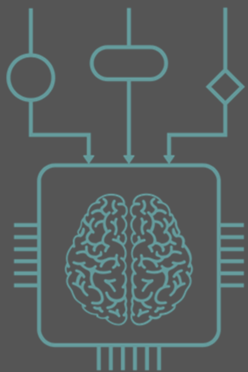
Machine learning
For medical data

Will doctors be AIs with a human touch?

Stefano Diciotti – DEI, UNIBO

Aperitivo con AI – November 18, 2020



Prediction of diagnosis and prognosis **in the single patient**

Biomarker discovery

Potentials

Just some examples.

Precision Medicine

Medical Data

We need data!!!!

Garbage-in Garbage-out paradigm

f(garbage) = garbage

A system is only as good as the data you put in

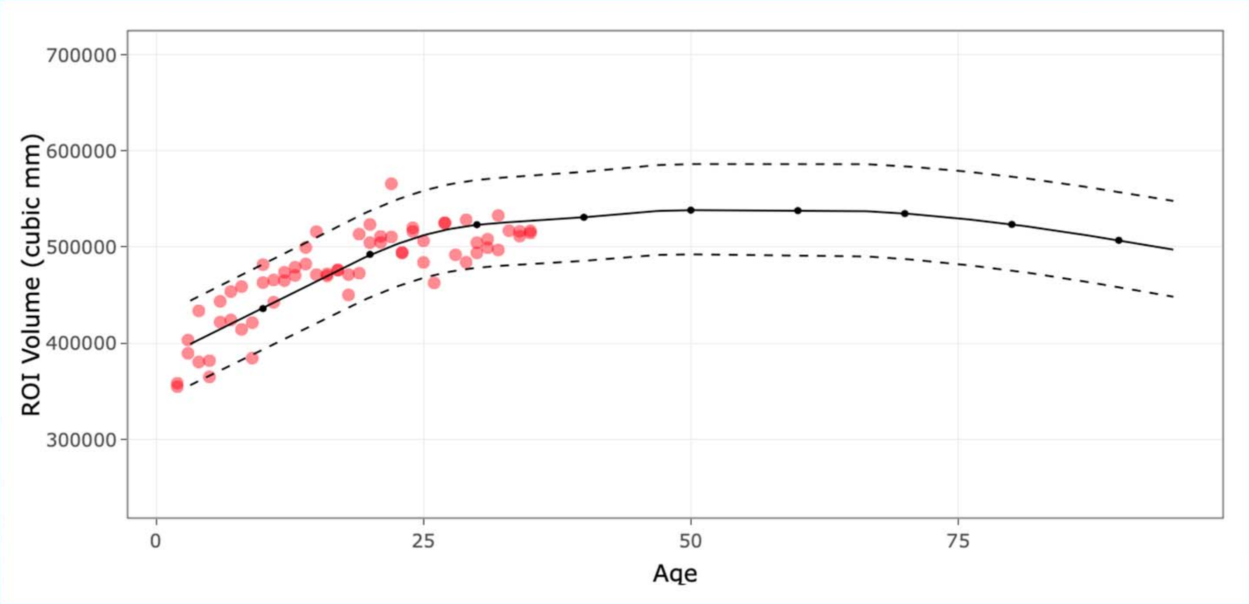
Quality control: the Fridge Rule

"When in doubt, throw it out!"

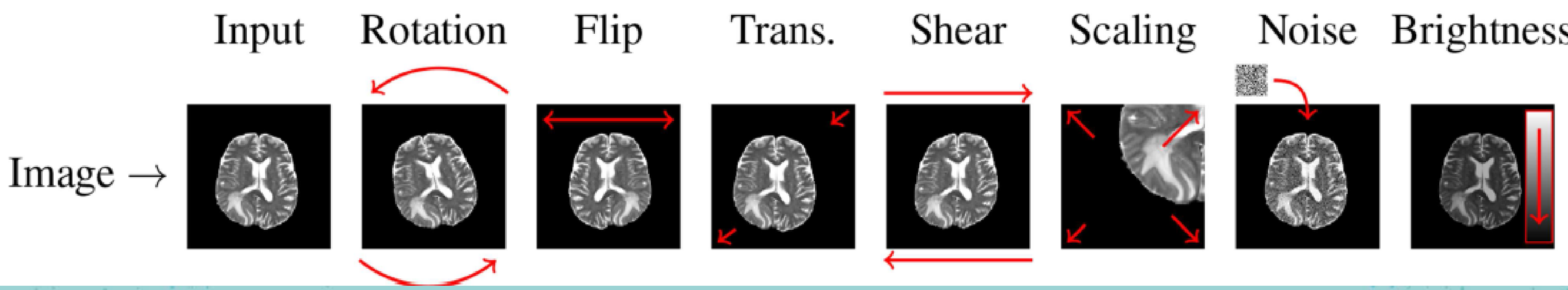
Adapted from fMRI 4 newbies

Data Harmonization

Cerebral White Matter volume



Data augmentation



Nalepa et al., 2019

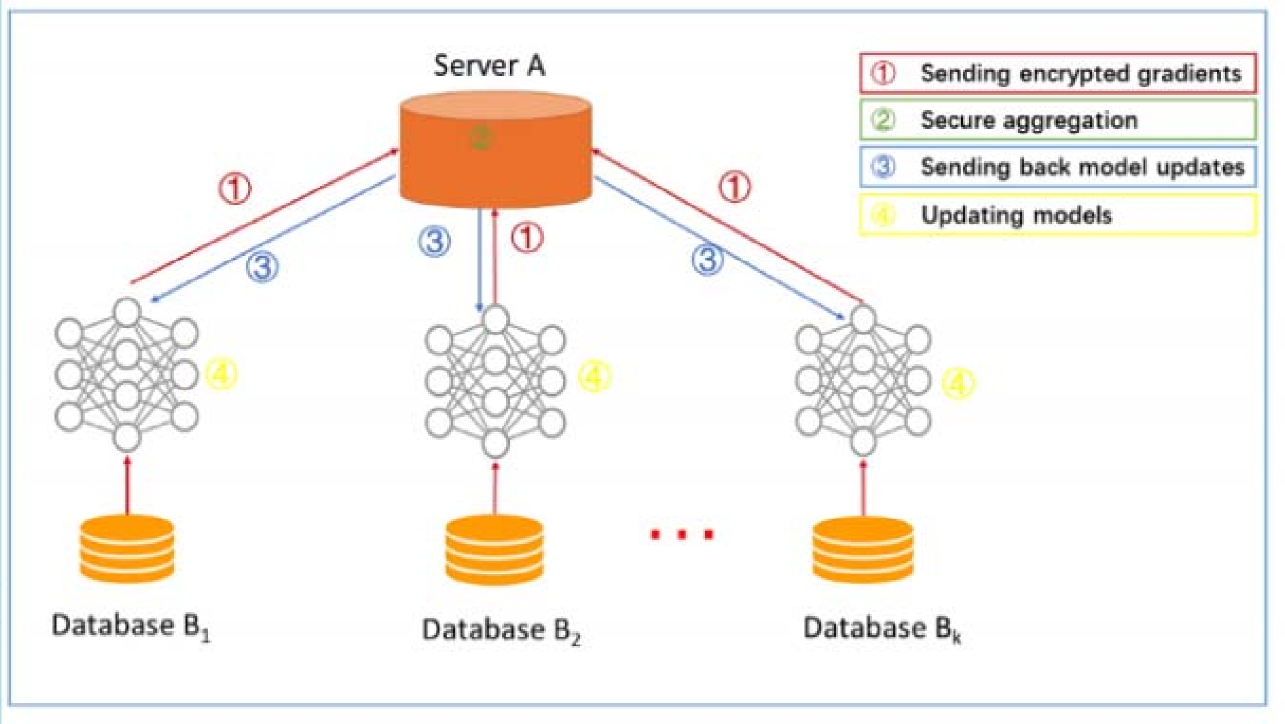
Data augmentation

Which is real?

Generative Adversarial Networks (GANs)

$ 432,500

Federated Learning



https://medium.com/disassembly/architecture-of-federated-learning-a36905c1d225

Toy Datasets

European Radiology
https://doi.org/10.1007/s00330-020-07453-w

LETTER TO THE EDITOR

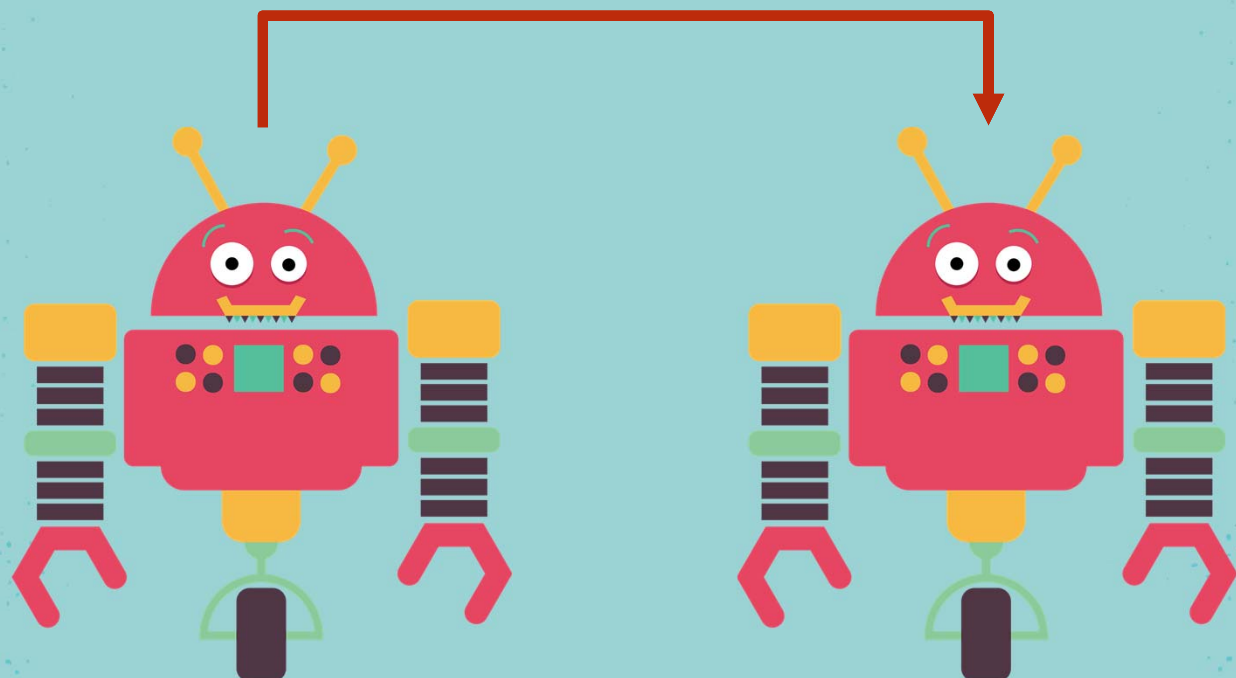
Check for updates

COVID-19, AI enthusiasts, and toy datasets: radiology without radiologists

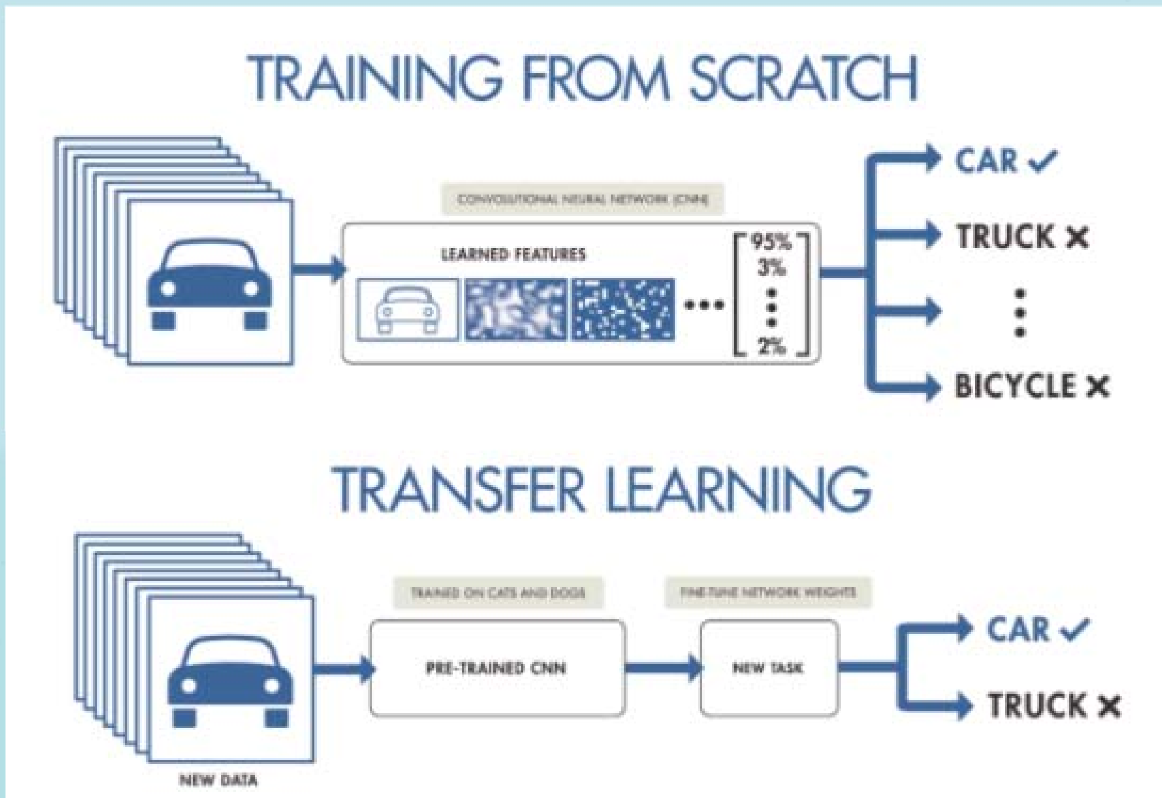
H. R. Tizhoosh[1,2] · Jennifer Fratesi[3]

Received: 4 September 2020 / Revised: 23 September 2020 / Accepted: 2 November 2020

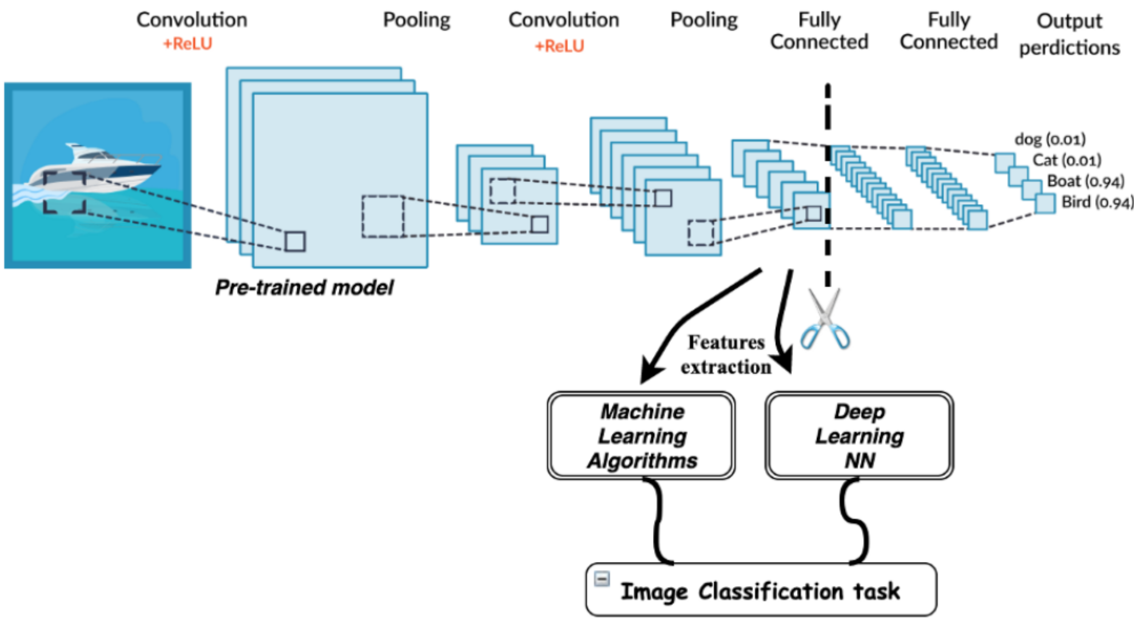
Transfer Learning

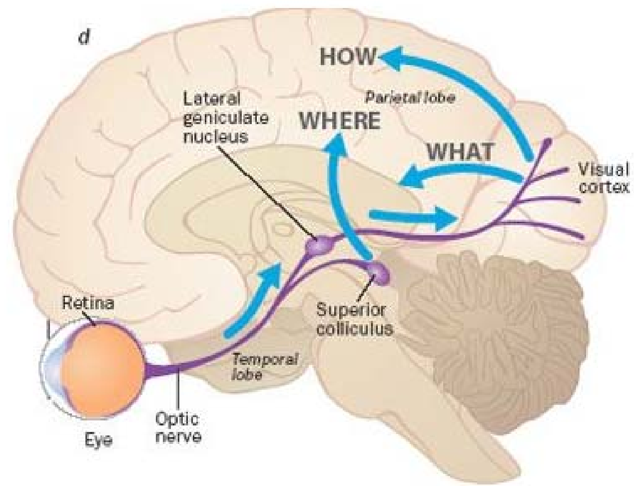


Transfer Learning



Transfer Learning





Interpretability

nature machine intelligence

ARTICLES

https://doi.org/10.1038/s42256-020-0180-7

Check for updates

An interpretable mortality prediction model for COVID-19 patients

Li Yan[1,10], Hai-Tao Zhang[2,10], Jorge Goncalves[3,4,10], Yang Xiao[2], Maolin Wang[2], Yuqi Guo[2], Chuan Sun[2], Xiuchuan Tang[5], Liang Jing[1], Mingyang Zhang[2], Xiang Huang[2], Ying Xiao[2], Haosen Cao[2], Yanyan Chen[6], Tongxin Ren[7], Fang Wang[1], Yaru Xiao[1], Sufang Huang[1], Xi Tan[8], Niannian Huang[8], Bo Jiao[8], Cheng Cheng[2], Yong Zhang[9], Ailin Luo[8], Laurent Mombaerts[3], Junyang Jin[7], Zhiguo Cao[2], Shusheng Li[1] ✉, Hui Xu[8] ✉ and Ye Yuan[2] ✉

Table 2 | Epidemiological, demographic, clinical, laboratory and mortality outcome information collected from medical records

Characteristics	Overall
Age, mean (s.d.) (years)	58.83 (16.46)
Gender, *n* (%)	
Male	224 (59.7)
Female	151 (40.3)
Epidemiological history, *n* (%)	
Wuhan residents	142 (37.9)
Contact with confirmed or suspected patients	2 (0.5)
Familial cluster	24 (6.4)
Health worker	7 (1.9)
Contact with Huanan Seafood Market	2 (0.5)
Undefined contact history	198 (52.8)
Symptoms on onset, *n* (%)	
Fever	187 (49.9)
Cough	52 (13.9)
Fatigue	14 (3.7)
Dyspnoea	8 (2.1)
Chest distress	7 (1.9)
Muscular soreness	2 (0.5)
Outcomes, *n* (%)	
Survival rate	201 (53.6)
Mortality rate	174 (46.4)
Laboratory test (patient's last measurements)	
LDH, median (range, Q1–Q3) ($U\,l^{-1}$)	273.50 (199.00, 617.75)
Lymphocytes, median (range, Q1–Q3) (%)	14.35 (4.17, 27.53)
High-sensitivity C-reactive protein ($mg\,l^{-1}$)	26.3 (2.0, 99.10)
Sodium median (range, Q1–Q3) ($mmol\,l^{-1}$)	140.7 (138.3, 143.3)
Chlorine median (range, Q1–Q3) ($mmol\,l^{-1}$)	102.3 (99.53, 105.58)
International normalized ratio (range, Q1–Q3)	1.10 (1.02, 1.30)
Eosinophils, median (range, Q1–Q3) ($\times 10^9\,l^{-1}$)	0.02 (0.00, 0.09)
Eosinophils, median (range, Q1–Q3) (%)	0.25 (0.00, 1.50)
Monocytes, median (range, Q1–Q3) (%)	6.25 (2.98, 8.90)
Albumin, mean (s.d.) ($g\,l^{-1}$)	32.67 (6.31)

Data were first tested for normality. The Kolmogorov–Smirnov test was used to test whether a single sample was from a particular distribution, then this single-sample Kolmogorov–Smirnov test checked the normality of the data. A test level of $\alpha = 0.05$ and $P < 0.05$ indicate that a sample does not fit a normal distribution.LDH, lactic dehydrogenase. The continuity variables of normal distributions are described by the mean (s.d.) and the continuity variables of non-normal distributions by the median and quartiles.

Table 3 | Performances of the Multi-tree XGBoost classification in discriminating between mortality outcomes using 100-round fivefold cross-validation using Supplementary algorithm 1

Features	AUC score for training sets (%)	AUC score for validation sets (%)
LDH	94.27 ± 0.82	92.29 ± 2.62
LDH, lymphocyte	96.74 ± 0.45	94.40 ± 2.31
LDH, lymphocyte, hs-CRP	97.84 ± 0.37	95.06 ± 2.21

Data presented as mean ± s.d.

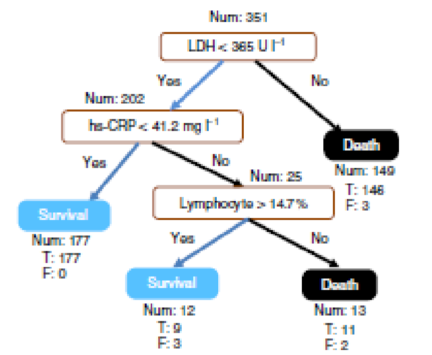


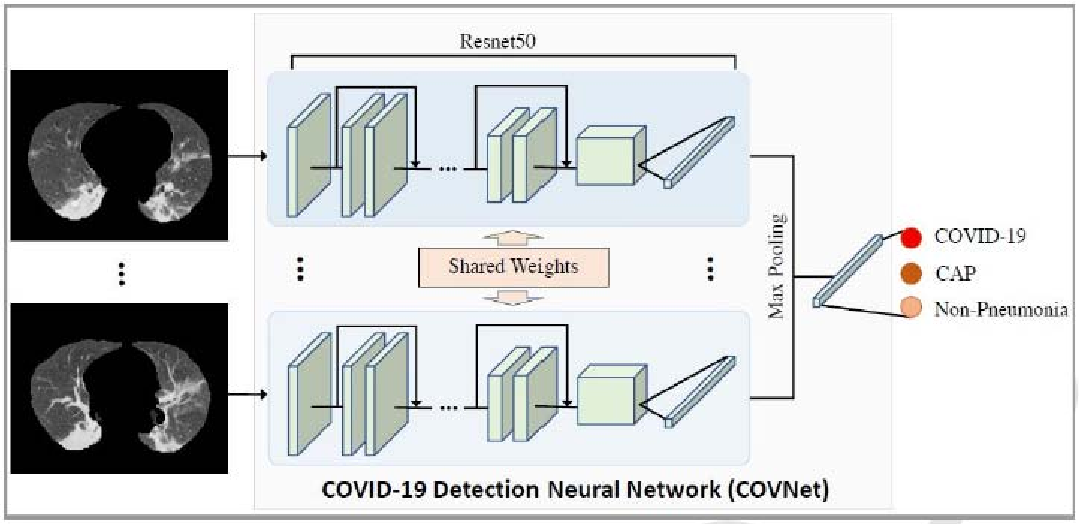
Fig. 2 | A decision rule using three key features and their thresholds in absolute value. Num, the number of patients in a class; T, the number of correctly classified; F, the number of misclassified patients.

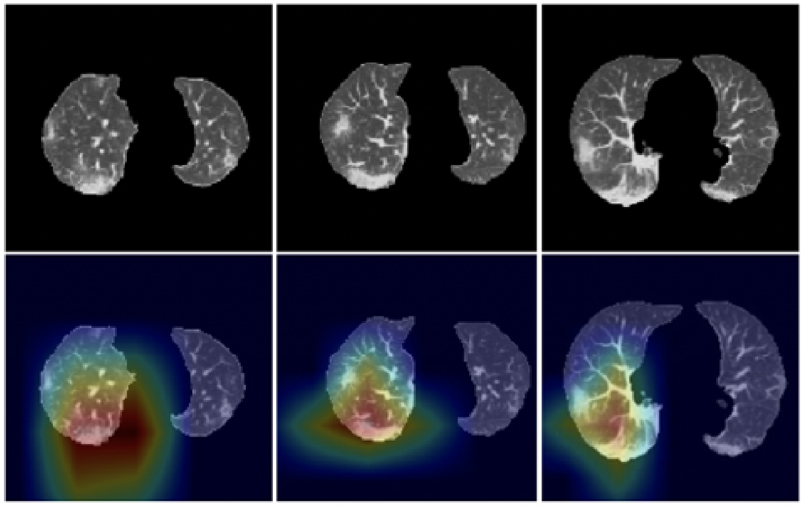
Interpretability

Radiology

Artificial Intelligence Distinguishes COVID-19 from Community Acquired Pneumonia on Chest CT

Lin Li*[1a,1b], Lixin Qin*[2], Zeguo Xu[1a], Youbing Yin[3], Xin Wang[3], Bin Kong[3], Junjie Bai[3], Yi Lu[3], Zhenghan Fang[3], Qi Song[3], Kunlin Cao[3], Daliang Liu[4], Guisheng Wang[5], Qizhong Xu[6], Xisheng Fang[1a], Shiqin Zhang[1a], Juan Xia[1a], Jun Xia*[6]

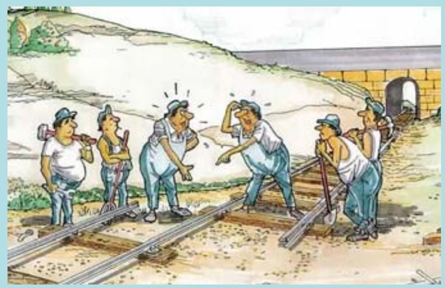




Take home messages

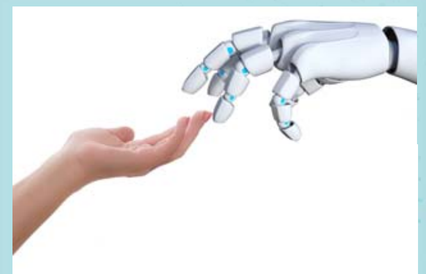
AI for Health

Dedicated methods
and data



Team work

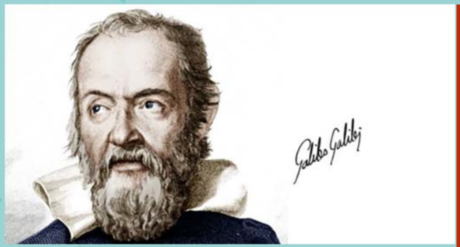
Strongly
multidisciplinary



Patient-centered AI

And also the
human touch…

Thank You



> *Conta quello che è contabile,*
> *misura quello che è misurabile,*
> *e rendi misurabile quello che non lo è"*
>
> —Galileo Galilei

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Thanks!

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