Breast Journal Club

L'importanza della Ricerca in Oncologia

Machine learning per la diagnosi precoce

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Conflicts of interest

- Member of the IBA Victoria Advisory Committee
- Scientific consultant for Varian Medical Systems
- Scientific consultant for KBMS.com & KBO Labs
- Scientific consultant for Medipass srl
- Scientific consultant for Roche
- Scientific consultant for Radius srl
- Sponsored researcher for InnovationSprint
- Sponsored researcher for Nanovi
- Sponsored researcher for Sophia genetics
- Sponsored researcher for View Ray Inc.
- Inventor patent #20202000005950

Background | Oncology: multiomics medicine by design



Background | Artificial intelligence



Rationale for using AI

To do quicker (and better?) what humans can already do and to do what humans can not do

Machine learning

It is a method where the *target* (goal) is defined and the *steps to reach* that target is learned by the machine itself by *training* (gaining experience)

Background | Artificial intelligence



Deep learning

- It is a specific **subfield** of ML
- It puts emphasis on learning successive layers of increasingly meaningful representations



Background | Artificial intelligence



Background | Is radiology an optical illusion?



Background | Imaging biomarkers



Practical objectives of imaging analysis

- **Characterization** of tumour through quantitative features
- Therapeutic response prediction
- Patient stratification for therapy choice
- Radiotherapy treatment **optimiziation**

Background | Imaging biomarkers



Background | Imaging biomarkers



Radiomics | Definitions

Radiomics

- Converts medical images into quantitative data using mathematical algorithms
- Extracts features such as texture, shape, and intensity to assess tissue characteristics and heterogeneity

Radiogenomics

- Integrates radiomic features with genomic data to uncover the biological basis of imaging phenotypes
- Facilitates non-invasive prediction of tumor molecular characteristics and resposse to therapy

Radiomics | Definitions

Histological evaluation



- Invasive
- Difficult to repeat
- Tumor heterogeneity
- General risks
- Expensive

Radio(geno)mics evaluation



- Not invasive
- Repeatable
- Analyzes entire tumor volume : genomics
- Uses already available diagnostic exams
- Cheap



1998

R2 Technology's ImageChecker M1000 system

- Risk prediction
- Screening
- Diagnosis and characterization

International evaluation of an AI system for breast cancer screening



Objectives

- Develop and evaluate the accuracy of an AI system applied to nearly 29.000 mammographic screening images
- Compare it with human performance (6 radiologists)







AUC 0.62

AUC 0.74

Al system exceeded human performance ($\Delta AUC = +0.12$; p = 0.0002)



– 9,4% of FN and – 5,7% of FP

FDA approved AI tools

Product Name	Vendor	Country of Origin	Modality				
Cancer Detection							
cmAssist®	CureMetrix	United States	Mammography				
Genius AI™ Detection	Hologic [®] , Inc.	United States	Mammography and Tomosynthesis				
Lunit INSIGHT MMG	Lunit	South Korea	Mammography				
MammoScreen [®] 2.0	Therapixel	France	Mammography and Tomosynthesis				
ProFound AI [®]	ound AI [®] iCAD, Inc. United States		Mammography and Tomosynthesis				
Saige-Dx™	DeepHealth, Inc.	United States	Mammography				
Transpara®	ScreenPoint Medical B.V.	Netherlands	Mammography and Tomosynthesis				



AUC standalone **AI** compared with the mean **reader** (0.84 vs 0.81; *p*= 0.002)

5182 DBT examinations

5 radiologists performance417 of 459 detected cancers [90.8%]477 recalls in 5182 [9.2%]

Al performance 413 of 459 detected cancers [90.0%] 358 recalls in 5182 [6.9%] p 0.002

Use of AI to automatically filter out cases results in 39.6% less workload

FDA approved AI tools

Triage						
cmTriage®	CureMetrix, Inc.	United States	Mammography			
HealthMammo	Zebra Medical Vision	Israel	Mammography			
Saige-Q TM	DeepHealth, Inc.	United States	Mammography and Tomosynthesis			
Syngo.BreastCare	Siemens®	Germany	Mammography			

- Improve exam management
- Categorize cases by complexity
- Replace the second reader in double-reading sites





Table 2 Single and multiparametric entropy values corresponding to benign and malignant breast tumors

	Benign tumor	Malignant tumor	p value	AUC
MRI metrics				
ADC map values ($\times 10^{-3}$ mm ² /s)	1.89 ± 0.10	1.15 ± 0.03	0.0001	
K ^{trans} (1/sec)	0.27 ± 0.05	0.80 ± 0.32	0.005	
Single parameter entropy				
Entropy T1	4.14 ± 0.11	4.66 ± 0.06	0.00008	0.72 (0.64-0.79)
Entropy T2	4.98 ± 0.12	5.42 ± 0.06	0.002	0.68 (0.59-0.75)
Entropy b0	4.44 ± 0.17	5.06 ± 0.09	0.002	0.67 (0.59-0.75)
Entropy b600	3.00 ± 0.20	3.77 ± 0.09	0.0009	0.67 (0.59-0.75)
Entropy ADC	4.90 ± 0.12	5.40 ± 0.06	0.0004	0.70 (0.62-0.77)
Entropy post-contrast DCE (High spatial resolution)	5.00 ± 0.10	5.54 ± 0.05	0.00001	0.75 (0.67-0.82)
Entropy PK-DCE Pre	4.32 ± 0.12	4.65 ± 0.05	0.02	0.62 (0.54-0.70)
Entropy PK-DCE post (wash-in)	4.89 ± 0.08	5.30 ± 0.05	0.00006	0.72 (0.64-0.79)
Entropy PK-DCE post (wash-out)	4.90 ± 0.09	5.24 ± 0.04	0.00007	0.69 (0.60-0.76)
Multiparametric entropy				
TSPM entropy (all Parameters)	7.06 ± 0.27	8.93 ± 0.17	< 0.00001	0.82 (0.74-0.88)
TSPM entropy (PK-DCE)	7.06 ± 0.27	8.92 ± 0.17	< 0.00001	0.82 (0.74-0.88)
TSPM entropy (high spatial resolution DCE)	6.74 ± 0.19	8.28 ± 0.12	< 0.00001	0.82 (0.75-0.88)
TSPM entropy (DWI)	6.66 ± 0.22	8.20 ± 0.15	< 0.00001	0.78 (0.70-0.85)

DWI diffusion-weighted imaging, *ADC* apparent diffusion coefficient, *PK* pharmacokinetic, *DCE* dynamic contrast enhancement, *FOS* first order statistics, *TSPM* tissue signature probability matrix

The mpRad features successfully classified breast lesions with excellent sensitivity and specificity of 82.5% and 80.5%, respectively, with AUC of 0.87 (0.81–0.93). **mpRad provided a 9-28% increase in AUC metrics over single radiomic parameters.**



Tumor boards | The role of Al

To the Editor: As I observed the tumor board, case after case of breast cancers were discussed and appropriate multidisciplinary management was planned for each individual patient. Then came one case that changed everything.

Case #9 was a patient with 2 sets of mammograms pulled up to the big screen for all to see. The radiologist explained that the first set of images taken 3 months ago appeared completely normal and no suspect pathology could be found. The radiologist went on further to point out the evident pathology on the second set of images taken this week, thereby raising suspicion for cancer. Everyone's eyes darted back and forth between the images, struggling to find some sort of hint of cancer in the first set of images. The radiologist continued, "This miss would be entirely acceptable if not for a recent advancement in our practice." She mentioned that a few days before having our patient's first images taken, we had implemented a new artificial intelligence (AI) software in our system. Although that software predicted a 35% chance of malignancy in the first images, we did not see it and waved it off. The radiologist pulled up an image with the AI prediction overlay, outlining the area of suspicious malignancy of which to the people in the board room could not appreciate. She said, "We dismissed AI's prediction because we did not see what it saw."

The surgeons, pathologists, oncologists, and fellow radiologists all looked visibly disturbed by this case and the new decision landscape they faced. A look of confusion at facing a new complicated ethical world could be seen on the

When another AI dilemma arises, will we be equipped to address the elephant in the board room?

Thank you for your kind attention



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