

L'ARTE DELLA CURA PERSONALIZZATA



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CONGRESSO
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18•19•20 MAGGIO 2023



Dipartimento di Diagnostica per Immagini e
Radiologia Interventistica
Radiologia 1 Universitaria



UNIVERSITÀ DEGLI STUDI DI TORINO
Scuola di Medicina
Dipartimento di Discipline Medico-Chirurgiche
Sezione di Radiodiagnostica

Big Data e intelligenza artificiale: la rivoluzione della diagnostica.

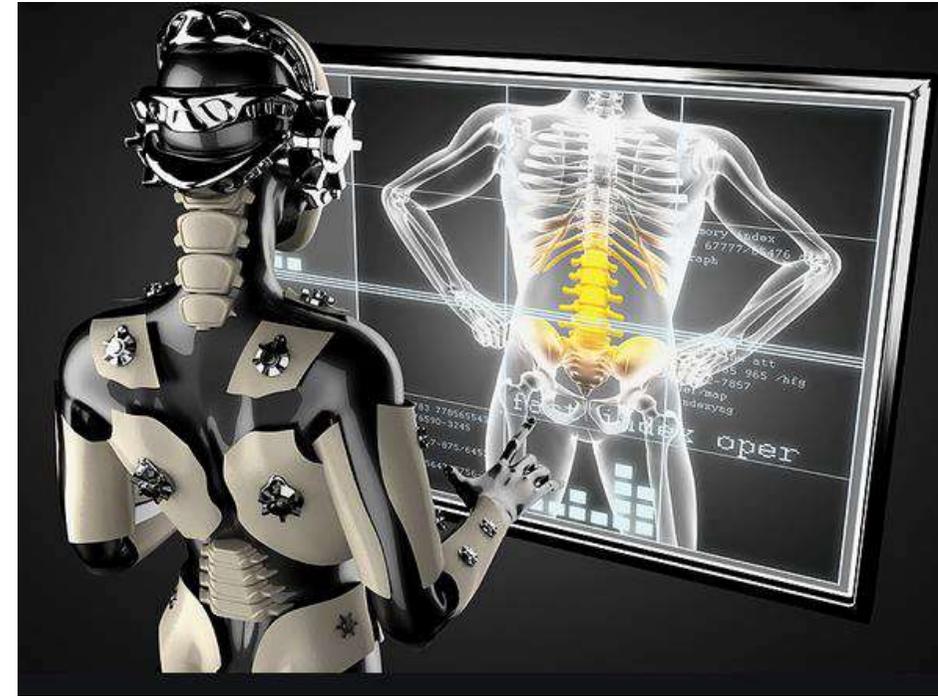
Paolo Fonio, Manuela Durando

Roma, 19 Maggio 2023



OUTLINE

- WHAT ABOUT **BIG DATA**?
- INTELLIGENZA ARTIFICIALE (**AI**)
 - MACHINE LEARNING
 - DEEP LEARNING
 - RETI NEURALI
- **AI** E APPLICAZIONI IN **DIAGNOSTICA (PER IMMAGINI)**
 - RADIOMICA
 - RADIOGENOMICA
- **AI** E APPLICAZIONI NELL'**IMAGING SENOLOGICO**



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BIG DATA, BIG FUTURE

With our increasing capabilities in research techniques and tools comes an inevitable increase in the amount of data and the complexity of datasets. But how do we cope with this plethora of data?

Vol. 68 | No. 4 | © 2020 Future Science Ltd

I Big Data sono associati alle enormi risorse computazionali necessarie a far fronte all'aumento del volume e della complessità dei dati provenienti da molte fonti, come Internet e remote sensor networks.

I Big Data includono:

- informazioni strutturate
- semi-strutturate
- non strutturate
- con interrelazioni complesse (sintattiche, semantiche, sociali, culturali, economiche, e di natura organizzativa).

La cultura dei Big Data abbraccia i sistemi cyber-fisici, il cloud computing e l'Internet of Things (IoT) ovvero Industria 4.0.

Questi enormi sistemi di elaborazione dei dati spesso coinvolgono livelli significativi di automazione dei processi.





BIG DATA, BIG FUTURE

I Big Data sono spesso associati a macrosistemi su larga scala, con elaborazione distribuita dei dati che va oltre le capacità dei computer desktop locali e dei software tradizionali, a causa di vincoli imposti dalla velocità e dai volumi di elaborazione.

L'elaborazione delle informazioni è diversificata e può includere streaming di messaggi di testo, immagini, video e file musicali.

5 «V» caratteristiche dei **BIG DATA**:

- **Volume** (enorme mole di dati);
- **Varietà** (di formati e di sorgenti);
- **Velocità** (di trasmissione ed elaborazione dei dati);
- **Variabilità** (mancanza di struttura, coerenza e contesto);
- **Veridicità** (accuratezza e qualità nei dati).



BIG DATA – HEALTH CARE



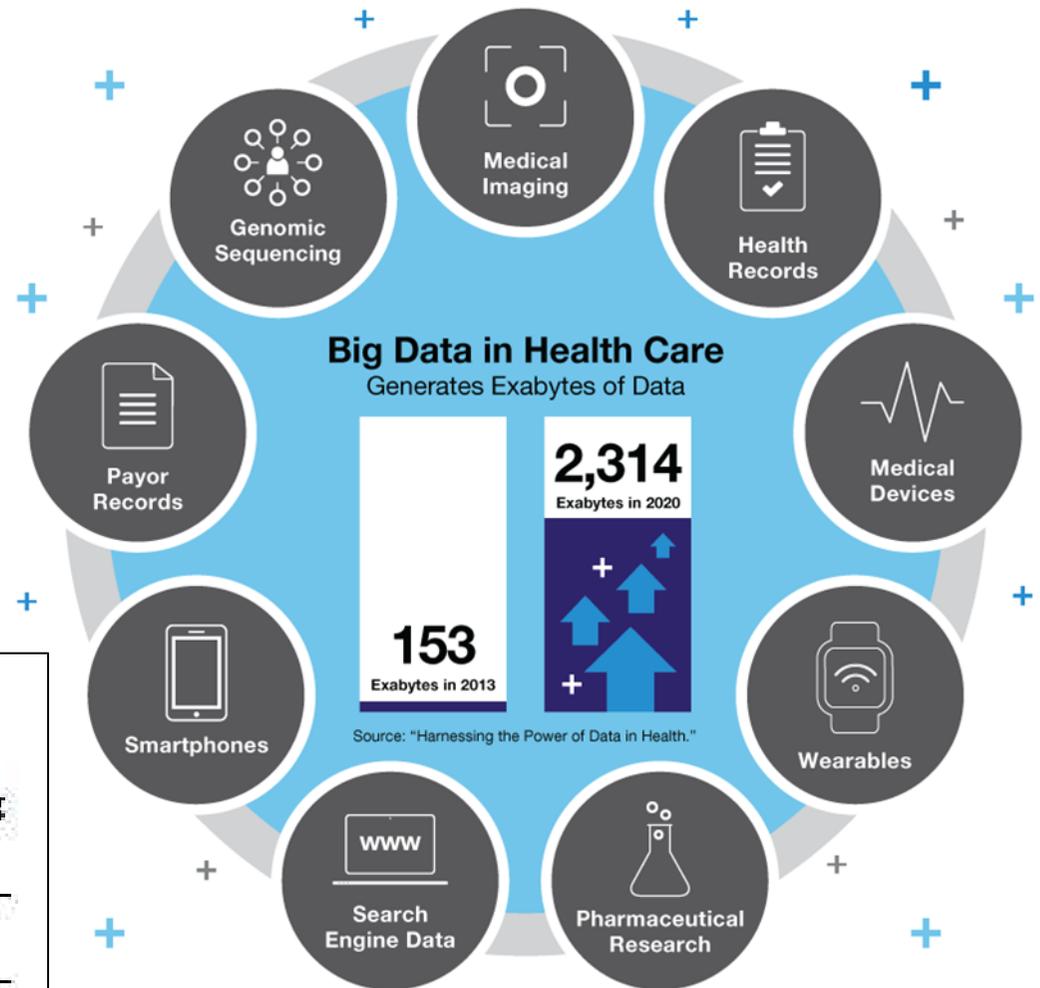
Stanford Medicine 2017 Health Trends Report

Harnessing the Power of Data in Health

The Road Ahead

The opportunities presented by data in health care are immense, but so are the obstacles the sector faces as it evolves. To move forward, the following challenges must be addressed:

- Rising costs
- Data sharing and security
- Policy and legislation



Commentary

Artificial Intelligence and Big Data in Public Health

Kurt Benke ^{1,2,*} and Geza Benke ³

Int. J. Environ. Res. Public Health **2018**, *15*, 2796; doi:10.3390/ijerph15122796

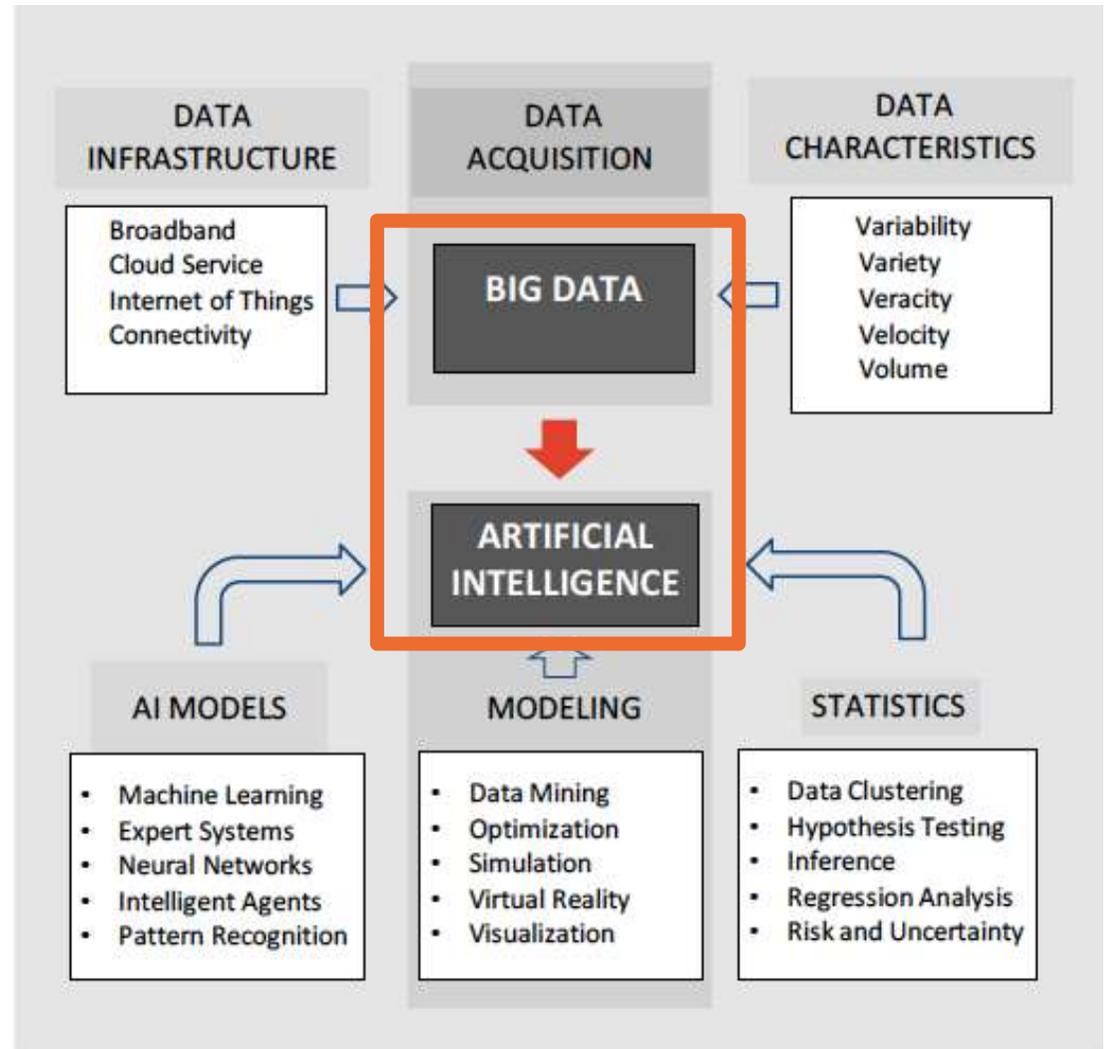


Seminars in
NUCLEAR
MEDICINE

Emergence of “Big Data” and its Potential and Current Limitations in Medical Imaging

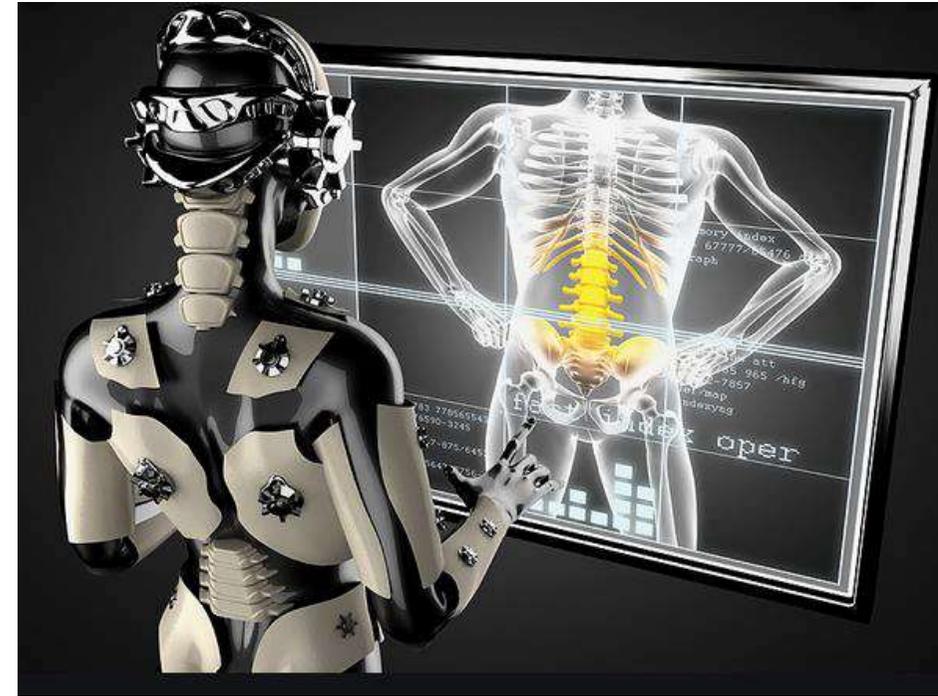
Martin J. Yaffe, PhD, CM

<https://doi.org/10.1053/j.semnuclmed.2018.11.010>



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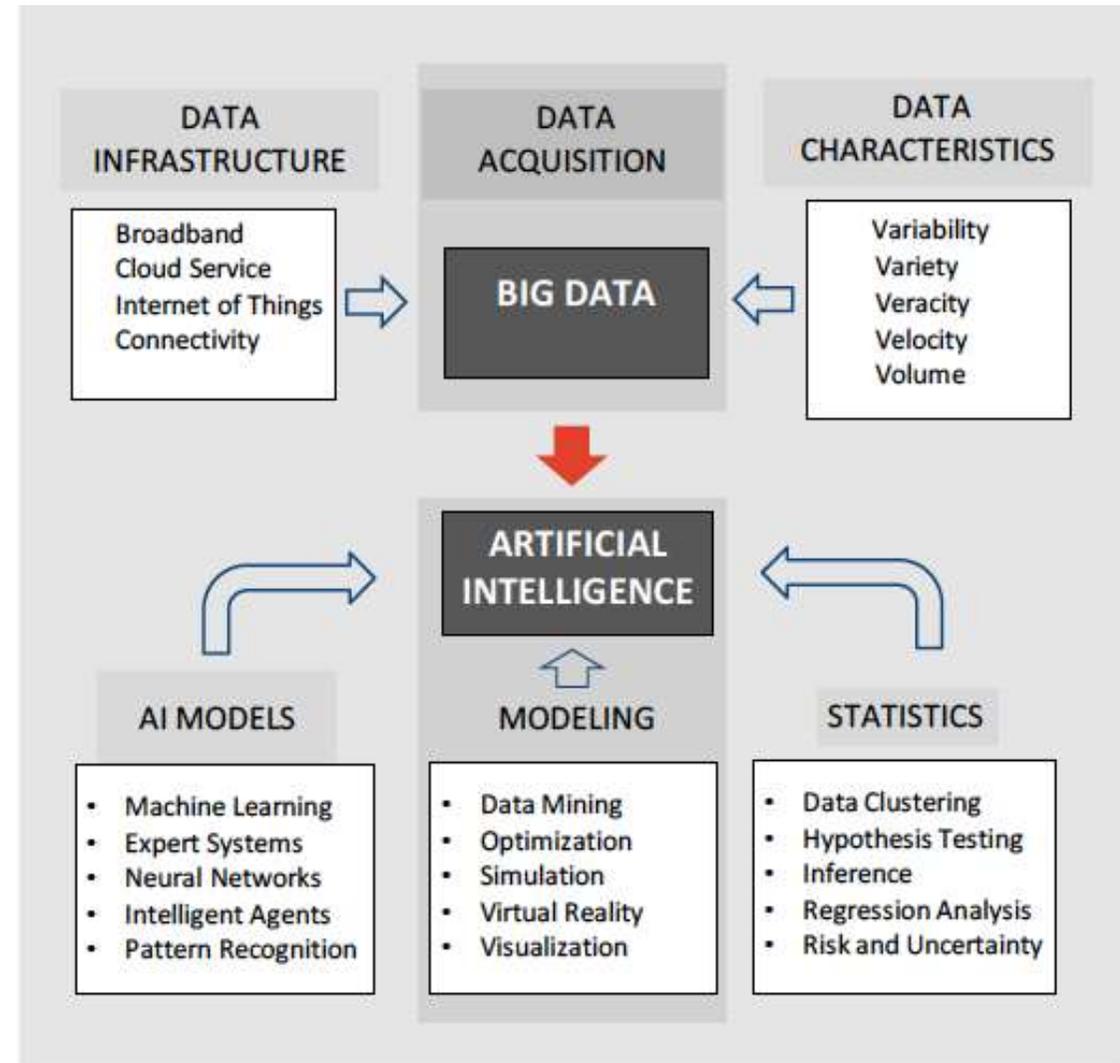


Intelligenza artificiale (AI)

È una branca della scienza informatica che ha lo scopo di dare ai computer o alle macchine alcune abilità che possano simulare l'intelligenza umana, come ad esempio imparare, risolvere problemi e assumere decisioni

“la capacità, da parte di un computer, di svolgere compiti o ragionamenti che vengono comunemente attribuiti all'intelligenza umana

“imitazione dell'intelligenza o del pattern di comportamento umani o di altre entità viventi”



Intelligenza artificiale (AI)

- Aumentare la produttività e l'efficienza dell'erogazione delle cure
- Migliorare l'attività quotidiana dei professionisti sanitari
- Incrementare l'accuratezza della diagnosi e la personalizzazione delle cure
- Velocizzare l'arrivo sul mercato di terapie efficaci
- Impatto su pazienti, professionisti e sistema sanitaria
- *Potenziali rischi*
- *Questioni etiche relative all'uso dell'AI*

Areas of impact of AI in health care



Intelligenza artificiale (AI)

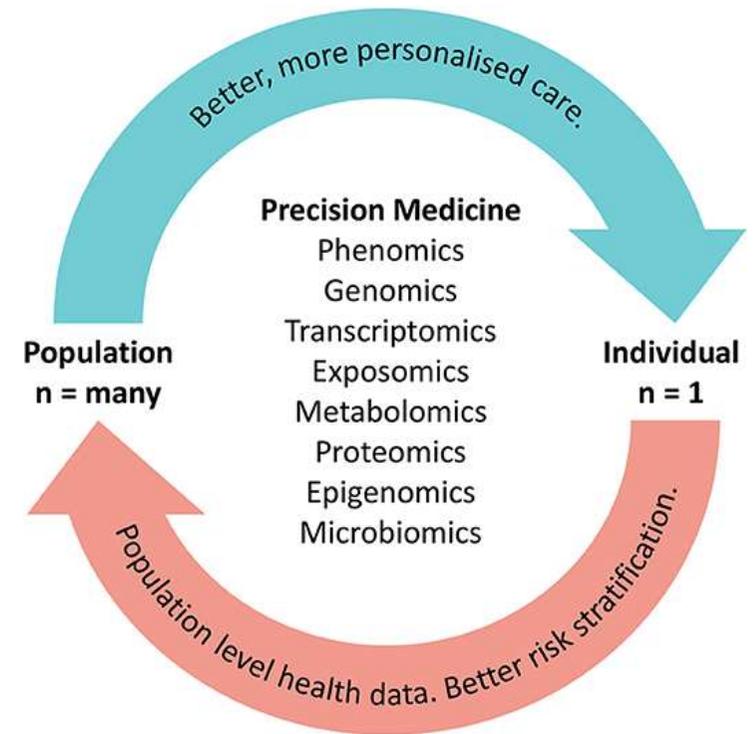
- Aumentare la produttività e l'efficienza dell'erogazione delle cure
- Migliorare l'attività quotidiana dei professionisti sanitari
- **Incrementare l'accuratezza della diagnosi e la personalizzazione delle cure**
- Velocizzare l'arrivo sul mercato di terapie efficaci
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Areas of impact of AI in health care



What is precision medicine?

Precision medicine is "an emerging approach for disease treatment and prevention that takes into account individual variability in genes, environment, and lifestyle for each person." This approach will allow doctors and researchers to predict more accurately which treatment and prevention strategies for a particular disease will work in which groups of people. It is in contrast to a one-size-fits-all approach, in which disease treatment and prevention strategies are developed for the average person, with less consideration for the differences between individuals.



Bilkey GA, Burns BL, Coles EP, Mahede T, Baynam G, Nowak KJ. Optimizing Precision Medicine for Public Health. Front Public Health. 2019 Mar 7;7:42.



Intelligenza artificiale (AI)

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- Migliorare l'attività quotidiana dei professionisti sanitari
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Areas of impact of AI in health care



Artificial Intelligence: Potential Benefits and Ethical Considerations

KEY FINDINGS

- The ability of AI systems to transform vast amounts of data into insight has the potential to reveal long-held secrets and solve some of the world's most enduring problems.
- However, like all powerful technologies, great care must be taken in their development and deployment. To reap the societal benefits of AI systems, we must ensure that they follow the same ethical principles, professional codes, and social norms that we humans would follow in the same scenario. Research and educational efforts, as well as carefully designed regulations, must be put in place to ensure that AI systems are used responsibly.
- International Bodies such as the OECD, as well as with the UN, must work together to make AI ethical and trustworthy.

But trust will also require a system of best practices that can help guide the safe and ethical management of AI systems including alignment with social norms and values; algorithmic responsibility; compliance with existing legislation and policy; assurance of the integrity of the data, algorithms and systems; and protection of privacy and personal information.

BIG DATA IN BIG TROUBLE?

Using big data comes with its own caveats. There is still a need to establish policies to protect the data of individuals in terms of confidentiality, privacy and security, while still ensuring that advancements in science can take advantage of the vast availability and open use of data.

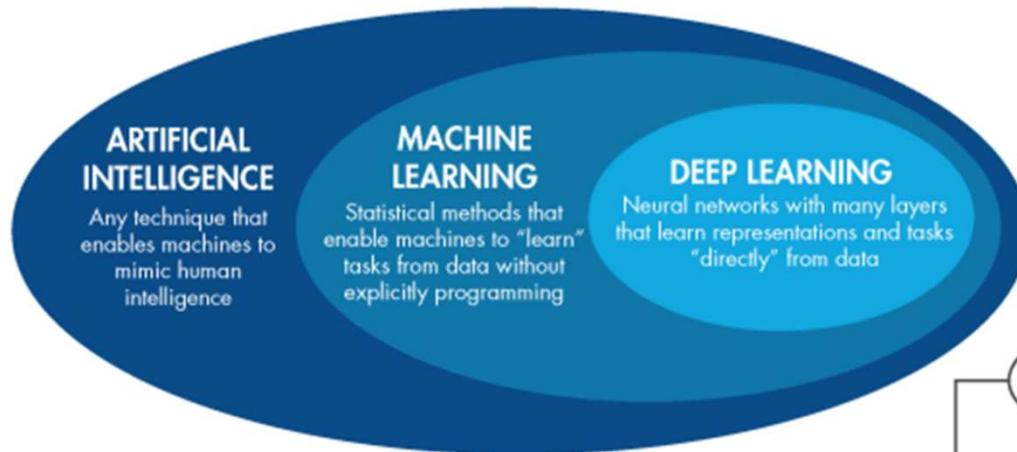
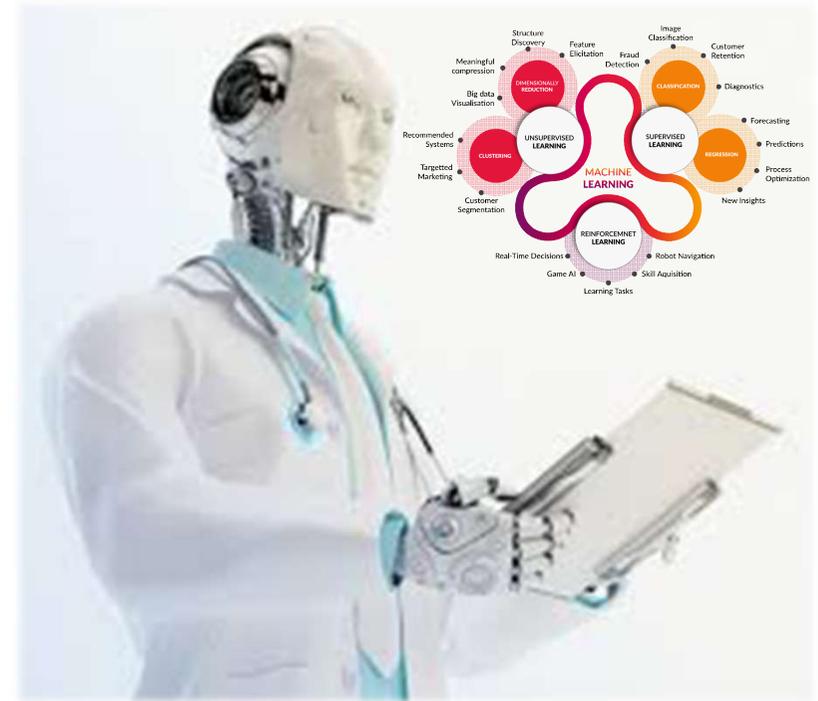
- 1) the risk of inadvertent disclosure of personally identifying information;
- 2) the potential for increasing dimensionality of data to make it difficult to determine if a **dataset is sufficiently de-identified** to prevent 'deductive disclosure' of personally identifying information;
- 3) the challenge of identifying and maintaining standards of ethical research in the face of emerging technologies that may shift the generally accepted norms regarding **privacy**

Big Data in Public Health: Terminology, Machine Learning, and Privacy. Mooney et al, Annu Rev Public Health. 2018.



AI E MACHINE LEARNING

Il **Machine learning** è un' applicazione dell'intelligenza artificiale (AI) che fornisce l'abilità dell'apprendimento automatico e del miglioramento attraverso l'esperienza, senza una programmazione esplicita. Il Machine learning si focalizza sullo sviluppo dei programmi computerizzati che possono accedere a dati ed utilizzarli per l'apprendimento.

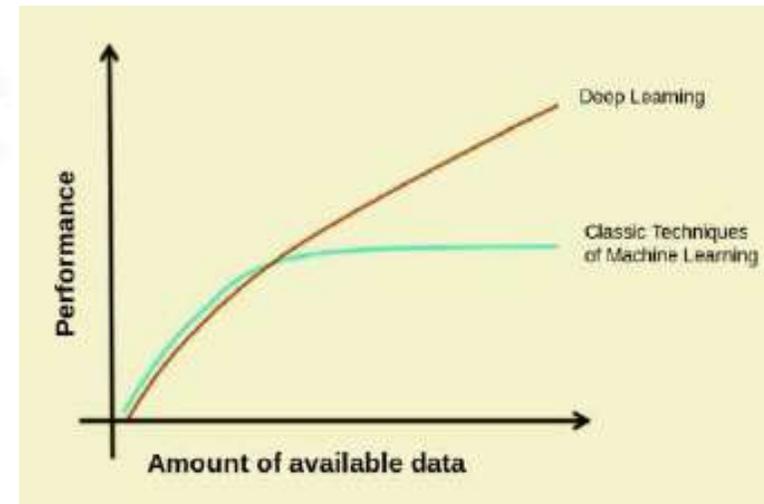
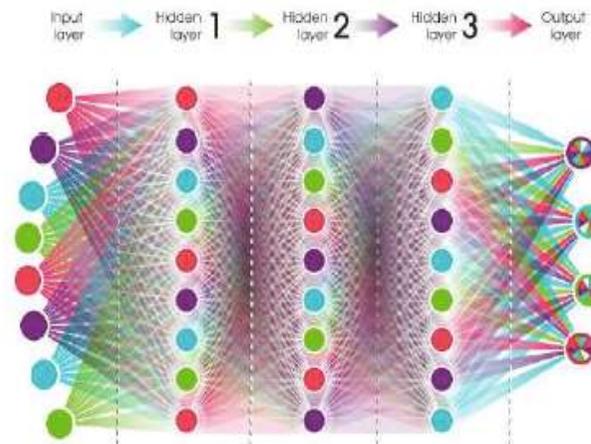
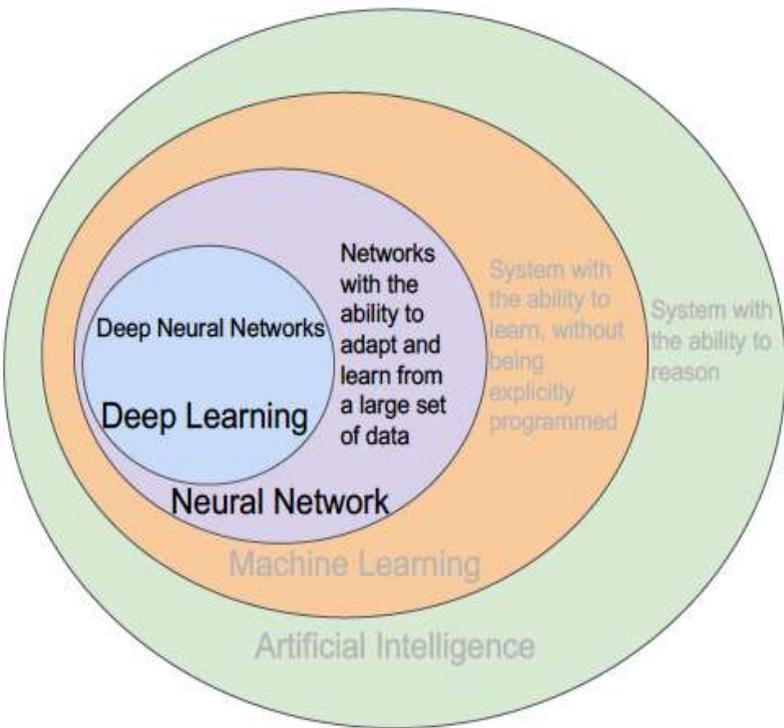


Deep learning more accurate than humans on image classification



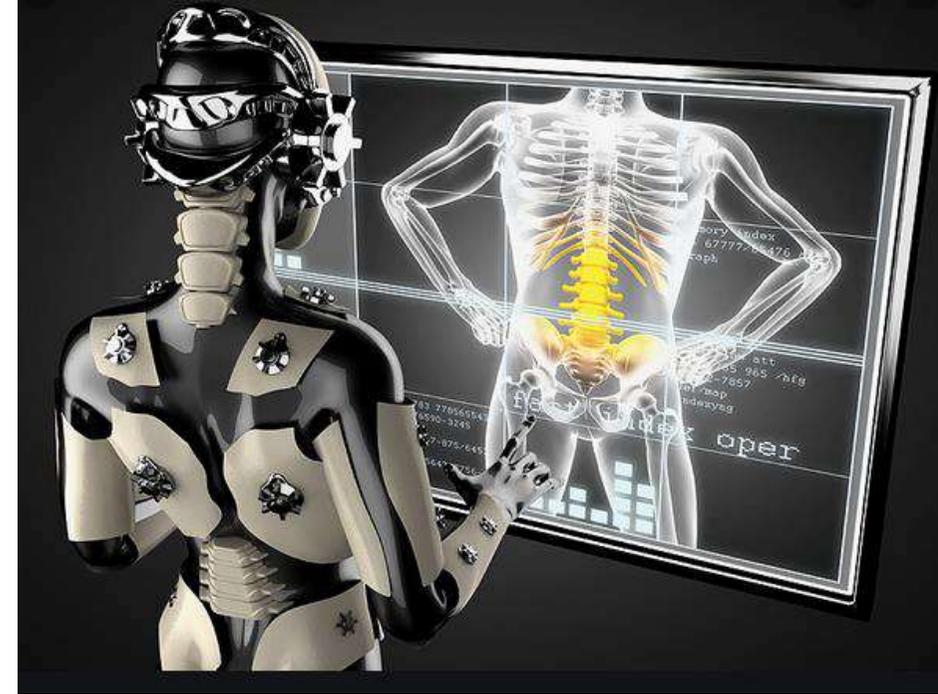
AI E DEEP LEARNING

Il **Deep learning** è un sottoinsieme degli algoritmi del machine learning che utilizza multiple tecniche per estrarre progressivamente features di livello sempre più alto da un input di dati grezzi.



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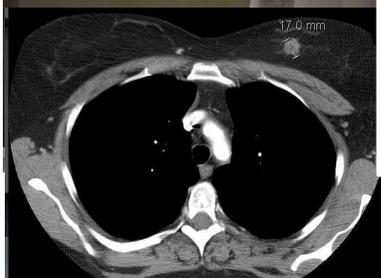
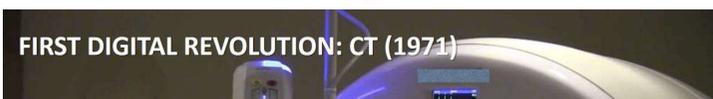
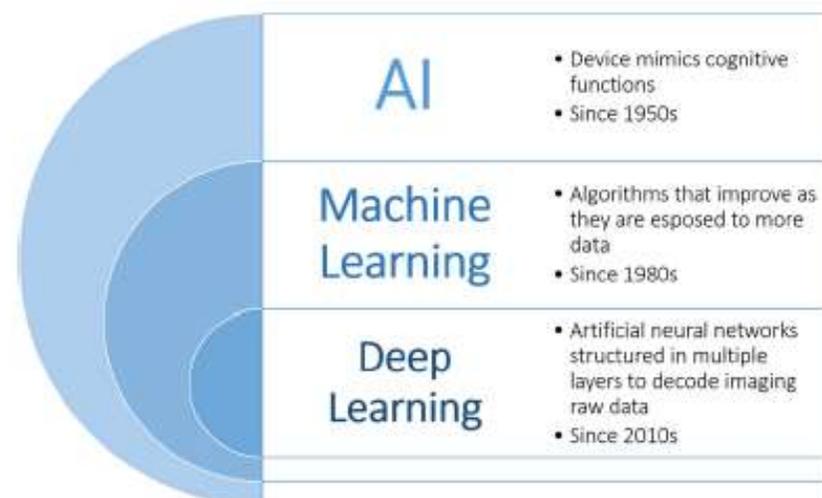
NARRATIVE REVIEW

Open Access

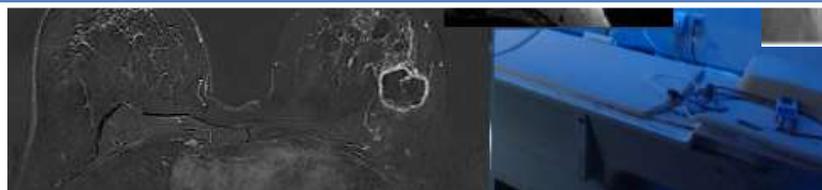


Artificial intelligence in medical imaging: threat or opportunity? Radiologists again at the forefront of innovation in medicine

Filippo Pesapane^{1†}, Marina Codari^{2†}  and Francesco Sardanelli^{2,3}



SECOND DIGITAL REVOLUTION: AI: ML/DL & RADIOMICS



RADIOMICA

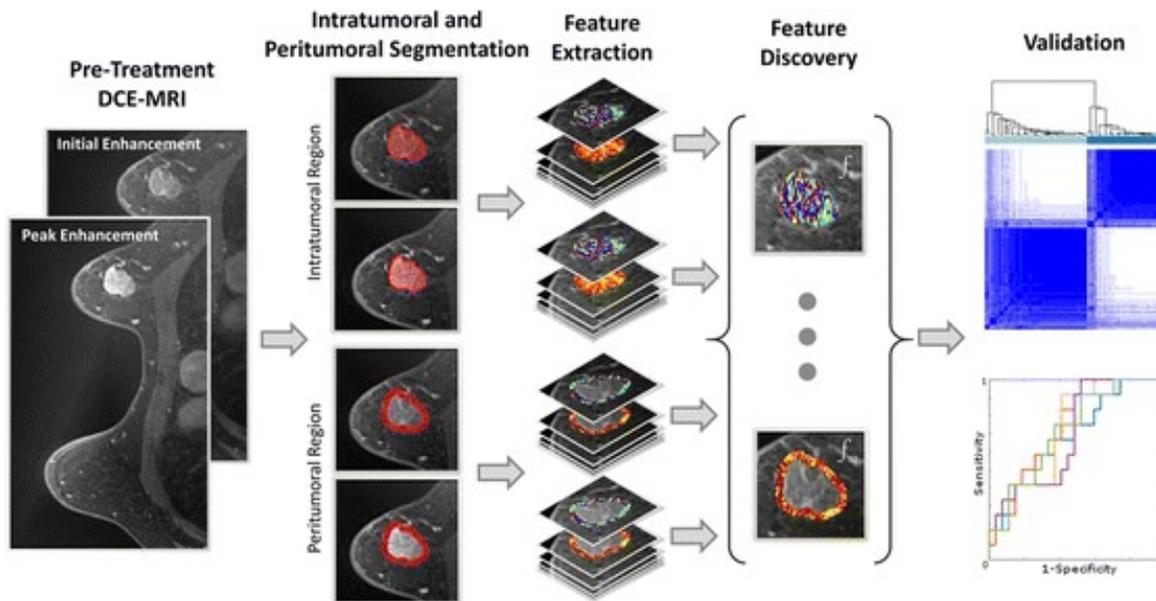
Oltre alle immagini



Metodi matematici e statistici per valutare:

Intensità dei livelli di grigio
Posizione dei pixel all'interno dell'immagine

Ricavandone descrittori complessi



> Radiology. 2016 Feb;278(2):563-77. doi: 10.1148/radiol.2015151169. Epub 2015 Nov 18.

Radiomics: Images Are More than Pictures, They Are Data

Robert J Gillies¹, Paul E Kinahan¹, Hedvig Hricak¹

Le features estratte possono essere correlate con dati clinico-radiologici e utilizzati in nell'evidence-based decision making. La Radiomica offre un ventaglio molto ampio di biomarker di imaging che possono avere potenzialità nel riconoscimento di lesioni neoplastiche, definire la prognosi, predire la risposta al trattamento e monitorare lo stato della malattia.



Analisi delle immagini

IMAGES ARE MORE THAN PICTURES, THEY ARE DATA

Eur Radiol. 2018 Jul 2. doi: 10.1007/s00330-018-5530-z. [Epub ahead of print]

Radiomics signature: a biomarker for the preoperative discrimination of lung invasive adenocarcinoma manifesting as a ground-glass nodule.

Fan L¹, Fang M^{2,3}, Li Z⁴, Tu W¹, Wang S⁵, Chen W⁶, Tian J^{2,3}, Dong D^{7,8}, Liu S⁹.

Radiomic Features on MRI Enable Risk Categorization of Prostate Cancer Patients on Active Surveillance: Preliminary Findings

Ahmad Alghohary, MS¹, Satish Viswanath, PhD¹, Rakesh Shiradkar, PhD¹

Delta-radiomics features for the prediction of patient outcomes in non-small cell lung cancer

Xenia Fave^{1,2}, Lifei Zhang¹, Jinzhong Yang¹, Dennis Mackin¹, Peter Balter¹, Daniel Gomez³, David Followill¹, Aaron Kyle Jones⁴, Francesco Stingo⁵, Zhongxing Liao³, Radhe Mohan¹ & Laurence Court^{1,2}

Radiomics: the process and the challenges.

Kumar V¹, Gu Y, Basu S, Berglund A, Eschrich SA, Schabath MB, Forster K, Aerts HJ, Dekker A, Fenstermacher D, Goldgof DB, Hall LO, Lambin P, Balagurunathan Y, Gatenby RA, Gillies RJ.

Can CT-based radiomics signature predict *KRAS/NRAS/BRAF* mutations in colorectal cancer?

ig^{2,3,4}, Mengjie Fang^{2,3}, Yongbei Zhu², Yali Zang², Zhenyu Liu², Jianming Ying⁵, Xinming Zhao¹, Jie Tian^{2,3,6}

The development and validation of a CT-based radiomics signature for the preoperative discrimination of stage I-II and stage III-IV colorectal cancer

Cuishan Liang^{1,2,*}, Yanqi Huang^{1,2,*}, Lan He^{1,3}, Xin Chen⁴, Zelan Ma^{1,2}, Di Dong⁵, Jie Tian⁵, Changhong Liang¹, Zaiyi Liu¹

Texture analysis as a radiomic marker for differentiating renal tumors

HeiShun Yu^{1,2}, Jonathan Scalapino¹, Maria Khalid¹, Anna Sophia Tavares¹, Nicolas Bloch¹, Baojun Li¹, Muhammad Stephan W. Anderson¹

Machine learning-based analysis of MR radiomics can help to improve the diagnostic performance of PI-RADS v2 in clinically relevant prostate cancer

Machine learning-based analysis of MR radiomics can help to improve the diagnostic performance of PI-RADS v2 in clinically relevant prostate cancer

Jing Wang¹, Chen-Jiang Wu², Mei-Ling Bao³, Jing Zhang², Xiao-Ning Wang², Yu-Dong Zhang²

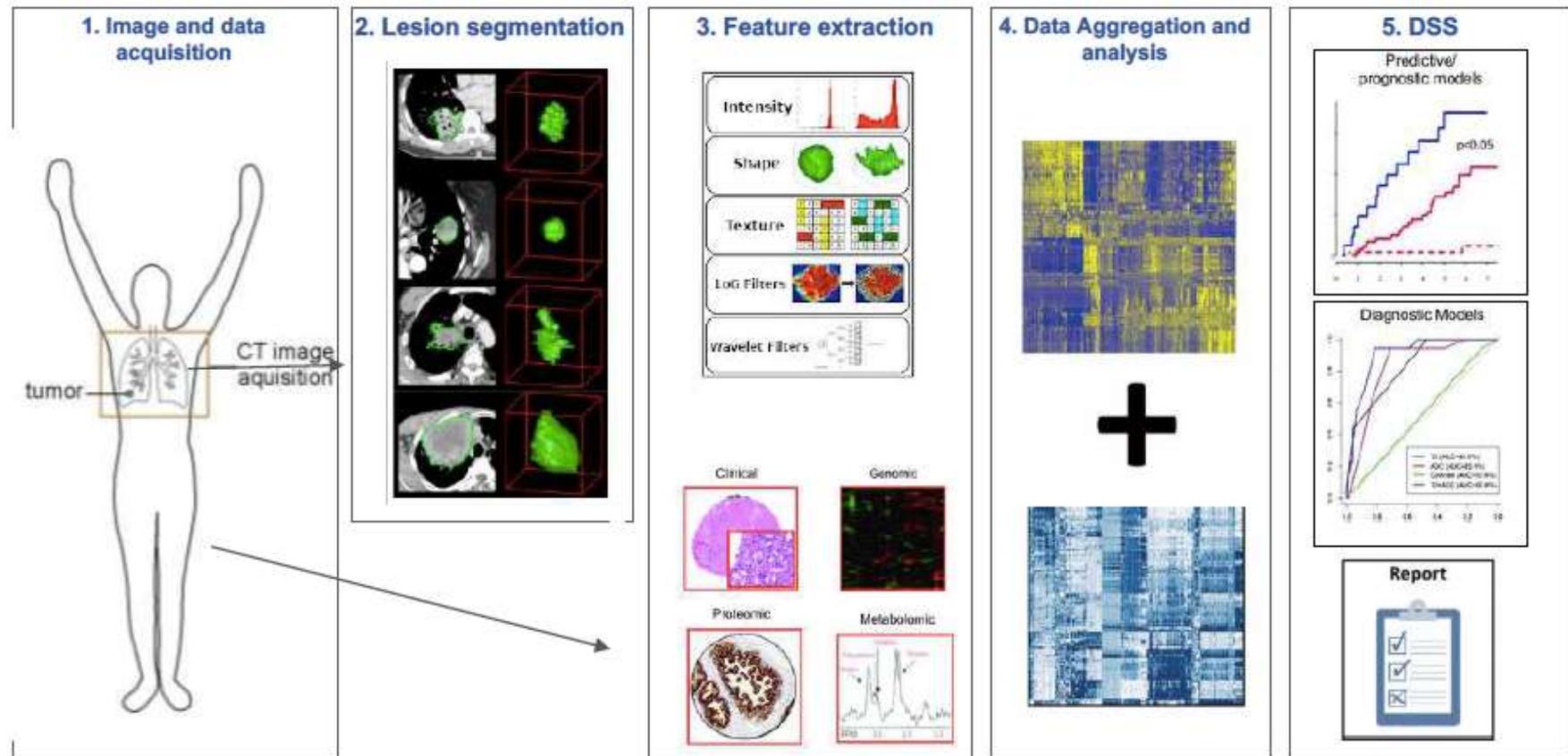
CT-based radiomics signature: a potential biomarker for preoperative prediction of early recurrence in hepatocellular carcinoma

Ying Zhou^{1,2,3}, Lan He⁴, Yanqi Huang², Shuting Chen^{1,2}, Penqi Wu^{1,2}, Weitao Ye², Zaiyi Liu^{1,2}, Changhong Liang^{1,2}

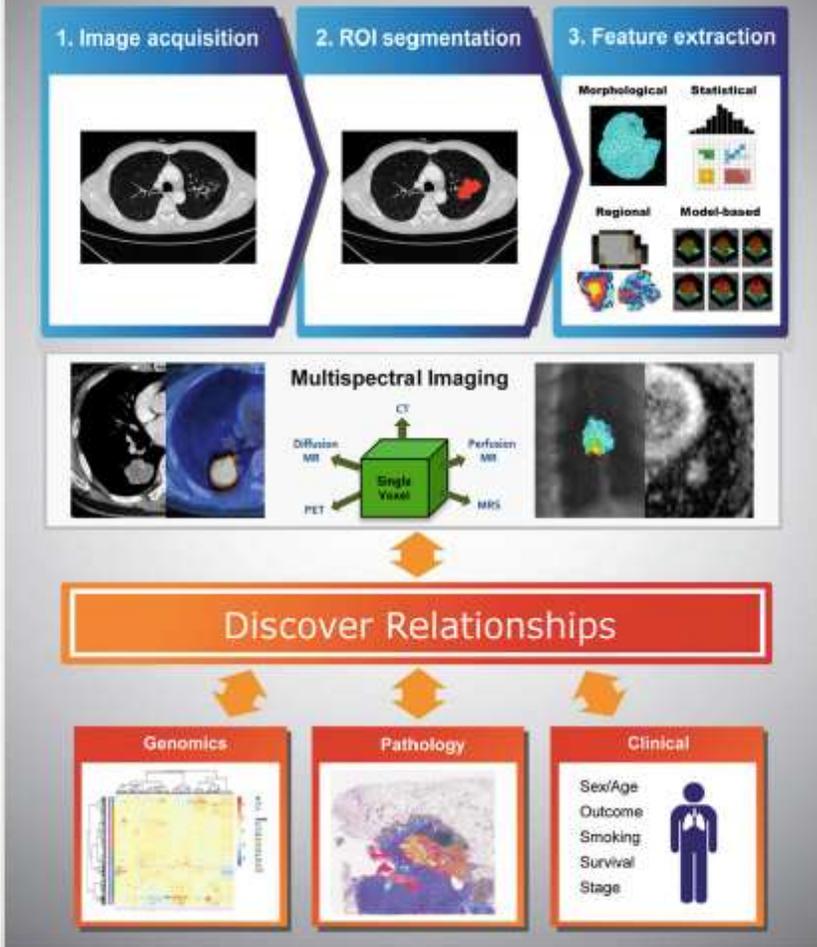
Assessment of tumor heterogeneity by CT texture analysis: Can the largest cross-sectional area be used as an alternative to whole tumor analysis?

Francesca Ng^a, Robert Kozarski^b, Balaji Ganeshan^c, Vicky Goh^{d,*}

RADIOMICA

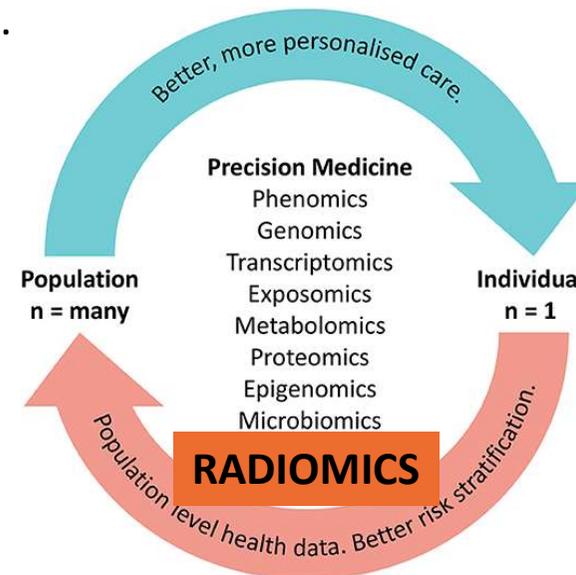


Radiomics : Processing of Radiological Imaging Data



RADIOMICA

L'ipotesi della radiomica è che le caratteristiche distintive di imaging tra le forme di malattia possano essere utili per **prevedere la prognosi e la risposta terapeutica** per varie condizioni, fornendo così preziose informazioni per una terapia personalizzata.



Radiomics and Precision Medicine

Image Analysis
Extraction of quantitative features from images

Big Data Analysis
Extraction of large amount of quantitative features

Clinical Data availability
Store and retrieval of large amount of clinical data and images

Computational Power
Increasing of processing power

What is new?

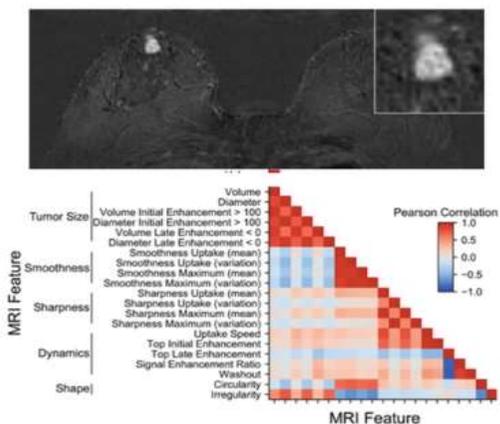
-omics

Data from other fields:
genetics, molecular, ...



RADIOGENOMICA

Radiogenomic Analysis of Breast Cancer by Linking MRI Phenotypes with Tumor Gene Expression



Heat map of Pearson correlation between MRI features

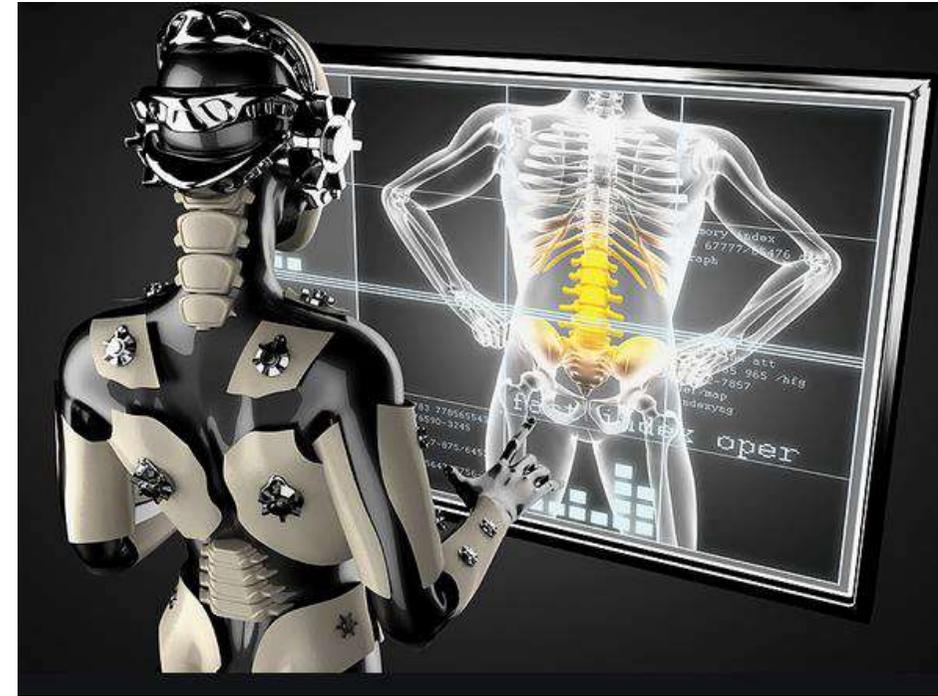
- The MRI phenotypes low initial enhancement, increased smoothness of enhancement, and low sharpness were associated with the expression of proteins within the ribosome, a target of anticancer drugs.
- Increased smoothness of enhancement, smaller tumor size, and a more irregular tumor shape were associated with the expression of genes related to the extracellular matrix, which is involved in breast cancer progression and metastasis.

Approccio non invasivo con lo scopo di associare i reperti di imaging con i sottotipi molecolari, le mutazioni genetiche e altre caratteristiche correlate con i geni dei tumori.

Nell'ambito del tumore mammario (soprattutto utilizzando dati RM), si è focalizzata nel correlare dati genomici derivanti dai sottotipi molecolari, espressione genomica individuale e score clinici di rischio di recidiva (OncotypeDx, MammaPrint, Mammostrat, PAM50/Prosigna).

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Artificial Intelligence: Is It Armageddon for Breast Radiologists?

Chiwome L, Okojie O M, Rahman A, et al. (June 30, 2020) Cureus 12(6): e8923.

Review

Technology in Cancer Research & Treatment
Volume 19: 1-16
© The Author(s) 2020

The Application of Radiomics

Table 1. Studies on Distant Recurrence

First Author, Year	Study Design
Bahreini et al (2010) ⁶	Retrospective
Bickelhaupt et al (2018) ⁷	Retrospective
Bickelhaupt et al (2017) ⁸	Prospective
Holli et al (2010) ⁹	Retrospective
Hu et al (2018) ¹⁰	Retrospective
Jiang et al (2018) ¹¹	Retrospective
Karahaliou et al (2010) ¹²	Not mentioned
Nie et al (2008) ¹³	Retrospective
Whitney et al (2019) ¹⁴	Retrospective
Gibbs and Tumbull (2003) ¹⁵	Retrospective

Table 2. Studies on Local Recurrence

First Author, Year	Study Design
Chai et al (2019) ¹⁶	Retrospective
Cui et al (2019) ¹⁷	Retrospective
Dong et al (2018) ¹⁸	Retrospective
Han et al (2019) ¹⁹	Retrospective
Liu et al (2019) ²⁰	Retrospective
Liu et al (2019) ²¹	Prospective

Table 3. Studies on Predicting Molecular Subtypes of Breast Cancer

First Author, Year	Study Design	Number of Patients	MRI Modality
Kirsi Holli-Helenius et al (2017) ²²	Nc		
Fan et al (2018) ²³	Re		
Fan et al (2017) ²⁴	Re		
Fan et al (2019) ²⁵	Re		
Grimm et al (2015) ²⁶	Re		
Juan et al (2018) ²⁷	Re		
Ko et al (2016) ²⁸	Nc		
Liang et al (2018) ²⁹	Re		
Ma et al (2018) ³⁰	Re		
Monti et al (2018) ³¹	Nc		
Saha et al (2018) ³²	Nc		

Table 4. Studies on Prediction of Tumor Response to Chemotherapy in Breast Cancer.

First Author, Year	Study Design	Number of Patients	MRI Modality	Magnetic Field	Radiomics Features	Studies Directions	Outcomes
Kim et al (2017) ⁴⁸	Retrospective	203	DCE-MRI	1.5 T	Texture features	To determine the relationship between tumor heterogeneity assessed by means of MRI texture analysis and survival outcomes in patients with primary breast cancer.	In multivariate analysis, a higher N stage (RFS hazard ratio, 11.15 (N3 stage); P = .002, Bonferroni adjusted a = 0.0167), triple-negative subtype (RFS hazard ratio, 16.91; P = .001, Bonferroni adjusted a = 0.0167), high risk of T1 entropy (less than the cutoff values (mean, 5.057; range, 5.022-5.167), RFS hazard ratio, 4.55; P = .018), and T2 entropy (equal to or higher than the cutoff values (mean, 6.013; range: 6.004-6.035), RFS hazard ratio = 9.84; P = .001) were associated with worse outcomes. The ROC curves of the model yielded AUC values of 0.88, 0.77 and 0.73, for the training, leave-one-out cross-validated and bootstrapped performances, respectively.
Chan et al (2017) ⁴⁹	Retrospective	563	DCE-MRI	1.5 T	Not mentioned	We present a radiomics model to discriminate between patients at low risk and those at high risk of treatment failure at long-term follow-up based on eigentumors.	The C-statistics for the association of METV with recurrence-free survival were 0.69 with 95% confidence interval of 0.58-0.80 at pretreatment and 0.72 (0.60-0.84) at early treatment. The hazard ratios calculated from Kaplan-Meier curves were 2.28 (1.08-4.61), 3.43 (1.83-6.75), and 4.81 (2.16-10.72) for the lowest quartile, median quartile, and upper quartile cutpoints for METV at early treatment.
Drukker et al (2018) ⁵⁰	Not mentioned	162	DCE-MRI	1.5 T	Not mentioned	To predict recurrence-free survival "early on" in breast cancer neoadjuvant chemotherapy.	The radiomics nomogram estimated DFS (C-index, 0.76; 95% confidence interval (CI): 0.74-0.77) better than the clinicopathological (C-index, 0.72; 95% CI: 0.70-0.74) or Rad-score only nomograms (C-index, 0.67; 95% CI, 0.65-0.69).
Park et al (2018) ⁵¹	Retrospective	294	DCE-MRI	1.5T	Morphological, histogram-based features, and higher-order texture features.	To develop a radiomics signature to estimate DFS in patients with invasive breast cancer and to establish a radiomics nomogram that incorporates the radiomics signature and MRI and clinicopathological findings.	The radiomics nomogram estimated DFS (C-index, 0.76; 95% confidence interval (CI): 0.74-0.77) better than the clinicopathological (C-index, 0.72; 95% CI: 0.70-0.74) or Rad-score only nomograms (C-index, 0.67; 95% CI, 0.65-0.69).
Pickles et al (2016) ⁵²	Retrospective	112	DCE-MRI	3.0 T	Texture, shape features	To determine if associations exist between pretreatment DCE-MRI and survival intervals and compare the prognostic value of DCE-MRI parameters against traditional pretreatment survival indicators.	Accuracy of risk stratification based on either traditional (59%) or DCE-MRI (65%) survival indicators performed to a similar level. However, combined traditional and MR risk stratification resulted in the highest accuracy (86%).

Table 5. Studies on Prediction of Survival Outcomes in Patients With Breast Cancer.

First Author, Year	Study Design	Number of Patients	MRI Modality	Magnetic Field	Radiomics Features	Studies Directions	Outcomes
Kim et al (2017) ⁴⁸	Retrospective	203	DCE-MRI	1.5 T	Texture features	To determine the relationship between tumor heterogeneity assessed by means of MRI texture analysis and survival outcomes in patients with primary breast cancer.	In multivariate analysis, a higher N stage (RFS hazard ratio, 11.15 (N3 stage); P = .002, Bonferroni adjusted a = 0.0167), triple-negative subtype (RFS hazard ratio, 16.91; P = .001, Bonferroni adjusted a = 0.0167), high risk of T1 entropy (less than the cutoff values (mean, 5.057; range, 5.022-5.167), RFS hazard ratio, 4.55; P = .018), and T2 entropy (equal to or higher than the cutoff values (mean, 6.013; range: 6.004-6.035), RFS hazard ratio = 9.84; P = .001) were associated with worse outcomes. The ROC curves of the model yielded AUC values of 0.88, 0.77 and 0.73, for the training, leave-one-out cross-validated and bootstrapped performances, respectively.
Chan et al (2017) ⁴⁹	Retrospective	563	DCE-MRI	1.5 T	Not mentioned	We present a radiomics model to discriminate between patients at low risk and those at high risk of treatment failure at long-term follow-up based on eigentumors.	The C-statistics for the association of METV with recurrence-free survival were 0.69 with 95% confidence interval of 0.58-0.80 at pretreatment and 0.72 (0.60-0.84) at early treatment. The hazard ratios calculated from Kaplan-Meier curves were 2.28 (1.08-4.61), 3.43 (1.83-6.75), and 4.81 (2.16-10.72) for the lowest quartile, median quartile, and upper quartile cutpoints for METV at early treatment.
Drukker et al (2018) ⁵⁰	Not mentioned	162	DCE-MRI	1.5 T	Not mentioned	To predict recurrence-free survival "early on" in breast cancer neoadjuvant chemotherapy.	The radiomics nomogram estimated DFS (C-index, 0.76; 95% confidence interval (CI): 0.74-0.77) better than the clinicopathological (C-index, 0.72; 95% CI: 0.70-0.74) or Rad-score only nomograms (C-index, 0.67; 95% CI, 0.65-0.69).
Park et al (2018) ⁵¹	Retrospective	294	DCE-MRI	1.5T	Morphological, histogram-based features, and higher-order texture features.	To develop a radiomics signature to estimate DFS in patients with invasive breast cancer and to establish a radiomics nomogram that incorporates the radiomics signature and MRI and clinicopathological findings.	The radiomics nomogram estimated DFS (C-index, 0.76; 95% confidence interval (CI): 0.74-0.77) better than the clinicopathological (C-index, 0.72; 95% CI: 0.70-0.74) or Rad-score only nomograms (C-index, 0.67; 95% CI, 0.65-0.69).
Pickles et al (2016) ⁵²	Retrospective	112	DCE-MRI	3.0 T	Texture, shape features	To determine if associations exist between pretreatment DCE-MRI and survival intervals and compare the prognostic value of DCE-MRI parameters against traditional pretreatment survival indicators.	Accuracy of risk stratification based on either traditional (59%) or DCE-MRI (65%) survival indicators performed to a similar level. However, combined traditional and MR risk stratification resulted in the highest accuracy (86%).

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Opportunities in Breast Imaging: Clinical needs and possible AI solutions

CLINICAL NEEDS

1. Personalized screening
2. More efficient screening
3. Reducing biopsy rate of benign lesions
4. Personalized therapy
5. Prediction of response to NAC

AI ROLE

- BC risk stratification
- AI reader, reduced human time
- Lesion classification (mal vs. ben)
- Cancer “molecular” characterization
- Advanced image analysis



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ECR 2022 / C-21877

Machine Learning Algorithm in Tomosynthesis and Synthetic Mammography Images: a Decision Support System for the characterization of breast masses lesions

Lesion Characterization

MANUAL SEGMENTATION OF LESION BOUNDARY

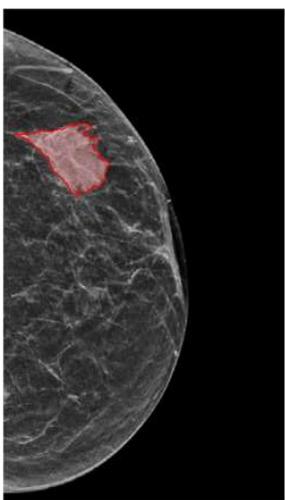
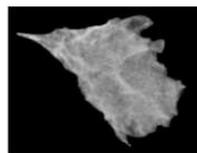
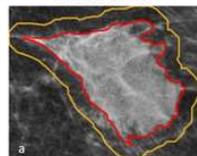


Image Processing

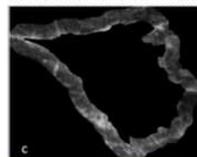
MASK OF TUMOR



PADDING



PERITUMORAL MASK



Feature Extraction

SHAPE AND INTENSITY

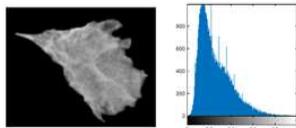
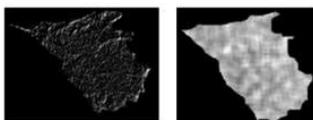
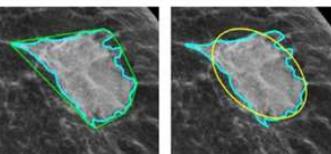


IMAGE FILTERING

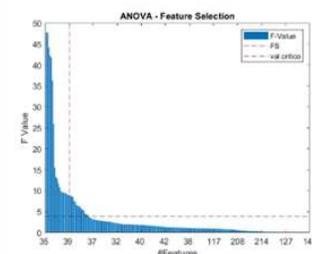


CONVEX ENVELOPE AND ELLIPSE



Extraction of 219 features

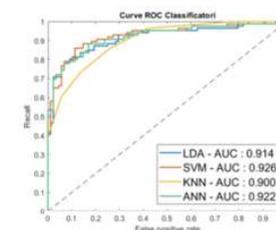
Feature Selection



ANOVA method and F-Test : selection of 20 significant features

Classification

Benign vs Malignant



Sensitivity, Specificity, and Accuracy in Training and Validation

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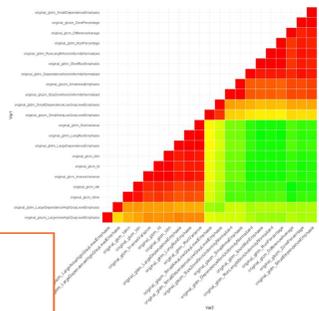
ANALYSIS OF RADIOMIC FEATURES IN THE MRI ASSESSMENT OF THE RESPONSE TO NEOADJUVANT CHEMOTHERAPY IN PATIENTS WITH TRIPLE-NEGATIVE BREAST CANCER

N. Damiani, F. Galioto, M. Durando, G. Bartoli, V. Rossetti, E. Regini, I. Landolfi, P. Fonio, O. Rampado.

Department of Diagnostic Imaging and Interventional Radiology
University of Turin, Turin/IT

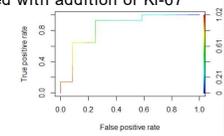
Results – pCR (multivariate analysis)

- Radiomic features correlation in the **subtraction images**.



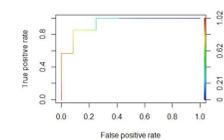
- Predictive model obtained with 3 Radiomic features (glcm_Id, glrlm_LongRunEmphasis e glszm_SmallAreaLow GrayLevelEmphasis);

a) AUC = 0,84



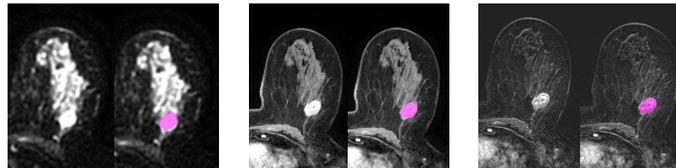
- Predictive model obtained with addition of Ki-67 index.

b) AUC = 0,94

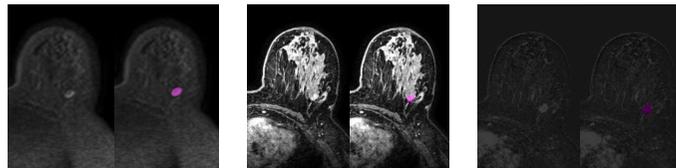


Methods – Lesions Segmentation

- PreTreatment



- PostTreatment



- Manually drawn ROI on the lesions in DW and DCE (5th acquisition after mdc injection and the 3rd subtraction images) with software LIFEX 7.1, analysed with Py-Radiomics (Python package).



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Artificial intelligence in medical imaging: threat or opportunity? Radiologists again at the forefront of innovation in medicine



Filippo Pesapane^{1†}, Marina Codari^{2†} and Francesco Sardanelli^{2,3}

AI as an opportunity....

*AI will not replace radiologists.
Yes, those radiologists who take advantage of the potential of
AI will replace the ones who refuse this crucial challenge*





Grazie per l'attenzione

Grazie A.N.D.O.S.

Grazie Comitato Torino

4 
CONGRESSO
NAZIONALE
ANDOS.ROMA
18-19-20 MAGGIO 2023



L'ARTE DELLA CURA PERSONALIZZATA

Radiomics role in the clinics

- Imaging is routinely performed for oncological patients:
 - diagnosis
 - treatment planning
 - follow-up

→ - large amount of retrospective data
- database continuously updated
- no additional cost
- Imaging is not invasive and minimally detrimental:
 - invasive alternative: biopsy or blood sampling

→ no additional patient discomfort
- Radiomics quantifies the properties of the whole volume:
 - reduce risk of under -sampling as compared to e.g. biopsy

→ more complete information

Radiomics challenges

- Differentiate malignant/benign tissue
- Tumor staging: differentiate between early and advanced stage disease
- Prognostic models: correlation with survival
- Predictive models: predict treatment response (chemotherapy, radiation therapy)
- Assessment of metastatic potential of tumors
- Assessment of cancer genetics / biological or histopathological properties (biological basis of clinical application of radiomics)
- Improve predictivity of models based on clinical, biological, genetic data

- Volume segmentation
- Dimension of volume
- Rigorous methodology
- Standardization
- Redundancy