Machine Learning for Applications in Medical Physics

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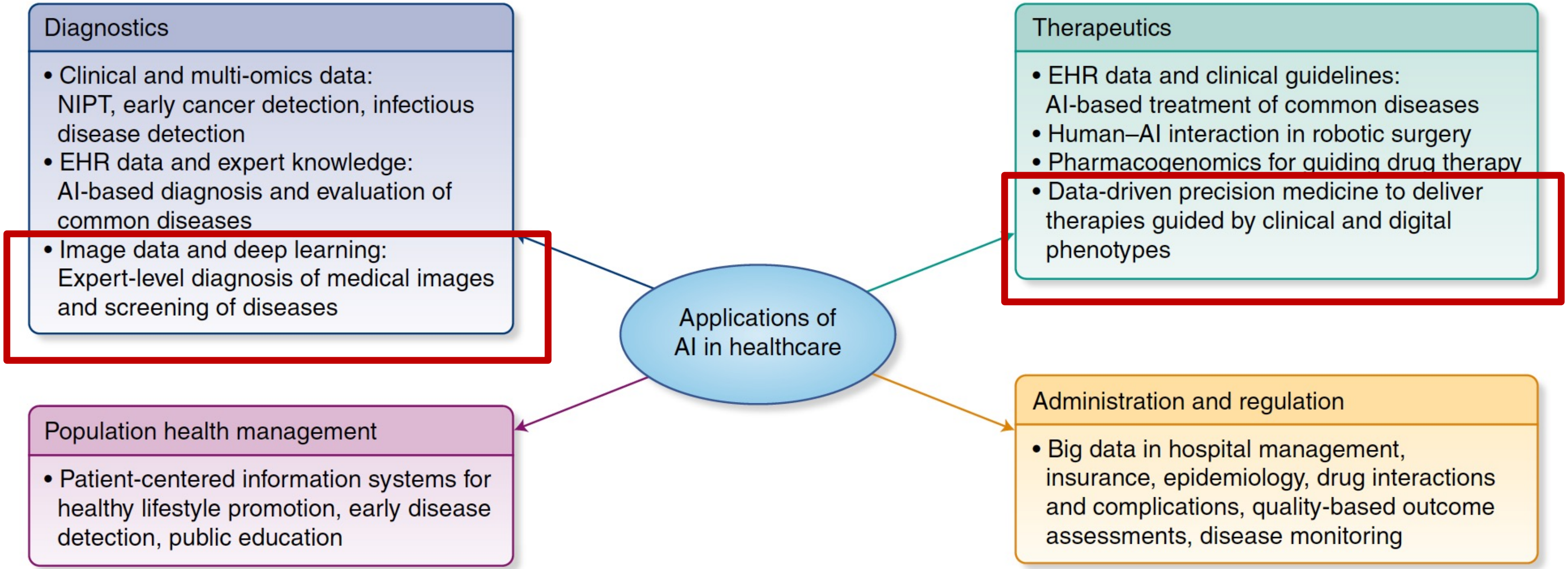
Artificial Intelligence applications in Healthcare

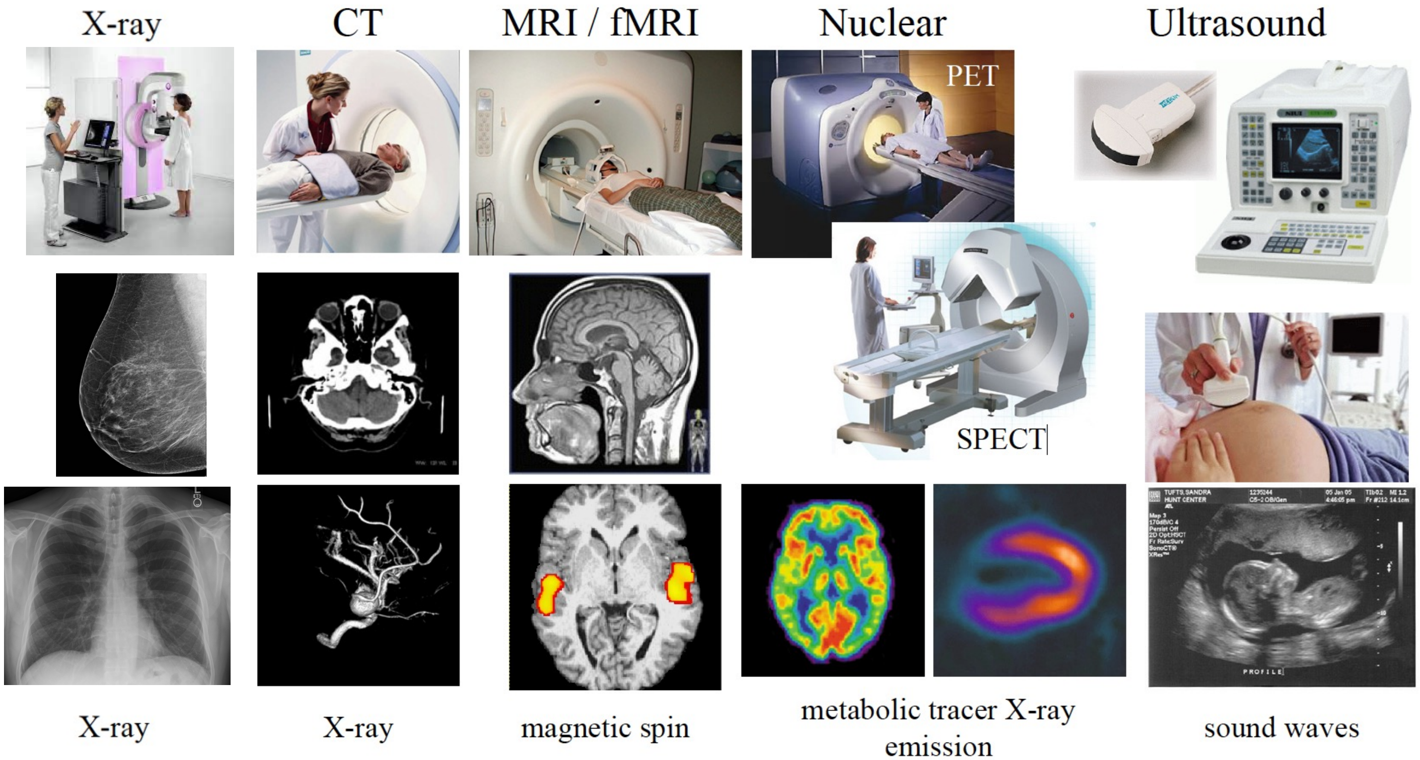


Legend: HER, Electronic Health Records; NIPT, noninvasive prenatal test

[J. He et al., The practical implementation of artificial intelligence technologies in medicine, Nature Medicine ***25****, 30–36 (2019)]*

Medical Imaging: there are many techniques based on different physical principles

Alessandra Retico



Medical images are more than pictures!!!

Decision Support Systems (DSS) for Detection/Diagnosis

Image processing and analysis techniques can help:

- to improve image visualization
- to detect abnormalities in diagnostic images (lesions, etc.)
- to follow up pathological conditions (growth rate of lesions)
- to evaluate the efficacy of treatment

Computer Aided Detection/Diagnosis (CAD) systems
or Decision Support Systems (DSS)
are developed to assist clinicians in their tasks, not to replace them!

Historical overview

Artificial Intelligence (AI) methods used in the development of DSS:

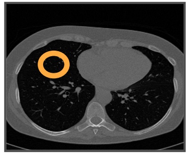
- In the 90s - Old-fashion systems (rule-based)
- Since the 2000s - Hand-crafted feature and Machine Learning classification (Radiomics and ML)
- Since 2015 – Deep-Learning image classification

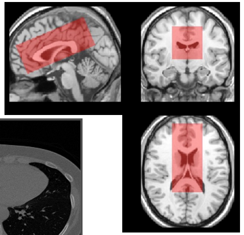
INFN CSN5 funded projects

1998-2001 **CALMA**

2002-2004 **GP-CALMA**

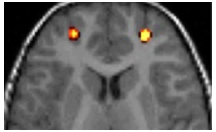
2005-2011 **MAGIC V**



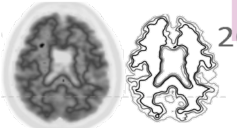


2011-2012 **SEVEN**

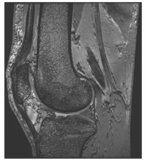
2012-2013 **M5L**

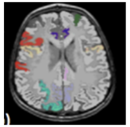


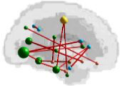
2012-2014 **MIND**



2013-2014 **TESLA**







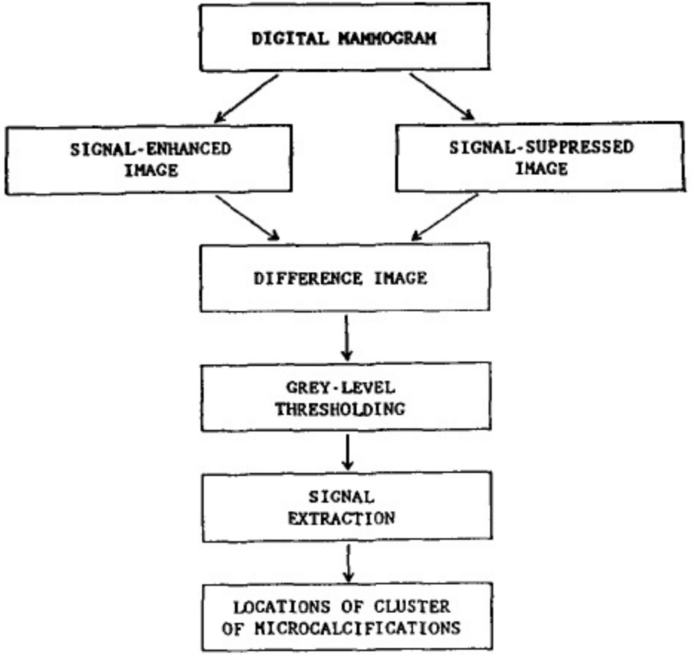
2015-2017 **nextMR**

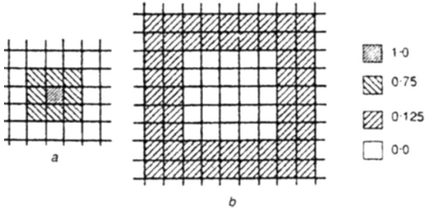
2019-today

Old-fashion CAD systems

Analysis pipeline for automated detection of microcalcification clusters on mammograms

"Old-fashion" decision-making systems were based on explicitly coding of specific rules



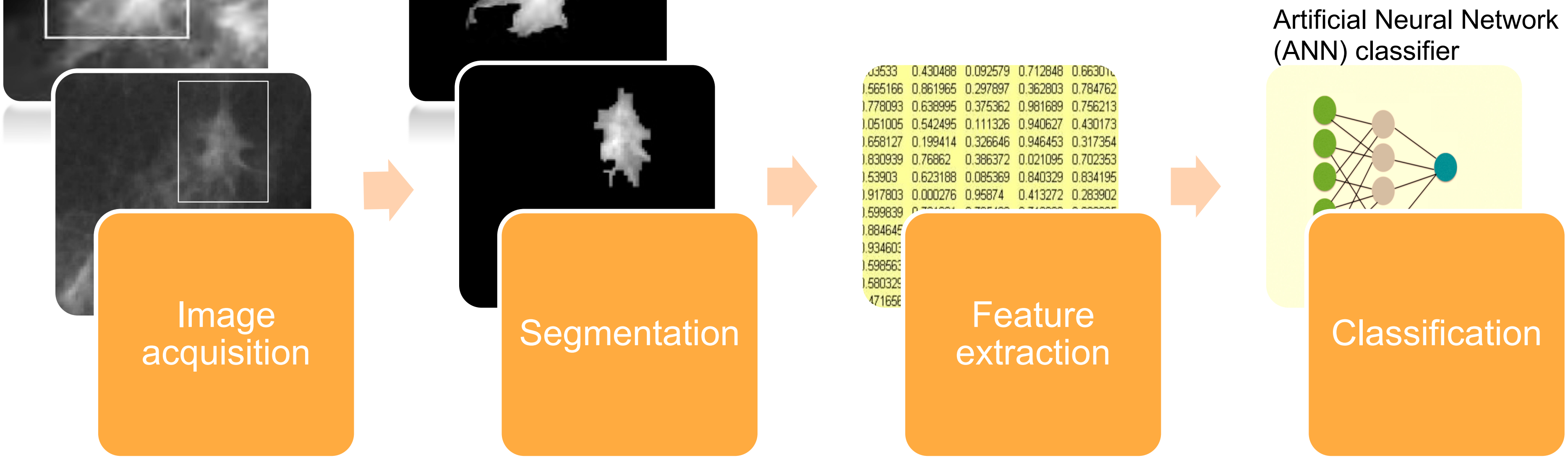


Kernels used for (a) enhancement filter and (b) suppression filter

[Chan HP et al., "Image feature analysis and computer-aided diagnosis in digital radiography. 1. Automated detection of microcalcifications in mammography," Med. Phys. 14, 538–548, 1987]

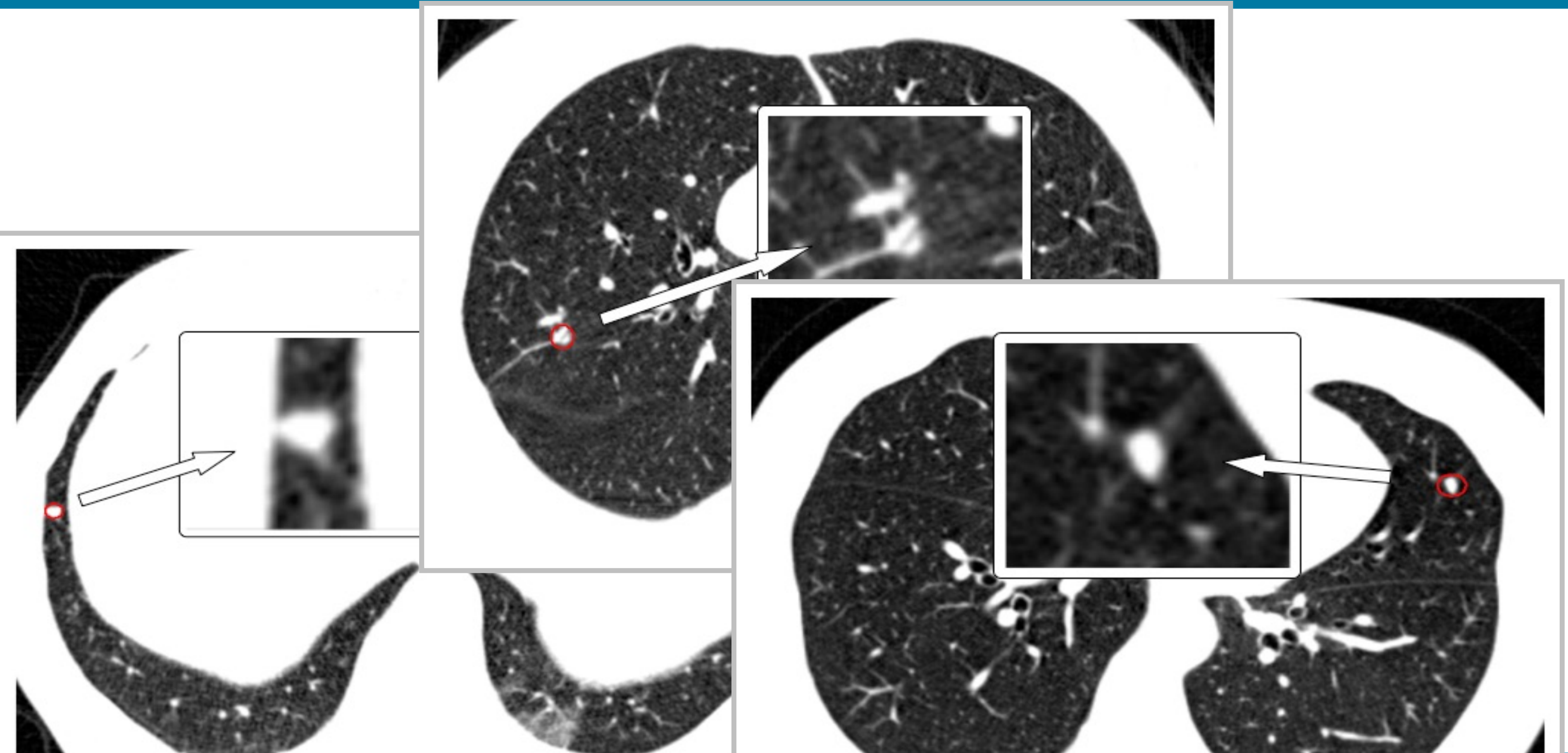
Hand-crafted feature + Machine Learning classification

- Semiautomated lesion segmentation of mass lesions in mammograms
- Automated classification into benign/malignant category

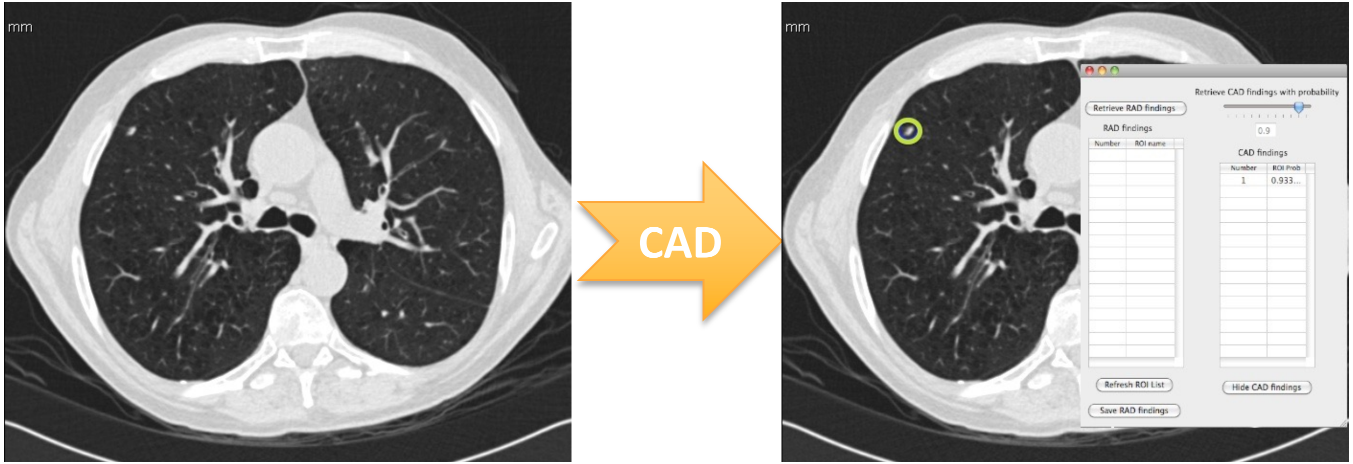


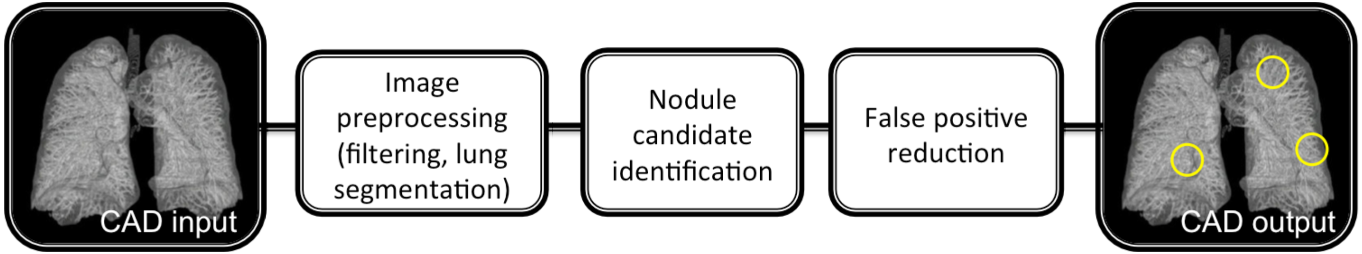
[Delogu P., Fantacci M.E., Kasae P., Retico, A., Computers in Biology and Medicine 37 (2007) 1479 – 1491]

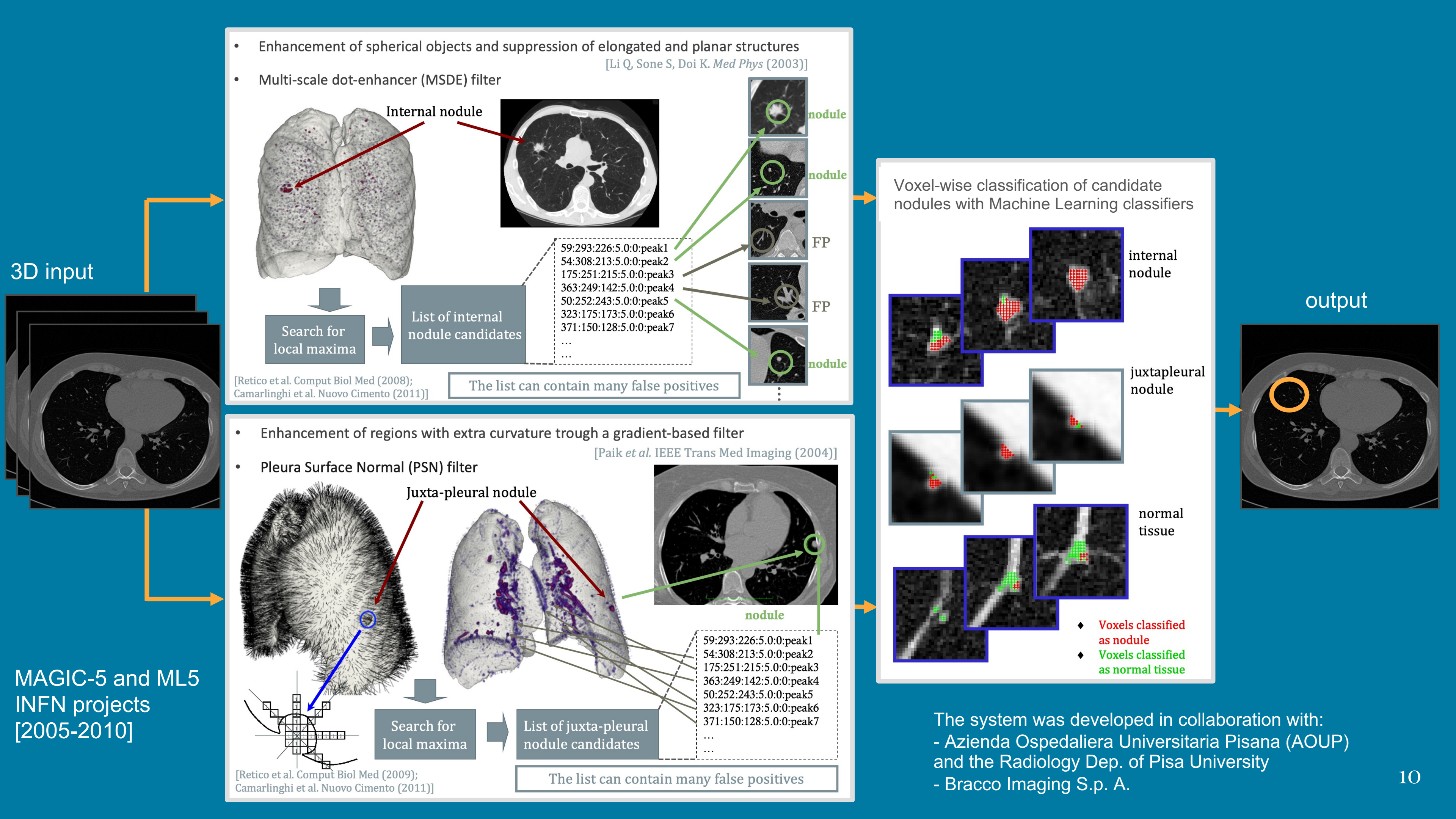
Automated detection of lung nodules in CT images



CAD system for lung nodule detection

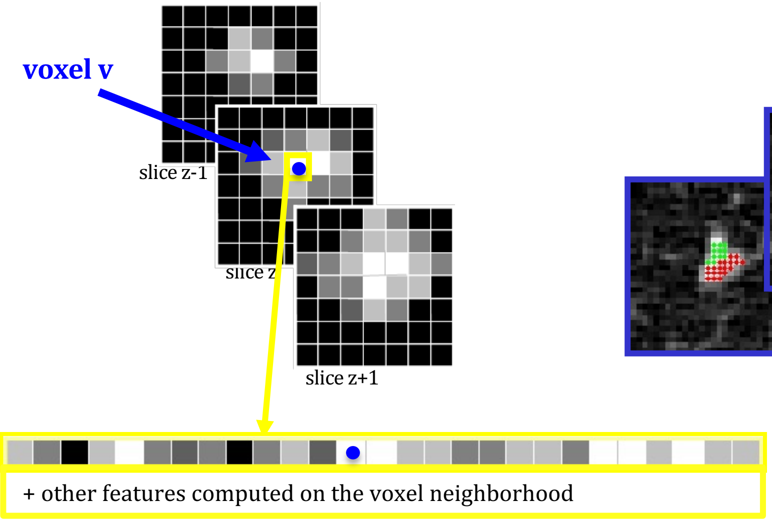




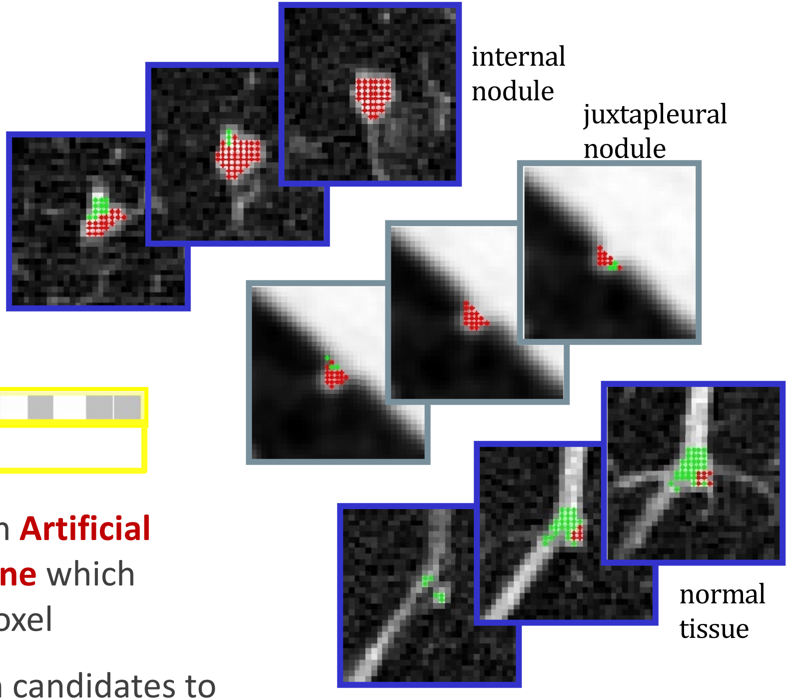

3D input
Enhancement of spherical objects and suppression of elongated and planar structures
[Li Q, Sone S, Doi K. Med Phys (2003)]
Multi-scale dot-enhancer (MSDE) filter
Internal nodule
nodule
nodule
FP
FP
nodule
59:293:226:5.0:0:peak1
54:308:213:5.0:0:peak2
175:251:215:5.0:0:peak3
363:249:142:5.0:0:peak4
50:252:243:5.0:0:peak5
323:175:173:5.0:0:peak6
371:150:128:5.0:0:peak7
…
…
Search for local maxima
List of internal nodule candidates
[Retico et al. Comput Biol Med (2008); Camarlinghi et al. Nuovo Cimento (2011)]
The list can contain many false positives
Enhancement of regions with extra curvature trough a gradient-based filter
[Paik et al. IEEE Trans Med Imaging (2004)]
Pleura Surface Normal (PSN) filter
Juxta-pleural nodule
nodule
59:293:226:5.0:0:peak1
54:308:213:5.0:0:peak2
175:251:215:5.0:0:peak3
363:249:142:5.0:0:peak4
50:252:243:5.0:0:peak5
323:175:173:5.0:0:peak6
371:150:128:5.0:0:peak7
…
…
Search for local maxima
List of juxta-pleural nodule candidates
[Retico et al. Comput Biol Med (2009); Camarlinghi et al. Nuovo Cimento (2011)]
The list can contain many false positives
Voxel-wise classification of candidate nodules with Machine Learning classifiers
internal nodule
juxtapleural nodule
normal tissue
Voxels classified as nodule
Voxels classified as normal tissue
output
MAGIC-5 and ML5 INFN projects [2005-2010]
The system was developed in collaboration with:
- Azienda Ospedaliera Universitaria Pisana (AOUP) and the Radiology Dep. of Pisa University
- Bracco Imaging S.p. A.
10

Example: voxel-based nodule characterization

- Each voxel v of a nodule candidate is described in terms of a vector of features



- Voxels classified as nodule
- Voxels classified as normal tissue



Supervised classification

Each vector of features is analyzed by an **Artificial Neural Network/Support Vector Machine** which assigns the class membership to each voxel

A majority criterion is adopted to assign candidates to either the “nodule” or the “healthy tissue” class

Final CAD performance

Combining different CAD methods increases the performance in the identification of pulmonary nodules

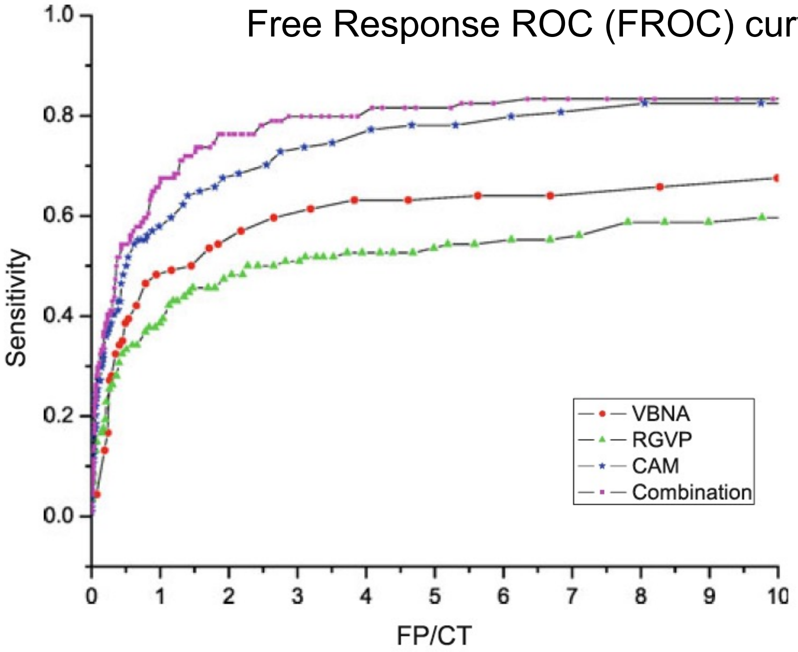
Train + validation sets:

- 69 CTs with 138 nodules (96 internal and 42 juxtapleural)

Independent Test set:

- 69 CTs with 114 nodules (95 internal and 19 juxtapleural)

Free Response ROC (FROC) curve



[Camarlinghi et al, Int. Journal of Computer Assisted Radiology and Surgery, IJCARS (2011)]

M5L lung CAD on-demand

Lung nodule detection SW developed by INFN MAGIC-5 and M5L projects

→ laboratory performance: 80% sensitivity to nodules @ 5 FP/exam

→ clinical validation

Assisted reading improves nodule detection by +7% in the per-patient analysis

MAGIC-5 and M5L project leader:
P. Cerello, INFN, Turin

Collaboration with Candiolo Cancer Institute-FPO, IRCCS and Univ. of Turin

European Radiology
https://doi.org/10.1007/s00330-018-5528-6

COMPUTER APPLICATIONS

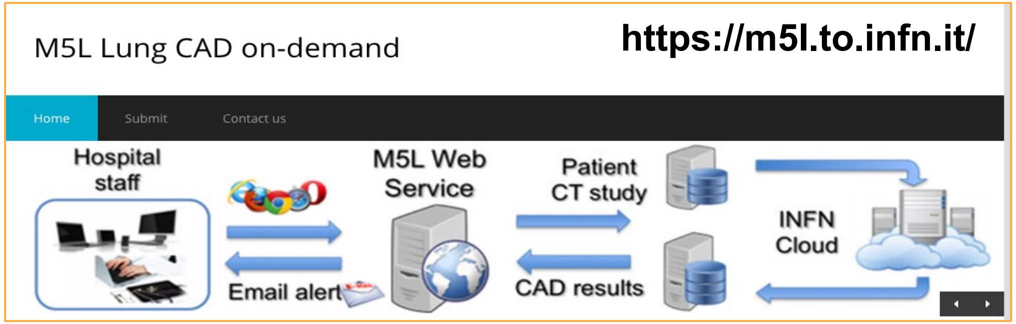
CrossMark

A cloud-based computer-aided detection system improves identification of lung nodules on computed tomography scans of patients with extra-thoracic malignancies

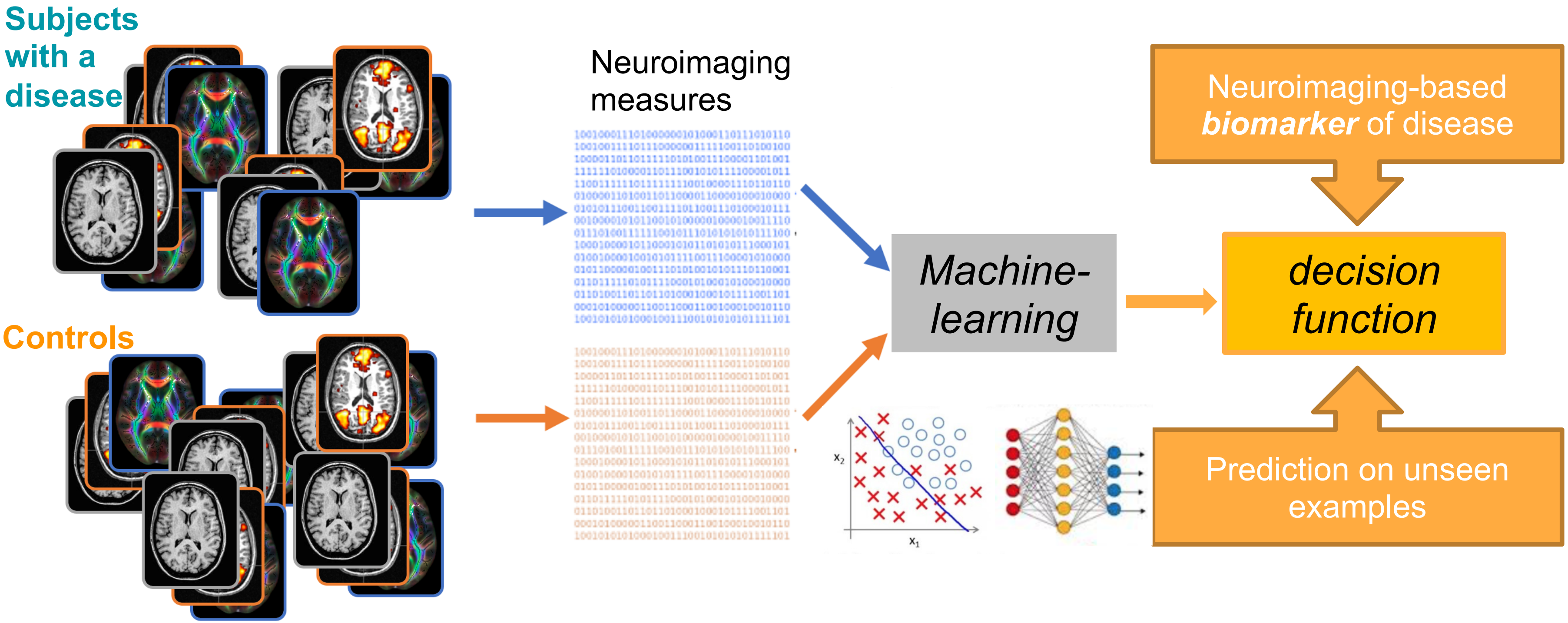
Lorenzo Vassallo[1,2] · Alberto Traverso[3,4] · Michelangelo Agnello[3] · Christian Bracco[5] · Delia Campanella[1] · Gabriele Chiara[1] · Maria Evelina Fantacci[6] · Ernesto Lopez Torres[7] · Antonio Manca[1] · Marco Saletta[7] · Valentina Giannini[1,2] · Simone Mazzetti[1,2] · Michele Stasi[5] · Piergiorgio Cerello[7] · Daniele Regge[1,2]

Received: 21 March 2018 / Revised: 27 April 2018 / Accepted: 7 May 2018

Abstract
Objectives To compare unassisted and CAD-assisted detection and time efficiency of radiologists in reporting lung nodules on CT scans taken from patients with extra-thoracic malignancies using a Cloud-based system.



Human Neuroimaging: a “Big Data Challenge”



Predictive models based on multimodal and multidimensional data can be used to characterize the pathology-specific brain correlates (neuroimaging-based ***biomarker*** of a disease/condition), and then to ***predict*** the single subject’s group membership

Characterization of subjects with Autism Spectrum Disorders

Research in collaboration with INFN and IRCCS FONDAZIONE STELLA MARIS

ARIANNA project

https://arianna.pi.infn.it [2016-2018]

Ambiente di **R**icerca **I**nterdisciplinare per l'**A**nalisi di **N**euroimmagini **N**ell'**A**utismo

Regione Toscana | FAS Fondo Aree Sottoutilizzate 2007-2013 | REPUBBLICA ITALIANA

FONDAZIONE STELLA MARIS – ISTITUTO DI RICOVERO E CURA A CARATTERE SCIENTIFICO IRCCS Stella Maris Foundation, Viale del Tirreno 331, Pisa, Italy Prof. Filippo Muratori (Neuropsichiatria) Dr. Michela Tosetti (Lab. Risonanza Magnetica) www.irccs-stellamaris.it FiRM lab	INFN – Istituto Nazionale di Fisica Nucleare INFN, Sezione di Pisa, Largo Pontecorvo 3, 56127 Pisa, Italy Dr. Alessandra Retico www.pi.infn.it	I+ S.r.l, Piazza Puccini 26, 50144 Firenze, Italy Dr Elena Tamburini www.i-piu.it
	ittig – Istituto di Teoria e Tecniche dell'Informazione Giuridica del CNR ITTIG (CNR), Via de'Barucci 20, 50127 Firenze, Italy Dr. Pietro Mercatli www.ittig.cnr.it	net7 Net7 S.r.l, Via G. Carducci 60, 56017 Ghezzano - San Giuliano Terme, Pisa, Italy www.netseven.it/ Dr. Luca De Santis

Computers in Biology and Medicine 87 (2017) 1–7
Contents lists available at ScienceDirect
Computers in Biology and Medicine
journal homepage: www.elsevier.com/locate/compbiomed

ARIANNA: A research environment for neuroimaging studies in autism spectrum disorders

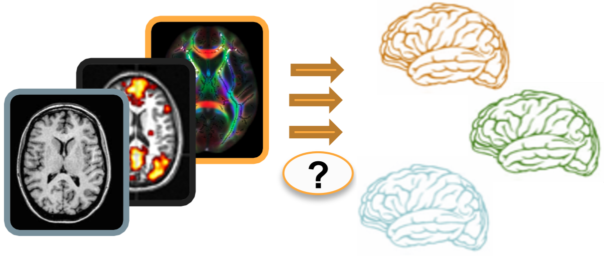
Alessandra Retico [a,*], Silvia Arezzini [a], Paolo Bosco [a], Sara Calderoni [b,c], Alberto Ciampa [a], Simone Coscetti [a], Stefano Cuomo [a], Luca De Santis [e], Dario Fabiani [a], Maria Evelina Fantacci [a,f], Alessia Giuliano [a], Enrico Mazzoni [a], Pietro Mercatali [d], Giovanni Miscali [e], Massimiliano Pardini [e], Margherita Prosperi [b], Francesco Romano [d], Elena Tamburini [g], Michela Tosetti [b], Filippo Muratori [b,c]

EJN European Journal of Neuroscience FENS
European Journal of Neuroscience, pp. 1–11, 2017 doi:10.1111/ejn.13527

The effect of age, sex and clinical features on the volume of Corpus Callosum in pre-schoolers with Autism Spectrum Disorder: a case–control study

Alessia Giuliano,[1,2,*] Irene Saviozzi,[3,*] Paolo Brambilla,[4,5] Filippo Muratori,[6,7] Alessandra Retico[2] and Sara Calderoni[7]
[1]Physics Department, University of Pisa, Pisa, Italy
[2]Pisa Division, National Institute for Nuclear Physics, Largo Pontecorvo 3, 56127 Pisa, Italy

Open issue: *stratification of the heterogeneous ASD population?*



frontiers in Psychiatry
ORIGINAL RESEARCH
published: 20 September 2019
doi: 10.3389/fpsyt.2019.00620

Evaluation of Altered Functional Connections in Male Children With Autism Spectrum Disorders on Multiple-Site Data Optimized With Machine Learning

Giovanna Spera[1], Alessandra Retico[1*], Paolo Bosco[2], Elisa Ferrari[1,3], Letizia Palumbo[1], Piernicola Oliva[4,5], Filippo Muratori[2,6] and Sara Calderoni[2,6]

Received: 2 January 2018 | Revised and accepted: 1 August 2018
DOI: 10.1002/hbm.24351
WILEY

RESEARCH ARTICLE

Brainstem enlargement in preschool children with autism: Results from an intermethod agreement study of segmentation algorithms

Paolo Bosco[1] | Alessia Giuliano[1] | Jonathan Delafield-Butt[2] | Filippo Muratori[3,4] | Sara Calderoni[3,4] | Alessandra Retico[1]
[1]Pisa Division, INFN - National Institute for Nuclear Physics, Pisa, Italy
[2]Faculty of Humanities and Social Science, University of Strathclyde, Glasgow, United Kingdom
[3]Department of Clinical and Experimental Medicine, University of Pisa, Pisa, Italy

Abstract
The intermethod agreement between automated algorithms for brainstem segmentation is investigated, focusing on the potential involvement of this structure in Autism Spectrum Disorders (ASD). Inconsistencies highlighted in previous studies on brainstem in the population with ASD may in part be a result of poor agreement in the extraction of structural features between

The Artificial Intelligence in Medicine (AIM) INFN-CSN5 Project

artificial intelligence in medicine AIM

Project coordinator: A. Retico

Bari (S. Tangaro)
Bologna (D. Remondini)
Cagliari (P. Oliva)
Catania (M. Marrale)
Firenze (C. Talamonti)
Genova (A. Chincarini)
Lab. Naz. Sud (G. Russo)
Milano (C. Lenardi)
Napoli (G. Mettivier)
Pavia (A. Lascialfari)
Pisa (M.E. Fantacci)

Artificial Intelligence to become the next revolution in **medical diagnostics** and **therapy**.

- New image processing and data analysis strategies, including radiomics approaches, need to be developed and extensively validated.

Objectives	Methods	Applications	
AIM1: Multicenter data harmonization	image processing; data filtering; feature extraction; feature classification; data harmonization; image classification; pattern recognition; radiomics; complex network analysis; network models; machine learning; deep learning	Reliability of multicenter studies in neuroimaging and in mammography.	MRI; RX
AIM2: Quantification		Quantification of radiotracer uptake in PET. Quantitative MRI methods.	MRI; PET; omics
AIM3: Predictive models		Radiomics and dosiomics in oncology. ML and DL for disease diagnosis	MRI; RX; RT dose; CT; omics

Analysis of lung CT in Covid-19

Long-standing collaboration with Italian & European centers (Hospitals / IRCCS) and with international consortia for data sharing

Harmonization of multicenter data in the study of Autism Spectrum disorders (ASD)

Alessandra Retico

Caltech_51456_mprage.nii

Caltech_51463_mprage.nii

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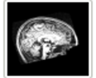
KKI_50778_mprage.nii



NYU_50957_mprage.nii

Data gathered by different scanner and/or acquisition systems encode the site "signature", which can confound ML algorithms and hide subtle information of interest.

ABIDE

Autism Brain Imaging Data Exchange (2200 MRI scans, 40 acquisition sites)

AUC	NYU ABIDE1	NYU-1 ABIDE2	NYU-2 ABIDE2	OHSU ABIDE1	OHSU ABIDE2	USM ABIDE1	USM ABIDE2	UM-1 ABIDE1	UM-2 ABIDE1
NYU ABIDE1	-	0.78	0.89	0.99	1.00	0.99	1.00	0.99	0.98
NYU-1 ABIDE2		-	0.70	0.99	1.00	1.00	1.00	0.99	0.98
NYU-2 ABIDE2			-	1.00	0.98	0.99	0.99	1.00	1.00
OHSU ABIDE1				-	0.63	0.97	0.96	1.00	1.00
OHSU ABIDE2					-	0.99	0.96	0.98	0.98
USM ABIDE1						-	0.75	0.99	0.99

ML classifiers can easily distinguish brain features of subjects from site A vs. site B (AUC ~1), whereas barely distinguish ASD vs. controls (AUC~0.6).

Artificial Intelligence In Medicine 108 (2020) 101926

Contents lists available at ScienceDirect

Artificial Intelligence In Medicine

ELSEVIER

journal homepage: www.elsevier.com/locate/artmed

Dealing with confounders and outliers in classification medical studies: The Autism Spectrum Disorders case study

Elisa Ferrari[a,*], Paolo Bosco[b], Sara Calderoni[b,c], Piernicola Oliva[d,e], Letizia Palumbo[f], Giovanna Spera[f], Maria Evelina Fantacci[f,g], Alessandra Retico[f]

How to mitigate site effects?

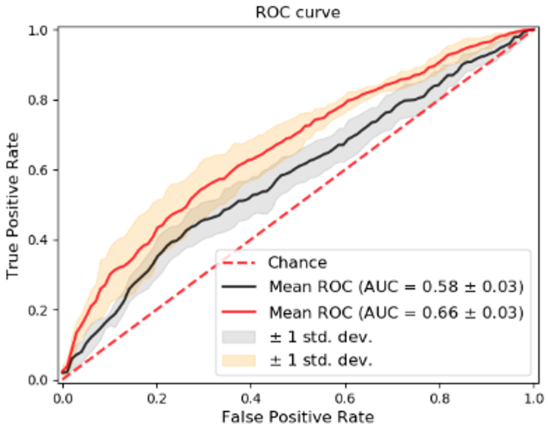
The site contribution to can be modelled and discarded, while keeping interesting data dependencies (e.g. on age and sex)

$$Y^*_{ijk} = (Y_{ijk} - f_k(x_{ij}, z_{ij}, w_{ij}) - g^*_{ik}) / d^*_{ik} + f_k(x_{ij}, z_{ij}, w_{ij})$$

non-linear function of age, sex, TIV

location

scale



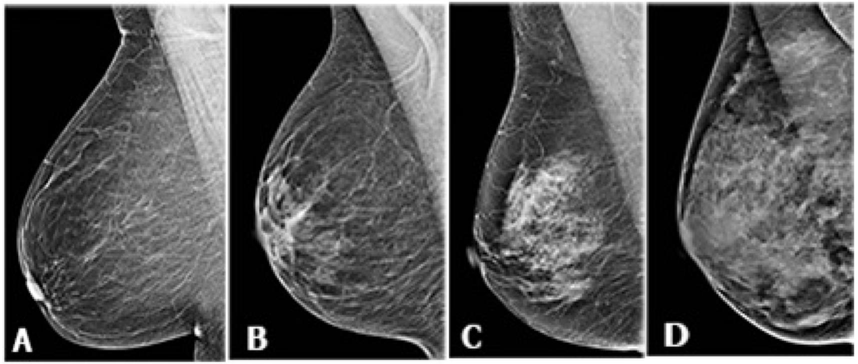
The case vs. control separation ability of the ML classifiers is significantly improved

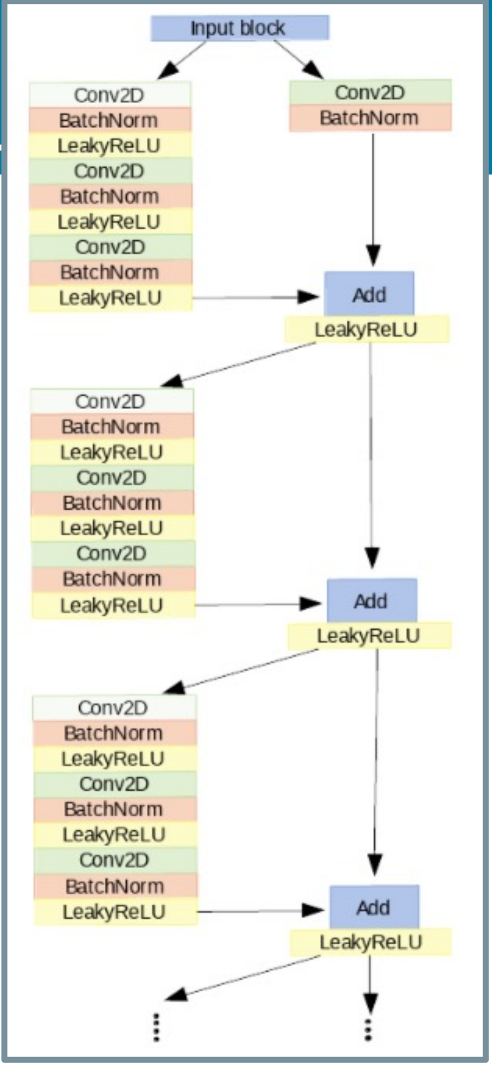
[S. Saponaro et al, in preparation]

Deep residual CNN for breast density classification

Automated identification of tissue density class (A, B, C, D) with a residual CNN (R-CNN)

Goal: To contribute to the development of a new personalized **dose index** (depending on breast density) for each patient and each mammographic exam.





Dataset: about **2000 digital mammographic exams** collected by Azienda Ospedaliero-Universitaria Pisana (AOUP).

Dense/Non-dense	Left (%)	Right (%)	All (%)	BI-RADS	Left (%)	Right (%)	All (%)
Accuracy	84.4	88.8	89.4	Accuracy	73.3	76.7	77.3
Recall	82.3	89.9	90.0	Recall	72.1	79.2	77.1
Precision	85.5	87.7	88.9	Precision	76.6	75.2	78.6

[Lizzi F. et al., Residual convolutional neural networks to automatically extract significant breast density features. vol. 1089. Springer International Publishing; 2019]

RADIOMA

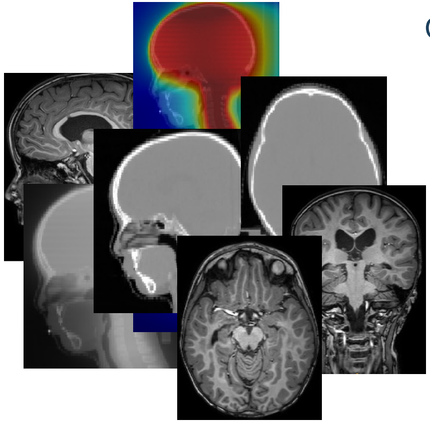
AZIENDA OSPEDALIERO UNIVERSITARIA PISANA

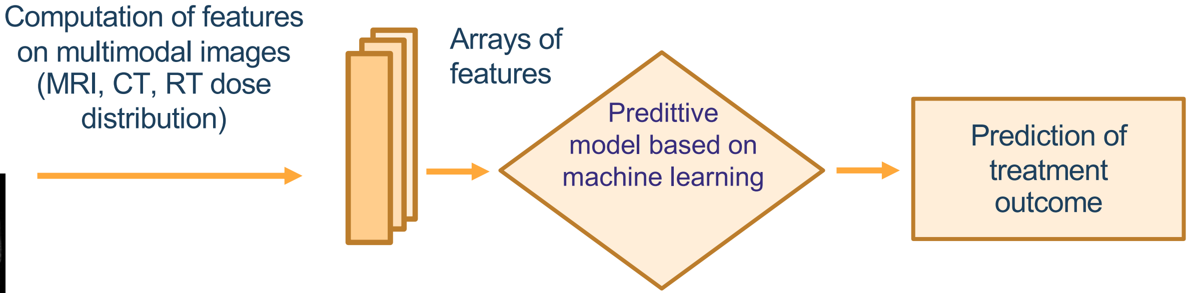
INFN Istituto Nazionale di Fisica Nucleare

FONDAZIONE PISA

Radiomics and Machine Learning to predict patients' outcome

- Radiomic features are analyzed with Machine Learning methods to develop predictive models of diagnosis, prognosis or treatment outcome.
- For example: Predictive models of outcome of Radiotherapy Treatment (RT) based on Radiomics and Dosiomic features





in collaborazione con

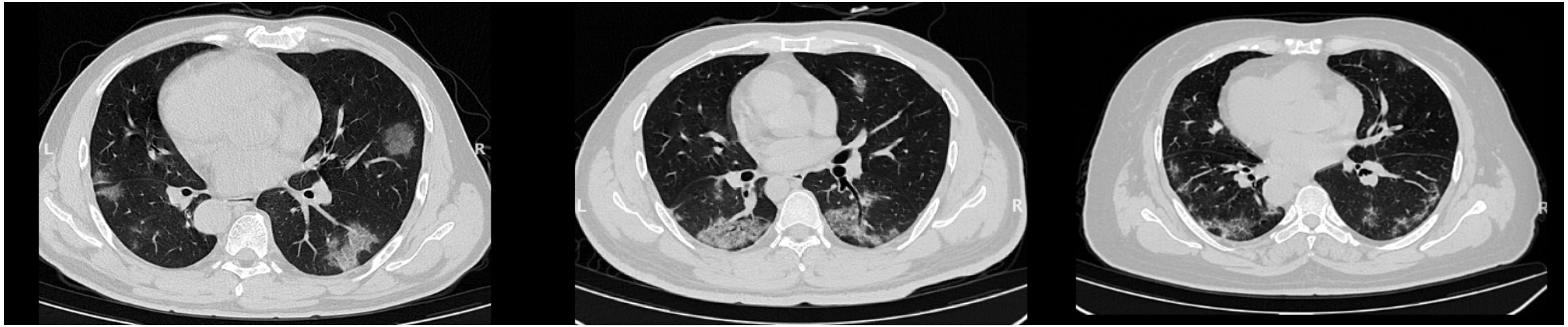
Talamonti C et al., *Radiomic and dosiomic profiling of paediatric Medulloblastoma tumours treated with Intensity Modulated Radiation Therapy*, Proc VIMABI2019

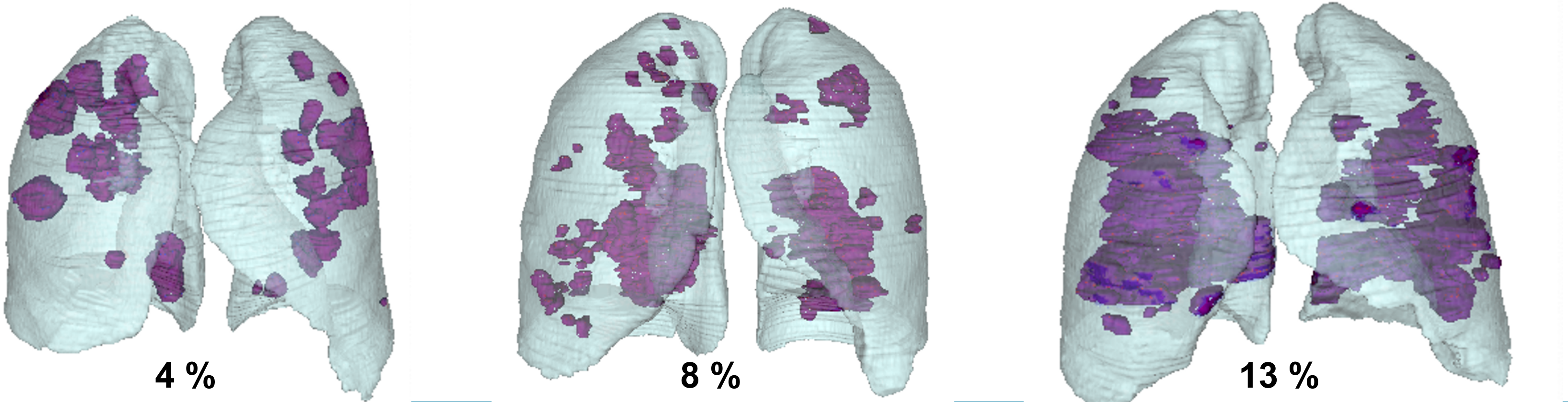
The AIM working group on lung CT analysis (AIM-Covid19-WG)

Objective: Automatic quantification of lung involvement on CT scans.

An index of severity of lung involvement has been defined [Yang, Radiology, 2020]: **CT-Severity Score (CT-SS)**

CT-SS= **1** (<5%), **2** (5%-25%), **3** (25%-50%), **4** (50%-75%), **5** (>75%)



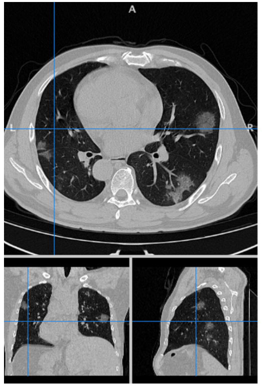


Steps for the automatic quantification of lung involvement in CT scans

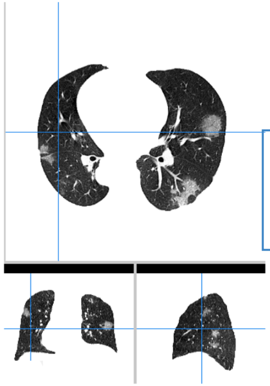
AIM1: Multicenter Data Harmonization

AIM2: Quantification

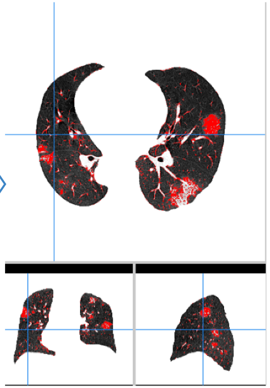
AIM3: Predictive Models



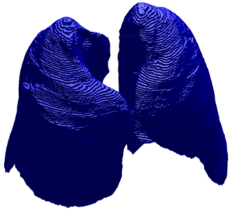
Lung volume segmentation



Quantification of lung parenchyma affected by COVID-19 lesions



Classical algorithms for lung segmentation fail when lung appearance is strongly affected by COVID-19 lesions

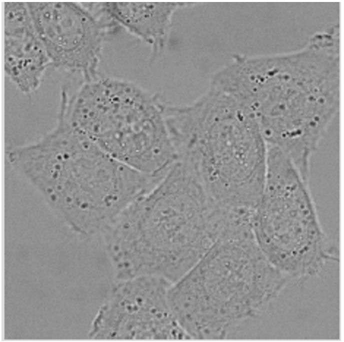


==> Deep learning segmentation methods need thousands of annotated cases to be "transferred" to accomplish this task

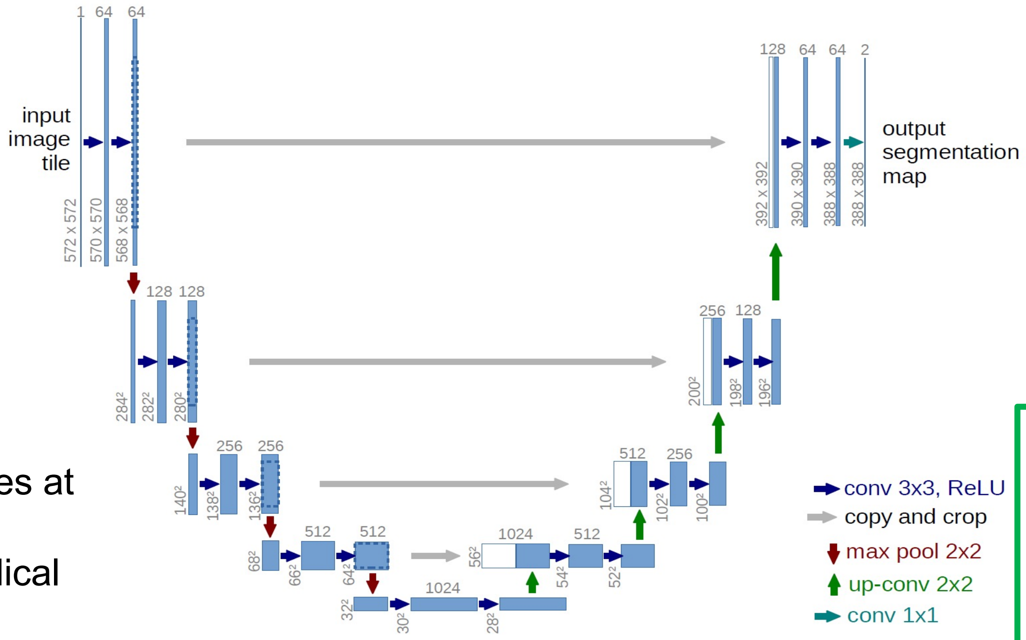
- Quantitative information on the amount of Covid-19 related lesions and their distribution, possibly combined with clinical and epidemiological patient's information, may be relevant to set up **predictive models for patients' stratification, prognosis prediction**, etc.
- Even only pure quantification modules, once properly validated, could be valuable tools for clinicians to set up large-scale population studies based on Radiomics

U-Net: Convolutional Networks for Biomedical Image Segmentation

[O. Ronneberger et al., U-Net: Convolutional Networks for Biomedical Image Segmentation, Medical Image Computing and Computer-Assisted Intervention (MICCAI), Springer, LNCS, Vol.9351: 234--241, 2015]



HeLa cells



segmentation masks

U-net won two segmentation challenges at the International Symposium on Biomedical Imaging (ISBI) 2015

The U-Net architecture is outperforming other methods in most segmentation tasks

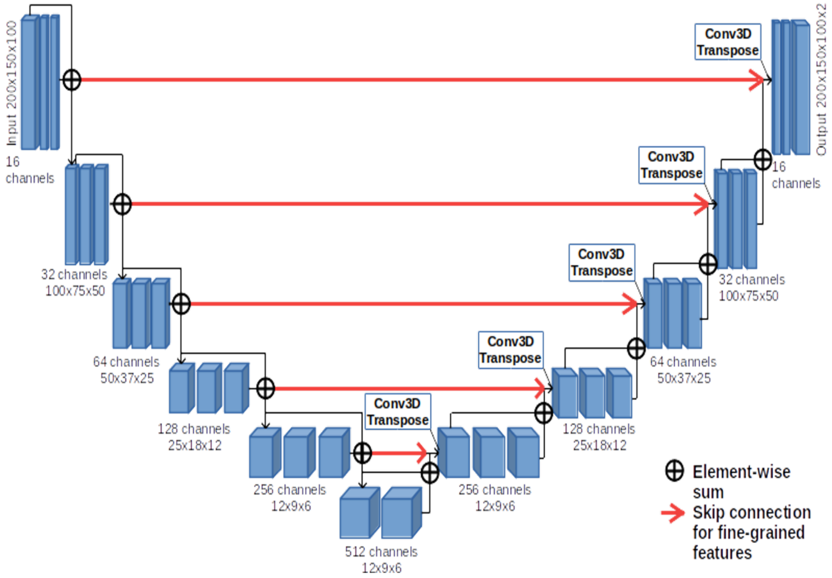
https://arxiv.org/abs/1505.04597
https://lmb.informatik.uni-freiburg.de/people/ronneber/u-net/

3D nnUNet by Fabian Isensee
https://github.com/MIC-DKFZ/nnUNet

Network architecture and available datasets

Input (3D, 16-bit data): CT data resampled to 200x150x100 arrays

Target: 200x150x100 arrays; 2-bit data



about 17 M trainable parameters

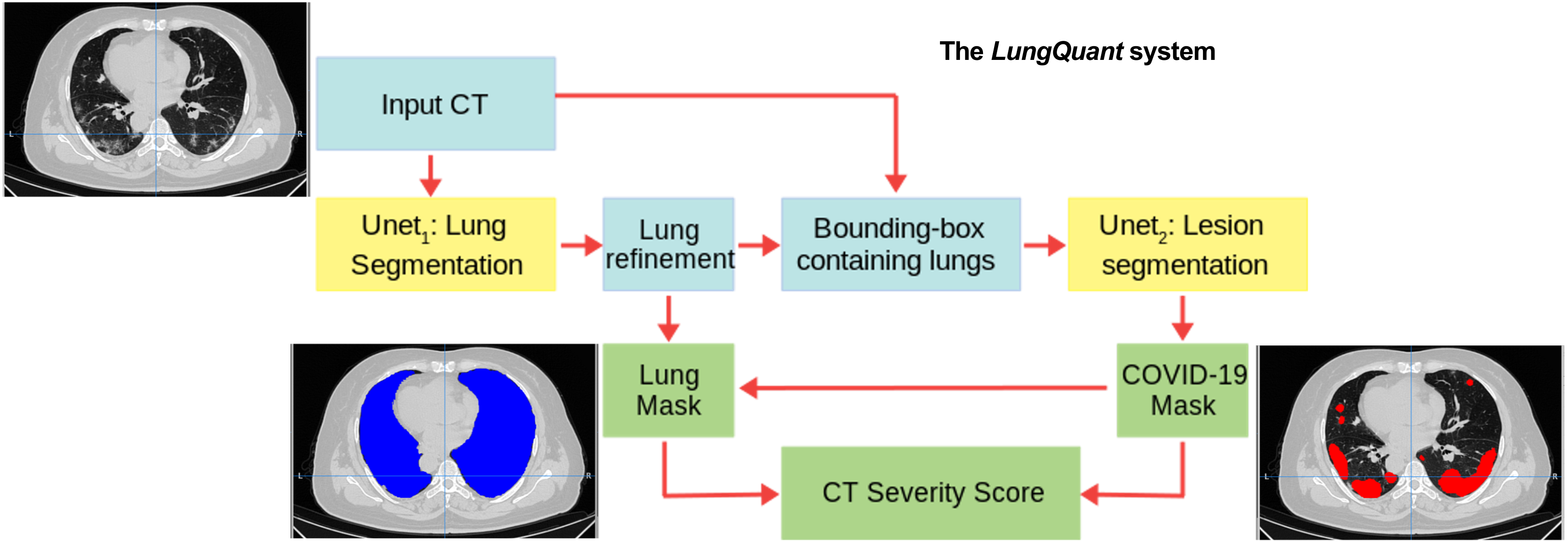
We used only **public datasets** with annotations (in part collected for other clinical purposes)

DATASETS	Clinical motivation	Number of cases	Lung mask	Lesion mask	CT-SS
COVID-19-Challenge [1]	COVID-19 pandemic	**199**	**No**	**Yes**	**No**
MosMed [2]	COVID-19 pandemic	1110	**Yes,** only for **91** CTs (made in house)	**Yes,** only for **50** CTs	**Yes**
TCIA-Plethora [3]	Lung/pleura diseases	**402**	**Yes**	**No**	**No**
TCIA-LCTSC Lung segmentation [3]	Lung cancer	**60**	**Yes**	**No**	**No**
COVID-19-CT-Seg Benchmark [4]	COVID-19 pandemic	**10**	**Yes**	**Yes**	**Yes**

[1] https://covid-segmentation.grand-challenge.org/
[2] https://mosmed.ai/
[3] https://www.cancerimagingarchive.net/
[4] https://zenodo.org/record/3757476

LungQuant1.0: a sequence of two U-nets to segment lungs and COVID-19 lesions on CT scans

Alessandra Retico



[Lizzi, F. *et al* (2021). Making data big for a deep-learning analysis: Aggregation of public COVID-19 datasets of lung computed tomography scans. *Proceedings of the 10th International Conference on Data Science, Technology and Applications, DATA 2021*, (Data), 316–321. https://doi.org/10.5220/0010584403160321]
[Lizzi, F., Agosti, A., Brero, F., Cabini, R. F., Fantacci, M. E., Figini, S., … Retico, A. (2021). Quantification of pulmonary involvement in COVID-19 pneumonia by means of a cascade of two U-nets: training and assessment on multiple datasets using different annotation criteria. *IJCARS*, https://link.springer.com/article/10.1007/s11548-021-02501-2]

LungQuant: training details and cross-validation scheme

Loss functions:

Unet_1:

$$Dice_{loss} = 1 - \frac{2 \cdot |M_{true} \cap M_{pred}|}{|M_{true}| + |M_{pred}|}$$

Unet_2:

$$L = Dice_{loss} + CE_{weighted}$$

$$CE_{weighted} = w(x) \sum_{x \in \Omega} log(M_{true}(x) \cdot M_{pred}(x))$$

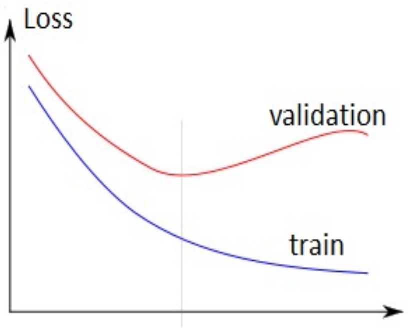
Evaluation metric:

$$Dice_{metric} = \frac{2 \cdot |M_{true} \cap M_{predict}|}{|M_{true}| + |M_{pred}|}$$

Computing resources available at INFN-Pisa, CINECA and Univ. of Pavia have been exploited:

- GPUs with at least 16 GB of RAM
- Each run required ~12h to complete 100 epochs

Train-validation-test data split (hold out)



We trained both the U-net for 300 epochs and we chose the epoch with the best metric on the validation set to evaluate the performance on the test set.

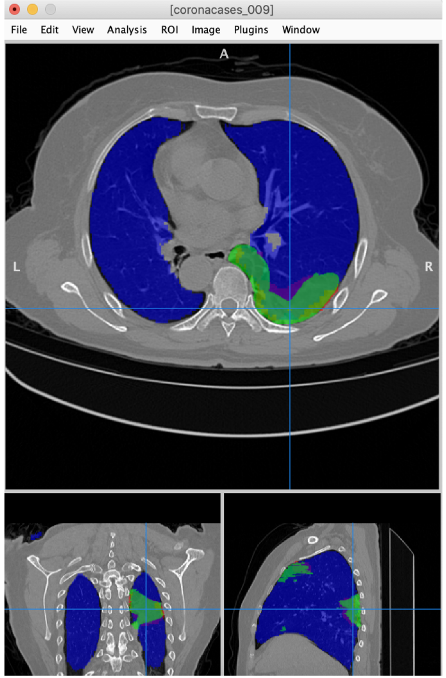
U-net$_1$	train	val	test
Plethora	319	40	40
MosMed (91 CT-0)	55	18	18
LCTSC	36	12	12

U-net$_2^{60\%}$	train	val	test
COVID-19 challenge	119	40	40
MosMed (50 CT-1)	30	10	10

U-net$_2^{90\%}$	train	val	test
COVID-19 challenge	179	20	/
MosMed (50 CT-1)	45	5	/

COVID-19-CT-Seg (indipendent test)	/	/	10

The *LungQuant* system performance

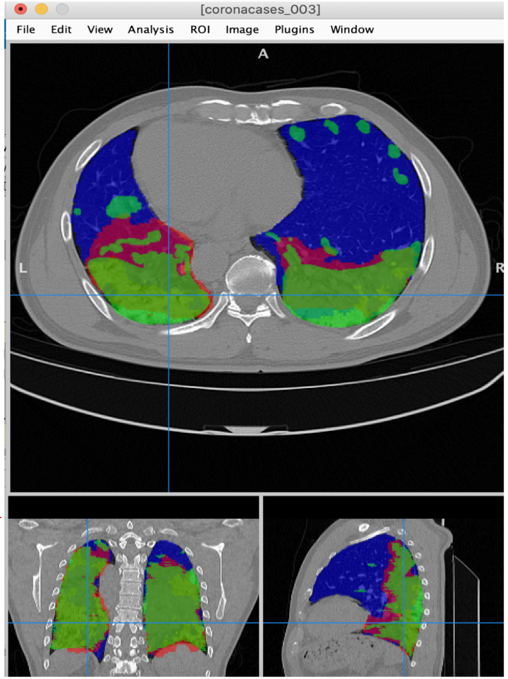


Test on the COVID-19-CT-Seg benchmark set of 10 fully annotated CT scans

Blue: U-net lung mask
Red: U-net lesion mask
Green: reference lesion segmentation

Dice coefficients:
0.95 ± 0.01 for lung segmentation
0.66 ± 0.13 for lesion segmentation

best ← → worst



International Journal of Computer Assisted Radiology and Surgery
https://doi.org/10.1007/s11548-021-02501-2

ORIGINAL ARTICLE

Check for updates

Quantification of pulmonary involvement in COVID-19 pneumonia by means of a cascade of two U-nets: training and assessment on multiple datasets using different annotation criteria

Francesca Lizzi[1,2] · Abramo Agosti[6] · Francesca Brero[4,5] · Raffaella Fiamma Cabini[4,6] · Maria Evelina Fantacci[2,3] · Silvia Figini[4,11] · Alessandro Lascialfari[4,5] · Francesco Laruina[1,2] · Piernicola Oliva[8,9] · Stefano Piffer[7,10] · Ian Postuma[4] · Lisa Rinaldi[4,5] · Cinzia Talamonti[7,10] · Alessandra Retico[2]

F. Lizzi et al. IJCARS,
doi: 10.1007/s11548-021-02501-2

Clinical validation of the SW with radiologists from 5 Italian Hospitals (PI, PV, FI, PA, MI), *in progress*

Deep Learning vs. traditional Machine Learning approaches

- Deep Neural Networks are replacing traditional handcrafted feature extraction + ML approaches in many Medical Physics applications, thus fostering ***data driven decision making***
  - **Pros:**
    - **No prior selection of problem-related features ⟹ no loss of information**
  - **Cons:**
    - **Larger and larger samples of annotated data are needed to train the models**
    - **Deep Neural Networks are black boxes: which image features are relevant for making a decision?**

Data augmentation (flip, rotate, scale images to augment data sets)

Model interpretability, explainable AI

Mandatory in medical applications

Conclusions

- Medical imaging daily produces an incredible amount of digital information which is not fully exploited neither for diagnosis/therapy nor for research!

- Clinicians need to be supported by reliable, effective and easy-to-use DSS for diagnosing and monitoring a wide range of diseases

- The development of AI-based clinical DSS has multiple levels of complexity, thus it requires multidisciplinary skills

➔ There is still lot of room to make original contributions in this field of research!

Thank you for your attention!

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