



XXXIII CONGRESSO NAZIONALE AIRO

AIRO2023

**BOLOGNA,
27-29 OTTOBRE 2023**
PALAZZO DEI CONGRESSI

Radioterapia Oncologica: l'evoluzione al servizio dei pazienti

Intelligenza Artificiale, come cambierà
il futuro delle nostre discipline: SIRM, AIMN, AIRO
Il punto di vista del radiologo

Dott.ssa Serena Carriero
Università degli studi di Milano



Società Italiana di
Radiologia Medica
e Interventistica

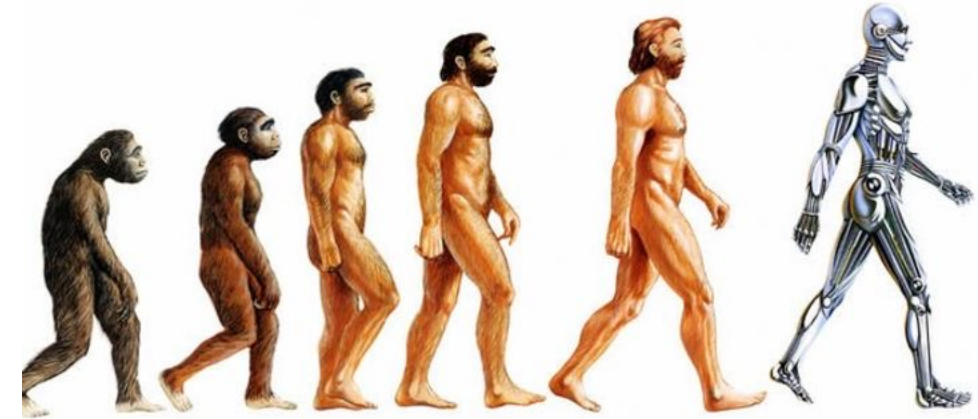
Definizioni

John McCarthy coined the term “artificial intelligence” in 1955, defining it as “**the science and engineering of making intelligent machines**”.

<<una scienza che coinvolge macchine in grado di eseguire compiti caratteristici dell'intelligenza umana>>

Abilità di una macchina di mostrare capacità umane:

- ragionamento
- apprendimento
- pianificazione
- creatività



L'IA permea la nostra realtà quotidiana

Circa 4.670.000.000 risultati (0,27 secondi)

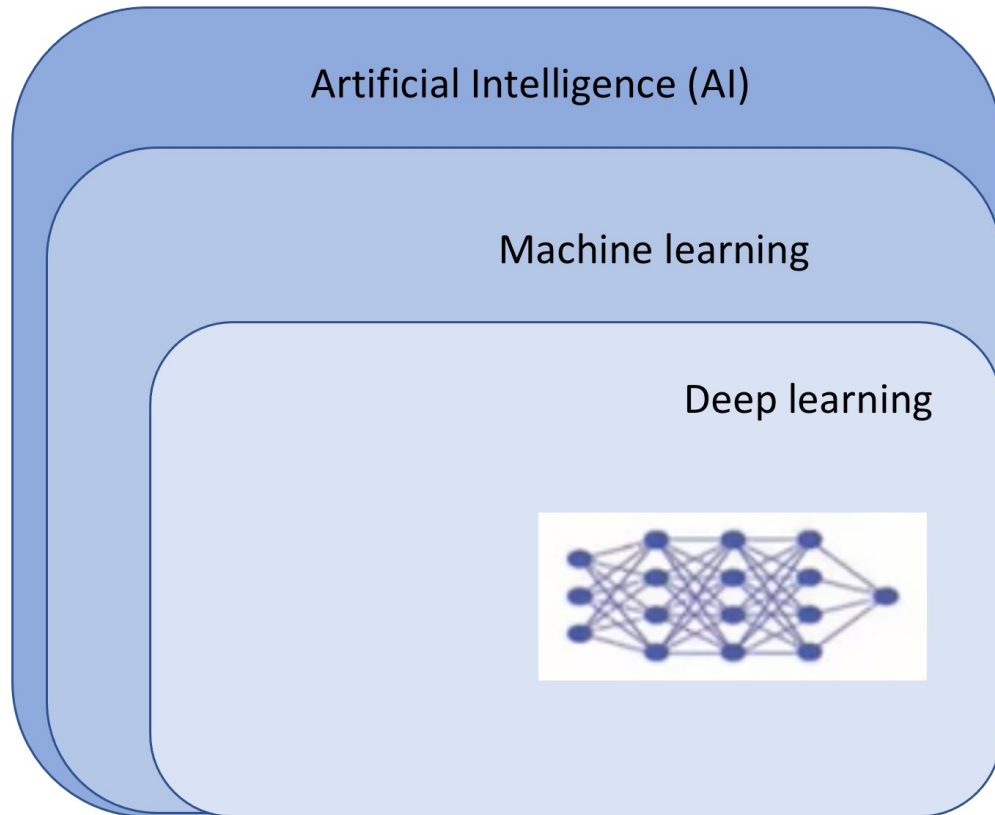
Italiano ↕ Giapponese

Inserisci il testo

Traduzione

Apri in Google Traduttore • Feedback



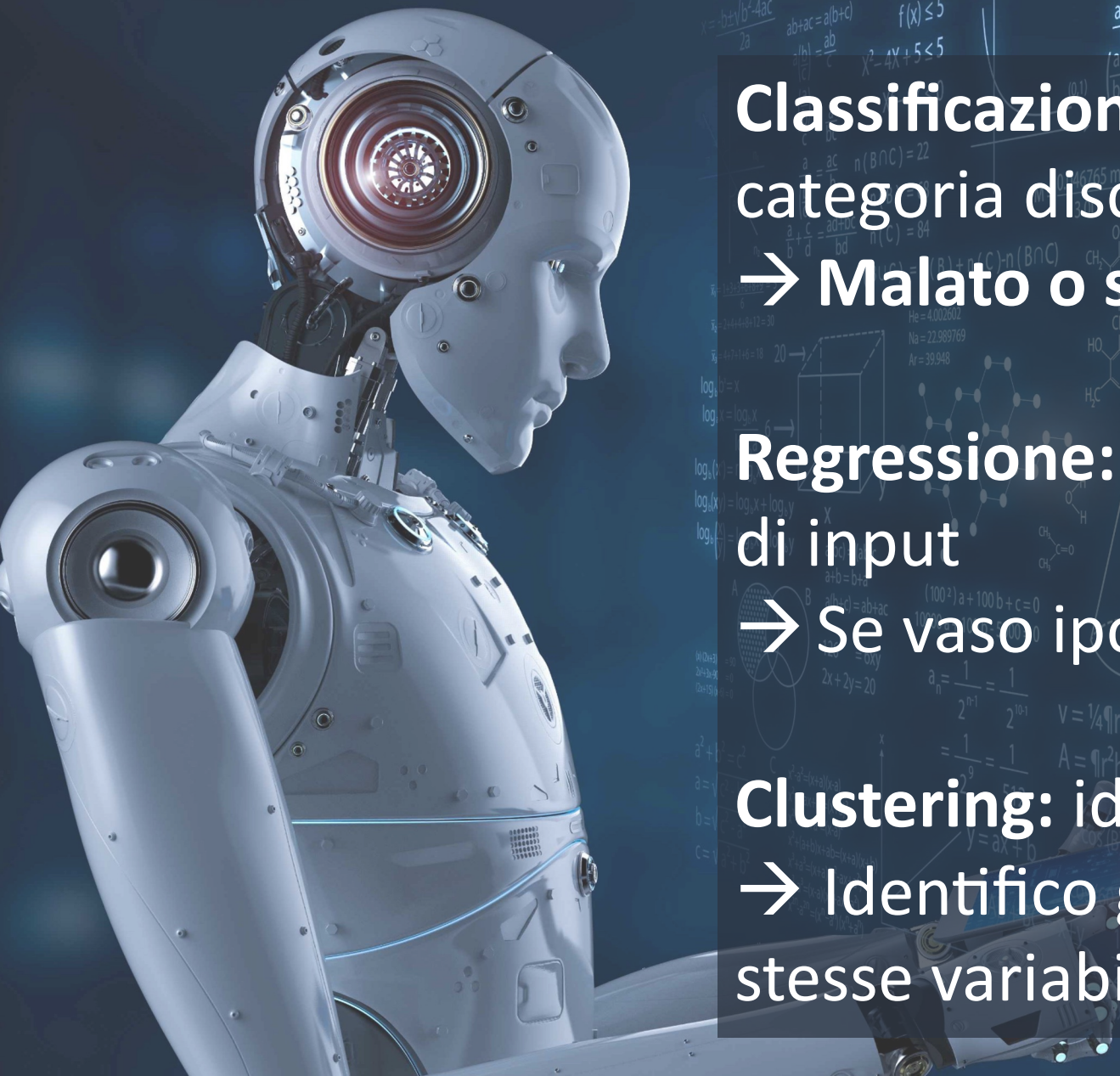


Algoritmi: Insieme di studi e tecniche che realizzano macchine in grado di risolvere problemi e di riprodurre attività proprie dell'intelligenza umana

Machine learning: algoritmi informatici che si addestrano a svolgere dei compiti e migliorano attraverso l'esperienza
Algoritmi che imparano con l'esperienza: dati hanno ruolo fondamentale



Deep learning: algoritmi di apprendimento profondo che utilizzano reti complesse di «neuroni artificiali»
Funzionamento ispirato al cervello umano



Classificazione: assegnare un input ad una categoria discreta

→ Malato o sano?

Regressione: trovare la relazione tra le variabili di input

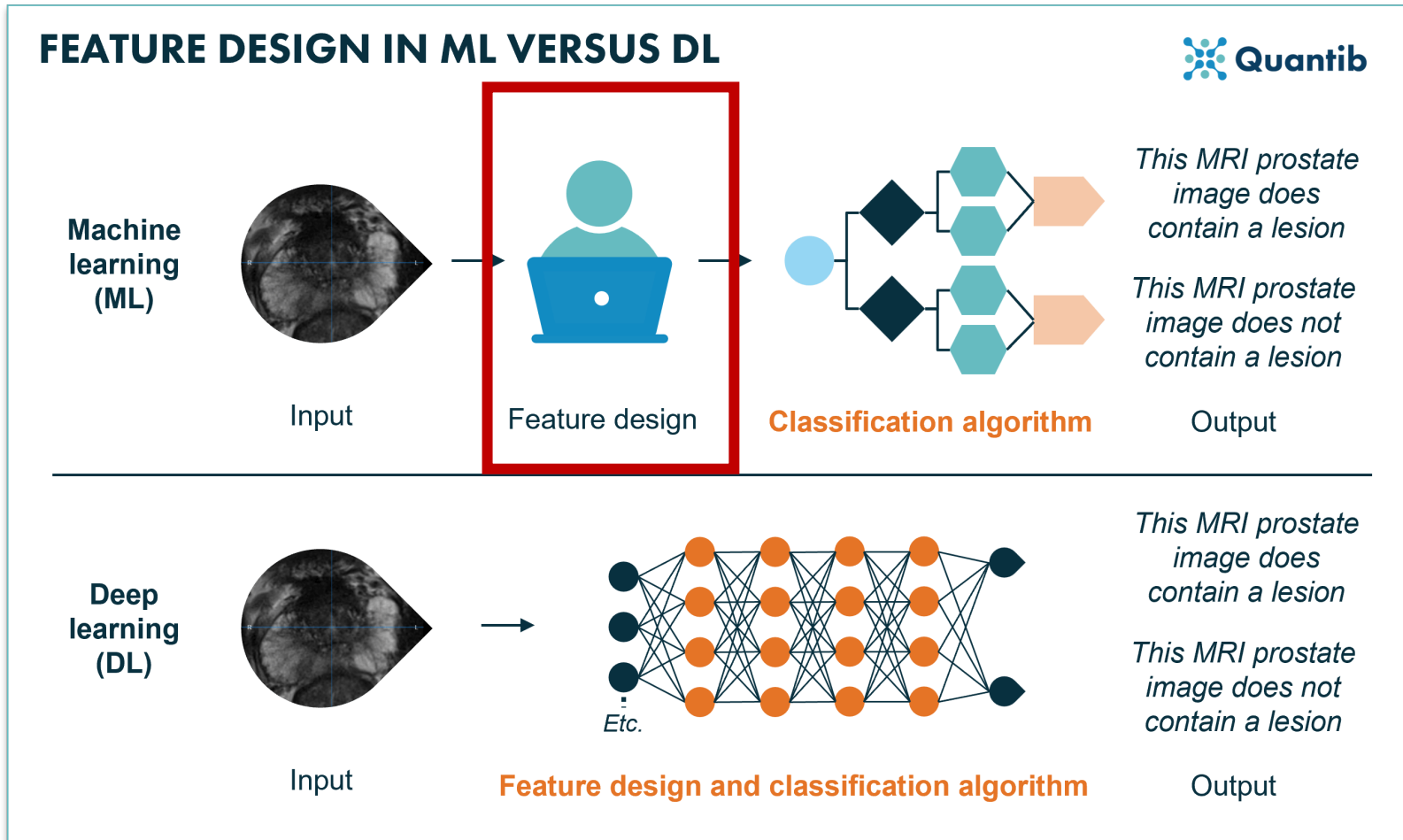
→ Se vaso ipodenso = trombo

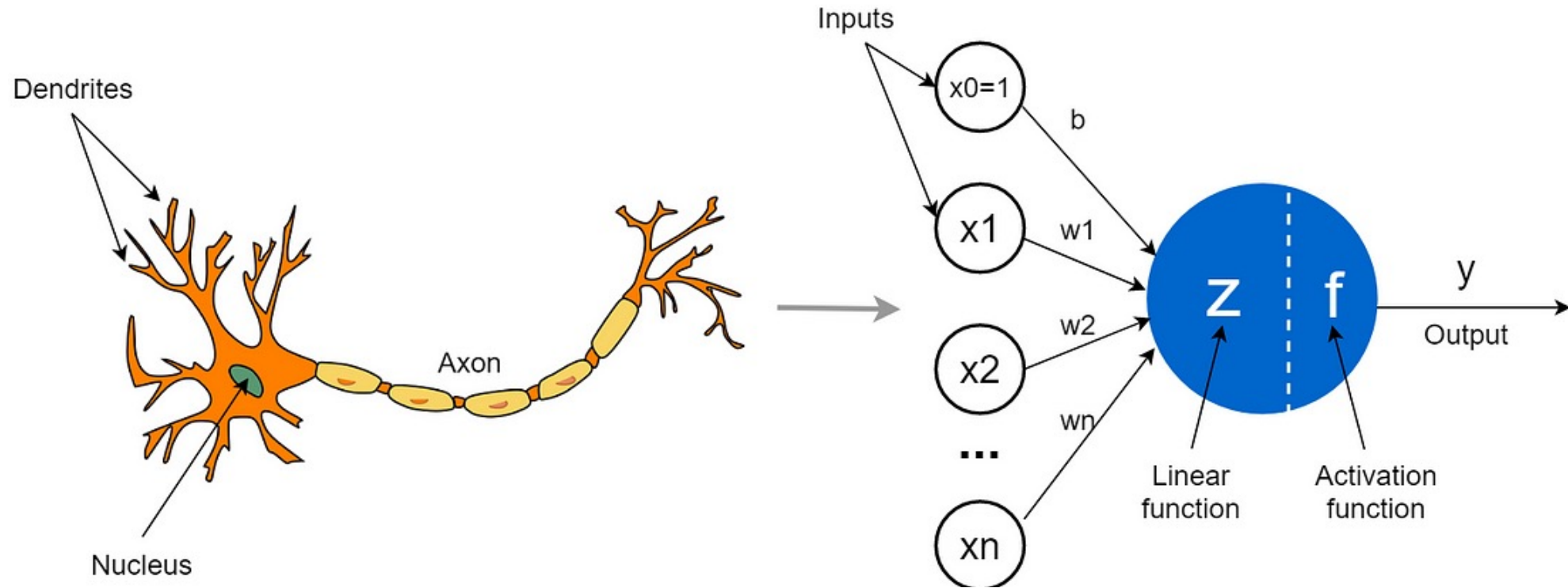
Clustering: identificare pattern nascosti nei dati

→ Identifico gruppi di pazienti che hanno le stesse variabili

Il deep learning elimina una parte della pre-elaborazione dei dati.

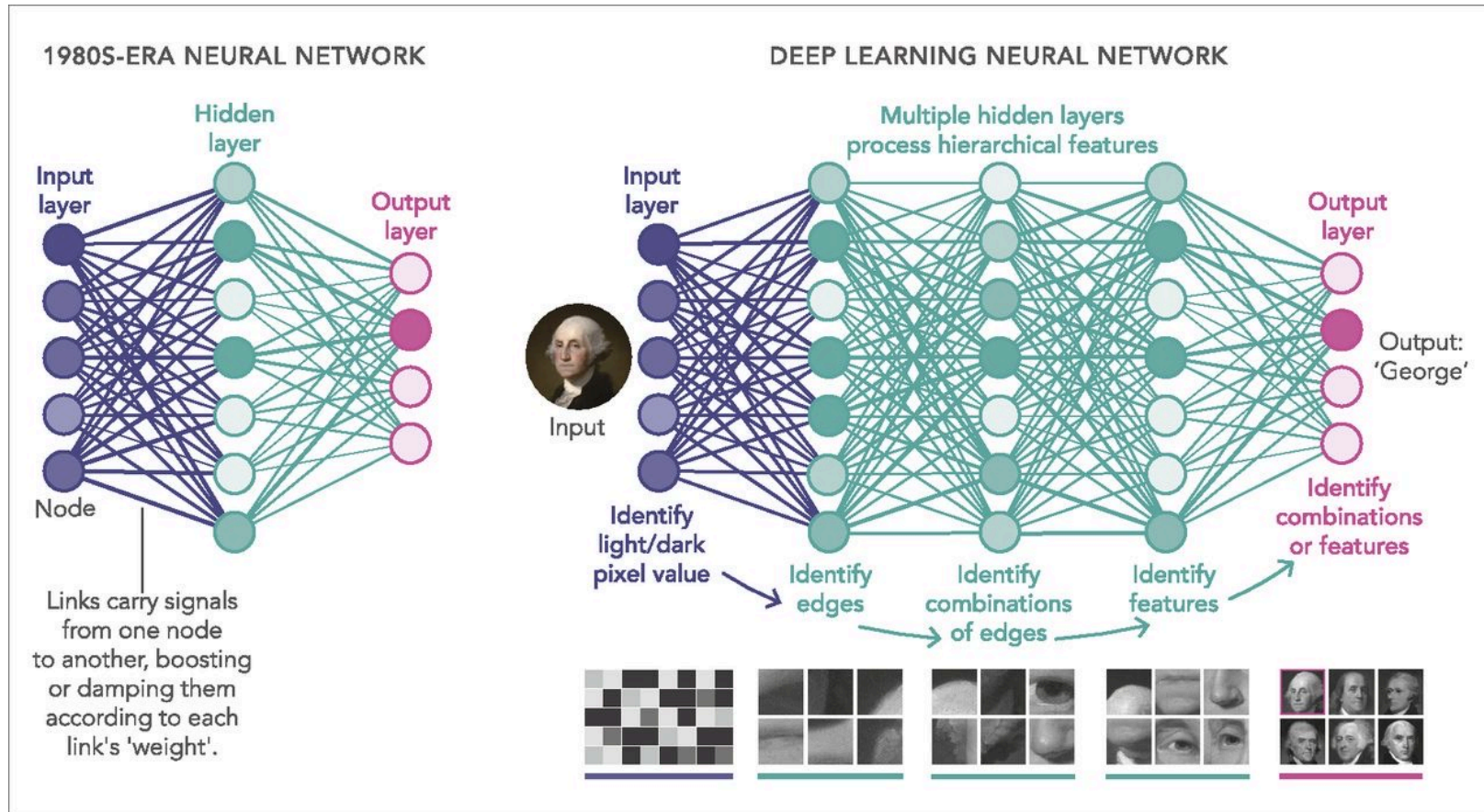
Algoritmi possono acquisire ed elaborare dati non strutturati, come testi e immagini, e **automatizzano** l'estrazione di componenti eliminando una parte di dipendenza dagli esperti umani





Reti Neurali Artificiali

Ricevono input \rightarrow pesano i segnali \rightarrow sommano i segnali \rightarrow se la somma supera un certo valore emettono output



Neuroni sono connessi in strati e strutture
Strati connessi in parallelo tra loro (miliardi di connessioni)

- Connessione: Architettura
- Ogni architettura si adatta bene alla risoluzione di determinati problemi
 1. **Convoluzionali:** analisi immagini
 2. **Trasformers:**
traduzione/riconoscimento
linguaggio (chat gtp)
- Reti profonde sono più performanti



Intelligenza artificiale: ristretta, generale, super



Narrow AI

Dedicated to assist with or take over specific tasks.



General AI

Takes knowledge from one domain, transfers to other domain.



Super AI

Machines that are an order of magnitude smarter than humans.

Siamo lontani dall'intelligenza umana poiché AI non

- apprende da pochi esempi
- ha nozioni di base pre-codificate

Radiologia oggi:

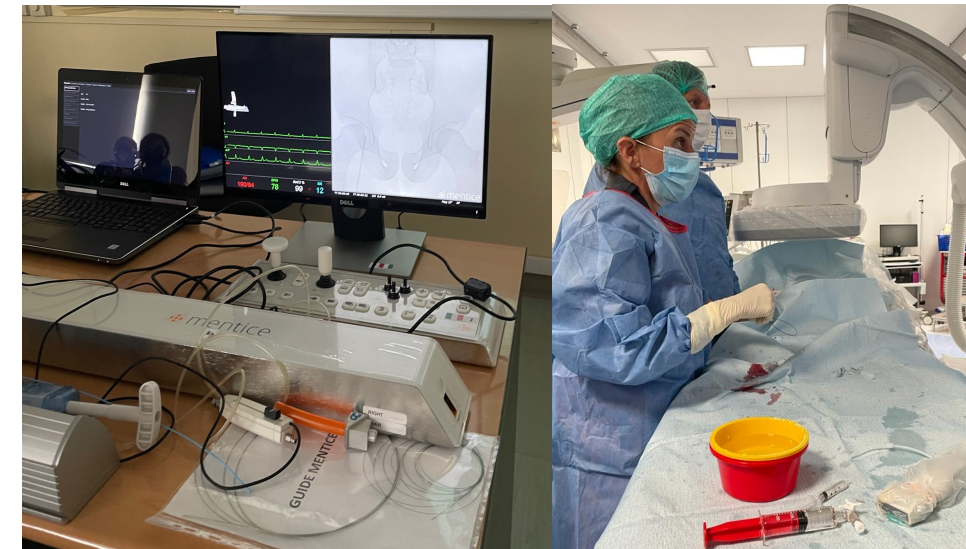
Diagnosis

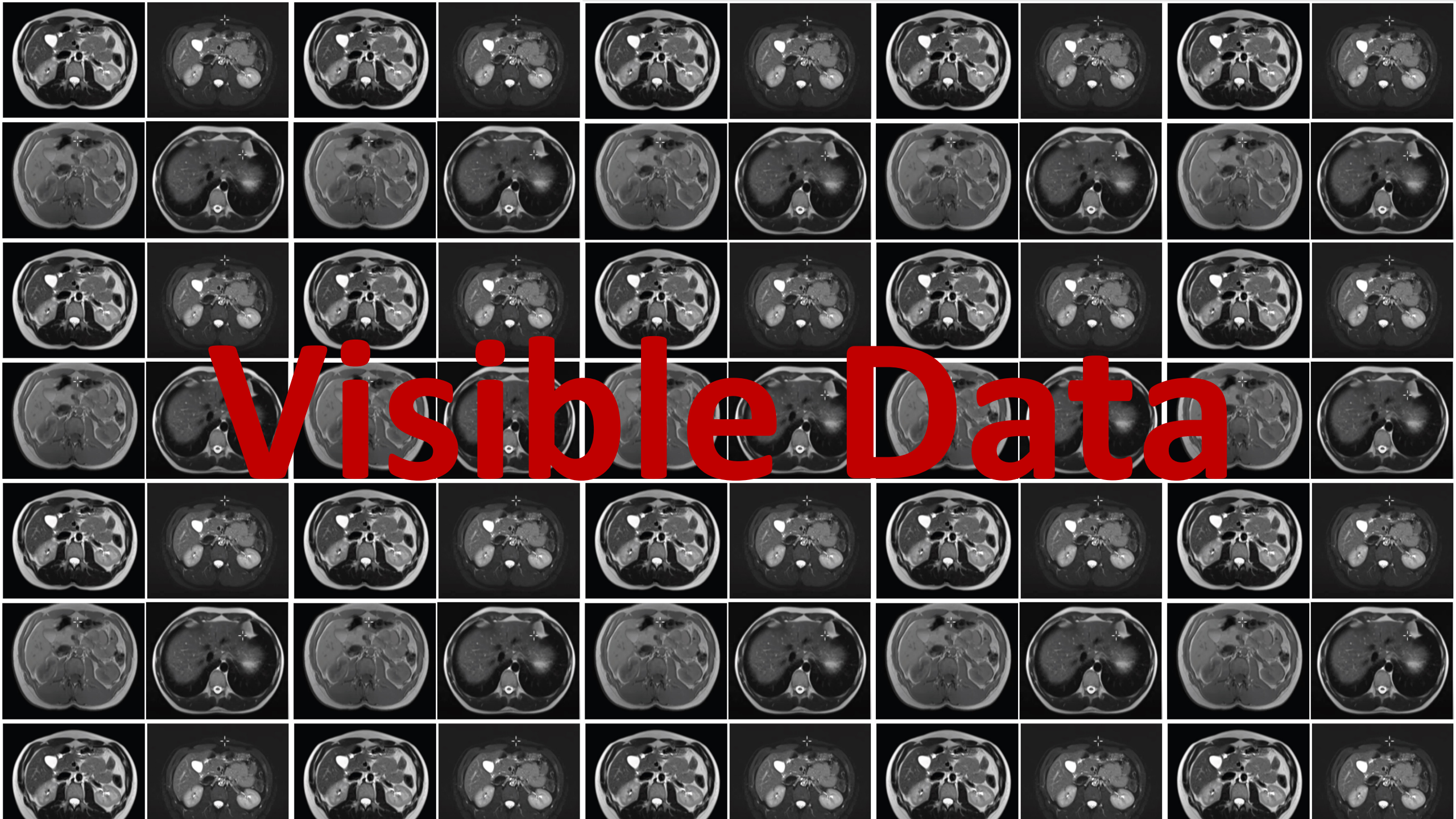
Visible Data

Unvisible Data

Imaging guided
Treatment

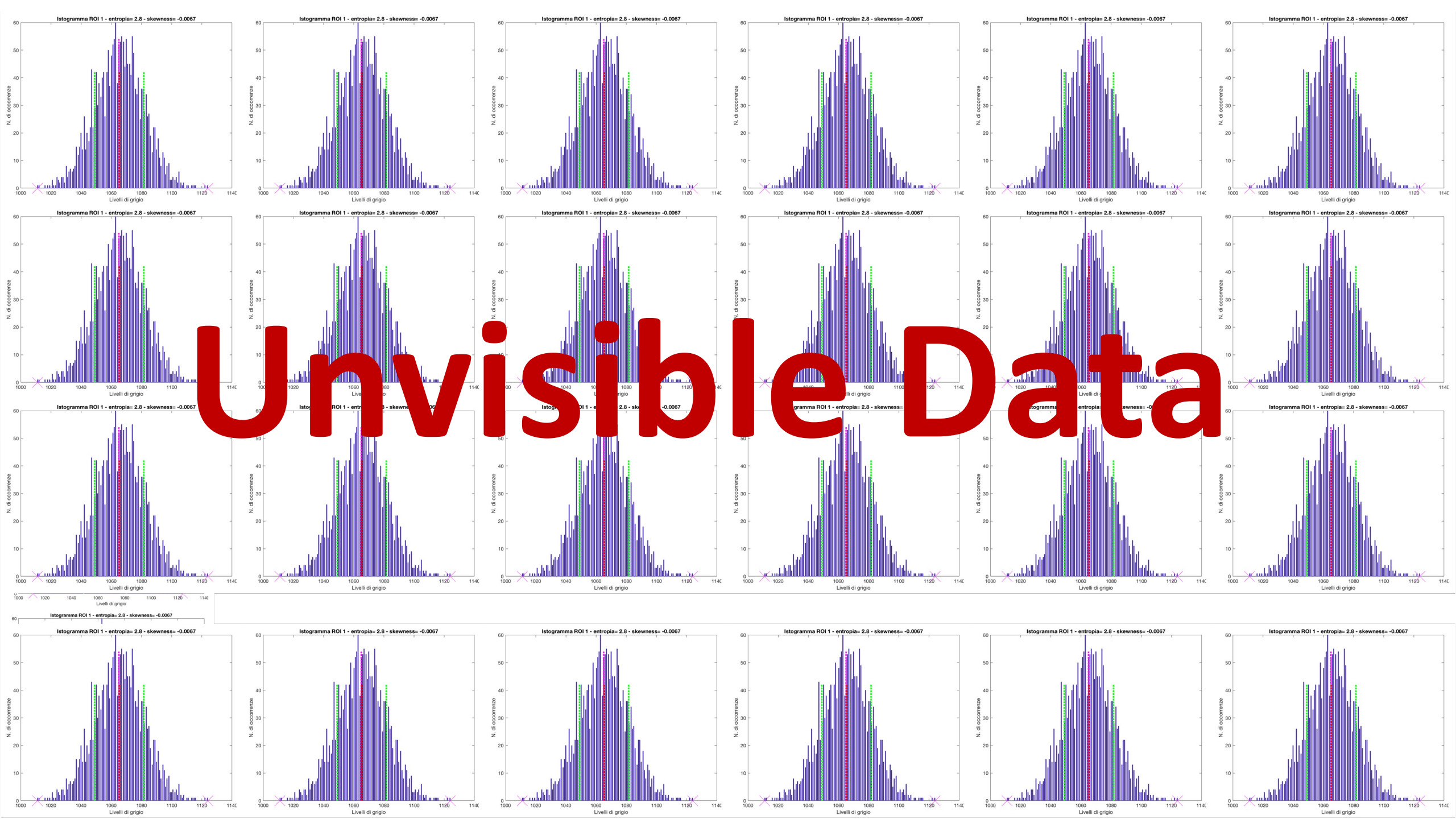
Interventional





Visible Data

Unvisible Data



An abstract digital visualization featuring two glowing spheres, one light blue on the left and one fiery red on the right, connected by a bright blue horizontal beam of light. The background is dark with intricate, glowing orange and yellow fiber-like structures that resemble a complex network or data flow. The word "Data" is centered in a large, white, sans-serif font.

Data

**Radiology is
not only
imaging**

**Radiology is
not general
radiology**



Medicina personalizzata

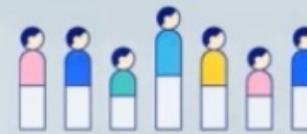
Assegnare giusto trattamento al giusto paziente

Passato: uno stesso trattamento per una patologia

Presente: un diverso trattamento basato sulle caratteristiche del paziente per la stessa patologia

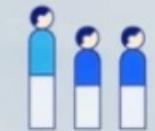
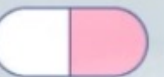
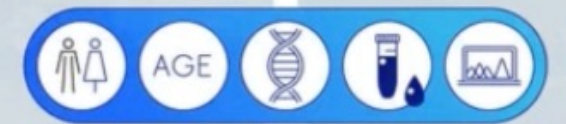
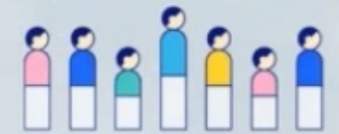
Conventional Medical Care and Precision Medicine

Conventional medical care



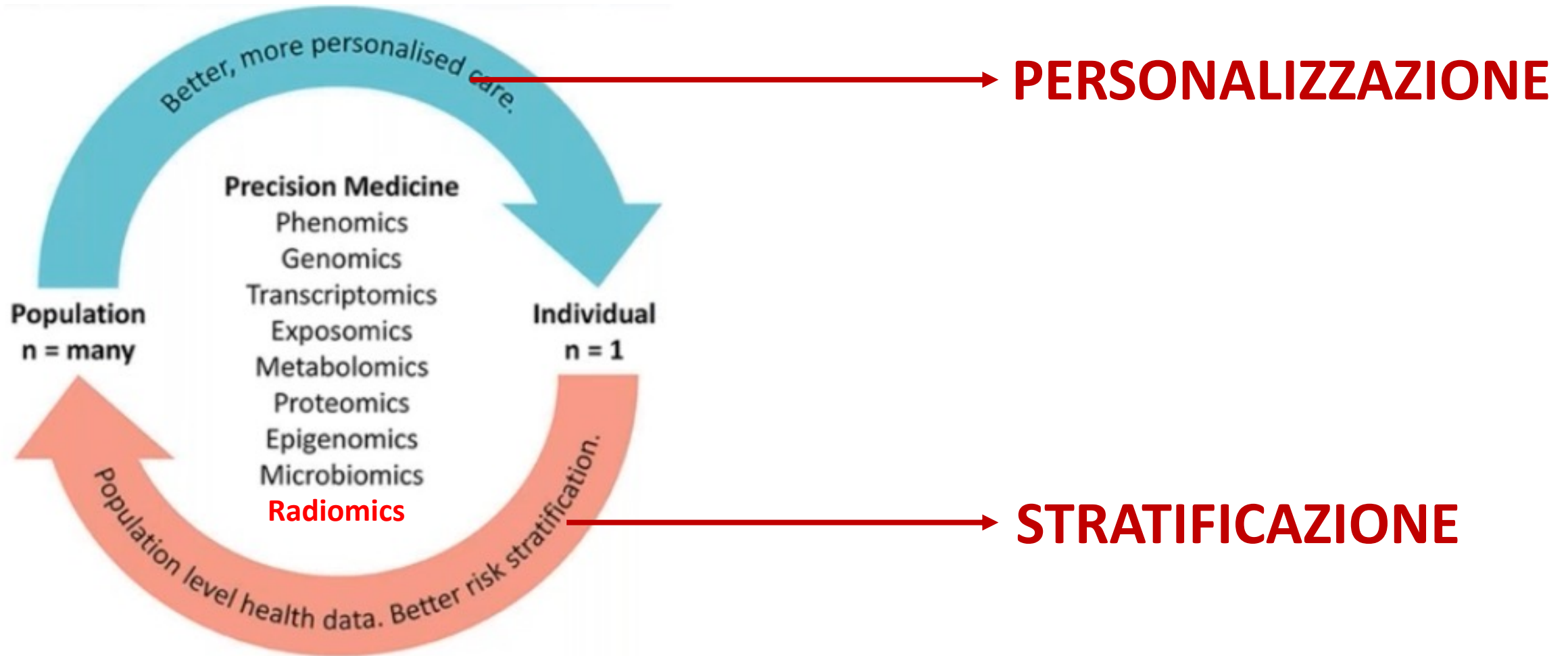
One treatment method for diverse patients

Precision medicine



Provide several options depending on the patient group by using various analysis technologies

Medicina personalizzata



Radiomica e IA



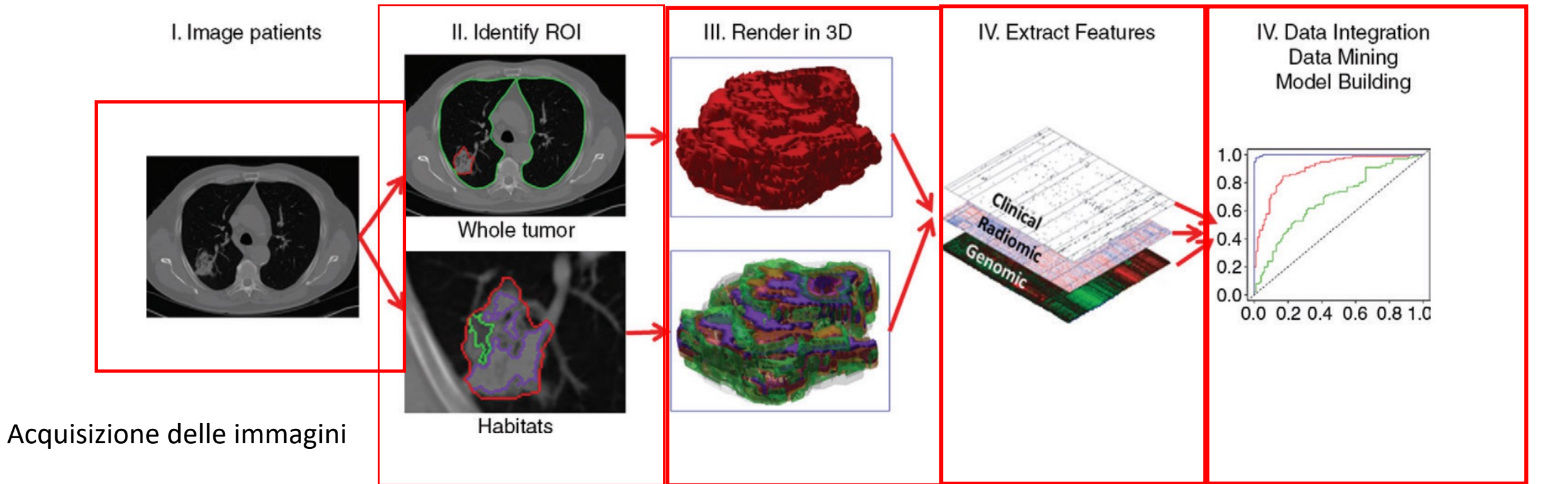
Nella nuova era della *medicina di precisione* la **radiomica** è un campo di ricerca traslazionale emergente il cui scopo è quello di trovare relazioni tra informazioni qualitative e quantitative estratte da immagini e dati clinici, integrate eventualmente da dati di genomica, allo scopo di supportare le decisioni cliniche

La radiomica affonda le sue radici nella **Computer Aided Diagnosis (CAD)**, tecnica di analisi d'immagini diagnostiche che risale già agli anni '80, che utilizza le variabili quantitative dell'immagine stessa (geometria, intensità, "texture") per identificare un tessuto anomalo mediante metodi statistici o di "machine learning" e che viene considerata dai radiologi alla stregua di una "seconda opinione" per la localizzazione e l'identificazione di lesioni.

La radiomica può essere vista come un'evoluzione della CAD, presentando tuttavia due importanti aspetti innovativi:

- prende in considerazione un numero molto elevato di variabili (centinaia o anche migliaia);
- l'ambito di indagine consiste nell'associazione di variabili estratte da immagini radiologiche con endpoint clinici o biologici, quali: istologia del tumore, risposta alla terapia, sopravvivenza.

Radiomics framework

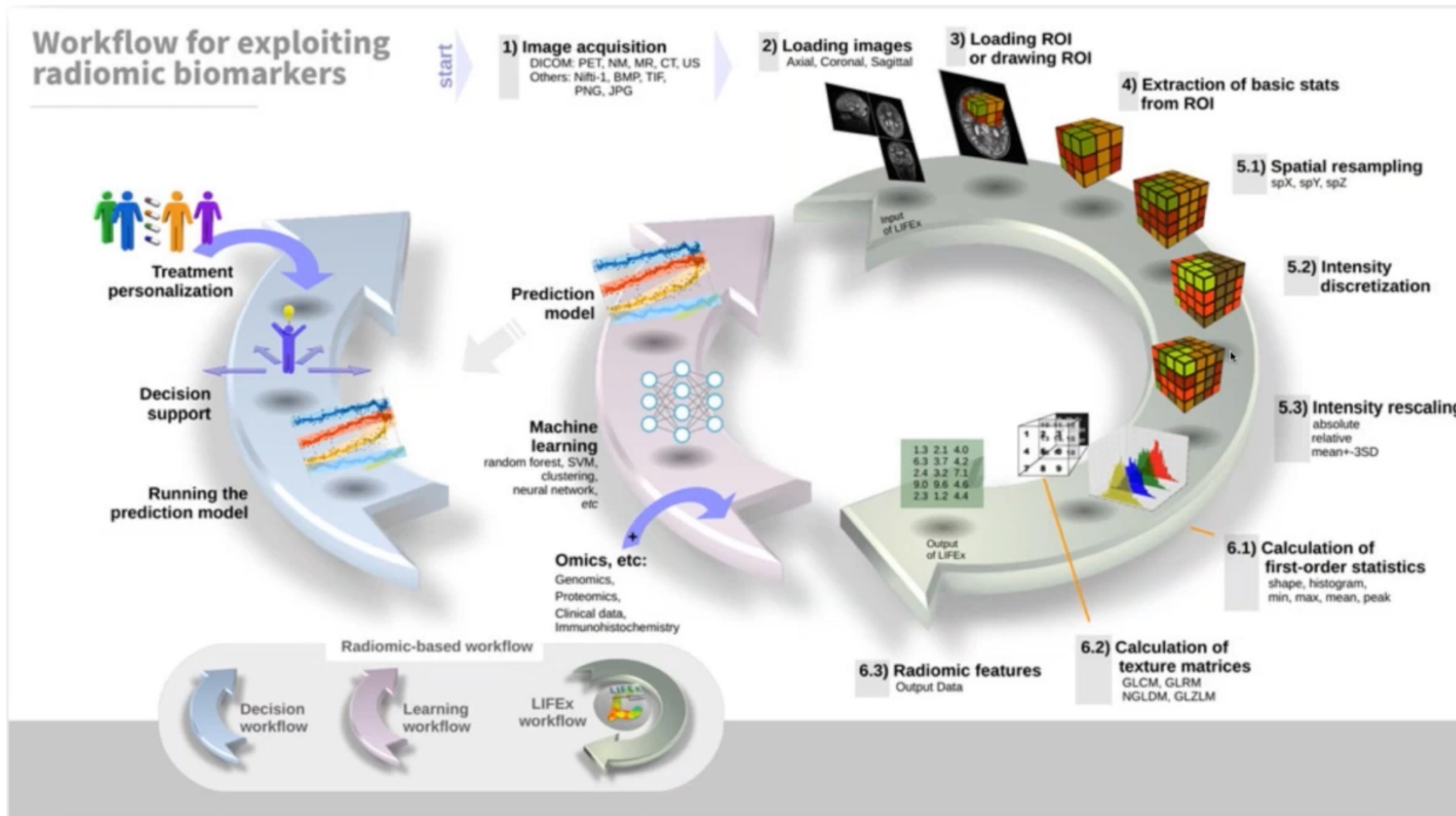


Identificazione e segmentazione della regione di interesse contenente tutto il tumore o Sub-regioni (habitats) all'interno del tumore

Estrazione e qualificazione delle features descrittive dai volumi e dagli habitats segmentati

Integrazione dei dati radiomici in algoritmi di ML e DL per poterli correlare ai dati clinici Effettuare analisi approfondite personalizzate e **costruire modelli predittivi sulla base dell'integrazione dei dati.**

Medicina personalizzata



Estrazione dei dati dall'immagine (ML o DL) → creare modelli predittivi → indirizzano il singolo paziente al singolo trattamento.

Campi di applicazione dell'intelligenza artificiale

Radiology: Artificial Intelligence

SPECIAL REPORT

Imaging AI in Practice: A Demonstration of Future Workflow Using Integration Standards

Walter F. Wiggins, MD, PhD* • Kirti Magudia, MD, PhD* • Teri M. Sippel Schmidt, MS •
Stacy D. O'Connor, MD, MPH • Christopher D. Carr, MA • Marc D. Kohli, MD • Katherine P. Andriole, PhD, MD

From the Department of Radiology, Duke University School of Medicine, DUMC Box 3808, 2301 Erwin Rd, Durham, NC 27710 (W.F.W.); Department of Radiology & Biomedical Imaging, University of California, San Francisco, Calif (K.M., M.D.K.); Department of Biomedical Engineering, Marquette University, Milwaukee, Wis (T.M.S.S.); Department of Biomedical Engineering (T.M.S.S.) and Radiology (C.D.C.), Medical College of Wisconsin, Milwaukee, Wis; Department of Informatics, Rad-

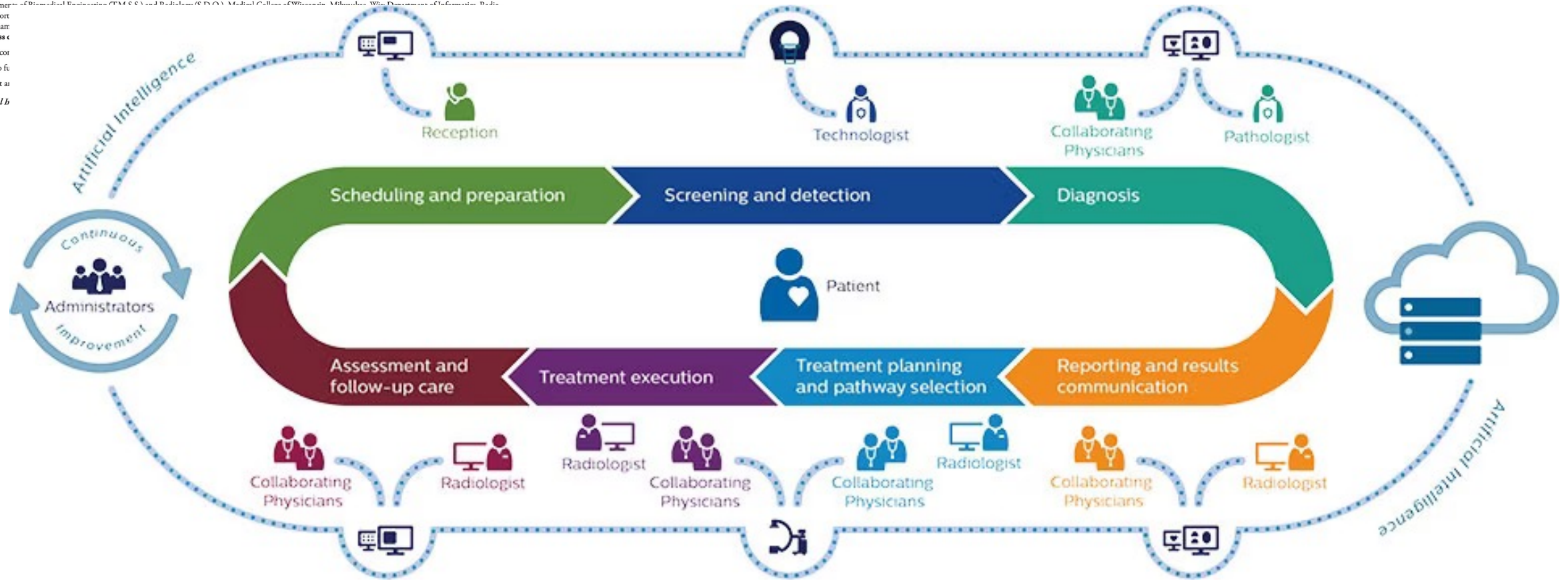
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*W.F.W. and K.M. cor

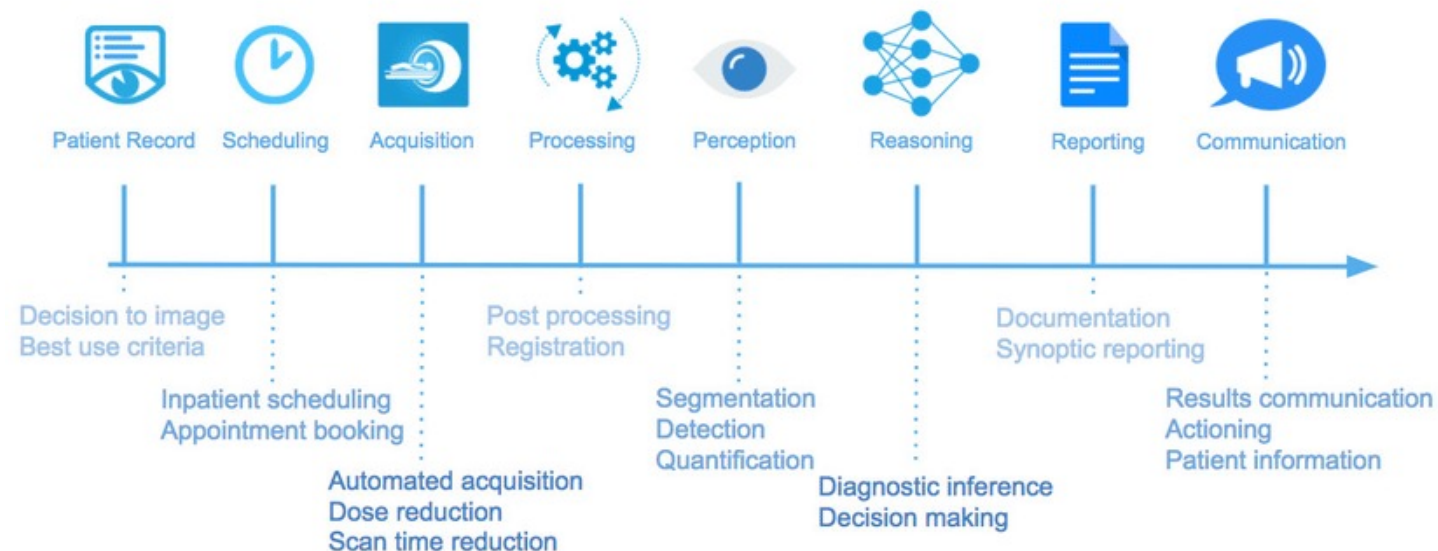
Authors declared no fu

Conflicts of interest at

Radiology: Artificial In



Campi di applicazione dell'intelligenza artificiale



Radiology: Artificial Intelligence

REVIEW

Overview of Noninterpretive Artificial Intelligence Models for Safety, Quality, Workflow, and Education Applications in Radiology Practice

Yasavi Tadavarthi, MD • Valeria Makeeva, MD • William Wagstaff, MD • Henry Zhan, MD • Anna Podlasek, MD • Neil Bhatia, BS • Marta Heilbrun, MD • Elizabeth Krupinski, PhD • Nabile Safdar, MD • Imon Banerjee, PhD • Judy Gichoya, MD • Hari Trivedi, MD

From the Department of Medicine, Medical College of Georgia, Augusta, Ga (Y.T.); Department of Radiology and Imaging Sciences (V.M., W.W., H.Z., M.H., E.K., N.S., J.G., H.T.), School of Medicine (N.B.), and Department of Biomedical Informatics (I.B.), Emory University, 1364 E Clifton Rd NE, Atlanta, GA 30322; and Southend University Hospital NHS Foundation Trust, Westcliff-on-Sea, UK (A.P.). Received April 28, 2021; revision requested June 24; revision received December 17; accepted January 11, 2022. Address correspondence to H.T. (e-mail: hari.trivedi@emory.edu).

Authors declared no funding for this work.

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

Radiology: Artificial Intelligence 2022; 4(2):e210114 • <https://doi.org/10.1148/ryai.210114> • Content code: AI

Radiology: Artificial Intelligence

SPECIAL REPORT

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*W.F.W. and K.M. contributed equally to this work.

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[Home](#) > [European Radiology](#) > [Article](#)

Computed Tomography | [Published: 30 August 2023](#)

Inappropriate CT examinations: how much, who and where? Insights from a clinical decision support system (CDSS) analysis

[Shani Rosen](#), [Clara Singer](#), [Sharona Vaknin](#), [Arielle Kaim](#), [Osnat Luxenburg](#), [Arnon Makori](#), [Natalia Goldberg](#), [Moran Rad](#), [Shani Gitman](#) & [Mor Saban](#) 

[European Radiology](#) (2023) | [Cite this article](#)

Application of the ESR iGuide clinical decision support system to the imaging pathway of patients with hepatocellular carcinoma and cholangiocarcinoma: preliminary findings

[Michela Gabelloni](#)¹, [Matteo Di Nasso](#)², [Riccardo Morganti](#)³, [Lorenzo Faggioni](#)², [Gianluca Masi](#)⁴, [Alfredo Falcone](#)⁴, [Emanuele Neri](#)²

Affiliations + expand

PMID: 32020528 DOI: [10.1007/s11547-020-01142-w](https://doi.org/10.1007/s11547-020-01142-w)

LEARN MORE

[ESR iGuide](#) / [Learn More](#)

Learn how to use the web portal to access the European Society of Radiology's guidance for appropriate imaging

The ESR iGuide portal provides a stand-alone decision support solution for appropriate imaging using the ESR's imaging referral guidelines. Users consult the ESR's guidelines across 10 topic areas, developed in cooperation with the American College of Radiology, via two workflow options.

Indication-driven workflow: the indication driven workflow is initiated by selecting one or more clinical indications as reasons for requesting an imaging exam. Once the indications are selected, ESR iGuide provides feedback on the appropriateness of different imaging exams according to the ESR's guidelines.

Procedure-driven workflow: in this workflow, users start with the imaging service they would like to request for a patient, before entering the relevant clinical indication(s). ESR iGuide then provides appropriateness information on the selected exam, as well as alternative exams to consider for this indication.

[Read the full ESR iGuide Portal User Guide.](#)

- Sceglie l'esame di imaging di più appropriato in funzione del:
- problema di salute del paziente,
 - ridurre l'utilizzo non idoneo di tecniche di imaging,
 - evita esposizione inutile a radiazioni ionizzanti

Selezione automatica protocolli

Radiology:Artificial Intelligence

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Overview of Noninterpretive Artificial Intelligence Models for Safety, Quality, Workflow, and Education Applications in Radiology Practice

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ever. At our institution, approximately 1–2 hours per day in each division is spent protocoling studies, totaling 50 hours per week across the department, which is the equivalent of the workload for one full-time equivalent radiologist. Protocoling is time-consuming for many reasons, including the frequent presence of dozens of protocol options, the need to look up information from the EMR, and the lack of intelligent aids within the protocol workflow.

> J Am Coll Radiol. 2020 Sep;17(9):1149–1158. doi: 10.1016/j.jacr.2020.03.012. Epub 2020 Apr 9.

Machine Learning for Automation of Radiology Protocols for Quality and Efficiency Improvement

Angad Kalra ¹, Amit Chakraborty ², Benjamin Fine ³, Joshua Reicher ⁴

Affiliations + expand

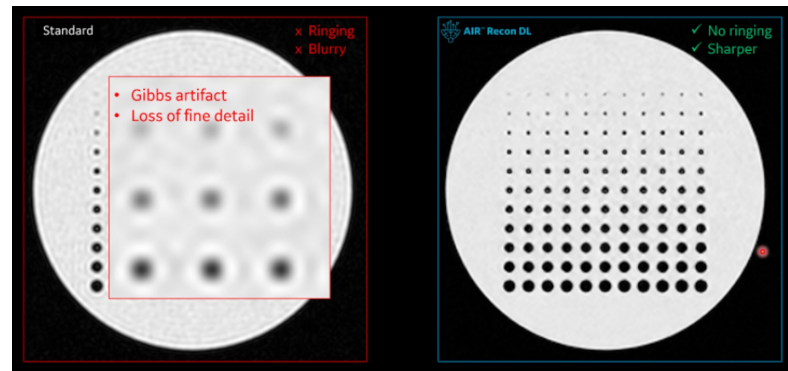
PMID: 32278847 DOI: [10.1016/j.jacr.2020.03.012](https://doi.org/10.1016/j.jacr.2020.03.012)

Results: Baseline protocol assignment performance achieved weighted precision of 0.757 to 0.824. Simulating real-world deployment using combined thresholding techniques, the optimized deep neural network model assigned 69% of protocols in automation mode with 95% accuracy. In the remaining 31% of cases, the model achieved 92% accuracy in CDS mode. Analysis of discordance with subspecialty radiologist labels revealed both more and less appropriate model predictions.

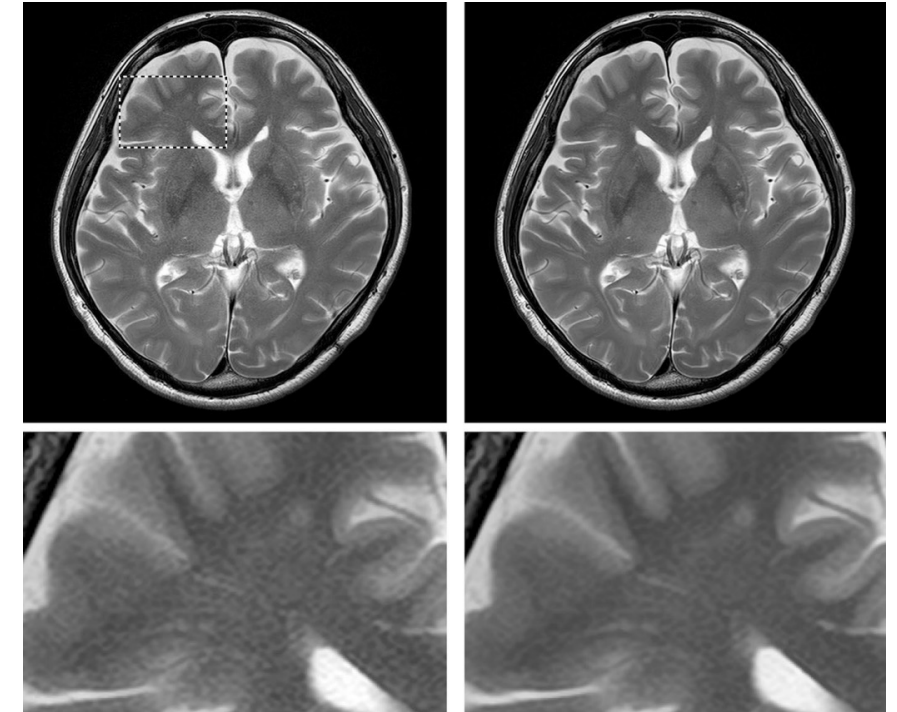
Conclusions: A multiclass NLP-based classification algorithm was designed to drive local operational improvement in CT and MR radiology protocol assignment at subspecialist quality. The results demonstrate a simulated workflow deployment enabling automated assignment of protocols in nearly 7 of 10 cases with very few errors combined with top-three CDS for remaining cases supporting a high-quality, efficient radiology workflow.

Acquisizione delle immagini e post-processing

- Incrementa efficienza acquisizione
- ottimizza dose e mdc
- reduce tempo acquisizione
- elimina artefatti



Artefatti di Gibbs -> repentino cambiamento di contrasto





Japanese Journal of Radiology (2019) 37:73–80





Artificial intelligence for breast cancer detection in screening mammography in Sweden: a prospective, population-based, paired-reader, non-inferiority study

Karin Dembrower, MD   • Alessio Crippa, PhD • Eugenia Colón, MD • Prof Martin Eklund, PhD • Fredrik Strand, MD • and the ScreenTrustCAD Trial Consortium [†] • [Show footnotes](#)

[Open Access](#) • Published: September 08, 2023 • DOI: [https://doi.org/10.1016/S2589-7500\(23\)00153-X](https://doi.org/10.1016/S2589-7500(23)00153-X) • [Check for updates](#)

Findings

From April 1, 2021, to June 9, 2022, 58344 women aged 40–74 years underwent regular mammography screening, of whom 55581 were included in the study. 269 (0·5%) women were diagnosed with screen-detected breast cancer based on an initial positive read: double reading by one radiologist plus AI was non-inferior for cancer detection compared with double reading by two radiologists (261 [0·5%] vs 250 [0·4%] detected cases; relative proportion 1·04 [95% CI 1·00–1·09]). Single reading by AI (246 [0·4%] vs 250 [0·4%] detected cases; relative proportion 0·98 [0·93–1·04]) and triple reading by two radiologists plus AI (269 [0·5%] vs 250 [0·4%] detected cases; relative proportion 1·08 [1·04–1·11]) were also non-inferior to double reading by two radiologists.

Interpretation

Replacing one radiologist with AI for independent reading of screening mammograms resulted in a 4% higher non-inferior cancer detection rate compared with radiologist double reading. Our study suggests that AI in the study setting has potential for controlled implementation, which would include risk management and real-world follow-up of performance.

Diagnosi e prognosi dei tumori

Clinical Applications of Machine Learning in Radiology

Order scheduling and patient screening

Automated clinical decision support and examination protocoling

Image acquisition

Automated detection of findings and features

Automated interpretation of findings

Image management, display and archiving (eg, picture archiving and communication systems)

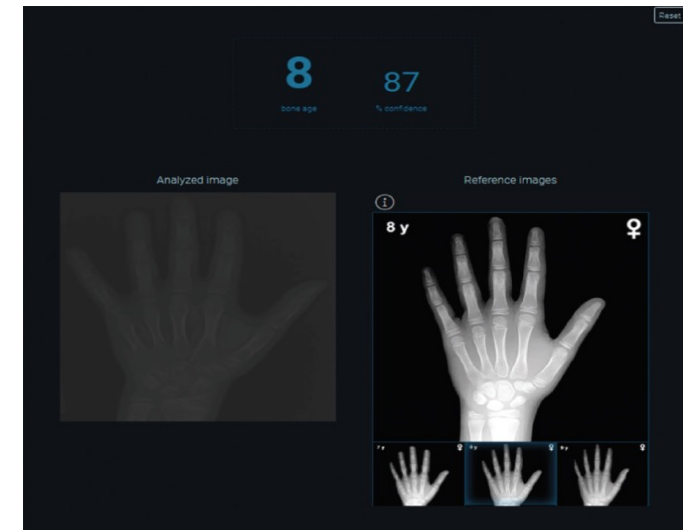
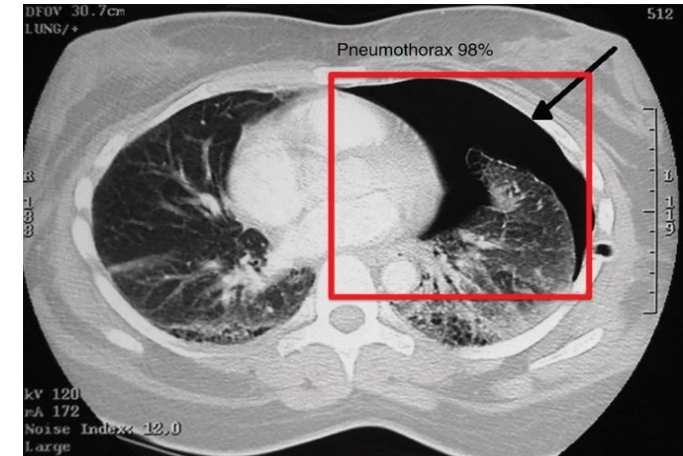
Postprocessing: image segmentation, registration, and quantification

Image quality analytics

Automated dose estimation

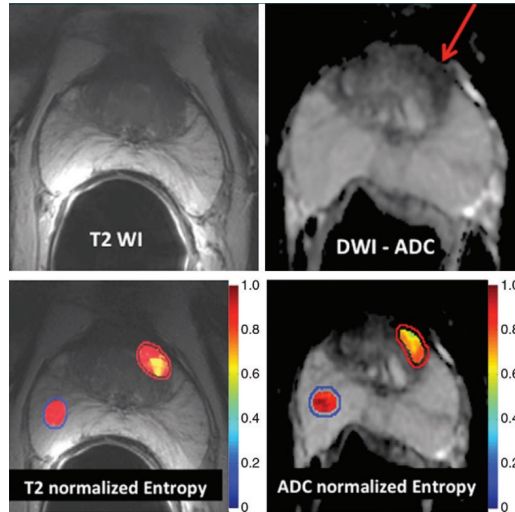
Radiology reporting and analytics

Automated correlation and integration of medical imaging data with other data sources

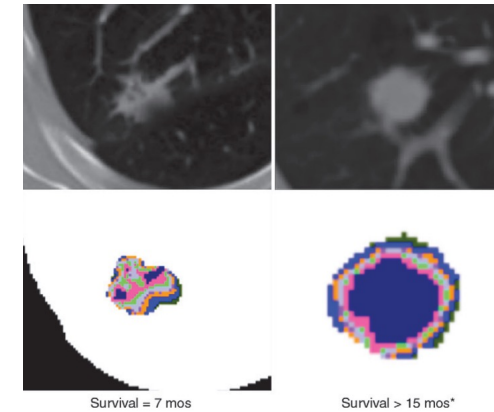


Diagnosi e prognosi dei tumori

ENABLING DIAGNOSIS



TUMOR PROGNOSIS



RADIOMICS IN CLINICAL PRACTICE

TREATMENT RESPONSE

Gillies et al

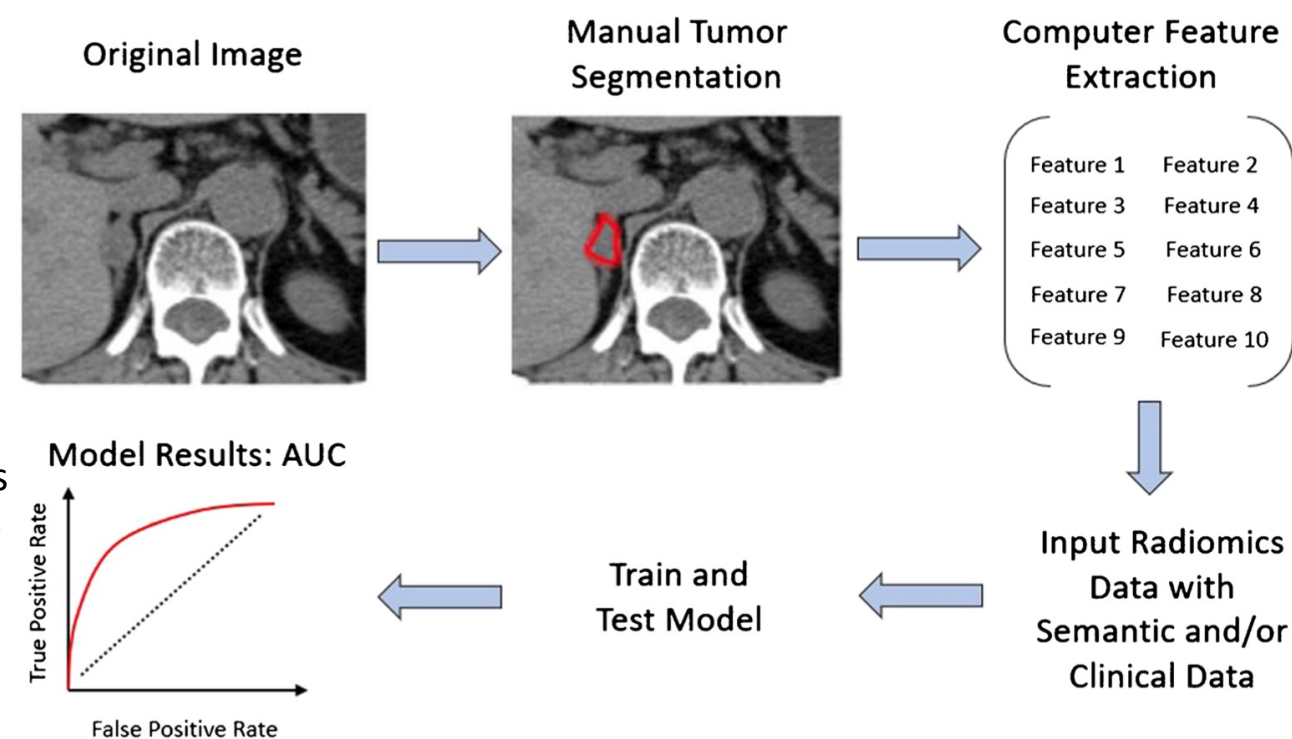
Texture analysis of dynamic contrast-enhanced MR imaging in **locally advanced breast cancer** could help predict **response to neoadjuvant chemotherapy** before its initiation

Jose R. Teruel et al.

CT Texture Analysis and Machine Learning Improve Post-ablation Prognostication in Patients with Adrenal Metastases: A Proof of Concept

Dania Daye¹ · Pedro V. Staziaki² · Vanessa Fiorini Furtado³ · Azadeh Tabari¹ · Florian J. Fintelmann¹ · Nathan Elie Frenk¹ · Paul Shyn⁴ · Kemal Tuncali⁴ · Stuart Silverman⁴ · Ronald Arellano¹ · Michael S. Gee¹ · Raul Nirmal Uppot¹

- Given the large amount of data contained in images, machine learning methods are useful to make sense of the them
- Addition of texture features from routine pre-procedural CT images significantly **improved the accuracy of models predicting outcome following thermal ablation of adrenal metastases.**
- **CT texture features are used as a marker of biological aggressiveness and responsiveness to percutaneous ablation**



Predizione dell'area di ablazione

Cone beam computed tomography images fusion in predicting lung ablation volumes: a feasibility study

Anna Maria Ierardi¹, Mario Petrillo², Genti Xhepa¹,
Domenico Laganà¹, Filippo Piacentino¹, Chiara Floridi¹,
Ejona Duka¹, Carlo Fugazzola¹ and Gianpaolo Carrafiello¹

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DOI: 10.1177/0284185115574874
acr.sagepub.com
SAGE

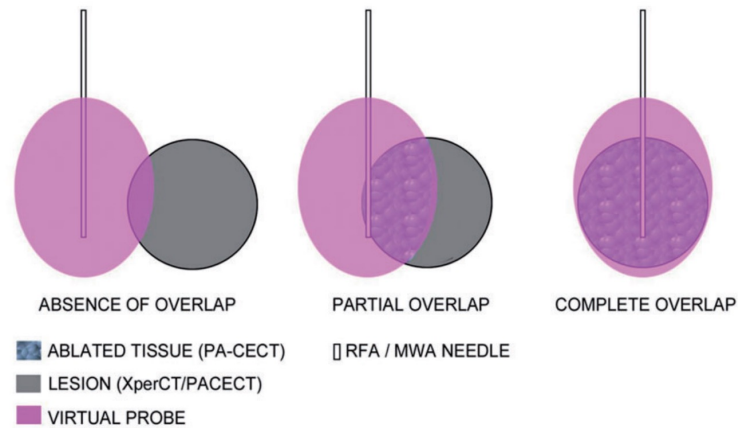
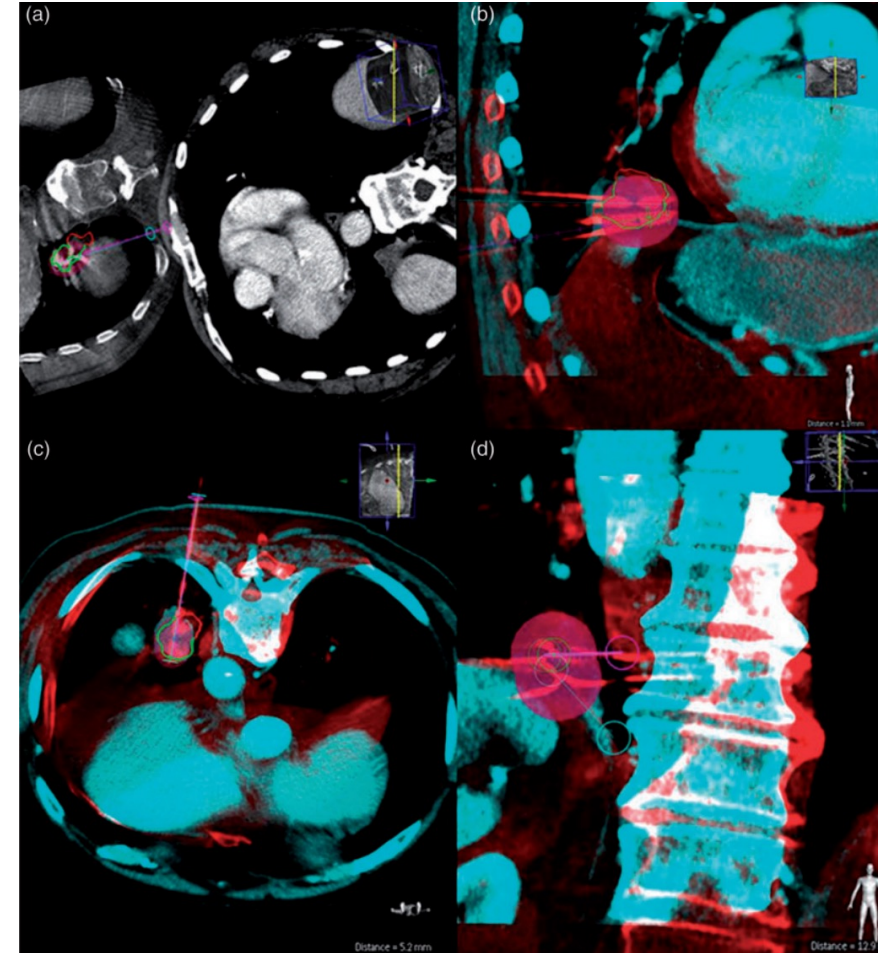


Fig. 3. Visual qualitative evaluation of accuracy (VE): adequate, partially adequate, or inadequate.

VOLUME OTTIMALE DI ABLAZIONE



RFA electrode (Cool-tipTM RF ablation system E Series, Covidien, Boulder, CO, USA) and MWA antenna (Evident Microwave Ablation System, Covidien, Boulder, CO, USA)

Refertazione Automatizzata

Informatics in Medicine Unlocked 24 (2021) 100557



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journal homepage: <http://www.elsevier.com/locate/imu>

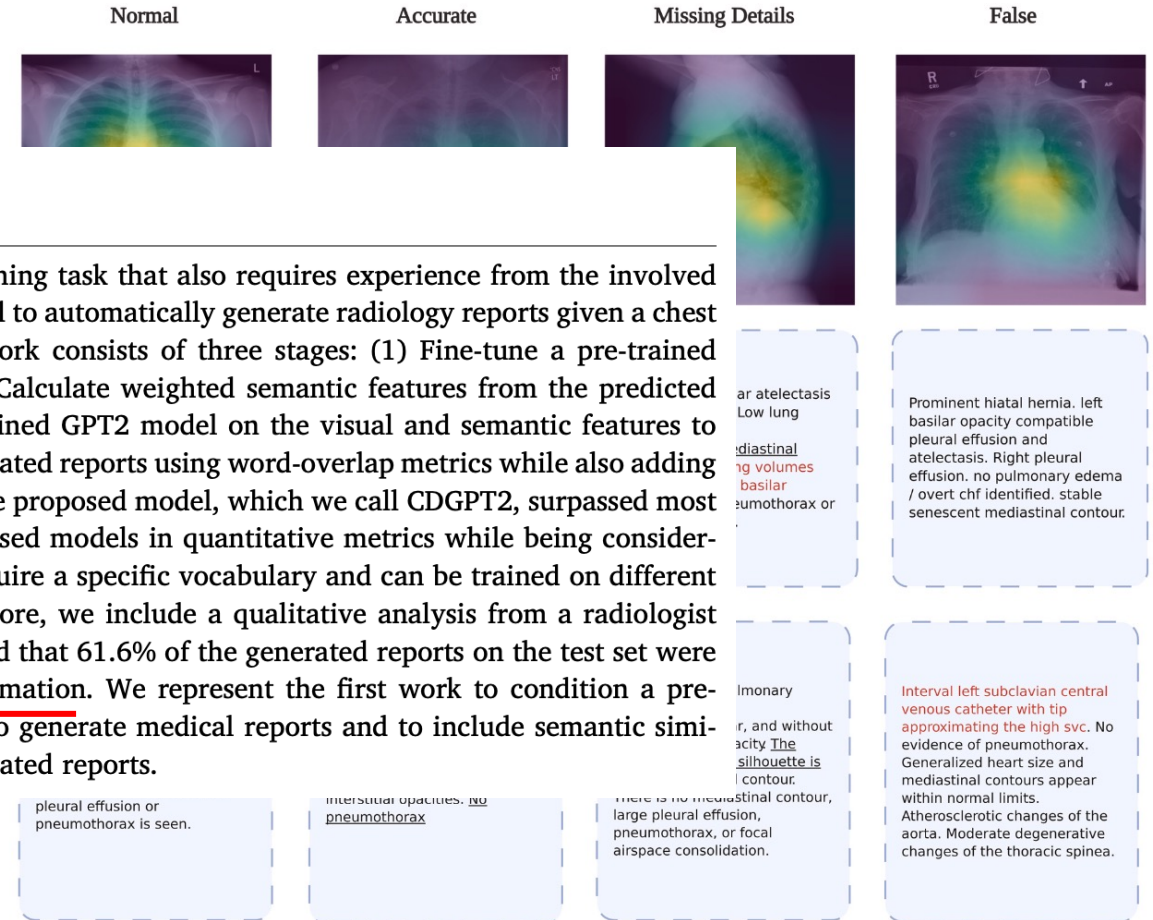


Fig. 6. Example predictions of our CDGPT2 model. The underlined texts are cases in which the model could detect abnormalities and describe them similar to the ground-truth reports. The red text shows wrong or missing information in the generated prediction. (For interpretation of the references to colour in this figure legend, the reader is referred to the Web version of this article.)

Automated radiology report generation using c

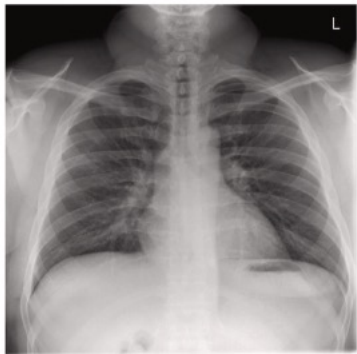
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ABSTRACT

Radiology report writing in hospitals is a time-consuming task that also requires experience from the involved radiologists. This paper proposes a deep learning model to automatically generate radiology reports given a chest x-ray image from the public IU-Xray dataset. Our work consists of three stages: (1) Fine-tune a pre-trained Chexnet to predict specific tags from the image. (2) Calculate weighted semantic features from the predicted tag's pre-trained embeddings. (3) Condition a pre-trained GPT2 model on the visual and semantic features to generate the full medical reports. We analyze the generated reports using word-overlap metrics while also adding new meaningful semantic-based similarity metrics. The proposed model, which we call CDGPT2, surpassed most non-hierarchical recurrent models and transformer-based models in quantitative metrics while being considerably faster to train. Moreover, the model does not require a specific vocabulary and can be trained on different datasets without changing the architecture. Furthermore, we include a qualitative analysis from a radiologist from Egypt's national institute of cancer which showed that 61.6% of the generated reports on the test set were expertly written, and only 10% contained false information. We represent the first work to condition a pre-trained transformer on visual and semantic features to generate medical reports and to include semantic similarity metrics in the quantitative analysis of the generated reports.



Impression: Normal

Findings: Cardiac silhouette is within normal limits. Bony structures are unremarkable.

Manual Tags: Normal

Fig. 2. A sample image from the IU-Chest X-ray dataset. The report consists of an *Impression* which serves as a title, *Findings* which contain the full report, and a *Manual Tags* section listing some keywords to describe the image.

Refertazione Automatizzata

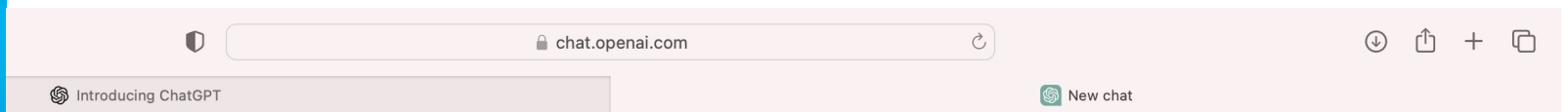


< RSNA News

The Good, the Bad and the Ugly of Using ChatGPT

How radiologists can harness the power of conversational AI programs to assist with specific tasks

With AI having come to a level at par with human authors, the use of **chatbots** and natural language processing **have the potential to revolutionize the field of medical writing**



ChatGPT

Examples	Capabilities	Limitations
"Explain quantum computing in simple terms" →	Remembers what user said earlier in the conversation	May occasionally generate incorrect information
"Got any creative ideas for a 10 year old's birthday?" →	Allows user to provide follow-up corrections	May occasionally produce harmful instructions or biased content
"How do I make an HTTP request in Javascript?" →	Trained to decline inappropriate requests	Limited knowledge of world and events after 2021

Send a message. 

Free Research Preview. ChatGPT may produce inaccurate information about people, places, or facts. [ChatGPT Mar 23 Version](#)

Refertazione Automatizzata

CHATGPT
OpenAI



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The Good, the Bad and the Ugly of Using ChatGPT

How radiologists can harness the power of conversational AI programs to assist with specific tasks

For example, once a radiologist finds a diagnosis, such as meningioma in the right frontal lobe, they can enter the following command into ChatGPT: Create MRI report on right frontal lobe meningioma. The program will create an entire report that only needs to be verified, edited and signed off. Based on the above prompt, ChatGPT provided Dr. Biswas with the following report:

Findings: The examination demonstrates a well-circumscribed, heterogeneously enhancing mass in the right frontal lobe, measuring {measurement}. The mass demonstrates intermediate signal intensity on T1-weighted images and high signal intensity on T2-weighted and fluid-attenuated inversion recovery (FLAIR) images, consistent with a meningioma. The mass demonstrates homogeneous contrast enhancement. No significant mass effect or surround edema is identified. No intralesional flow voids are identified to suggest a more aggressive neoplasm.

Some words in this report were not correct, that can be edited by the **human radiologist**. The majority of the report was good enough to be used as a **draft** that a radiologist could edit to significantly **reduce reporting time**.

Intelligenza artificiale nelle scuole di specializzazione

Review > [Semin Musculoskelet Radiol.](#) 2020 Feb;24(1):74-80. doi: 10.1055/s-0039-3400270.

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Artificial Intelligence in Radiology Residency Training

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Affiliations + expand

PMID: 31991454 DOI: [10.1055/s-0039-3400270](#)

Abstract

Artificial intelligence (AI) is an emerging technology that brings a wide array of new tools to the field of radiology. AI will certainly have an impact on the day-to-day work of radiologists in the coming decades, thus training programs must prepare radiology residents adequately for their future careers. Radiology training programs should aim to give residents an understanding of the fundamentals and types of AI in radiology, the broad areas AI can be applied in radiology, how to assess AI applications in radiology, and resources available to build their knowledge in IA applications in radiology.

Radiology: Artificial Intelligence

SPE

Preparing Radiologists to Lead in the Era of Artificial Intelligence: Designing and Implementing a Focused Data Science Pathway for Senior Radiology Residents

Walter F. Wiggins, MD, PhD* • M. Travis Caton, MD* • Kirti Magudia, MD, PhD • Sha-bar A. Glomski, MD • Elizabeth George, MBBS • Michael H. Rosenthal, MD, PhD • Glenn C. Gaviola, MD • Katherine P. Andriole, PhD

From the Department of Radiology, Brigham and Women's Hospital, Harvard Medical School, Boston, Mass (W.F.W., M.T.C., K.M., S.A.G., E.G., M.H.R., G.C.G., K.P.A.); and MGH & BWH Center for Clinical Data Science, Boston, Mass (W.F.W., M.T.C., K.M., K.P.A.). Received April 10, 2020; revision requested June 16; revision received June 30; accepted July 7. **Address correspondence to** W.F.W., Department of Radiology, Duke University Hospital, 2301 Erwin Rd, Durham, NC 27710 (e-mail: walter.wiggins@duke.edu).

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

Radiology: Artificial Intelligence 2020; 2(6):e200057 • <https://doi.org/10.1148/ryai.2020200057> • Content code:   

Artificial intelligence and machine learning (AI-ML) have taken center stage in medical imaging. To develop as leaders in AI-ML, radiology residents may seek a formative data science experience. The authors piloted an elective Data Science Pathway (DSP) for 4th-year residents at the authors' institution in collaboration with the MGH & BWH Center for Clinical Data Science (CCDS). The goal of the DSP was to provide an introduction to AI-ML through a flexible schedule of educational, experiential, and research activities. The study describes the initial experience with the DSP tailored to the AI-ML interests of three senior radiology residents. The authors also discuss logistics and curricular design with common core elements and shared mentorship. Residents were provided dedicated, full-time immersion into the CCDS work environment. In the initial DSP pilot, residents were successfully integrated into AI-ML projects at CCDS. Residents were exposed to all aspects of AI-ML application development, including data curation, model design, quality control, and clinical testing. Core concepts in AI-ML were taught through didactic sessions and daily collaboration with data scientists and other staff. Work during the pilot period led to 12 accepted abstracts for presentation at national meetings. The DSP is a feasible, well-rounded introductory experience in AI-ML for senior radiology residents. Residents contributed to model and tool development at multiple stages and were academically productive. Feedback from the pilot resulted in establishment of a formal AI-ML curriculum for future residents. The described logistical, planning, and curricular considerations provide a framework for DSP implementation at other institutions.

What Should Radiology Residency and Fellowship Training in Artificial Intelligence Include? A Trainee's Perspective— *Radiology In Training*

Ali S. Tejani, MD • Julia R. Fielding, MD • Ronald M. Pesbocck, MD

In conclusion, it is clear that an increasing number of trainees are beginning to embrace a future of working with AI apps; however, attempting to learn about AI without appropriate guidance can prove to be an arduous task without a clear starting point. A structured, standardized AI curriculum is warranted to equip trainees with skills for the creation, regulation, and implementation of ML algorithms. Future work should examine barriers to curriculum implementation, such as obtaining program support and addressing unequal distribution of AI expertise and resources across training programs.

it is important to familiarize our residents with AI and new technologies. To prepare them for the future and new technological innovations.

Conclusioni



More efficient
workflow



Shorter reading time



Early detection



Dose and contrast
reduction



Improved diagnostic
accuracy



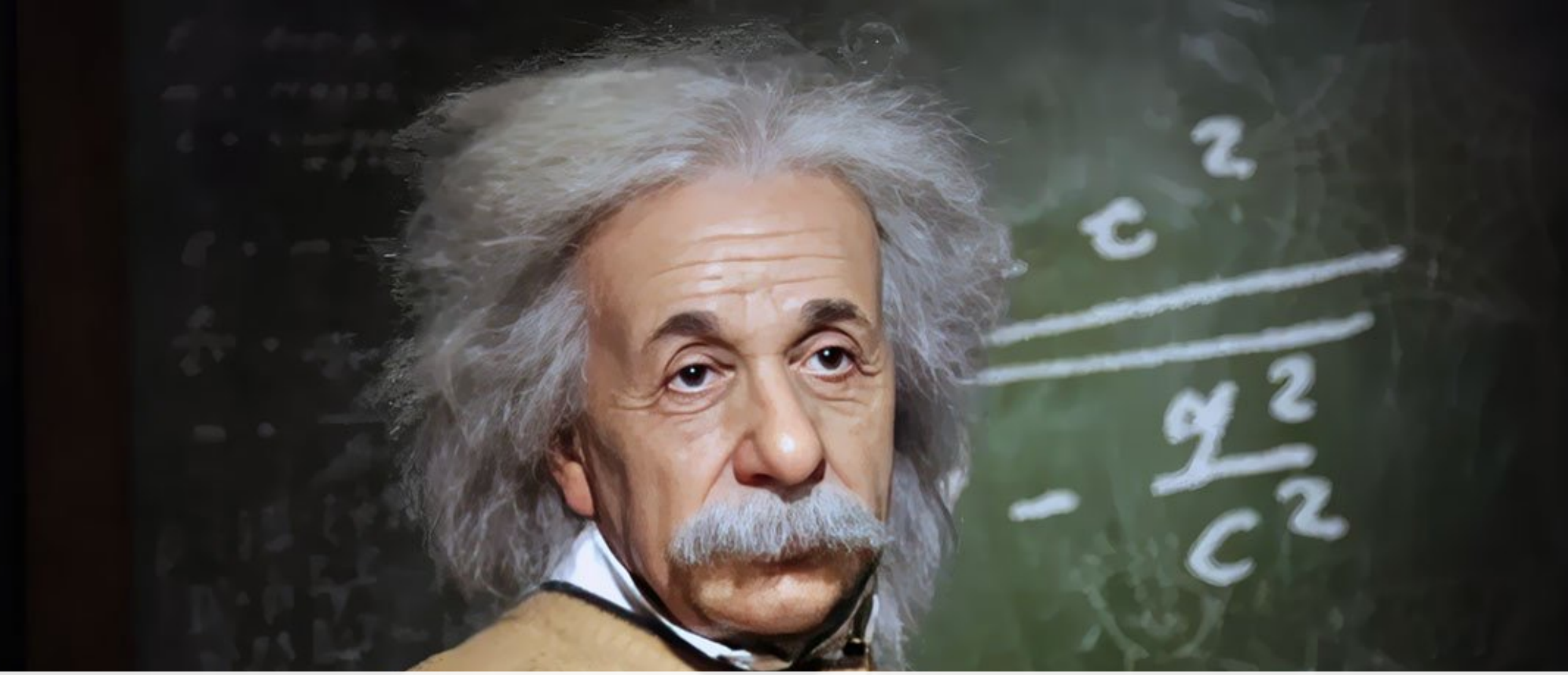
Personalized
diagnostics

Efficiency
Improvement

Increased
Health

Study AI
Be ready for AI
Menage AI





«Un giorno le macchine riusciranno a risolvere tutti i problemi, ma mai nessuna di esse potrà porne uno»

1879-1955

Grazie per l'attenzione!



Società Italiana di
Radiologia Medica
e Interventistica