Axial images of a patient with flank pain after trauma without evident injury. Axial 70 keV and 40 keV virtual MC images are displayed; slice thickness, 0.625 mm; pitch, 0.508:1. Figure 4 can be viewed online in color at www.jcat.org.

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DLR in Dual Energy TC

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Affiliations + expand

PMID: 35483100 DOI: 10.1097/RCT.0000000000001316

- **DLR riduce artefatti da indurimento del fascio e rumore, in pazienti con BMI medio pari a 39.5 (fino a 64.8)**

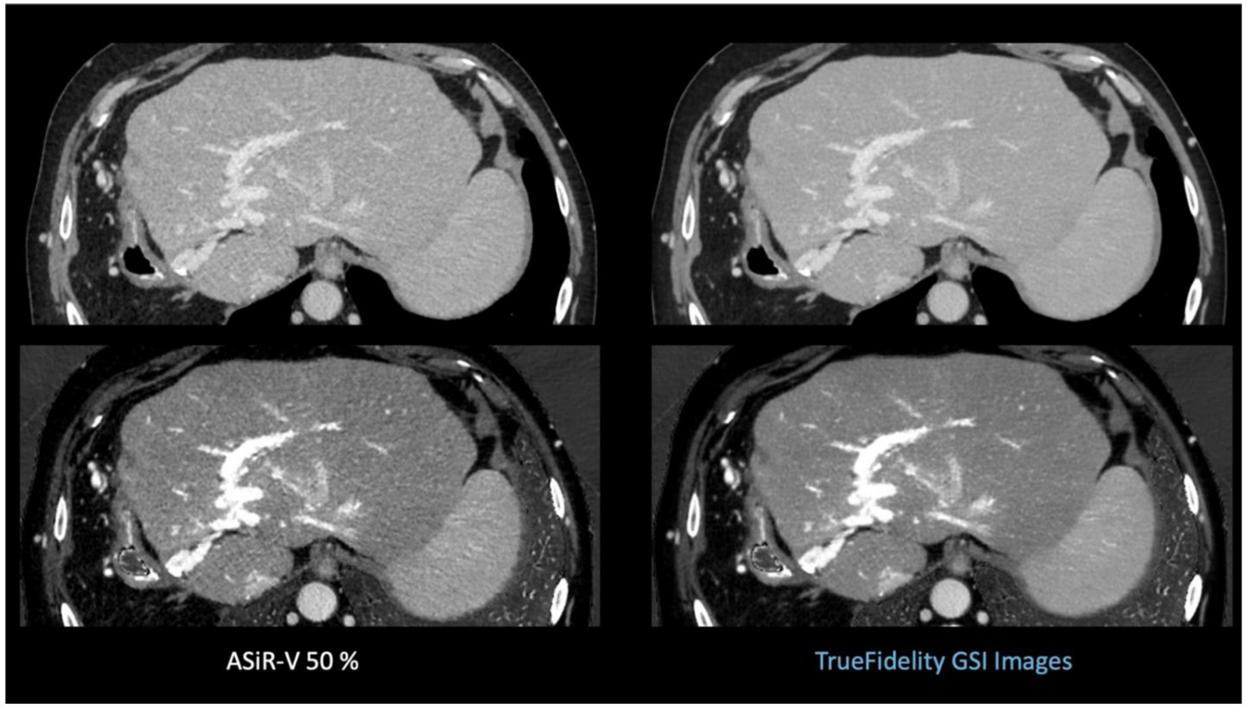

FIGURE 3. Example dual-energy CT images reconstructed with ASiR-V 50% and TrueFidelity-High in a patient with a BMI of 43. Axial images in a patient with history of metastatic colorectal cancer status post right hepatectomy. Axial 40 keV virtual MC images and iodine MD images are displayed; slice thickness, 0.625 mm; pitch, 0.508:1. Figure 3 can be viewed online in color at www.jcat.org.

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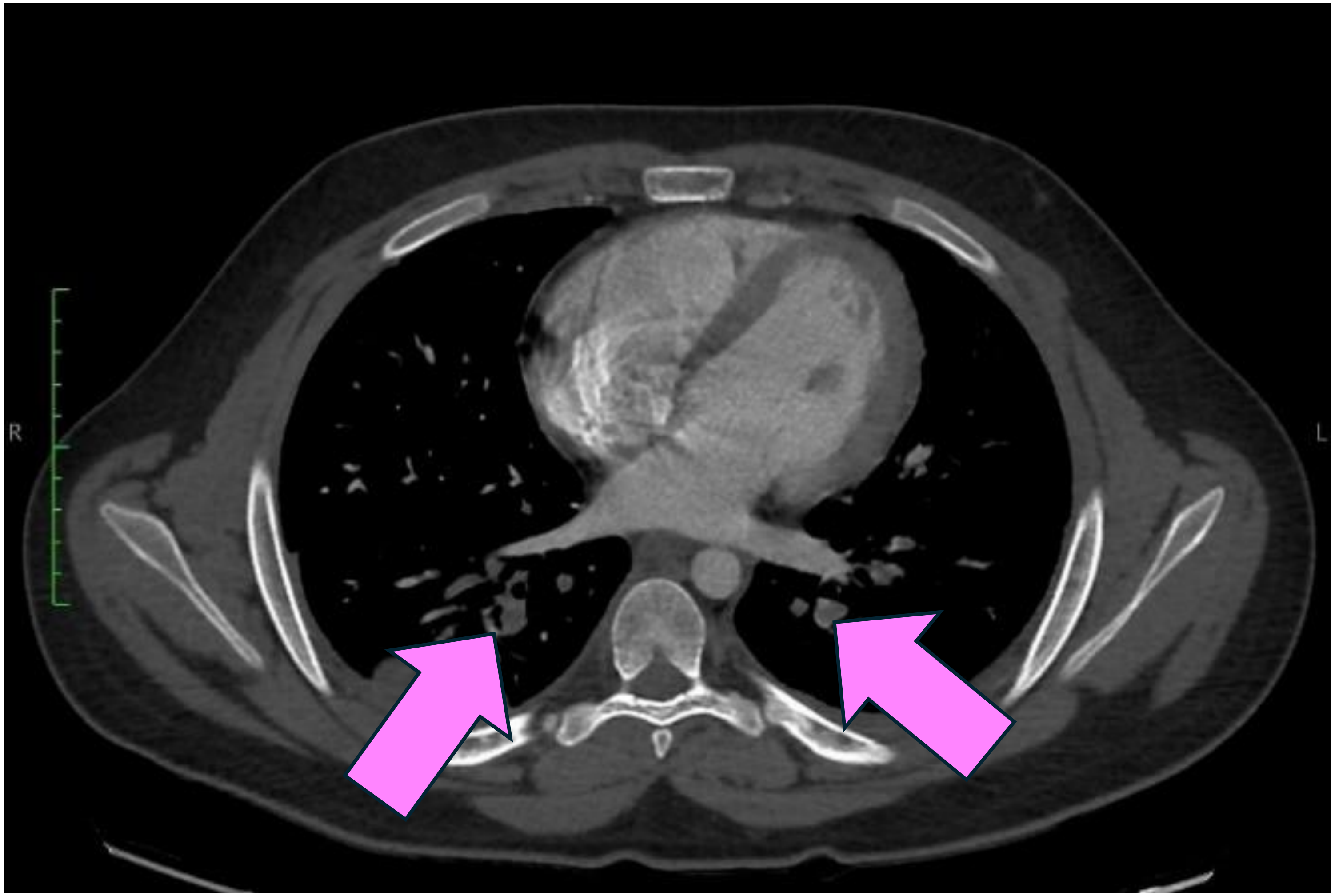
Caso clinico embolia polmonare

by courtesy of
P. O. San Filippo Neri

Helical 1280.250-110.250 15.77 501.32



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Caso clinico embolia polmonare

by courtesy of
P. O. San Filippo Neri

GSI embolia polmonare					
3	Helical	I7,684-I309,559	7,95	289,72	Body 32

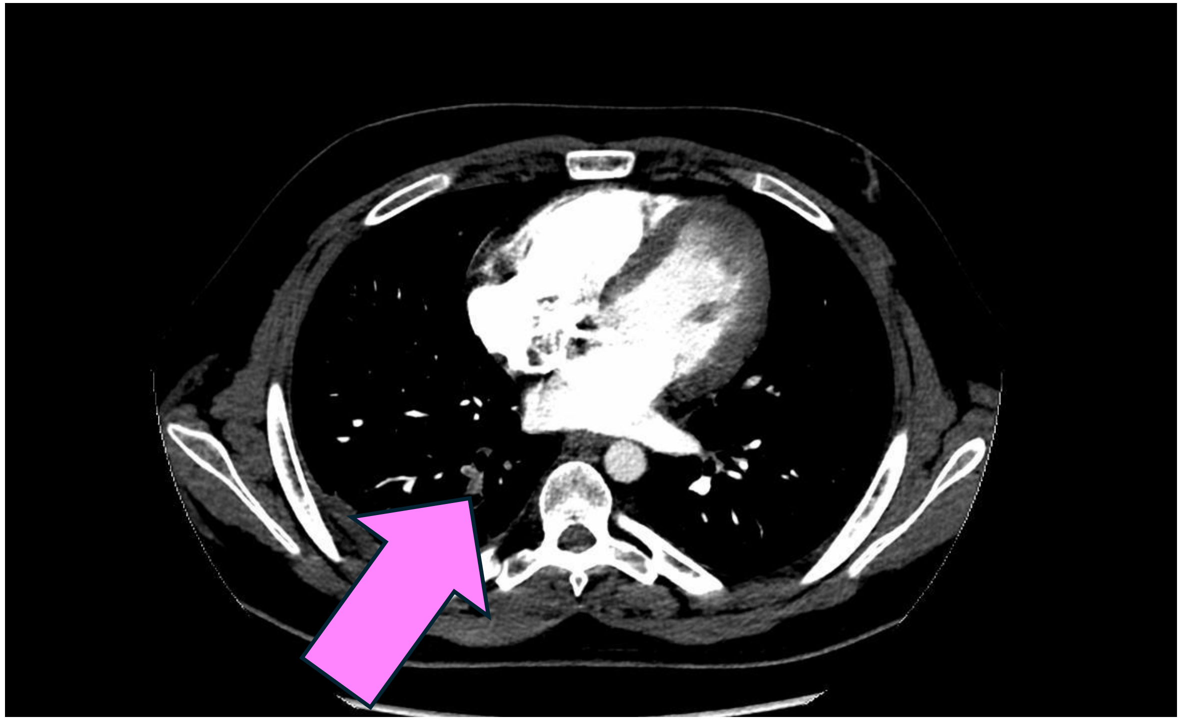


IMMAGINE
MONO-ENERGETICA 55 keV

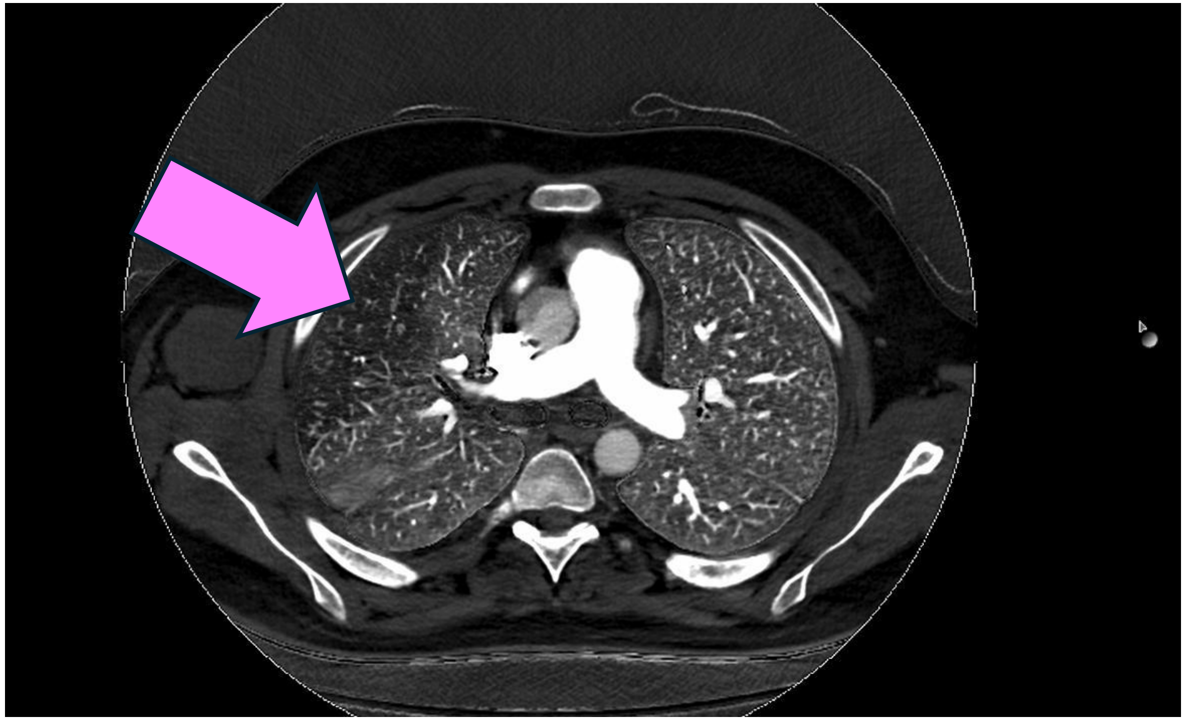


IMMAGINE
IODINE-WATER

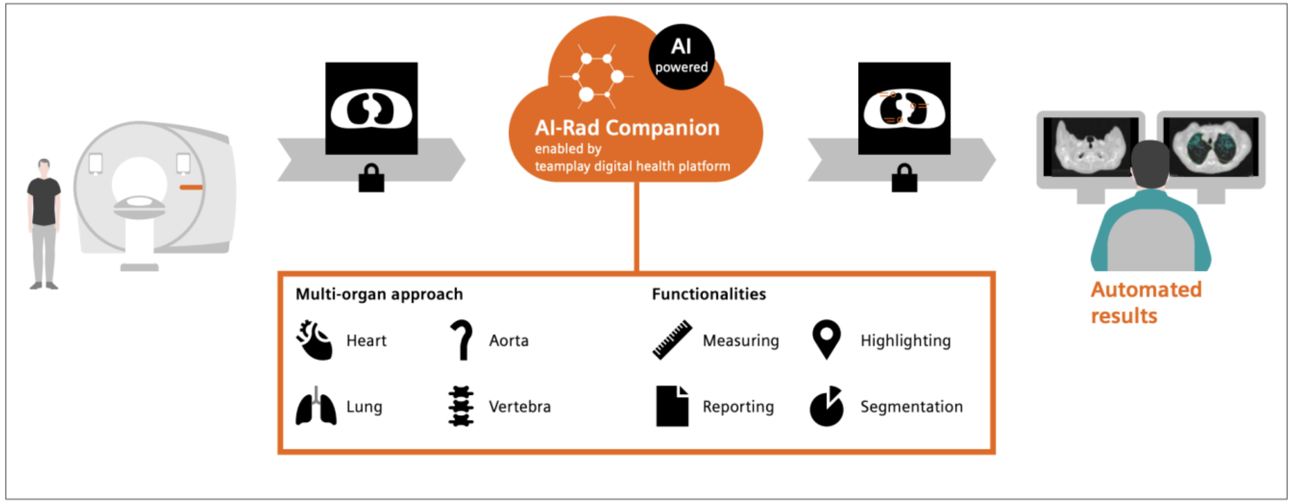
IMMAGINI DECT RICOSTRUITE CON DLIR-M

L'IA NEL POST SCAN TC

➢ AI-Rad Companion Chest CT è un software di supporto decisionale basato su IA che analizza TC torace

Segmenta automaticamente polmoni, cuore, aorta, vertebre

- Calcola misure chiave (diametri, volumi, HU, ecc.) secondo le linee guida cliniche
- Genera output in DICOM, compatibili col PACS e integrabili nel referto
- Funziona su immagini di qualsiasi vendor (vendor-neutral), offre workflow personalizzabile con risultati in tempo reale



➢ MODULO POLMONARE

- Rileva e misura noduli polmonari secondo linee guida Fleischner
- Quantifica enfisema (LAV < -950 HU) e opacità (es. polmoniti virali)
- Categorizza le anomalie polmonari con colori e soglie standardizzate

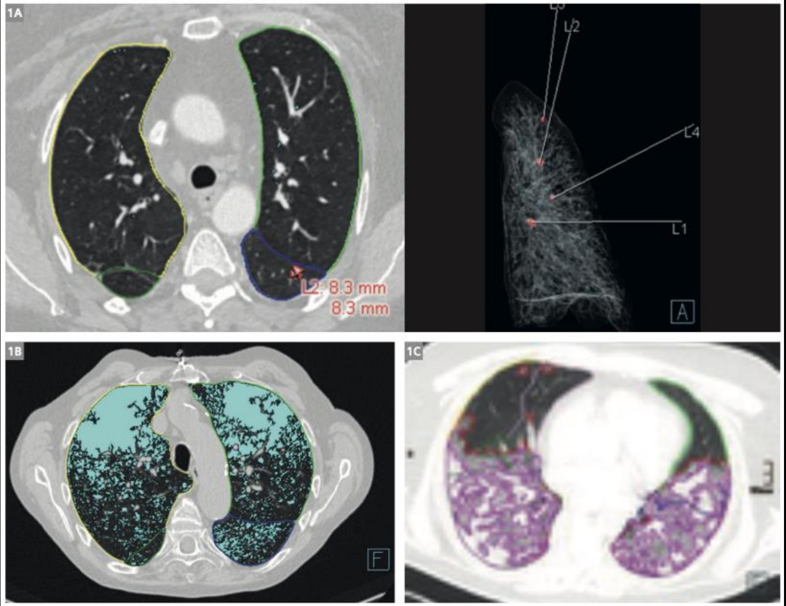


Figure 1: Outputs of the Pulmonary feature. Lung nodule detection and measurement **(1A)**, LAV-analysis **(1B)**, opacity detection **(1C)**.

➢ MODULO CARDIOVASCOLARE

- Misura il volume cardiaco e le calcificazioni coronariche anche su TC basali e TC NO-ECG gating
- Segmenta e misura l'aorta toracica in 9 punti (AHA guidelines)
- Calcificazioni: volume totale espresso in mm^3 → categorizzazione rischio (es. V ≥ 500 = rischio alto)

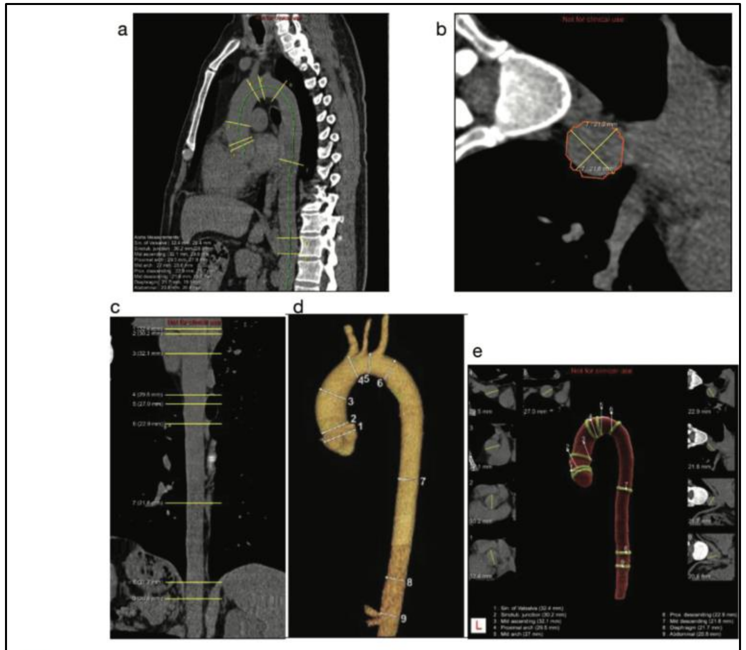


Figure 1. Schematic diagram of segmentation of 9 consecutive levels of the aorta.
Male, 39 years old, without hypertension a. sagittal plane; b. horizontal plane; c. coronal plane; d. 9 measured AD locations; e. three-dimensional cross

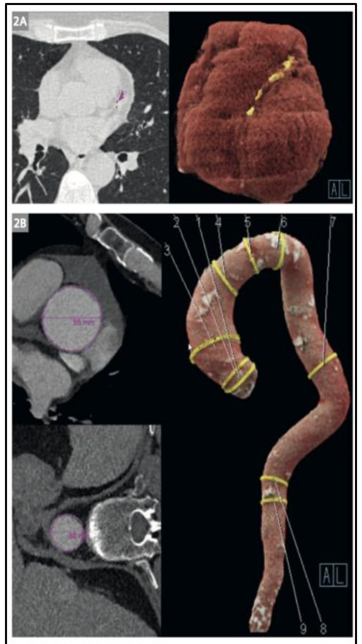


Figure 2: Outputs of the Cardiovascular device.
Coronary calcium detection (2A), aorta analysis (2B).

➢ MODULO MUSCOLOSCHELETRICO

- ***Segmenta*** vertebre T1–T12
- ***Misura:***
  - Altezza anteriore/media/posteriore (valuta fratture)
  - Densità trabecolare (HU) per diagnosi di osteoporosi

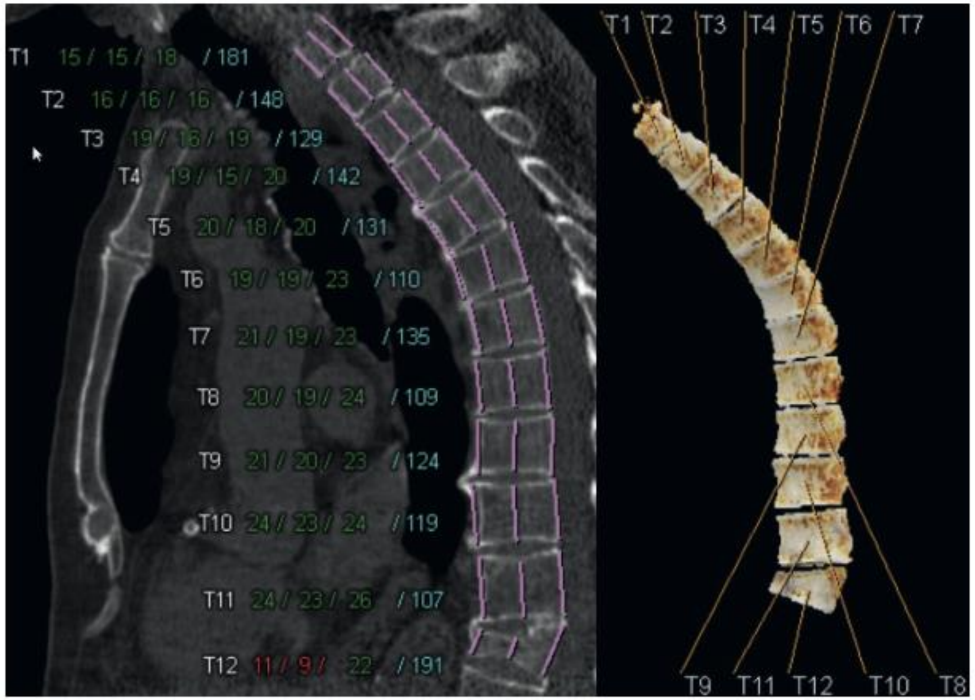


Figure 3: Output of the Musculoskeletal device: Height and density measurements of the thoracic vertebrae.

L'IA NEL POST SCAN TC

Eur Radiol. 2025 Jan 8. doi: 10.1007/s00330-024-11328-9. Online ahead of print.

Repeatability of AI-based, automatic measurement of vertebral and cardiovascular imaging biomarkers in low-dose chest CT: the ImaLife cohort

Iris Hamelink [1], Marcel van Tuinen [1], Thomas C Kwee [1], Peter M A van Ooijen [2] [3], Rozemarijn Vliegenthart [4] [5]

Affiliations + expand

PMID: 39779514 DOI: 10.1007/s00330-024-11328-9

➢ VALIDAZIONE SCIENTIFICA (studio ImaLife 2025)

- ***Accuratezza segmentazione*** > 80% per vertebre, aorta, calcio coronarico
- ***Ripetibilità eccellente*** (ICC > 0.9) per vertebre e aorta
- ***Concordanza del rischio CAC***: 81.2% su TC ripetute a 4 mesi

TRICK: Maggiore variabilità sul volume cardiaco per difficoltà a tracciare il pericardio!

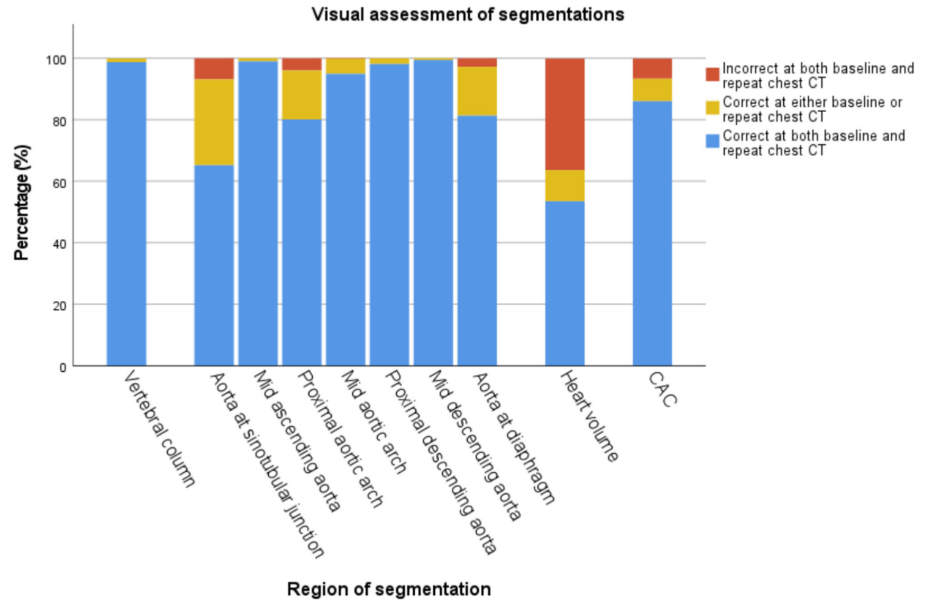


Fig. 1 Results of visual assessment indicating percentage of participants in which AI segmentations were assessed as correct in both, either or neither of baseline and repeat chest CT scan. Segmentation accuracy was high (> 80%) for all biomarkers, except for thoracic aortic diameter measurements at the sinotubular junction (66.1%) and heart volume (53.5%). CAC, coronary artery calcium

Rivista.AI

L'IA NEL POST SCAN TC

➢ TIPS PER TSRM E MEDICI RADIOLOGI

- Automatizza misurazioni complesse → riduce l'errore umano
- Supporta screening multipatologia su una singola TC
- Favorisce la standardizzazione → referti più rapidi e confrontabili
- Permette verifica finale rapida prima del referto ("IA come spell-checker")

Results

Pulmonary Density

AI-Rad Companion

LUNG OPACITY	Both Lungs	Right Lung	Left Lung
Opacity Score	1	1	0
Total Volume [ml]	3896.51	2102.85	1793.66
Opacity Volume [ml]	198.07	191.36	6.70
Opacity Percentage [%]	5.08	9.10	0.37
High Opacity Volume [ml]	2.94	2.93	0.01
High Opacity Percentage [%]	0.08	0.14	0.00
Mean HU Total [HU]	-838.34	-829.47	-848.74
Mean HU of Opacity [HU]	-661.06	-659.06	-718.27
Standard Deviation Total [HU]	153.15	158.63	145.78
Standard Deviation of Opacity [HU]	157.10	157.90	118.93

Not for diagnosis *

LUNG LOBE OPACITY	Right Upper	Right Middle	Right Lower	Left Upper	Left Lower
Opacity Score	0	0	1	0	0
Total Volume [ml]	846.59	375.78	880.48	944.82	848.84
Opacity Volume [ml]	1.83	1.38	188.16	5.13	1.58
Opacity Percentage [%]	0.22	0.37	21.37	0.54	0.19
High Opacity Volume [ml]	0.02	0.01	2.91	0.01	0.00
High Opacity Percentage [%]	0.00	0.00	0.33	0.00	0.00
Mean HU Total [HU]	-862.68	-862.86	-783.30	-862.77	-833.13
Mean HU of Opacity [HU]	-750.95	-765.15	-657.39	-732.84	-670.93
Standard Deviation Total [HU]	131.49	135.57	178.77	134.87	155.55
Standard Deviation of Opacity [HU]	172.65	165.59	157.16	110.79	131.52

* Colors are based on institutional settings.
They are not an indication or recommendation for treatment.
To interpret the results, please refer to the user documentation.

Rivista.AI

IL FUTURO DELL'IA IN TC

Synthetic dual-energy CT reconstruction from single-energy CT Using artificial intelligence

Jiwoong Jeong [1,2], Andrew Wentland [3], Domenico Mastrodicasa [4], Ghaneh Fananapazir [5], Adam Wang [4], Imon Banerjee [6], Bhavik N Patel [6]

Affiliations + expand

PMID: 37665385 DOI: 10.1007/s00261-023-04004-x

- LEARNING POINTS (Jeong et al.)

L'IA può creare sDECT (synthetic Dual Energy CT) a partire da esami convenzionali Single Energy (SECT)

Si usano reti GAN (Generative Adversarial Networks):

- Pix2PixHD → usa immagini accoppiate SECT+DECT
- CycleGAN → lavora con immagini non accoppiate

L'IA "impara" a generare:

- ✓ ***Immagini 50-keV***
- ✓ ***Mappe iodiche***
- ✓ ***VNC***

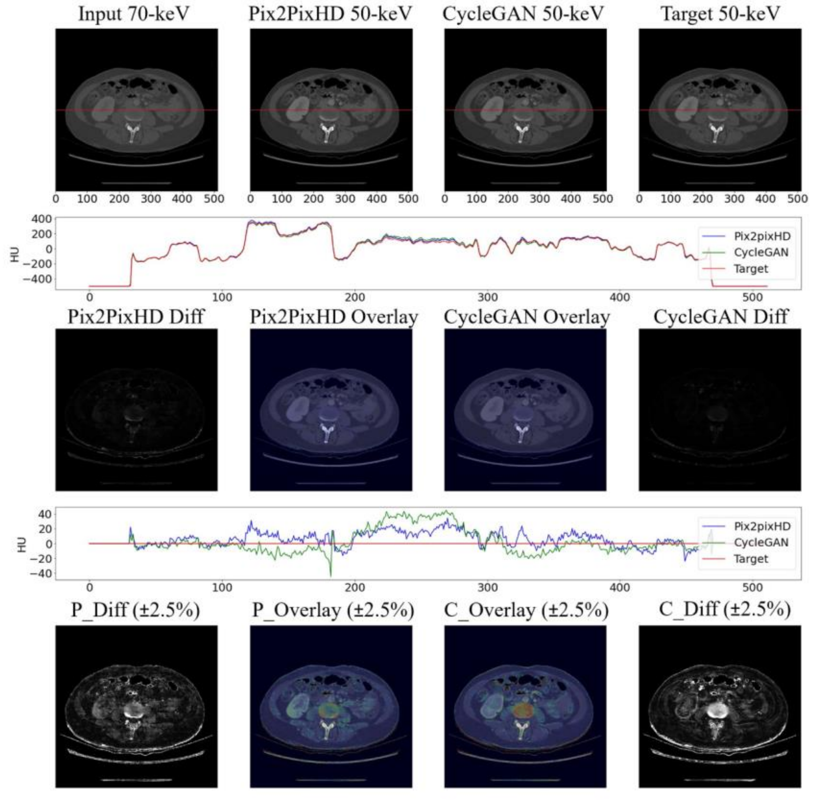


Fig. 3 Comparison of 50keV (**a**), VUE (**b**), and iodine (**c**) generation. In each subplot, the first row shows (left to right) the original SECT equivalent image, Pix2PixHD generated, CycleGAN generated, and true target. The second row shows the raw HU intensity plots of the annotated red line. The third row shows the raw intensity difference between the target and the Pix2PixHD generated image, overlay of the Pix2PixHD difference over the true target, overlay of the CycleGAN difference over the true target, and raw intensity difference between the target and the CycleGAN generated image. The fourth row shows the intensity difference against the target HU from the generated images. The final row shows an exaggerated difference of the same plots on the third row but is limited to differences between ±2.5%

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Affiliations + expand

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➢ Perché usare sDECT?

Le immagini sDECT sono diagnosticamente confrontabili alle vere DECT

- Aumentano la ***"conspicuity"*** dei sanguinamenti e delle piccole lesioni
- Le immagini VNC permettono la rimozione virtuale del mezzo di contrasto

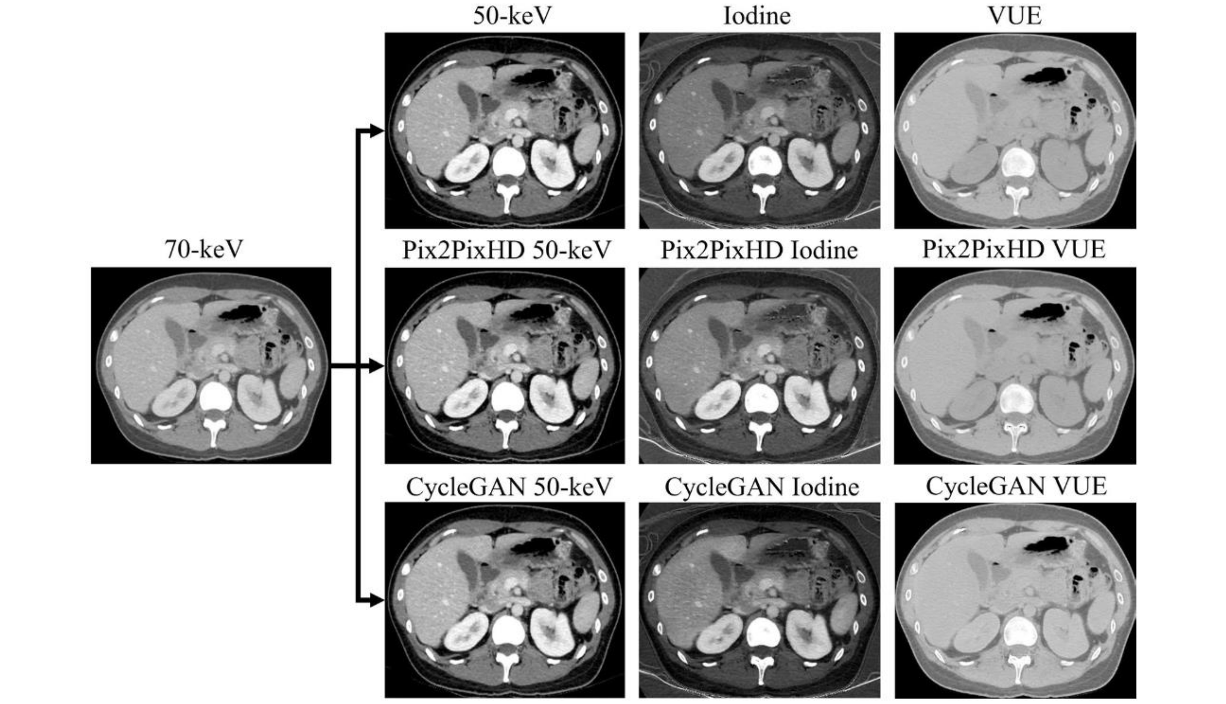

Fig. 4 Sample images of internal test showing input, target ground truth, and model generated images. 70-keV (left) image represents the input image. Ground truth target DECT datasets (top row) are shown, with 50-keV(left column), iodine (middle column), and VUE (right column). Generated outputs from Pix2PixHD (middle row) and CycleGAN are shown (bottom row)

IL FUTURO DELL'IA IN TC

Synthetic dual-energy CT reconstruction from single-energy CT Using artificial intelligence

Jiwoong Jeong [1,2], Andrew Wentland [3], Domenico Mastrodicasa [4], Ghaneh Fananapazir [5], Adam Wang [4], Imon Banerjee [6], Bhavik N Patel [6]

Affiliations + expand

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- TAKE-HOME MESSAGES

- ***L'IA può estendere le applicazioni della DECT a scanner convenzionali***

- ***sDECT migliora l'accuratezza diagnostica***

- Pix2PixHD è più affidabile quando abbiamo immagini accoppiate SECT/DECT

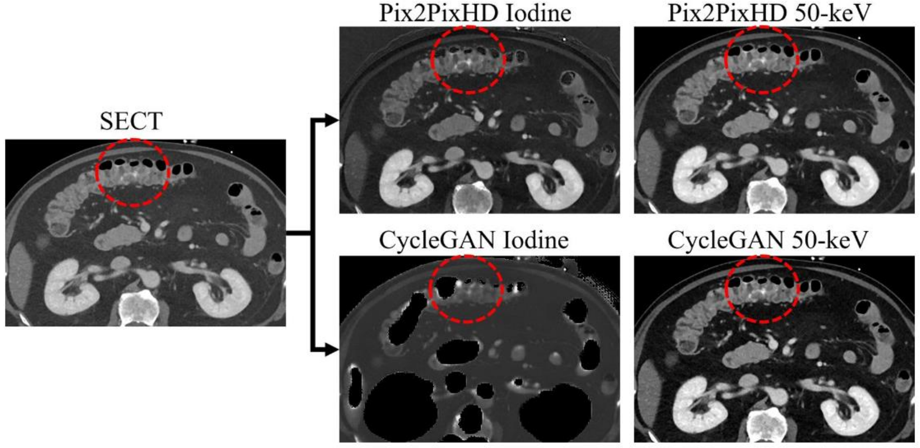

Fig. 5 SECT (left) shows gastrointestinal bleeding (red dotted circle) in the transverse colon. Pix2PixHD generated (top row) iodine (top left) and 50keV images (top right) qualitatively show increased conspicuity of gastrointestinal bleeding. While CycleGAN generated (bottom row) 50-keV (bottom right) also shows increased conspicuity compared to SECT, CycleGAN could not produce a realistic iodine image (bottom left)

Immagini accoppiate = stessa sezione anatomica del corpo acquisita:

- ***una volta con SECT***
- ***una volta con DECT***

- Sono immagini perfettamente allineate, pixel per pixel, come prima e dopo della stessa fetta, ma con modalità diverse

Il TSRM ha un ruolo centrale: TSRM + gestore dell'IA clinica

Formazione per l'eccellenza

Ordine dei tecnici sanitari di radiologia medica e delle professioni sanitarie tecniche, della riabilitazione e della prevenzione Viterbo

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LA RADIOMICA

Review > Mil Med Res. 2024 Dec 14;11(1):77. doi: 10.1186/s40779-024-00580-1.

Radiomics and radiogenomics: extracting more information from medical images for the diagnosis and prognostic prediction of ovarian cancer

Song Zeng [1], Xin-Lu Wang [1], Hua Yang [2]

Affiliations + expand

PMID: 39673071 PMCID: PMC11645790 DOI: 10.1186/s40779-024-00580-1

➢ Radiomica & Radiogenomica (Zeng et al.)

Nuove frontiere nella diagnosi e prognosi dei tumori (es. carcinoma ovarico)

- ***Radiomica*** = *estrazione quantitativa di dati da immagini*
- ***Radiogenomica*** = *integrazione tra immagini e dati genetici*

Obiettivo: diagnosi più precisa e medicina personalizzata

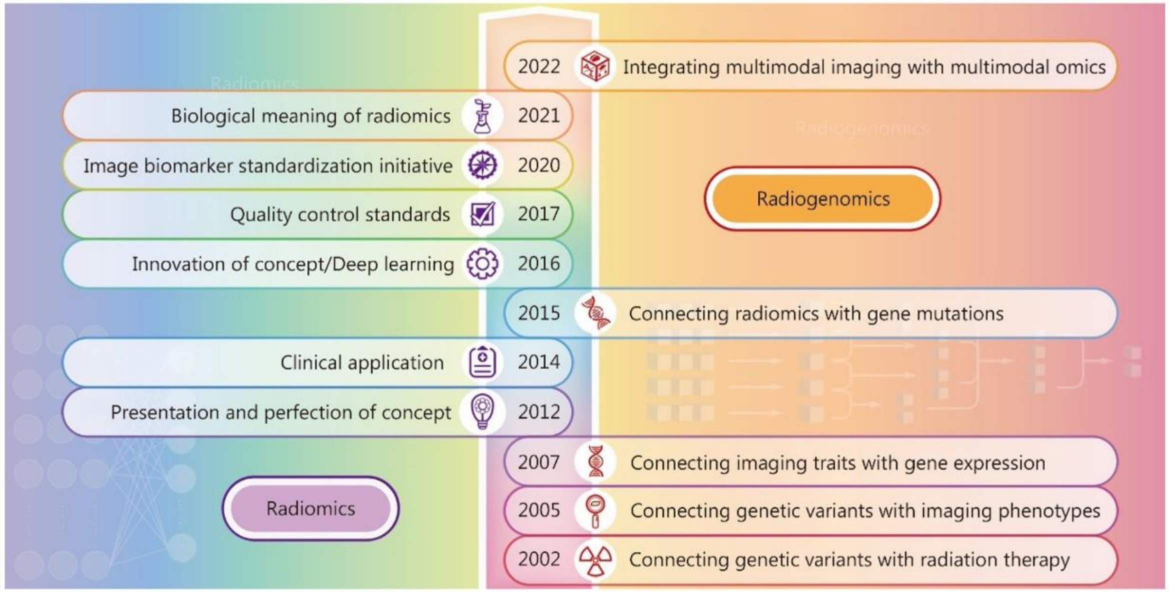
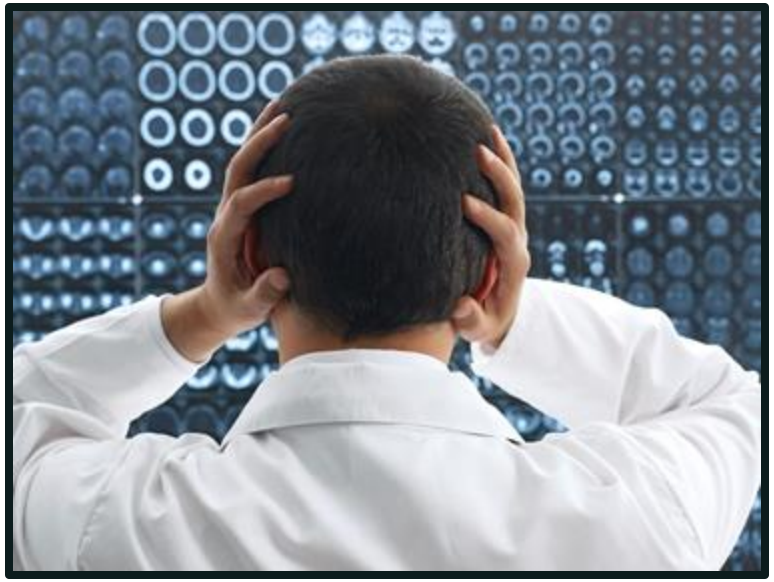


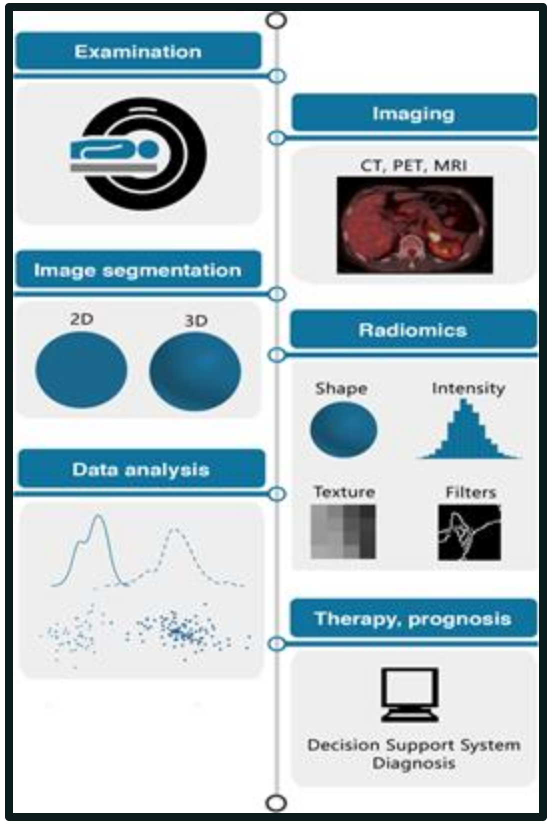
Fig. 1 The development and workflow of radiomics and radiogenomics

*Gli esami **TC, RM, SPECT e PET** producono un enorme patrimonio di dati numerici che l'uomo non riesce ad elaborare*

ANNO 2000



ANNO 2025



L'analisi visiva riesce a estrarre solo circa il 10% delle informazioni contenute in un'immagine digitale

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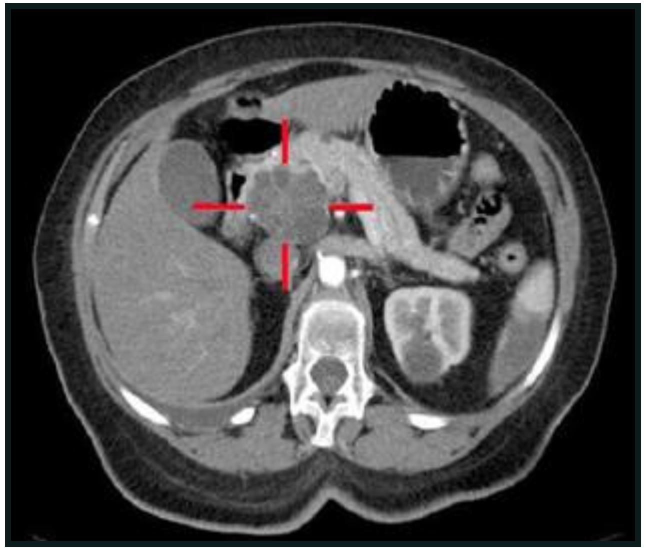
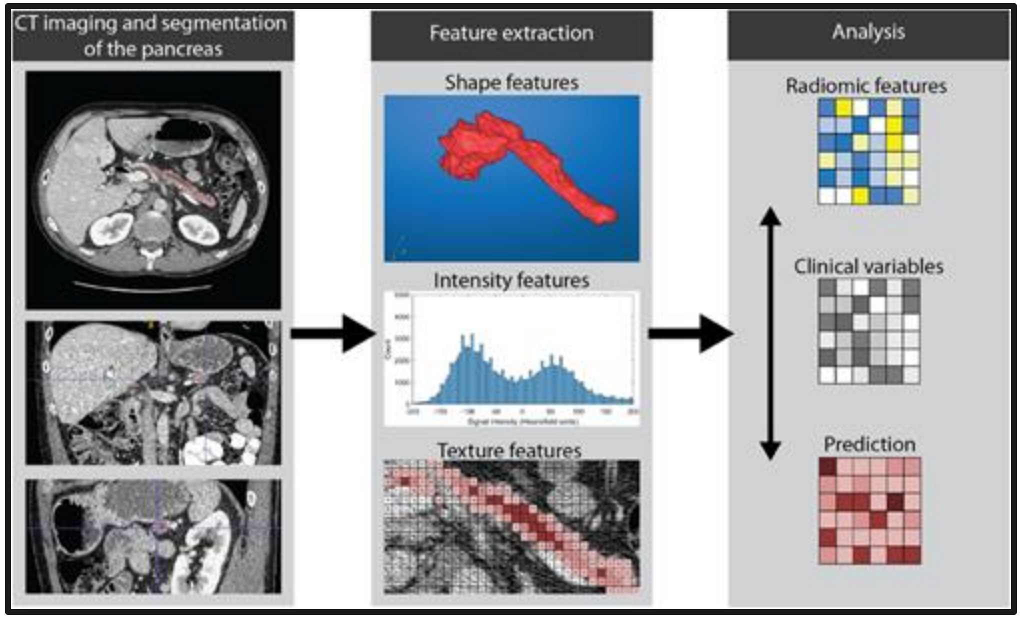
Con un esame TC siamo in grado di rilevare la presenza di una lesione

Definiamo qualitativamente la morfologia, i margini, la localizzazione anatomica e l'eventuale estensione tumorale





Se le immagini sono analizzate dall'IA, è possibile ottenere dati quantitativi oggettivi, in grado di fornire informazioni sui sottostanti fenomeni patofisiologici, inaccessibili all'occhio umano

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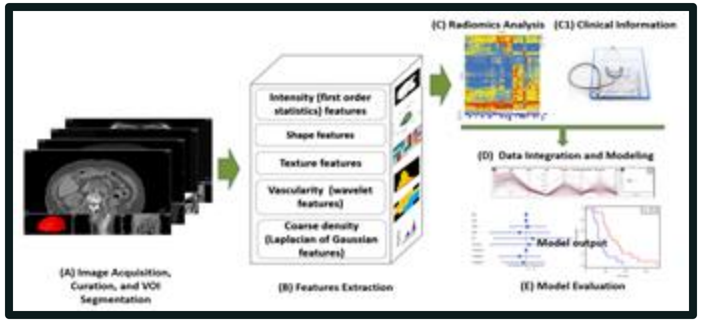
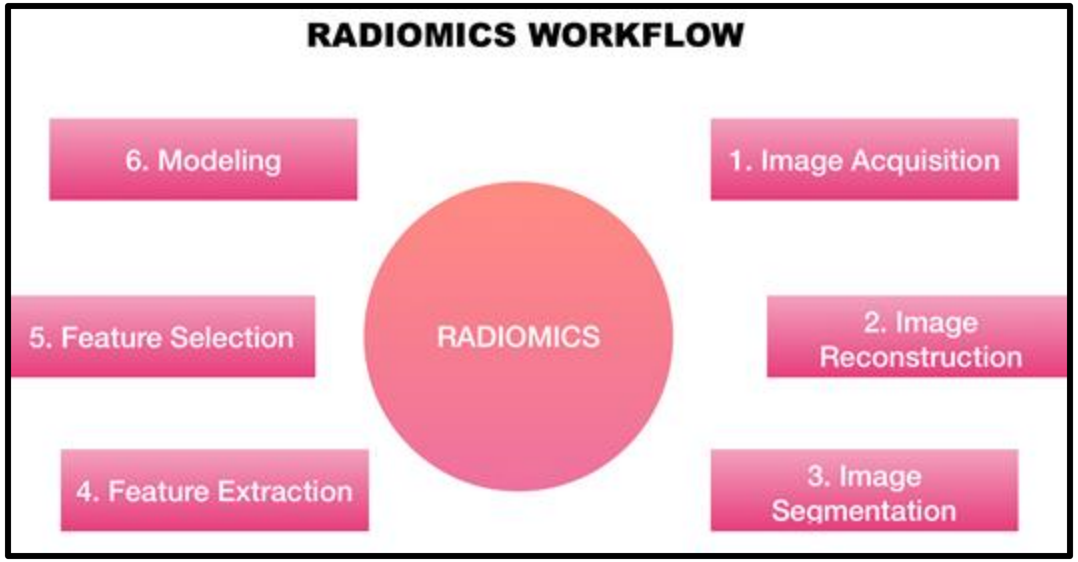
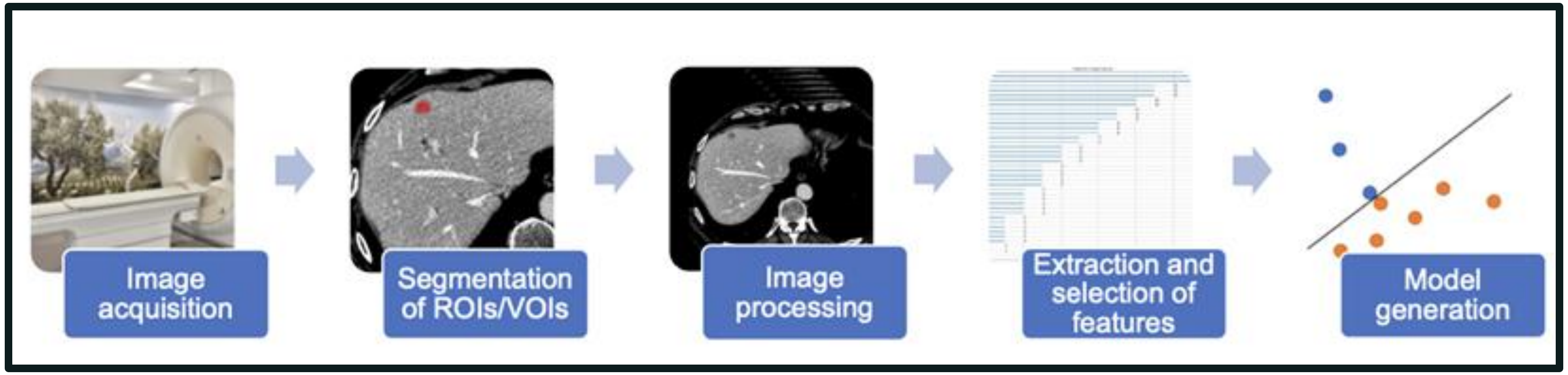
La radiomica è una branca interdisciplinare che unisce le scienze informatiche e le scienze radiologiche. Termine coniato nel 2012 da P. Lambin (MAASTRO Clinic, NL)

Riusciamo ad estrarre informazioni quantitative e pattern nascosti dalle immagini radiologiche (TC)





Workflow radiomico



1.0 Segmentazione delle immagini acquisite

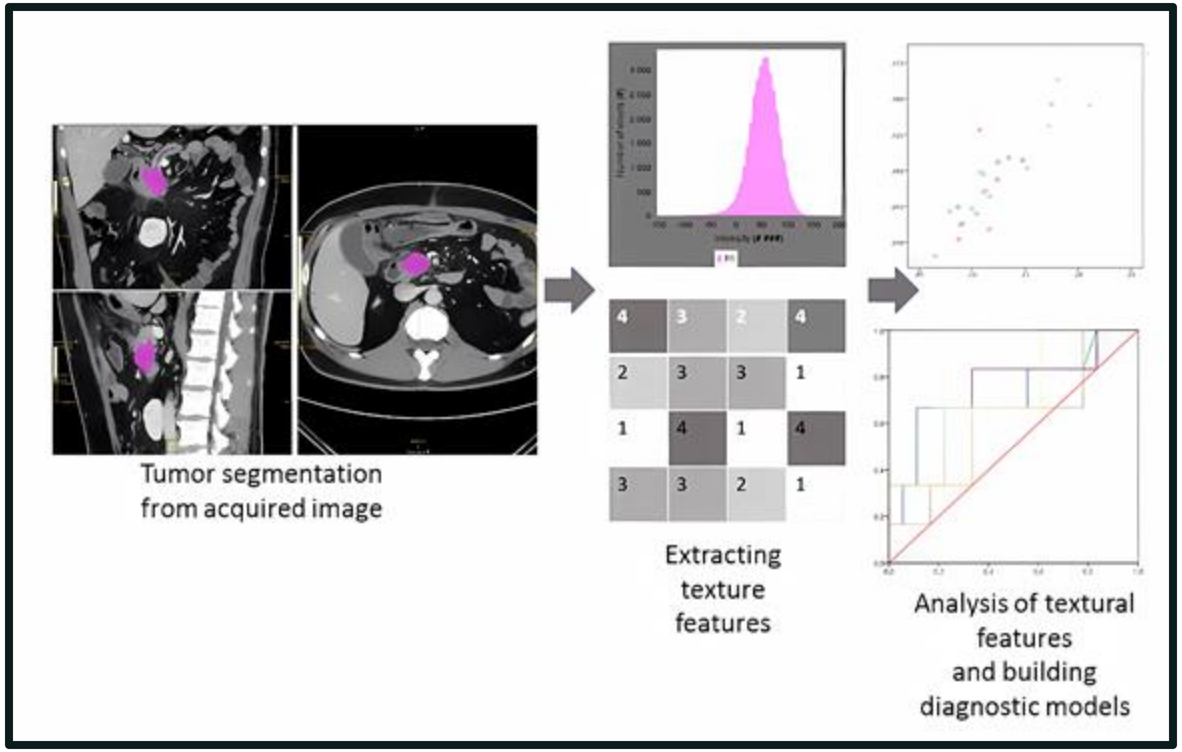
2.0 Estrazione e selezione delle features (parametri misurabili)

3.0 Modellazione

Le features vengono utilizzate per costruire modelli statistici in grado di predire, ad esempio, la natura benigna o maligna di una lesione, la sua aggressività o la risposta alla terapia

Solo con un esame TC ***non possiamo prevedere*** se un tumore risponderà alla terapia

Invece con l'analisi quantitativa della texture dell'immagine, può consentire di prevedere quali pazienti beneficeranno della terapia rispetto a quelli che non risponderanno al trattamento



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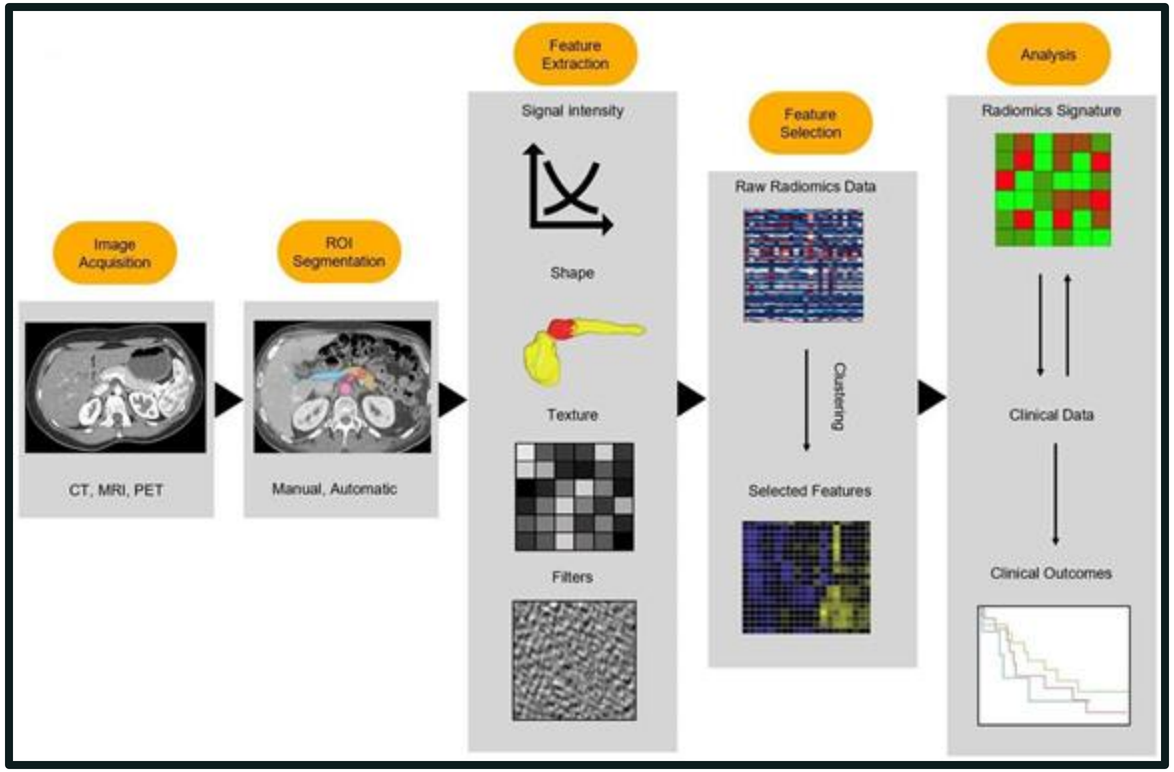
Ciò significa inviare subito i **Pazienti non responsivi alla terapia ad un trattamento diverso** da quello pianificato…

…senza aspettare di osservare in vivo la mancata risposta, fondamentale ad es. nel cancro del pancreas;

ciò può migliorare gli outcome di sopravvivenza e consentire una riduzione della mortalità e della spesa sanitaria



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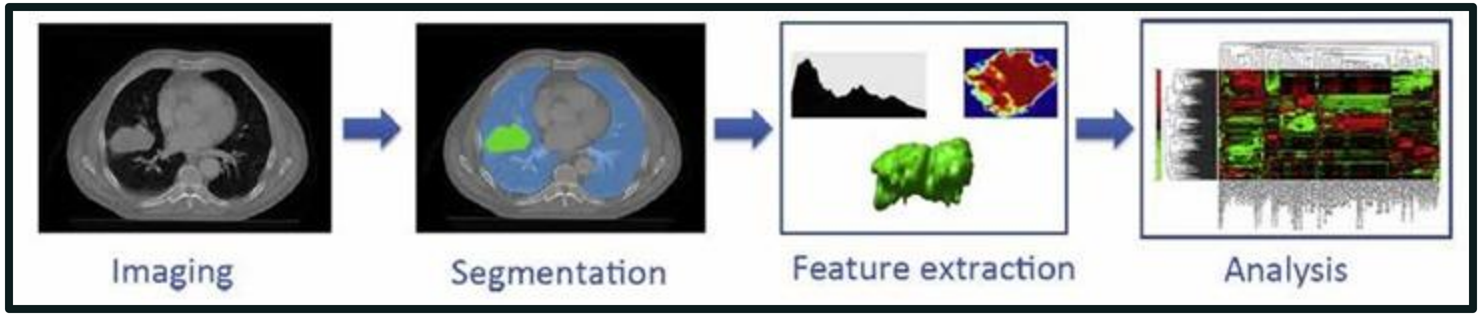
In un tipico workflow radiomico sono coinvolti ***diversi operatori*** volti alla gestione dei dati e alla ***costruzione del modello predittivo*** di cura

I TSRM hanno un ruolo centrale in tutti i processi di imaging essendo in prima linea nel determinare i parametri di acquisizione, di elaborazione e sono responsabili dell'archiviazione delle immagini..

...lo stesso vale per la radiomica !

Medical Imaging & Radiomics Challenges

Radiology	• Exposure parameters, Type of machine, Filtration, Tube angle, Type of film/detector, Image processing
CT	• Exposure parameters, Scanner type, Image Reconstruction, Image processing, Matrix size, Slice thickness, Pitch factor, Pixel spacing, FOV, Noise, Artifacts, Contrast agents, Scanner calibration
MRI	• Scanner type, Repitition Time, Echo time, Image reconstruction, Image processing, Matrix size, Slice thickness, Magnetic field strength, Pixel spacing, Flip angle, Band width, Scan duration, Pulse sequence, FOV Noise, Artifacts, Contrast agents, Scanner calibration
PET/SPECT	• Patient situation, Activity concentration, Scanner type, Image reconstruction, Image processing, Slice thickness, FOV, Scan time, Volume of interest, Noise, Artifacts, Scanner calibration



Review > Mil Med Res. 2024 Dec 14;11(1):77. doi: 10.1186/s40779-024-00580-1.

Radiomics and radiogenomics: extracting more information from medical images for the diagnosis and prognostic prediction of ovarian cancer

Song Zeng [1], Xin-Lu Wang [1], Hua Yang [2]

Affiliations + expand

PMID: 39673071 PMCID: PMC11645790 DOI: 10.1186/s40779-024-00580-1

LA RADIOMICA

- Applicazioni cliniche radiomiche (Zeng et al.)

Diagnosi, sottotipi e previsione dell'outcome

- ***Radiomica utile per distinguere tumori benigni, borderline, maligni***
- ***Identifica sottotipi (HGSOC, LGSOC, OCCC...)***
- ***Prevede sopravvivenza, metastasi e recidiva***

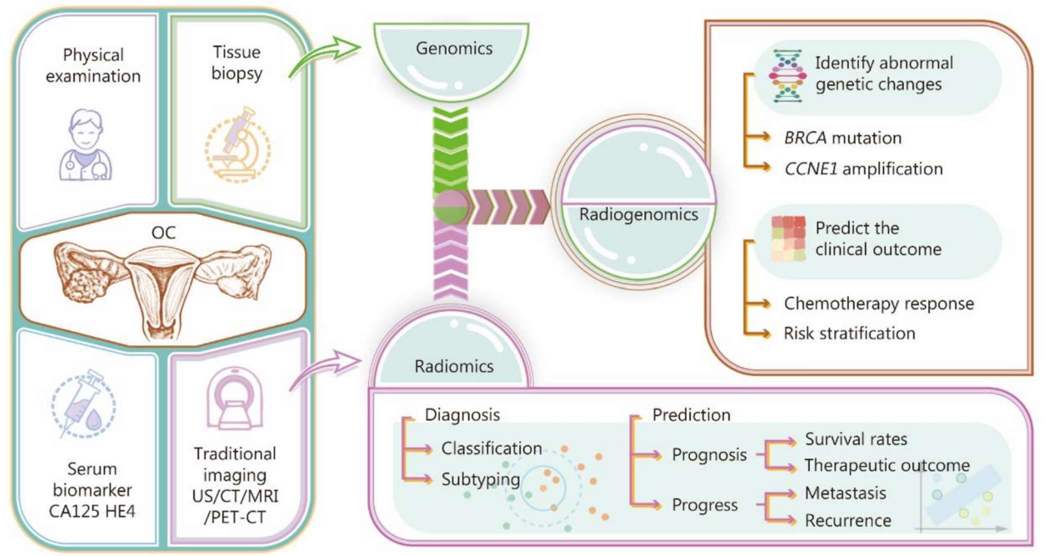


Fig. 3 The application of radiomics and radiogenomics in ovarian cancer (OC). The application of radiomics involves the diagnosis and prediction of OC, while the application of radiogenomics involves identifying abnormal genetic changes and predicting clinical outcomes in OC patients. CA125 cancer antigen 125, CT computed tomography, HE4 human epididymis protein 4, PET/CT positron emission tomography/CT, US ultrasound

LA RADIOMICA

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➢ Radiogenomica e Terapia (Zeng et al.)

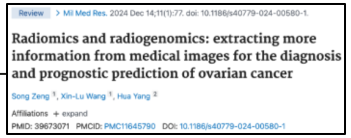
Dati genetici al servizio del trattamento

- ***Prevede mutazioni BRCA e amplificazioni CCNE1***
- ***Predice rischio di recidiva***
- ***Riduce necessità di biopsie invasive***

Table 1 The relationship and difference between machine learning (ML) and deep learning (DL)

Characteristics	ML	DL
Data dependency	It can work with less data	It requires a large amount of data input to achieve good performance
Type of data	Only structured data can be processed	Both structured and unstructured data can be processed
Image segmentation	Manual	Automatic
Feature extraction	Experts are required to perform feature extraction before proceeding further	There is no need to develop a feature extractor for every problem; instead, it tries to extract features from the data on its own
Feature categories	Typically predefined	Allow the creation of new features
Model construction	Models incorporating radiomics features are trained through algorithms	Simultaneously train model when learning features
Approach of operation	The problem is broken down into subparts and a result is produced after solving each part	Take input from a given problem and produce the result. Therefore, it follows an end-to-end approach
Execution time	Requires less time than DL to train models but a long time to test them	Requires a long time to train the model, but less time to test the model
Interpretation of results	Interpretation of the results for a given question is relatively easy	Interpreting the results for a given problem is very difficult because of the cryptic reasoning processes involved
Problem solved	Suitable for solving simple problems	Suitable for solving complex problems
Hardware dependency	Because ML models do not require large amounts of data, they can be run on low-end machines	Large amounts of data are required to work effectively, hence the need for high-end machines
Cost	Low	High

LA RADIOMICA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➢ Come integrare la radiomica nei flussi clinici (Zeng et al.)

- ***Acquisizione immagini + segmentazione ROI***
- ***Estrazione e selezione feature → costruzione modello***
- ***Validazione su dati multicentrici necessaria***

➢ Tips operativi:

- ***Combinare imaging con clinica e genomica***
- ***Usare DL per automatizzare processi e ridurre soggettività***

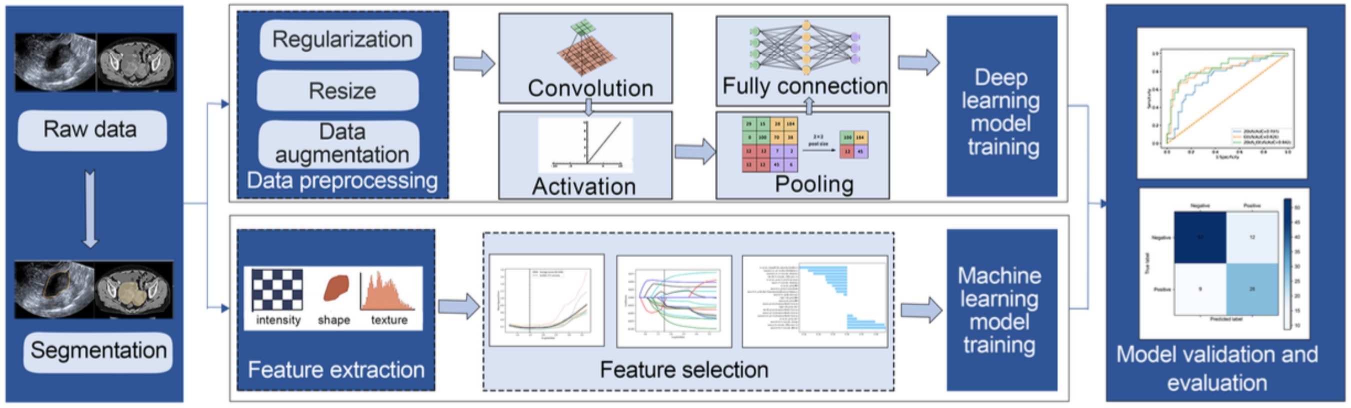

Fig. 2 General framework of radiomics. The process for radiomic research applying the machine learning (ML) method includes image acquisition, regions of interest (ROI) segmentation, feature extraction, feature selection, model training, and validation, whereas the deep learning (DL) method includes data preprocessing, convolution, activation, pooling, and full connection

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- Dalla teoria alla pratica: casistiche e vantaggi (Zeng et al.)

- ***Diagnosi: modelli radiomici distinguono borderline/maligni con AUC fino a 0.97***
- ***Prognosi: predizione di sopravvivenza e risposta alla chemio***

Riduzione della variabilità soggettiva e supporto alle decisioni terapeutiche

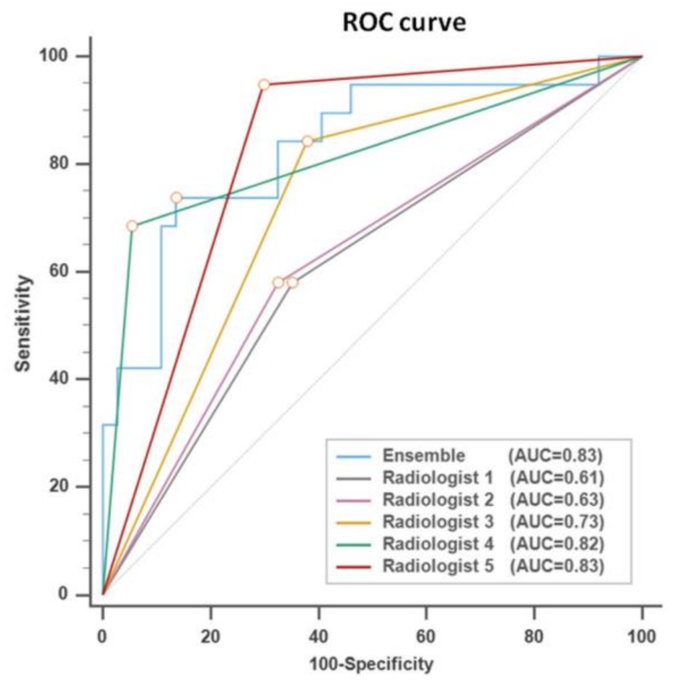
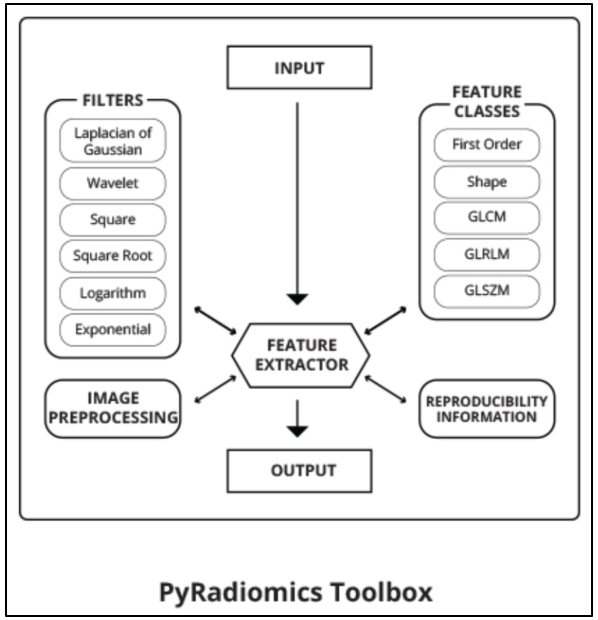


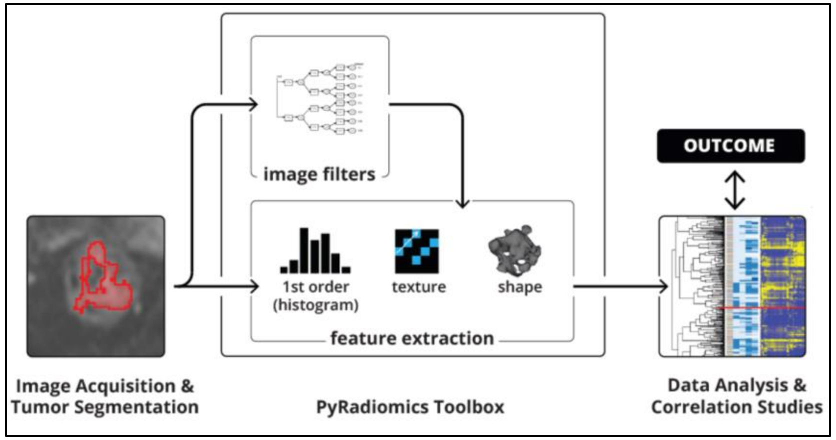
Fig. 4 ROC curves of ensemble model and radiologists

LA RADIOMICA

➢ PyRadiomics: la radiomica in pratica

- ***Libreria open-source per estrarre dati da immagini mediche***
- ***Estrae automaticamente caratteristiche quantitative da TC, RM, PET***
- ***Analizza forma, intensità, texture della lesione segmentata***
- ***Usato per creare modelli predittivi con l'IA***



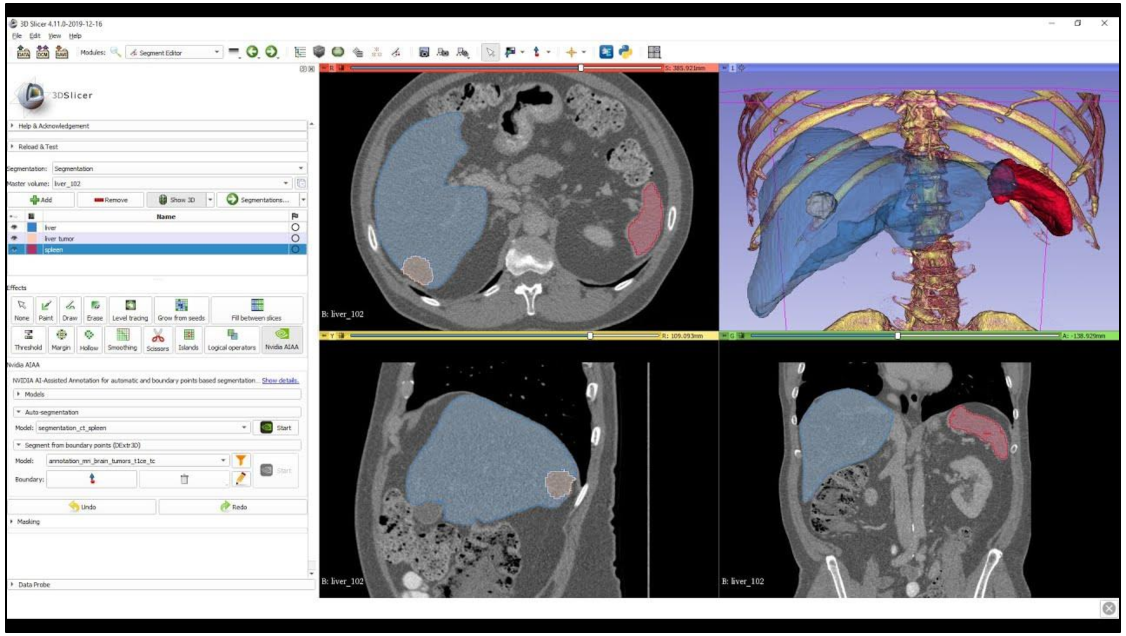


Il TSRM e la Segmentazione: competenze chiave per l'analisi radiomica

➢ Il TSRM può ricoprire un ruolo cruciale nella segmentazione manuale/semi-automatica delle ROI

CORE COMPETENCE:

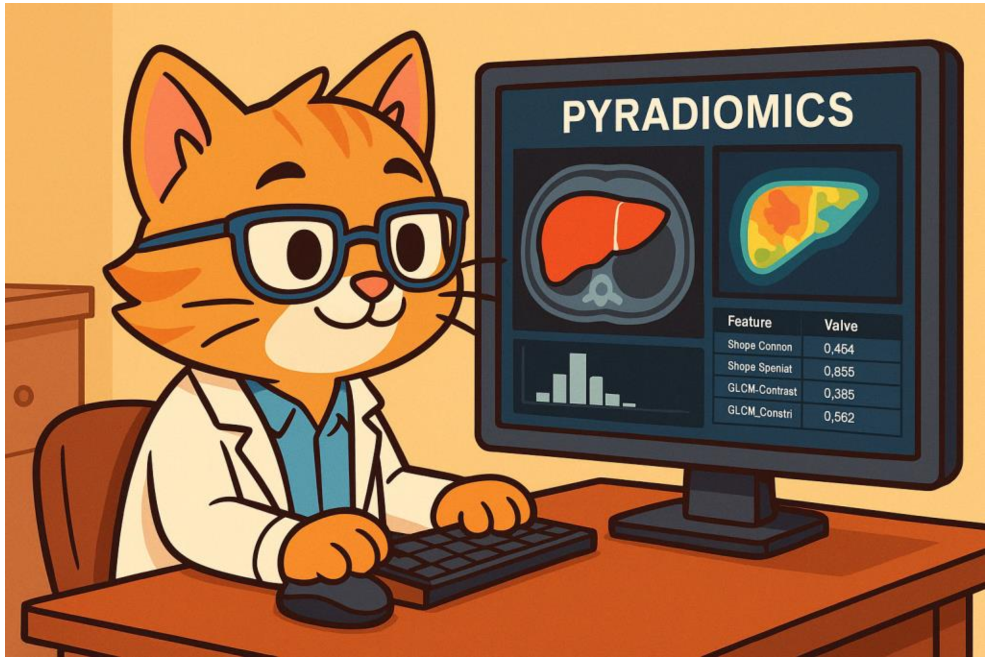
- ***Segmenta le ROI per l'analisi quantitativa delle immagini***
- ***Collaborazione in team multidisciplinari con radiologi, bioingegneri, data scientist***
- ***Necessaria formazione avanzata su IA, DL e software di image analysis***



Il TSRM e la Segmentazione: competenze chiave per l'analisi radiomica

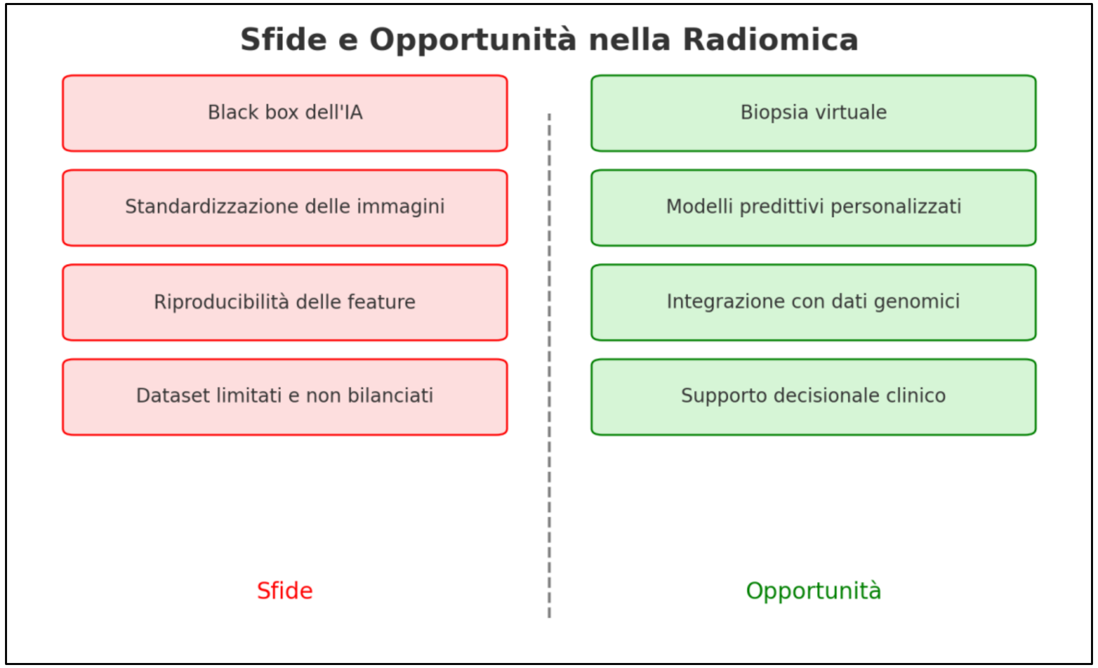
- PyRadiomics e il ruolo del TSRM

- ***Estrae feature da TC, RM, PET via segmentazione***
- ***TSRM può generare dataset e collaborare a modelli predittivi***
- ***Strumento chiave per la medicina personalizzata***



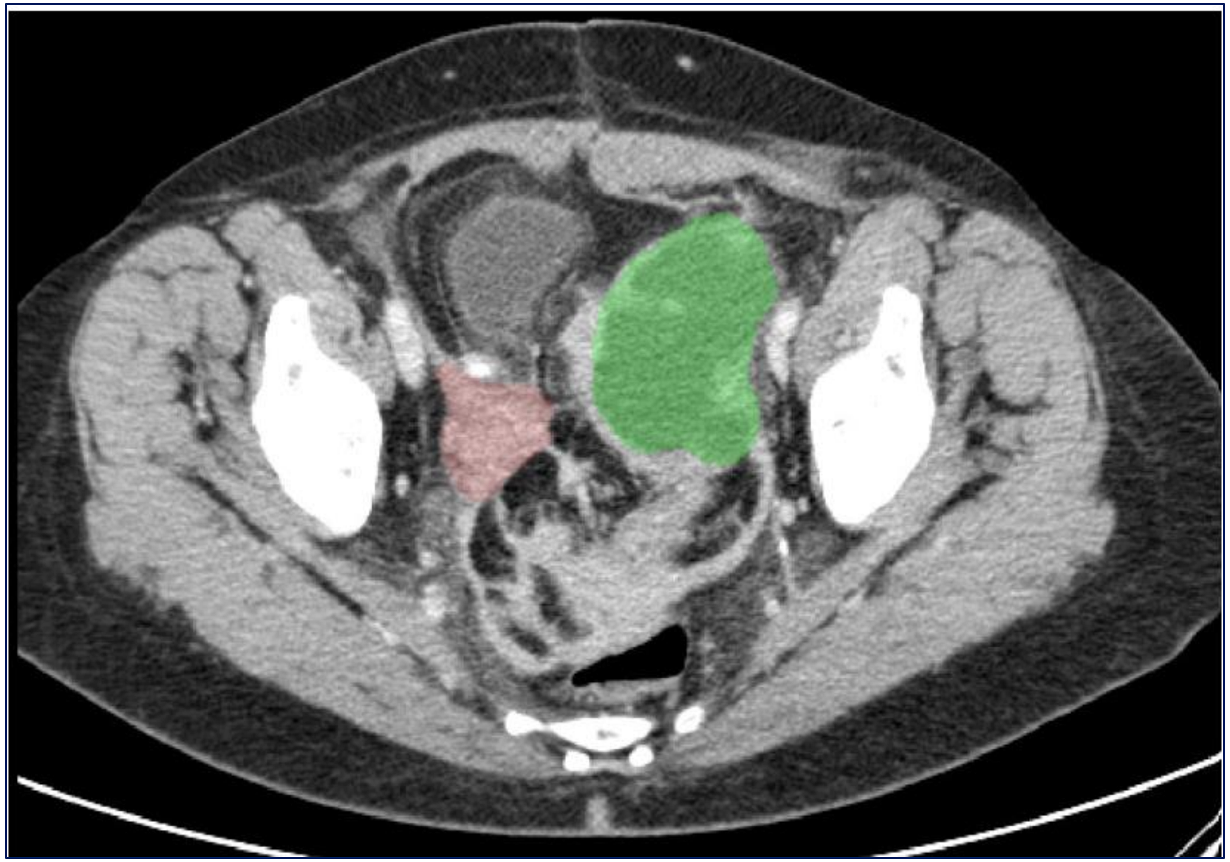
➢ Limitazioni e direzioni future per la radiomica

1. ***Sfide:*** riproducibilità, standardizzazione dei protocolli e necessità di dataset multicentrici
2. ***Prospettive future:*** integrazione con altre "omics" (es. proteomica) e virtual biopsy
3. ***Ruolo TSRM:*** aggiornamento universitario, formazione continua su IA e validazione clinica dei modelli



CASO CLINICO

by courtesy of Gemelli
Fondazione Policlinico Universitario Agostino Gemelli IRCCS
Università Cattolica del Sacro Cuore



Segmentazione di lesione ovarica (rosso a destra, verde a sinistra) mediante software 3D slicer

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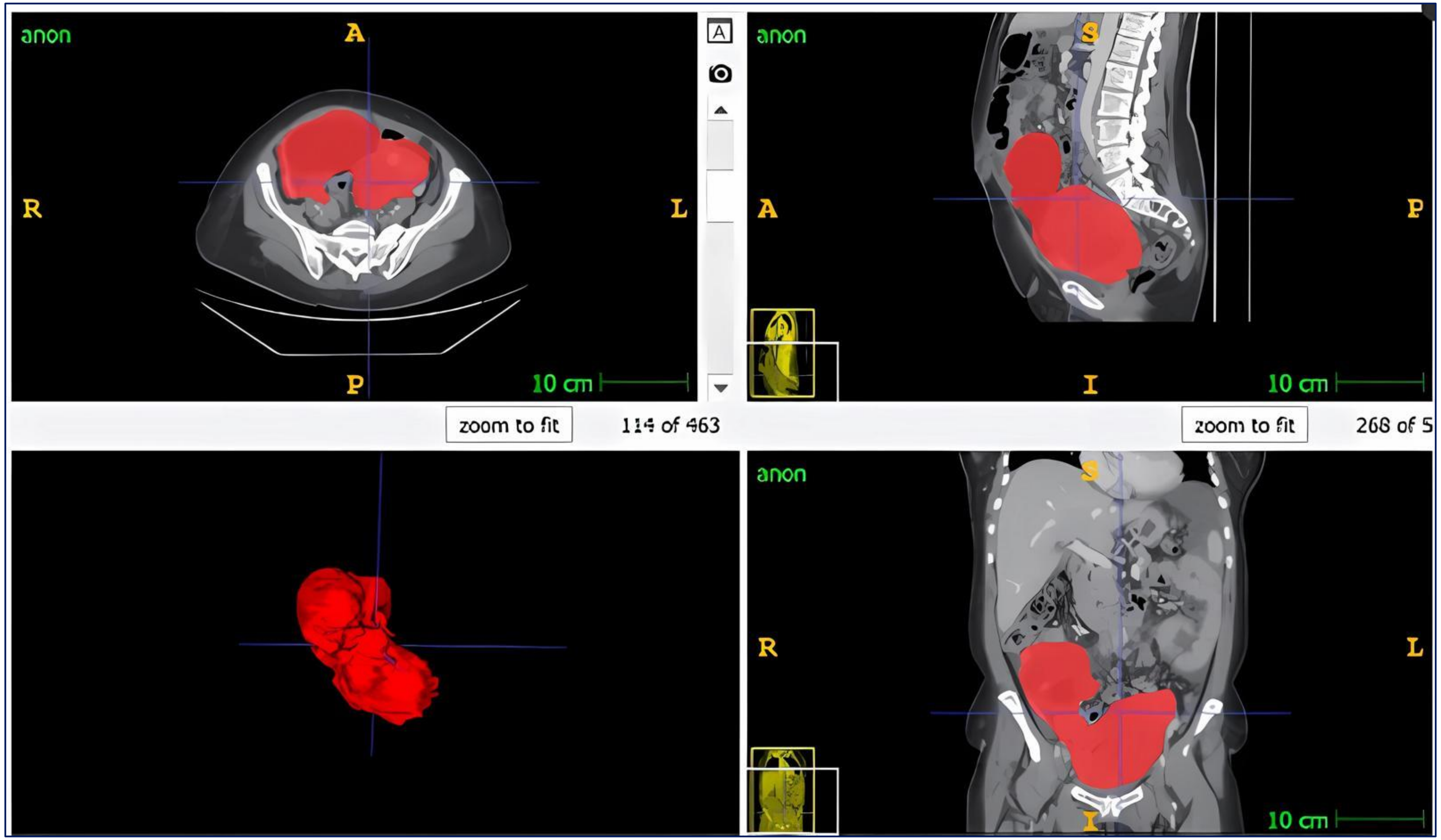

Massa ovarica segmentata e riprodotta in 3D tramite software ITKsnap

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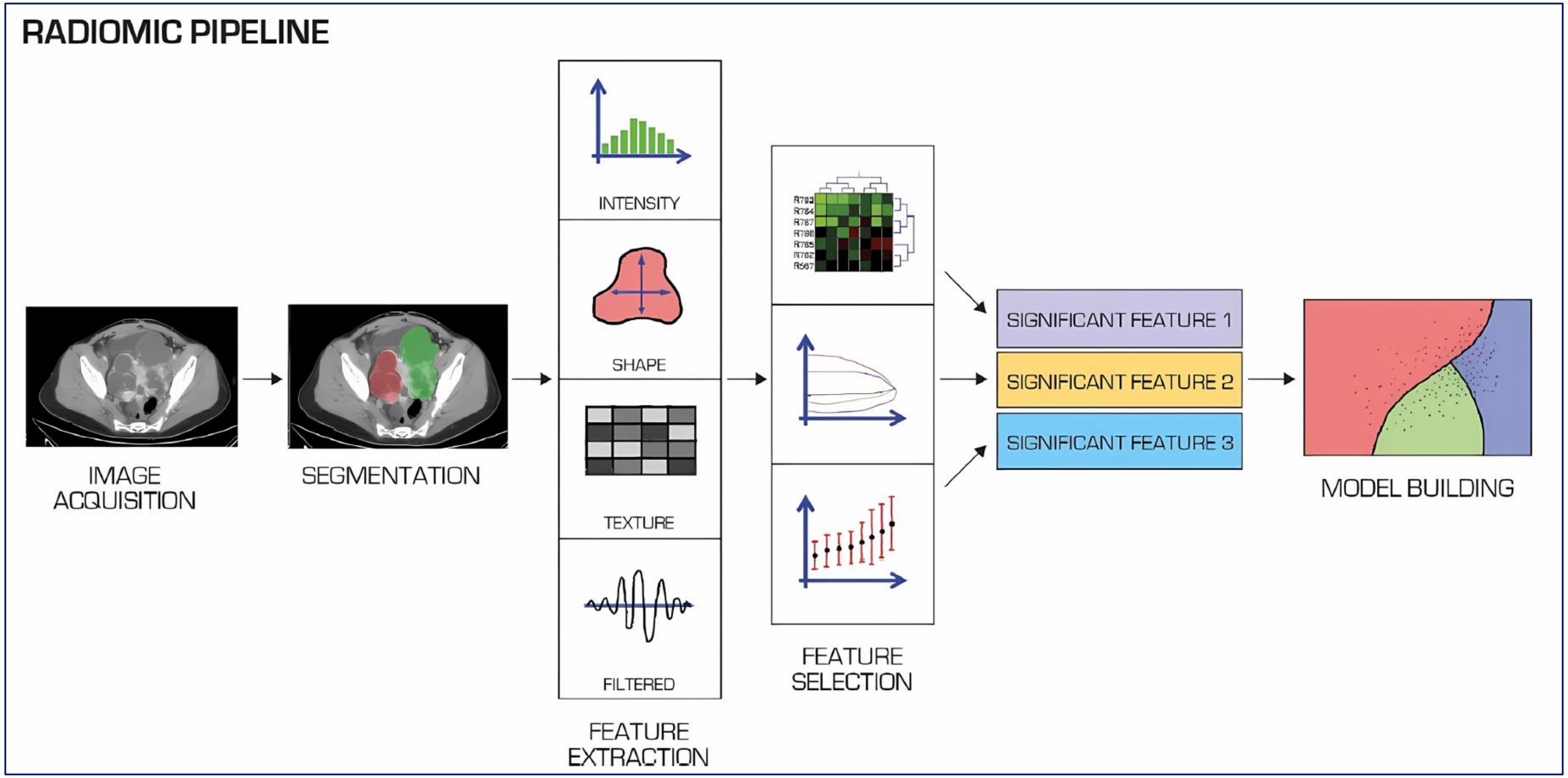

Flusso Radiomico - Implications for Treatment Monitoring and Clinical Management.
Radiol Clin North Am. 2023 Jul;61(4):749-760. doi: 10.1016/j.rcl.2023.02.006. Epub 2023 Mar 31. PMID: 37169435

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“L’IA NON SOSTITUISCE IL TSRM: LO POTENZIA”

- In questo scenario, il TSRM 4.0 diventa una figura strategica, capace di comprendere e ottimizzare le tecnologie avanzate — ***dall’acquisizione alla radiomica*** — per garantire il miglior imaging possibile, la massima radioprotezione e percorsi di cura sempre più personalizzati

- Ma ***accanto alla tecnologia***, restano centrali ***la figura umana e l’empatia***, che nessun algoritmo potrà mai replicare

AITeRTC Associazione Italiana Tecnici di Radiologia Tomografia Computerizzata

SISTEMA SANITARIO REGIONALE ASL ROMA 1

SAPIENZA UNIVERSITÀ DI ROMA

GRAZIE

«La tecnologia non tiene lontano l'uomo dai grandi problemi della natura, ma lo costringe a studiarli più approfonditamente»

Matteo Iacono

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Formazione per l'eccellenza

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