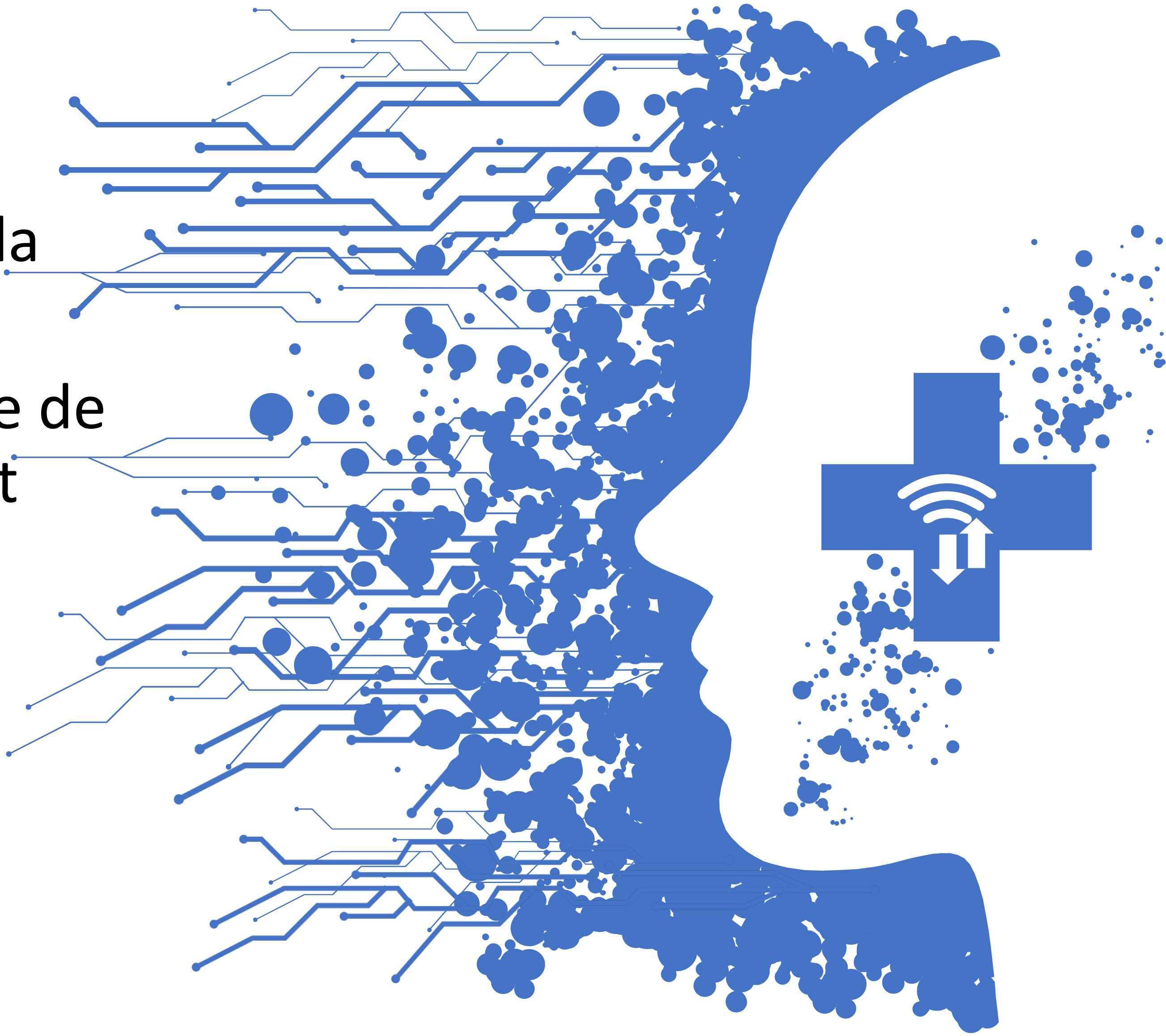
DR ZIED MOATEMRI
HOPITAL MILITAIRE DE TUNIS

le Pneumologue face au défi de l'intelligence artificielle

INTRODUCTION:

- Et si on regarde le coté positif de la pandémie COVID 19 ?
- Opportunité pour sortir de la zone de confort, changer notre pratique et chercher de Nouvelles options.
- On a travaillé avec les ingénieurs
- On s’est mis à la télémédecine
- Et ….. L’IA



INTRODUCTION:

- La Pneumologie à part le fait de s'être retrouvé aux premières loges lors de la pandémie, est une spécialité très riche.
- C'est le miroir de tout le corps
- Ca englobe les pathologies tumorales, bronchiques, les maladies immunitaires, les maladies de système, de la médecine interventionnelle, les pathologies infectieuses…

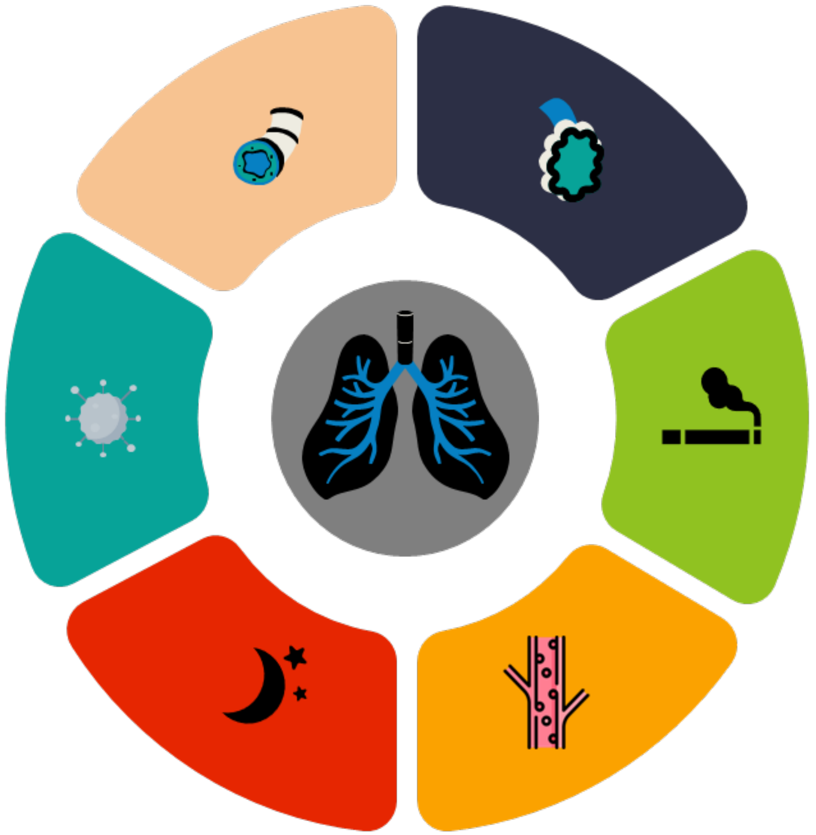
INTRODUCTION:

Bronchus Pathology

Asthma - COPD.

Lung injury

. Lung cancer – Intertitial disease - Emphysema



Infectious disease

Tuberculosis – Hydatic cyst – Bacterial – Viral infection

Addiction

Smoking cessation

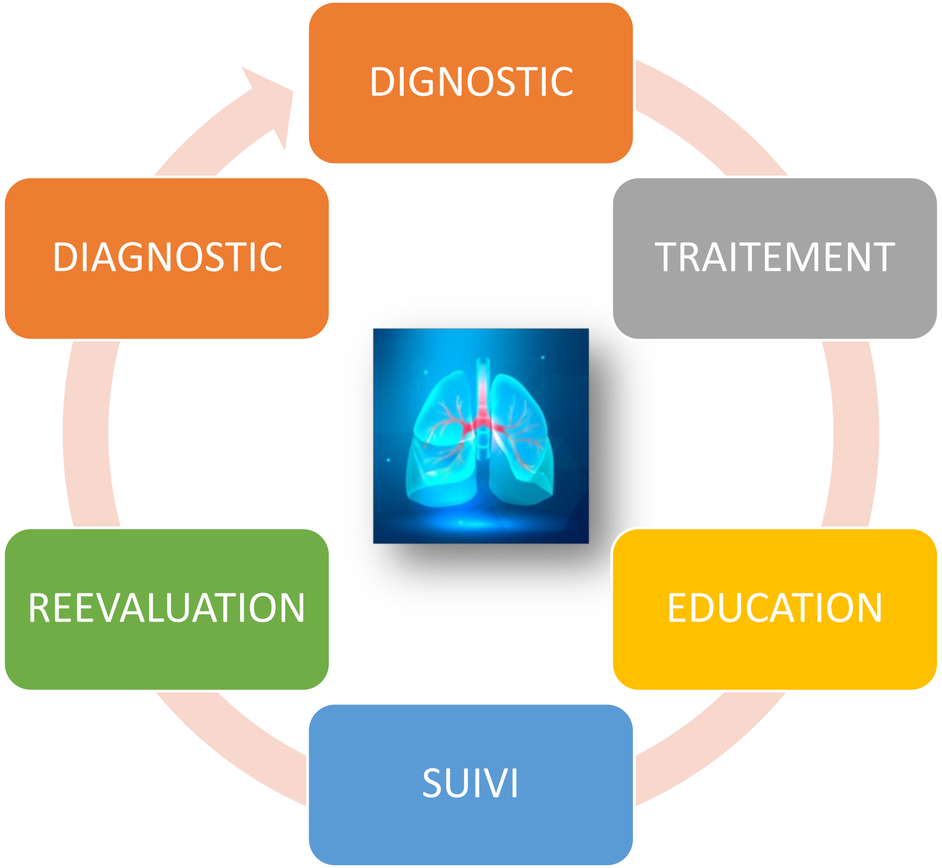
Allergology
Sleep Apnea and sleep disorder

Vascular Ds

P embolism – Pulmonary hypertension

CHALLENGE

- RAPIDE
- PRECISE
- PERTINENTE
- SUR MESURE



DEVELOPPEMENT DE L'IA

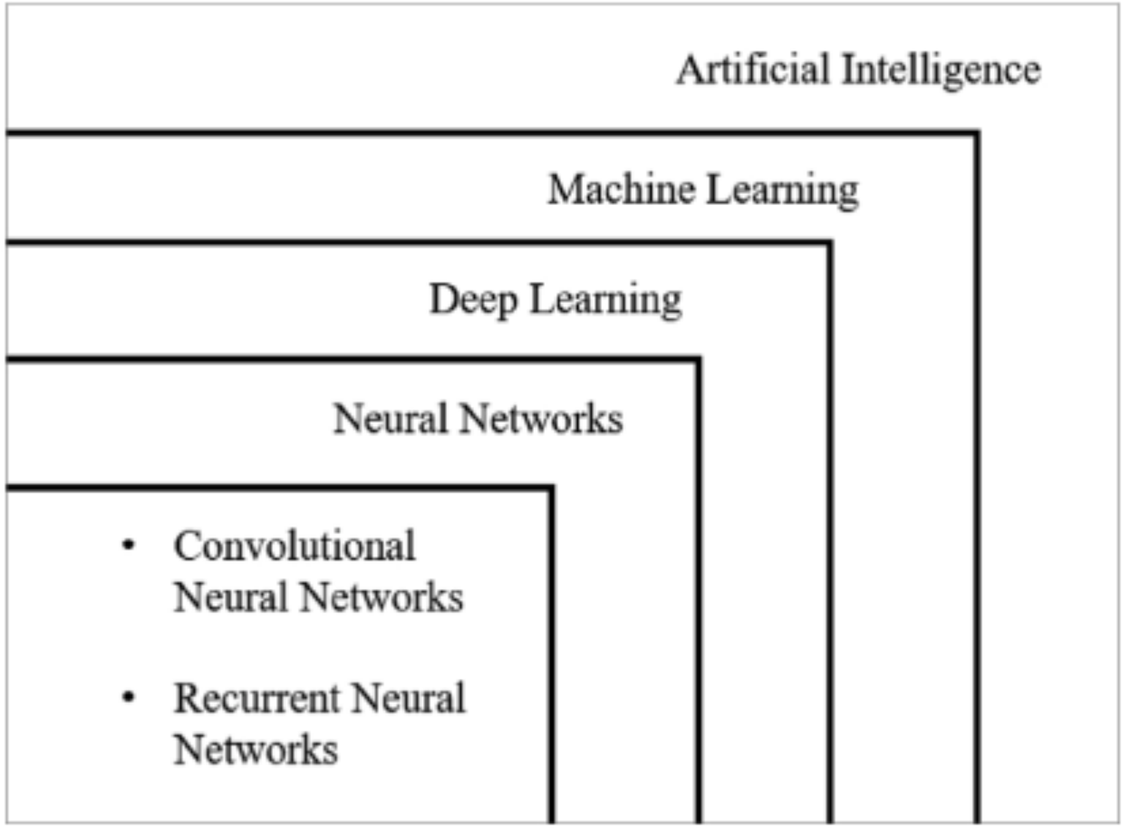


Fig. 2. The relationships of various aspects of artificial intelligence to one another. Artificial intelligence is the most general term encompassing the totality of the field and convolutional neural networks/recurrent neural networks are the most specific.

DIAGNOSTIC

An explainable AI system for automated COVID-19 assessment and lesion categorization from CT-scans

Matteo Pennisi [a,1], Isaak Kavasidis [a,*,1], Concetto Spampinato [a], Vincenzo Schinina [b], Simone Palazzo [a], Federica Proietto Salanitri [a], Giovanni Bellitto [a], Francesco Rundo [c], Marco Aldinucci [d], Massimo Cristofaro [b], Paolo Campioni [b], Elisa Pianura [b], Federica Di Stefano [b], Ada Petrone [b], Fabrizio Albarello [b], Giuseppe Ippolito [b], Salvatore Cuzzocrea [e], Sabrina Conoci

Artificial Intelligence In Medicine 118 (2021) 102114

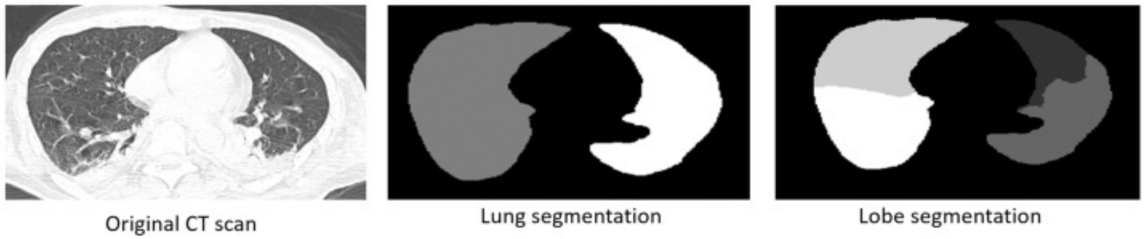


Fig. 2. Example of lung and lobes segmentation.

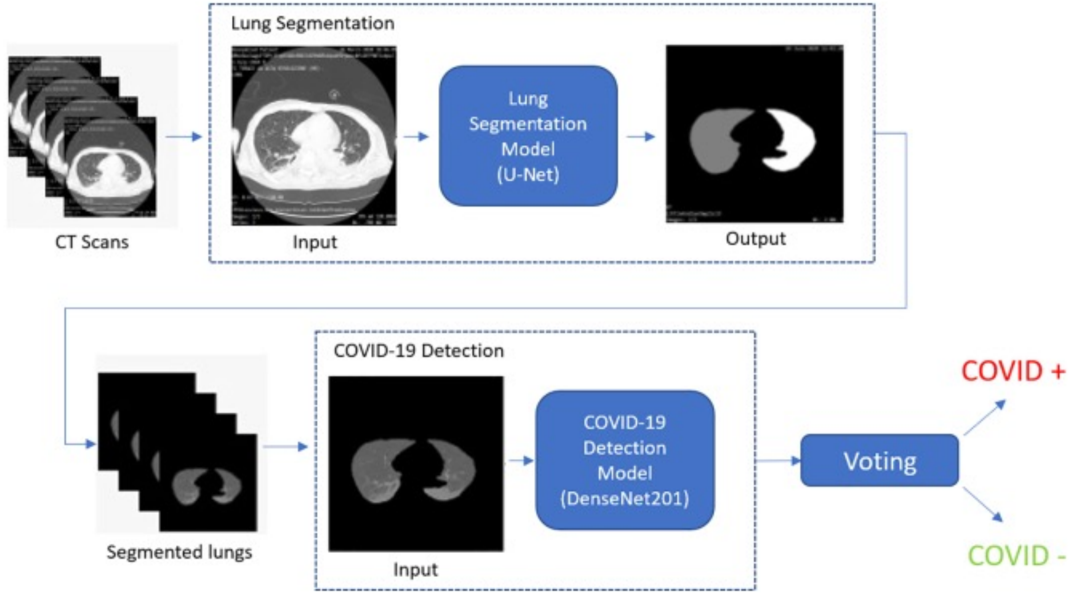


Fig. 3. Overview of the **COVID-19 detection approach** for CT scan classification as either COVID-19 positive or negative.

DIAGNOSTIC

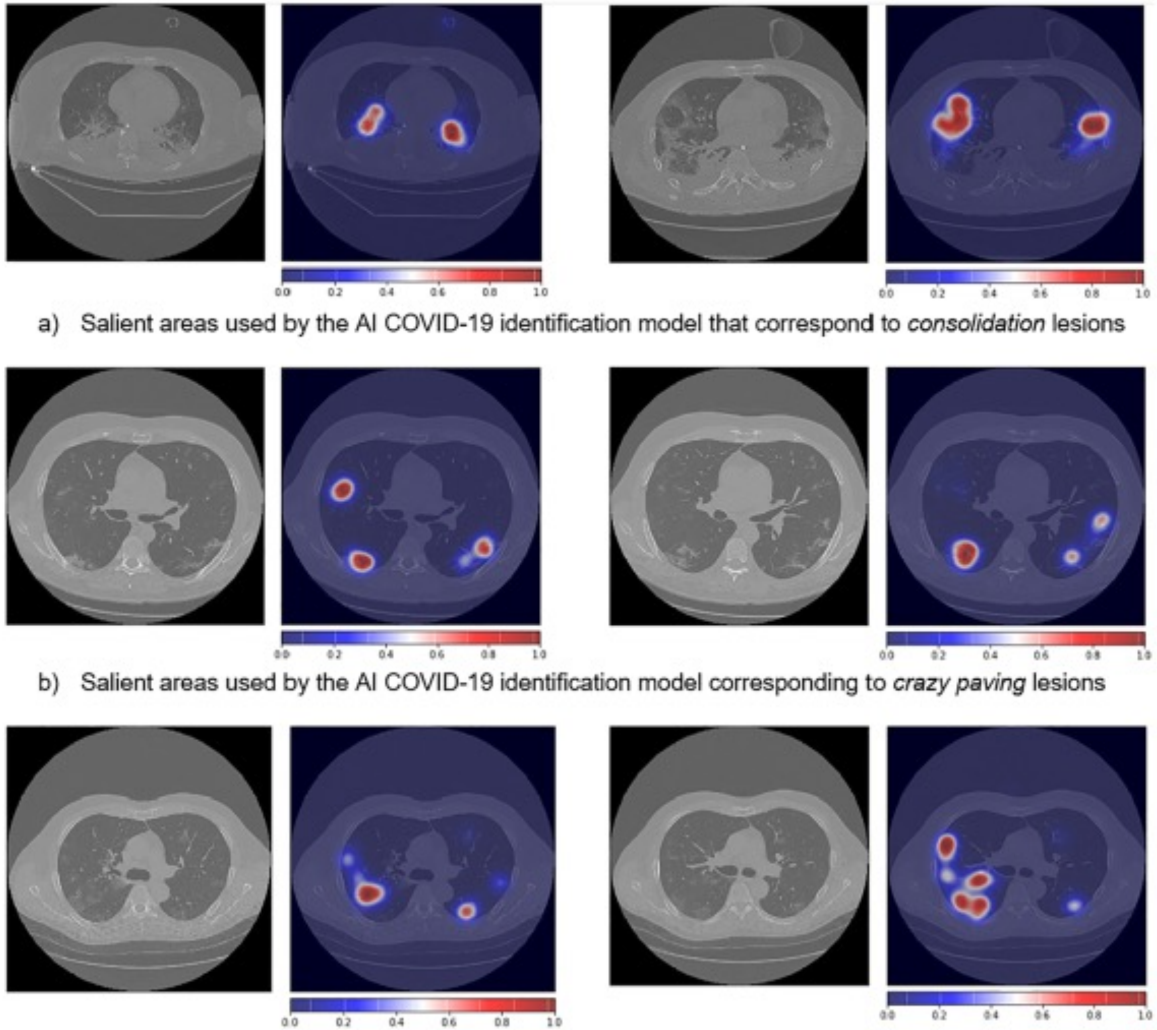
An explainable AI system for automated COVID-19 assessment and lesion categorization from CT-scans

Matteo Pennisi[a,1], Isaak Kavasidis[a,*,1], Concetto Spampinato[a], Vincenzo Schinina[b], Simone Palazzo[a], Federica Proietto Salanitri[a], Giovanni Bellitto[a], Francesco Rundo[c], Marco Aldinucci[d], Massimo Cristofaro[b], Paolo Campioni[b], Elisa Pianura[b], Federica Di Stefano[b], Ada Petrone[b], Fabrizio Albarello[b], Giuseppe Ippolito[b], Salvatore Cuzzocrea[e], Sabrina Conoci[e]

Artificial Intelligence In Medicine 118 (2021) 102114

5. Conclusions

In this work we have presented an AI-based pipeline for automated lung segmentation, COVID-19 detection and COVID-19 lesion categorization from CT scans. Results showed a sensitivity of 90.3% and a specificity of 93.5% for COVID-19 detection and average lesion categorization accuracy of about 84%. Results also show that a significant role is played by prior lung and lobe segmentation, that allowed us to enhance diagnosis performance of about 6 percent points.



a) Salient areas used by the AI COVID-19 identification model that correspond to *consolidation* lesions

b) Salient areas used by the AI COVID-19 identification model corresponding to *crazy paving* lesions

c) Salient areas used by the AI COVID-19 identification model corresponding to *ground glass* lesions

Fig. 8. Lung salient areas identified automatically by the AI model for CT COVID-19 identification.

DIAGNOSTIC

MAYO CLINIC

ORIGINAL ARTICLE

Rapid Exclusion of COVID Infection With the Artificial Intelligence Electrocardiogram

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Main Findings

We found that patients infected with SARS-CoV-2 develop electrocardiographic changes identified by the AI-ECG. If validated prospectively, these may permit the AI-enhanced ECG to be used as a screening test to exclude acute infection. Specifically,

DIAGNOSTIC

A meta-learning algorithm for respiratory flow prediction from FBG-based wearables in unrestrained conditions

Mariangela Filosa[a,b,*], Luca Massari[a,b], Davide Ferraro[a,b], Giacomo D'Alesio[a,b], Jessica D'Abbraccio[a,b], Andrea Aliperta[a,b,e], Daniela Lo Presti[c], Joshua Di Tocco[c], Martina Zaltieri[c], Carlo Massaroni[c], Maria Chiara Carrozza[a,b,d], Maurizio Ferrarin[d], Marco Di Rienzo[d], Emiliano Schena[c], Calogero Maria Oddo[a,b,*]

[a] *The BioRobotics Institute, Scuola Superiore Sant'Anna, Pisa, Italy*
[b] *Department of Excellence in Robotics & A.I., Scuola Superiore Sant'Anna, Pisa, Italy*
[c] *Department of Engineering, Università Campus Bio-Medico di Roma, Rome, Italy*
[d] *IRCCS Fondazione don Carlo Gnocchi, Milan, Italy*
[e] *ARTES4.0 Competence Center on Advanced Robotics and enabling digital TEchnologies and Systems, Pontedera, Italy*

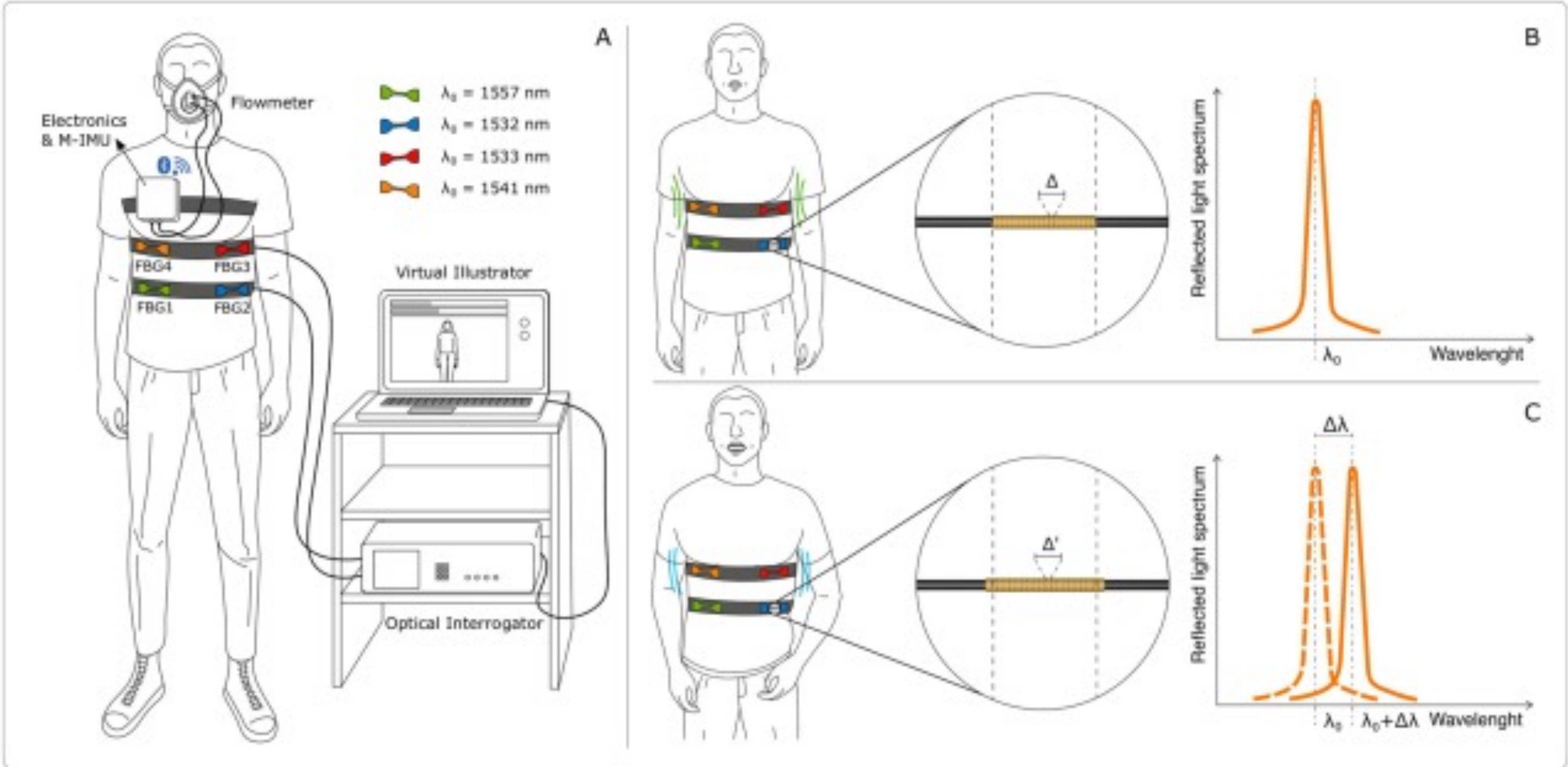
ELSEVIER

Contents lists available at ScienceDirect

Artificial Intelligence In Medicine

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

DIAGNOSIS


A
Electronics
& M-IMU
Flowmeter
λ_0 = 1557 nm
λ_0 = 1532 nm
λ_0 = 1533 nm
λ_0 = 1541 nm
FBG4
FBG3
FBG1
FBG2
Virtual Illustrator
Optical Interrogator
B
Δ
Reflected light spectrum
λ_0
Wavelenght
C
Δ'
Δλ
Reflected light spectrum
λ_0
$\lambda_0+\Delta\lambda$
Wavelenght

DIAGNOSTIC

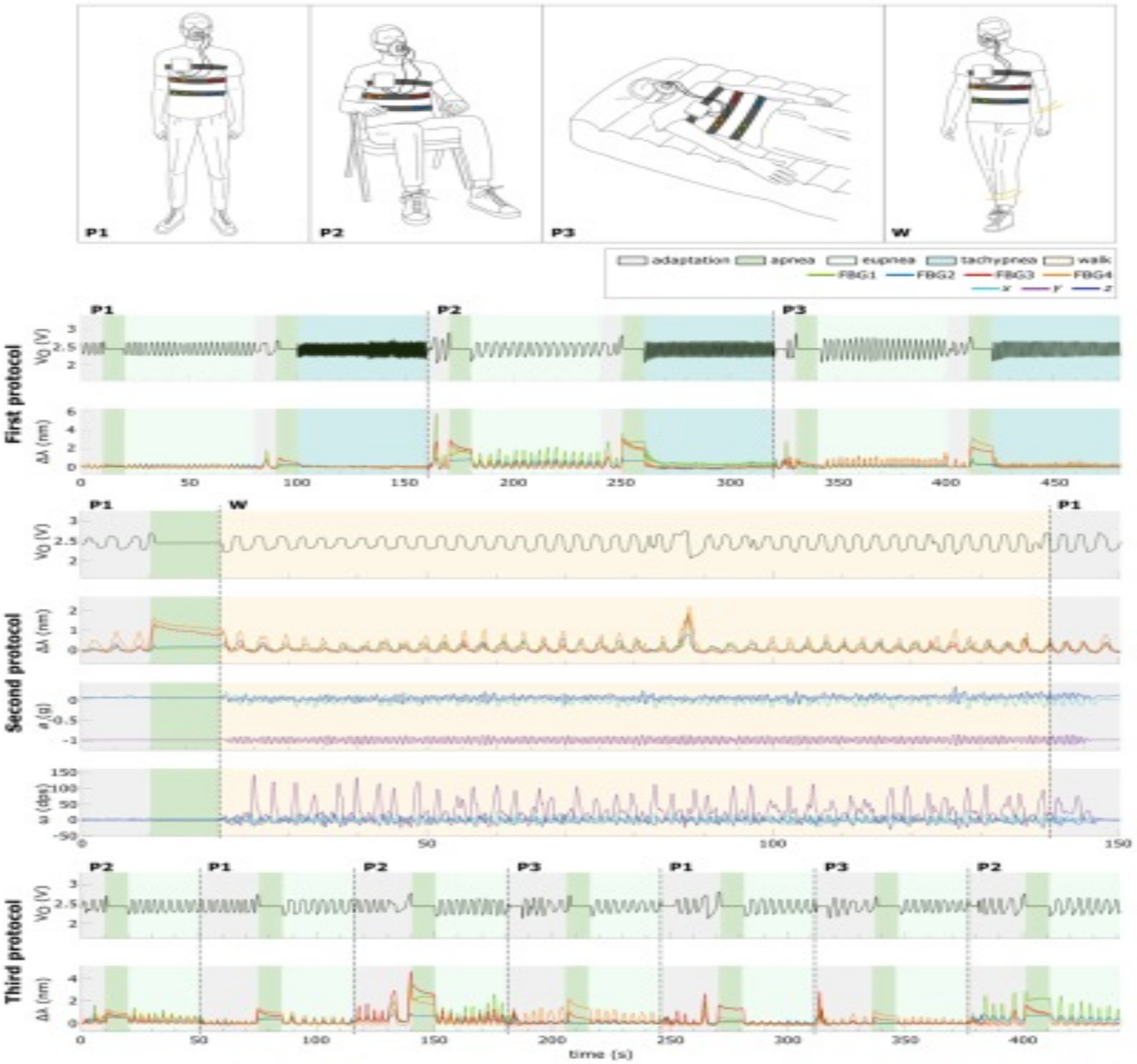
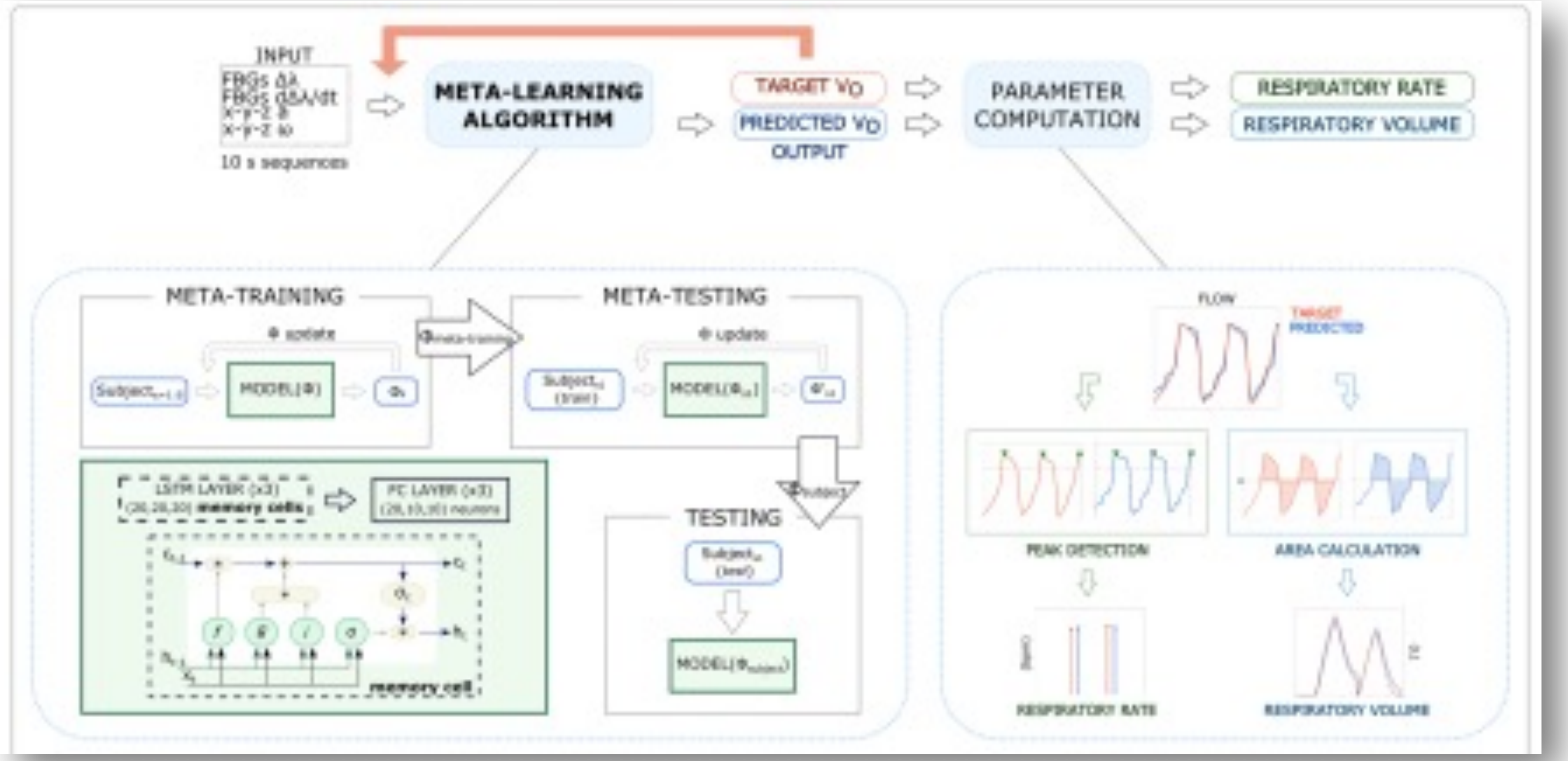


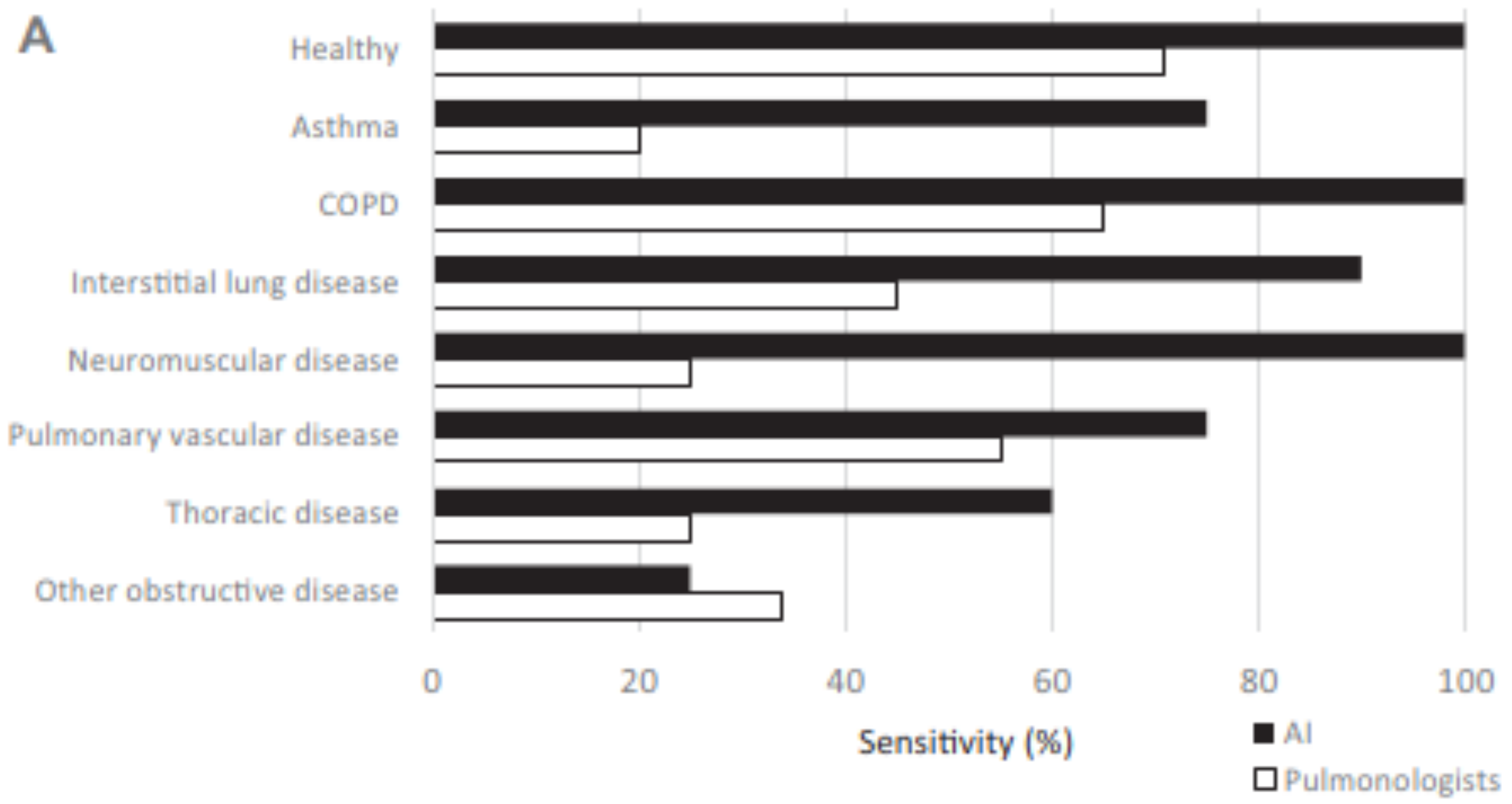
Fig. 2. Experimental session and raw signals. On top, the postures (P1, P2 and P3, i.e., *standing*, *sitting* and *lying on the back*, respectively) and the activity (W, i.e., *walk*) to be performed during the experiment. Each of them is reported accordingly in the *protocol* sequences. For each *protocol* the collected raw data are reported as well. M-IMU (accelerations (a) and angular velocities (ω)) data are illustrated for the second *protocol* only, since it included the dynamic walk task. In the other *protocols*, variations of M-IMU data were significantly smaller. Respiratory tasks (i.e., *apnea*, *eupnea* and *tachypnea*) are illustrated in the *protocols* through the colored background areas.

DIAGNOSTIC



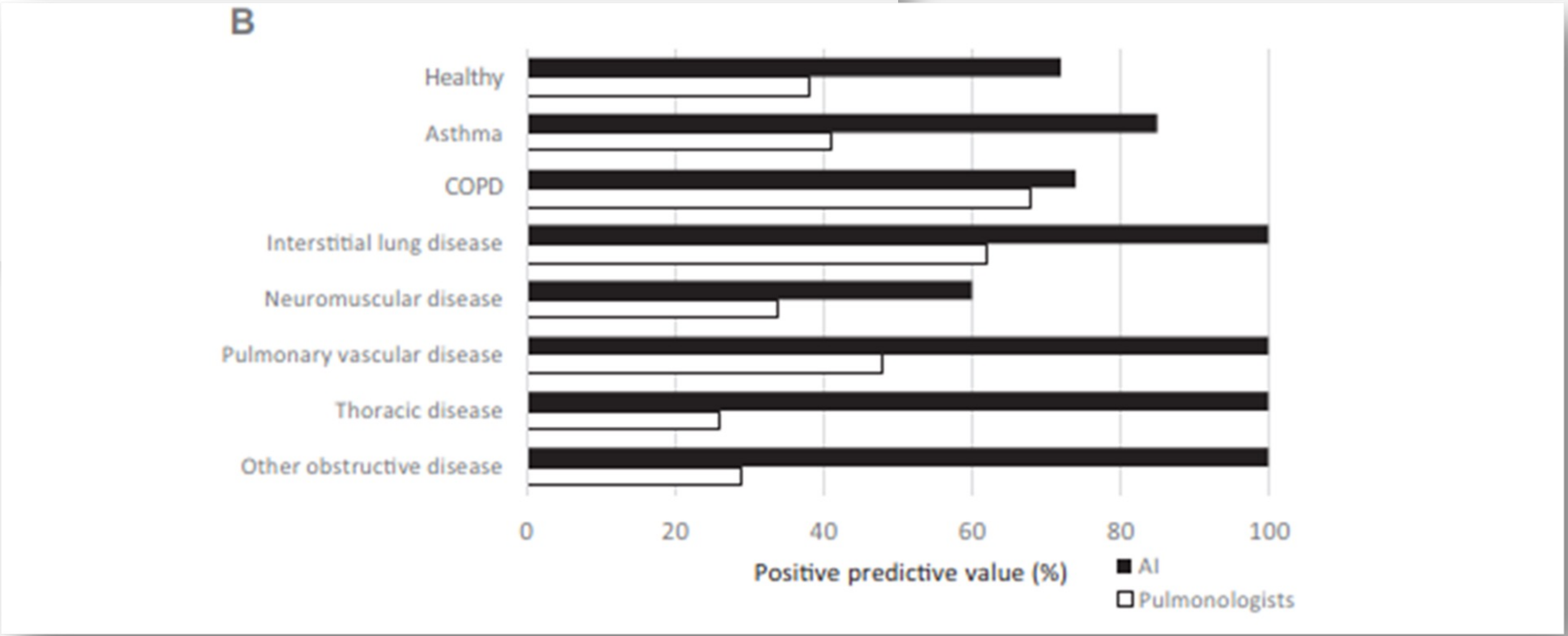
INPUT
10 s sequences
META-LEARNING ALGORITHM
TARGET V_D
PREDICTED V_D
OUTPUT
PARAMETER COMPUTATION
RESPIRATORY RATE
RESPIRATORY VOLUME
META-TRAINING
META-TESTING
TESTING
FLOW
PEAK DETECTION
AREA CALCULATION

DIAGNOSTIC



A
Healthy
Asthma
COPD
Interstitial lung disease
Neuromuscular disease
Pulmonary vascular disease
Thoracic disease
Other obstructive disease
0
20
40
60
80
100
Sensitivity (%)
AI
Pulmonologists

DIAGNOSIS



B
Healthy
Asthma
COPD
Interstitial lung disease
Neuromuscular disease
Pulmonary vascular disease
Thoracic disease
Other obstructive disease
0
20
40
60
80
100
Positive predictive value (%)
AI
Pulmonologists

DIAGNOSTIC

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European Journal of Radiology

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

ELSEVIER

Review

Artificial intelligence applications for oncological positron emission tomography imaging

Check for updates

Wanting Li[a,b,c], Haiyan Liu[b,c,d], Feng Cheng[a], Yanhua Li[a], Sijin Li[a,b,c,**], Jiangwei Yan[a,*]

DIAGNOSTIC

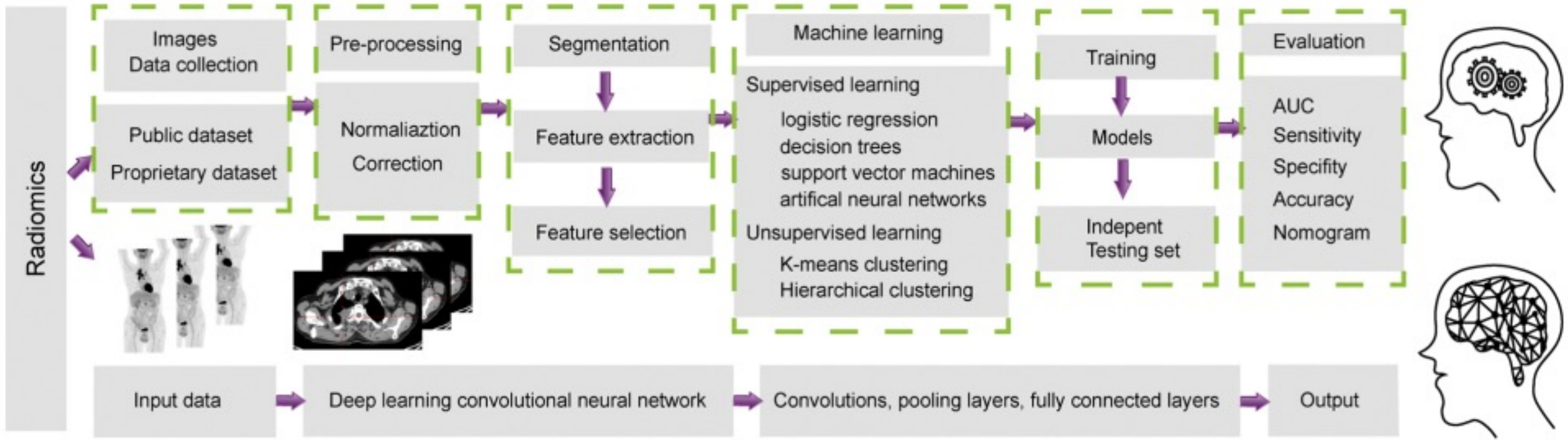


Fig. 2. The basic flow chart of radiomics with the machine learning and deep learning method.

DIAGNOSTIC

European Journal of Nuclear Medicine and Molecular Imaging (2021) 48:3961–3974
https://doi.org/10.1007/s00259-021-05242-1

REVIEW ARTICLE

Structural and functional radiomics for lung cancer

Guangyao Wu[1,2,3] • Arthur Jochems[1] • Turkey Refaee[1,4] • Abdalla Ibrahim[1,5,6,7] • Chenggong Yan[1,8] •
Sebastian Sanduleanu[1] • Henry C. Woodruff[1,5] • Philippe Lambin[1,5]

DIAGNOSTIC

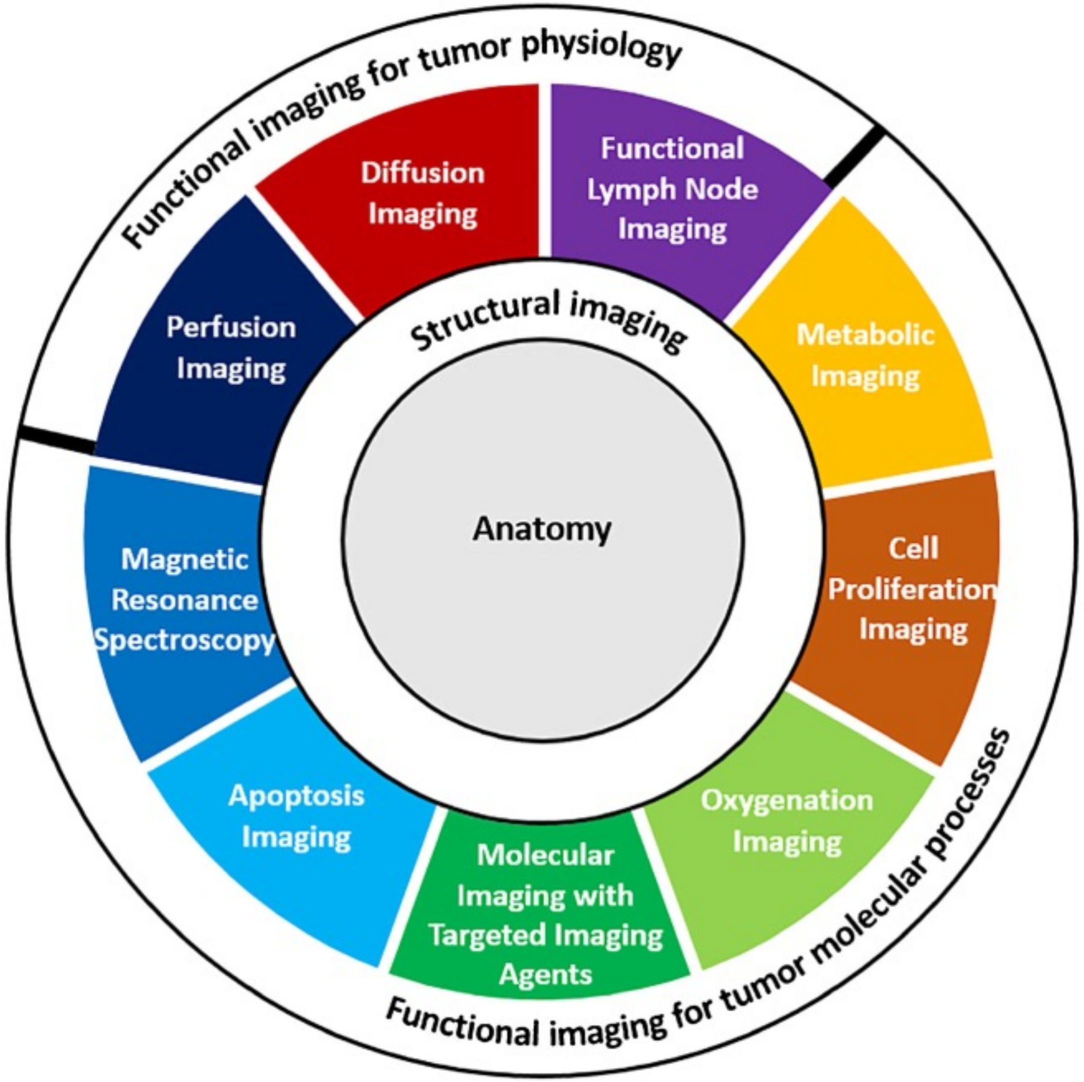


Fig. 1 Composition of functional and structural imaging for tumors. Structural imaging refers to techniques, which are used to visualize and analyze the anatomical information of the human body. Functional imaging refers to approaches that are the study of tumor physiology and molecular process

DIAGNOSTIC

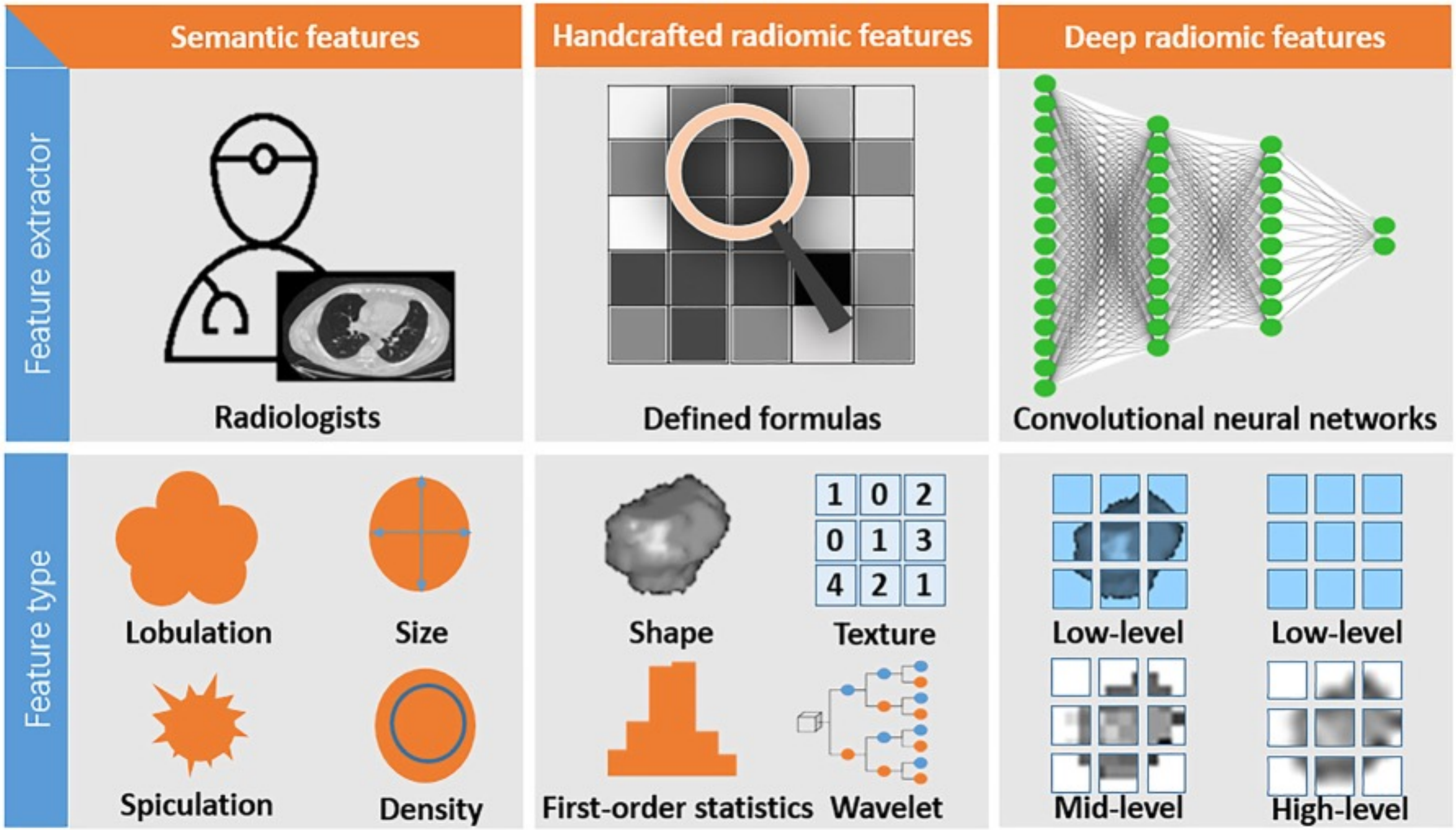
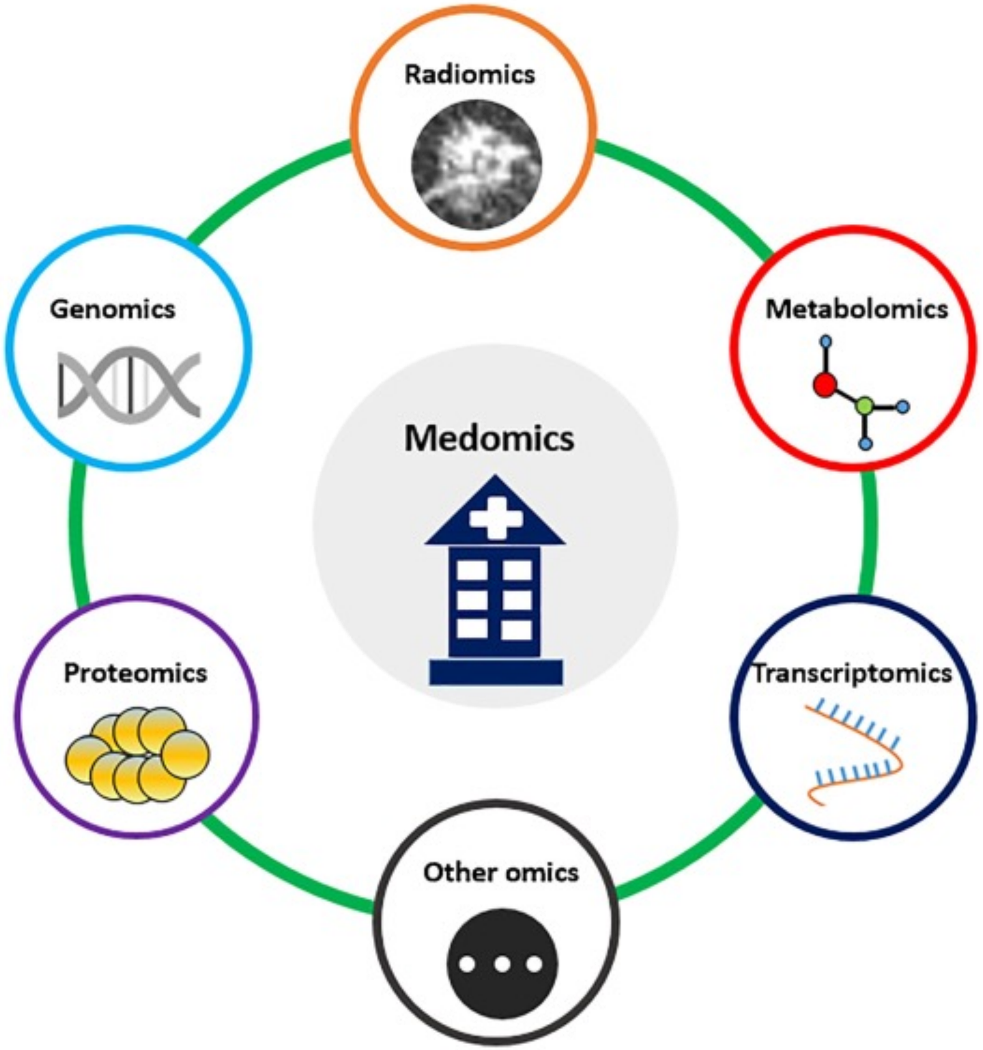


Fig. 2 A comparison of semantic, handcrafted radiomic, and deep radiomic features

DIAGNOSTIC

Fig. 4 A scope of fusion of multi-discipline or multi-omics to form a "Medomics." Other omics can be included in the Medomics, such as pathomics and lipidomics



DIAGNOSTIC

AI Aided Rapid On Site Evaluation of Respiratory Cytology

James Roberts, MD[1], Eric Flenaugh, MD[2], Gabriella Oprea-Ilies, MD[1].
[1]Emory University, Atlanta, Georgia; [2]Morehouse School of Medicine, Atlanta, Georgia

Conclusions: AI aided ROSE brings consistency and aims to eliminate subjectivity in lung cytology specimen evaluation. ROSE is not accesible in all facilities and AI aided evaluation can be beneficial in these settings allowing for standardization in these challenging specimens. AI applications in the future will allow for increased consistency and specific diagnoses in all clinical settings and specimen types.

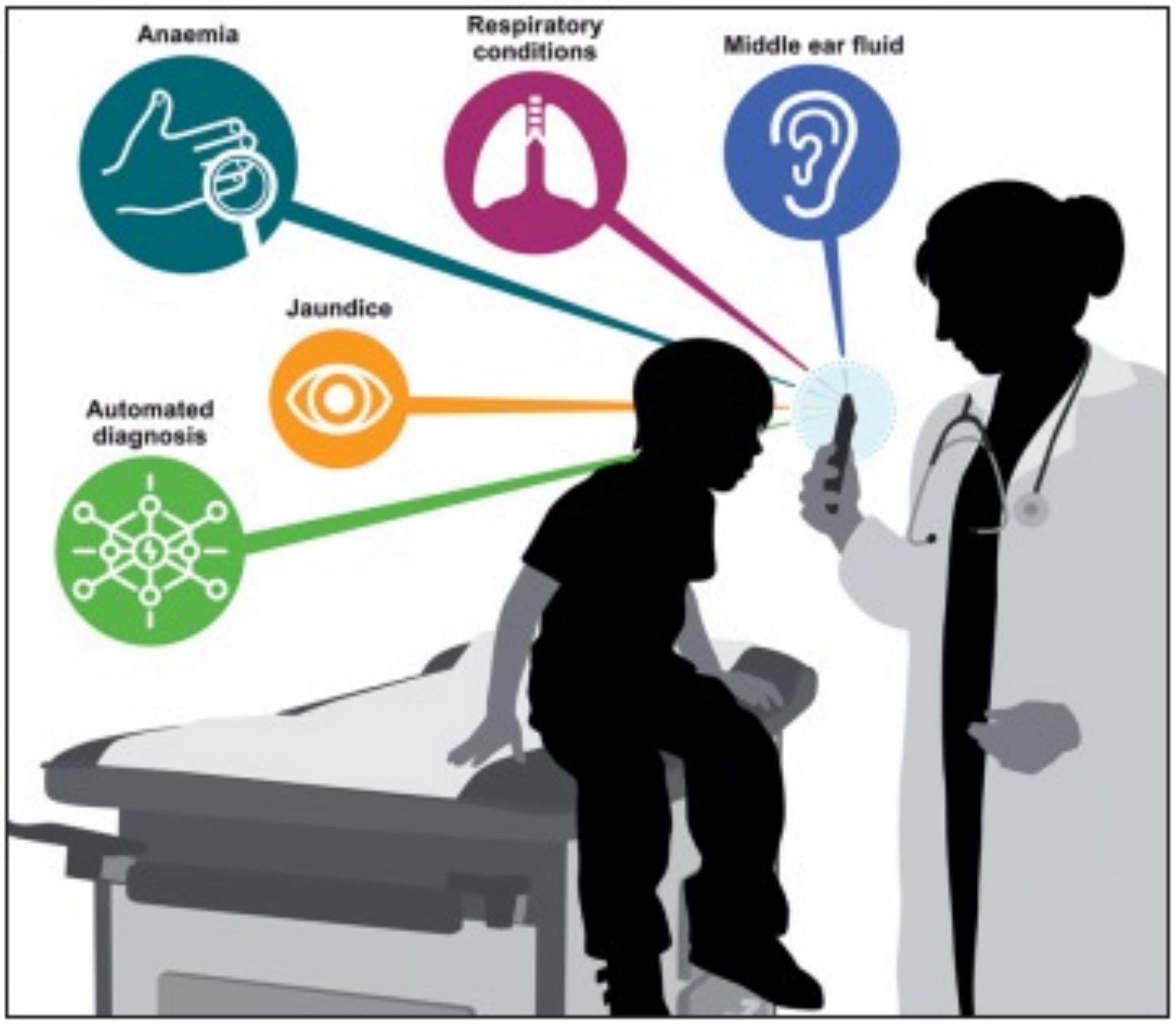
By Anamaria Tudorica

DIAGNOSTIC

Perspectives

Digital medicine

Towards a tricorder for diagnosing paediatric conditions



TRAITEMENT

Bousabarah *et al. Radiat Oncol* (2021) 16:74
https://doi.org/10.1186/s13014-021-01805-6

Radiation Oncology

RESEARCH **Open Access**

Radiomics for prediction of radiation-induced lung injury and oncologic outcome after robotic stereotactic body radiotherapy of lung cancer: results from two independent institutions

Khaled Bousabarah[1,2], Oliver Blanck[3,4], Susanne Temming[5], Maria-Lisa Wilhelm[4,6], Mauritius Hoevels[1], Wolfgang W. Baus[5], Daniel Ruess[1], Veerle Visser-Vandewalle[1], Maximilian I. Ruge[1], Harald Treuer[1] and Martin Kocher[1*]

TRAITEMENT

CURRENT OPINION

Robotic surgery for the treatment of early-stage lung cancer

Giulia Veronesi

TRAITEMENT

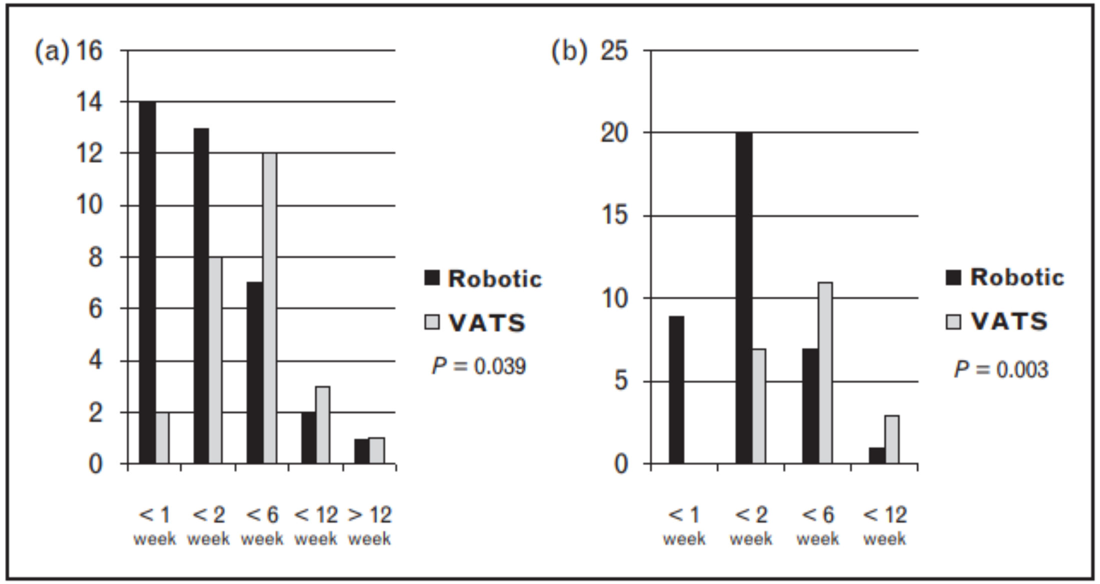


FIGURE 1. (a) Duration of narcotic use is shown at intervals by the number of patients who ceased using narcotics since discharge during that time. (b) The number of patients who returned to usual activities or work is shown at intervals. VATS, video-assisted thoracoscopic surgery. Data from Louie *et al.* [27▪▪].

TRAITEMENT

Table 1. Summary of surgical technique and outcomes in recently published series on robotic lung lobectomy (at least 30 cases presented)

Study	Year	No. of patients	Median operating time (range)	Conversion rate	Median length of stay	Technique	Total complication rate	Thirty-day mortality
Park *et al.* [29**]	2012	325	206 min (110–383)	8%	5 days	Arms: 3 or 4, UI: yes, CO_2: no	25%	0.3%
Dylewski *et al.* [24**]	2011	200	90 min	1.5%	3 days	Arms: 3+1, UI: no, CO_2: yes	26%	0
Cerfolio *et al.* [25**]	2011	160	140 min	13%	3 days	Arms: 4+1, UI: no, CO_2: yes	27%	0
Veronesi *et al.* [17]	2011	91	220 min	10% (excluding learning curve)	5 days	Arms: 4, UI: yes, CO_2: no	27%	0
Jang *et al.* [30]	2011	40	240 min	0	5 days	NR	10%	
Gharagozloo *et al.* [16]	2009	100	216 min	0	4 days	Arms: 3 (hybrid with VATS), UI: yes, CO_2: no	21%	3%
Giulianotti *et al.* [23]	2010	38	109 min	15.8%	10 days	Arms: 3, UI: yes, CO_2: no	10.5%	2.6%
Melfi and Mussi [21]	2008	107	220 min	9.4%	5 days	Arms: 3 or 4, UI: yes, CO_2: no	NR	1%

Arms, number of robotic arms used; CO_2, used to produce pneumothorax; NR, not reported; UI, utility incision; VATS, video-assisted thoracic surgery.

TRAITEMENT

Table 3. Summary of advantages and disadvantages of the robotic approach in comparison to VATS for lung major resection

Advantages	Disadvantages
Intuitive movements	High capital cost
Tremor filtration	High running costs including limited reusability of instruments
Increased degrees of freedom	Loss of tactile feedback
Motion scaling	Limited instrumentation available
Stereoscopic vision	Significant system set-up time
Stable camera platform	Need for at least one experienced assistant
Equivalence of dominant and nondominant hand	Possibility of delayed response by surgeon to catastrophic event
Motion analysis	
Eye–hand-target alignment	
Possibly shorter learning curve	

TRAITEMENT

Original Article

Artificial Intelligence Assesses Clinicians' Adherence to Asthma Guidelines Using Electronic Health Records

Elham Sagheb, MS[a], Chung-Il Wi, MD[b], Jungwon Yoon, MD, PhD[c], Hee Yun Seol, MD[d], Pragya Shrestha, MBBS[b], Euijung Ryu, PhD[e], Miguel Park, MD[f], Barbara Yawn, MD, MSPH, MSc[g], Hongfang Liu, PhD[a], Jason Homme, MD[b], Young Juhn, MD[b], and Sunghwan Sohn, PhD[a] *Rochester and Minneapolis, Minn; and Yangsan and Goyang, South Korea*

J ALLERGY CLIN IMMUNOL PRACT
VOLUME 10, NUMBER 4

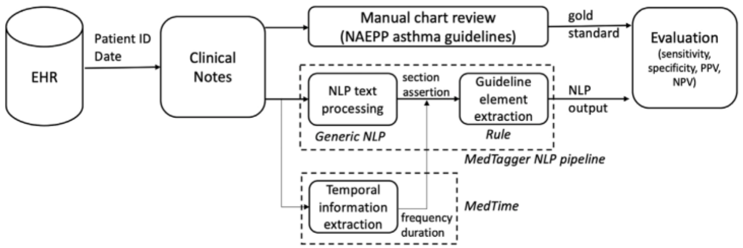
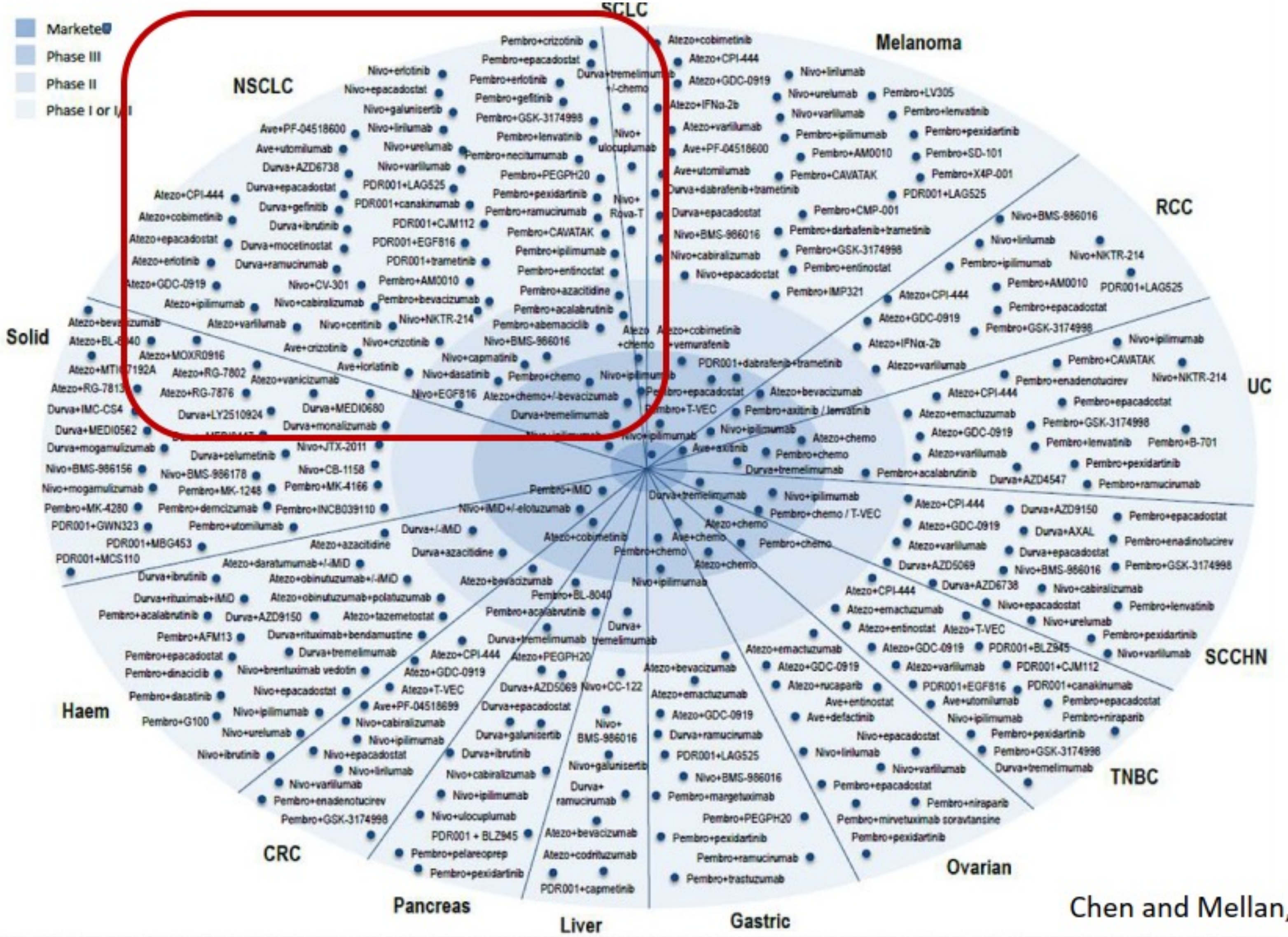


FIGURE 1. Process of asthma guideline element extraction and evaluation. *EHR*, electronic health record; *NAEPP*, National Asthma Education and Prevention Program; *NLP*, natural language processing; *NPV*, negative predictive value; *PPV*, positive predictive value.

Conclusion

Clinicians' adherence to asthma guidelines in primary care practices is low. This problem poses opportunities to improve asthma care quality through innovative approaches. In achieving this goal, an artificial intelligence approach using NLP technologies is a useful tool enabling an automated evidence-based assessment of clinicians' adherence to asthma guidelines by mining large-scale EHRs in near real time and providing personalized learning to clinicians in asthma care and documentation while reducing the burden of identifying asthma care with low adherence. The NLP tool may be useful for both specialty and primary care clinicians, especially for those in training. It supports evidence-based clinical effectiveness data assessments to enhance adherence to guidelines. Multisite studies with large and diverse EHR data are needed to assess the generalizability of our NLP algorithms.

TRAITEMENT DU CANCER DU POUMON



Chen and Mellan, Nature 2017

TRAITEMENT DU CANCER DU POUMON

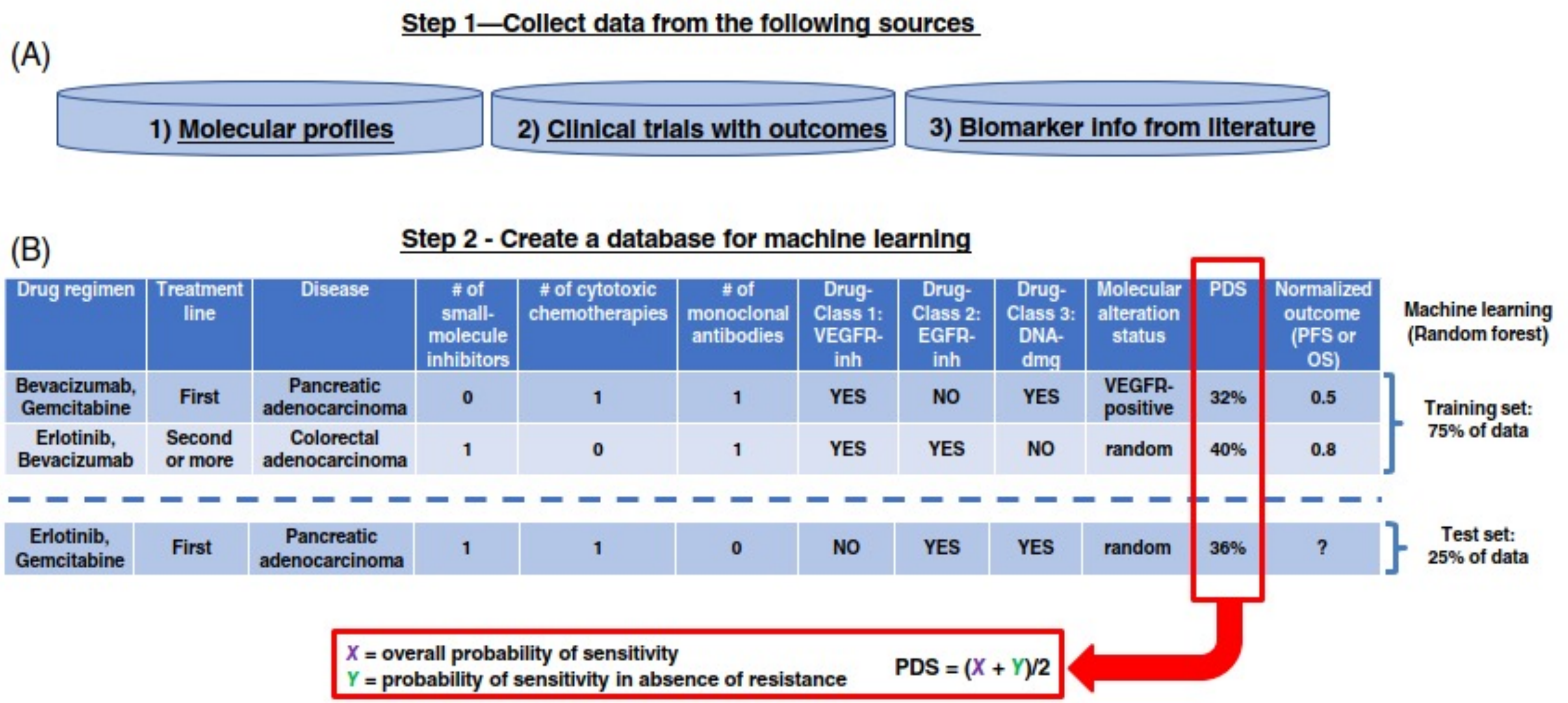
INNOVATIVE TOOLS AND METHODS

IJC International Journal of Cancer

Machine learning model to predict oncologic outcomes for drugs in randomized clinical trials

Alexander V. Schperberg[1,3] | Amélie Boichard[2] | Igor F. Tsigelny[1,4,5] | Stéphane B. Richard[1,6] | Razelle Kurzrock[2]

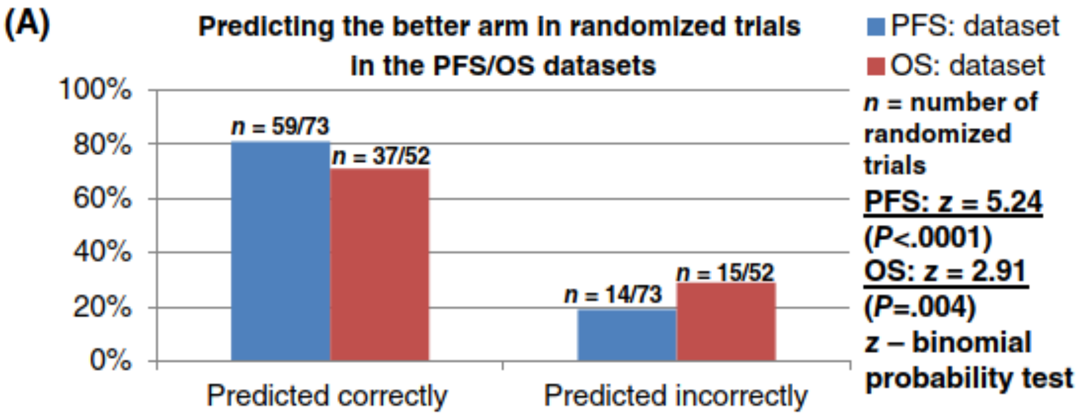
TRAITEMENT DU CANCER DU POUMON



Drug regimen	Treatment line	Disease	# of small-molecule inhibitors	# of cytotoxic chemotherapies	# of monoclonal antibodies	Drug-Class 1: VEGFR-inh	Drug-Class 2: EGFR-inh	Drug-Class 3: DNA-dmg	Molecular alteration status	PDS	Normalized outcome (PFS or OS)
Bevacizumab, Gemcitabine	First	Pancreatic adenocarcinoma	0	1	1	YES	NO	YES	VEGFR-positive	32%	0.5
Erlotinib, Bevacizumab	Second or more	Colorectal adenocarcinoma	1	0	1	YES	YES	NO	random	40%	0.8
Erlotinib, Gemcitabine	First	Pancreatic adenocarcinoma	1	1	0	NO	YES	YES	random	36%	?

FIGURE 1 Graphical representation of our overall design and methods of this study. A, We collected data from three sources: (1) molecular profiles from TCGA, (2) clinical trials from ClinicalTrials.gov and (3) drug-biomarker information from the literature. B, These data were entered into a table with the following attributes per intervention arm: treatment line (first or second or more), number of cytotoxic chemotherapies, number of small-molecule inhibitors, number of monoclonal antibodies, 1 column per drug class, disease, molecular alteration status of the clinical arm's population, PDS (Equation (1)) and outcome (PFS or OS, normalized from 0 to 1). Machine learning software was used to build our random forest decision algorithm using ~75% of our data (training set). Our algorithm was used to predict the outcome for the rest of the data (test set). This figure, along with Figure S1, provides a graphical approach to our methods, which is useful for analyzing complication relationships as emphasized by a comprehensive review.[66] OS, overall survival; PDS, probability of drug sensitivity; PFS, progression-free survival; TCGA, the cancer genome atlas

TRAITEMENT DU CANCER DU POUMON



(B)

NCT ID	Disease	Drugs used	PFS (months)	Prediction score	Predicted correctly?
NCT00326599 (randomized clinical trial)	Lung cancer	Active comparator arm: gemcitabine, carboplatin	4.5	36%	YES
		Experimental arm: cediranib, gemcitabine, carboplatin	6.3	40%	

FIGURE 5 Predicting the better outcome arm in randomized trials. A, Our PFS and OS test sets (see Figure 4) included 73 and 52 randomized

PRONOSTIC

nature medicine

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Article | Published: 09 January 2023

Multistain deep learning for prediction of prognosis and therapy response in colorectal cancer

Sebastian Foersch, Christina Glasner, Ann-Christin Woerl, Markus Eckstein, Daniel-Christoph Wagner, Stefan Schulz, Franziska Kellers, Aurélie Fernandez, Konstantina Tserea, Michael Kloth, Arndt Hartmann, Achim Heintz, Wilko Weichert, Wilfried Roth, Carol Geppert, Jakob Nikolas Kather & Moritz Jesinghaus

PRONOSTIC

Although it has long been known that the immune cell composition has a strong prognostic and predictive value in colorectal cancer (CRC), scoring systems such as the immunoscore (IS) or quantification of intraepithelial lymphocytes are only slowly being adopted into clinical routine use and have their limitations. To address this we established and evaluated a multistain deep learning model (MSDLM) utilizing artificial intelligence (AI) to determine the AImmunoscore (AIS) in more than 1,000 patients with CRC. Our model had high prognostic capabilities and outperformed other clinical, molecular and immune cell-based parameters. It could also be used to predict the response to neoadjuvant therapy in patients with rectal cancer. Using an explainable AI approach, we confirmed that the MSDLM's decisions were based on established cellular patterns of anti-tumor immunity. Hence, the AIS could provide clinicians with a valuable decision-making tool based on the tumor immune microenvironment.

PRONOSTIC

Chen *et al. Journal of Translational Medicine* (2022) 20:100
https://doi.org/10.1186/s12967-022-03298-7

Journal of Translational Medicine

RESEARCH Open Access

An artificial intelligence method to assess the tumor microenvironment with treatment outcomes for gastric cancer patients after gastrectomy

Tao Chen[1*†], Xunjun Li[1†], Qingyi Mao[1†], Yiyun Wang[1], Hanyi Li[2], Chen Wang[3], Yuyang Shen[3], Erjia Guo[3], Qinglie He[1], Jie Tian[1], Mansheng Zhu[1], Jing Wu[1], Weiqi Liang[1], Hao Liu[1], Jiang Yu[1] and Guoxin Li[1*]

PRONOSTIC

frontiers in Immunology

ORIGINAL RESEARCH
published: 23 March 2022
doi: 10.3389/fimmu.2022.835630

Check for updates

Development and Validation of an Immune-Based Prognostic Risk Score for Patients With Resected Non-Small Cell Lung Cancer

Lan He[1,2†], Yanqi Huang[1,2,3†], Xin Chen[4†], Xiaomei Huang[1,2], Huihui Wang[1,2], Yuan Zhang[1,2], Changhong Liang[1,2], Zhenhui Li[1,2,5], Lixu Yan[6*] and Zaiyi Liu[1,2*]*

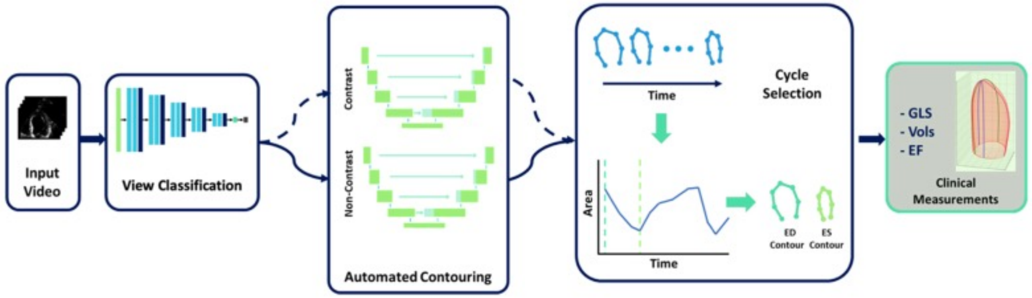
PRONOSTIC

Human versus Artificial Intelligence–Based Echocardiographic Analysis as a Predictor of Outcomes: An Analysis from the World Alliance Societies of Echocardiography COVID Study

Journal of the American Society of Echocardiography ■ 2022

CONCLUSION

Automated quantification of LVEF and LVLS using AI in the WASE COVID-19 Study had similar feasibility to manual contouring, minimized variability, and consequently increased the statistical power to predict mortality. AI-based but not manual analyses were significant predictors of in-hospital and follow-up mortality. Application of this technology to other diseases or clinical trials may increase the accuracy of predicting outcomes or detecting clinical changes over time.



2C	0.97	0.02	0.01	0.00
3C	0.01	0.99	0.00	0.00
4C	0.01	0.00	0.99	0.00
SAX	0.01	0.00	0.00	0.99

View classifier final performance matrix.

L'IA PRENDRA ELLE NOTRE PLACE?

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CLINICAL REVIEW

Artificial intelligence and sleep: Advancing sleep medicine☆

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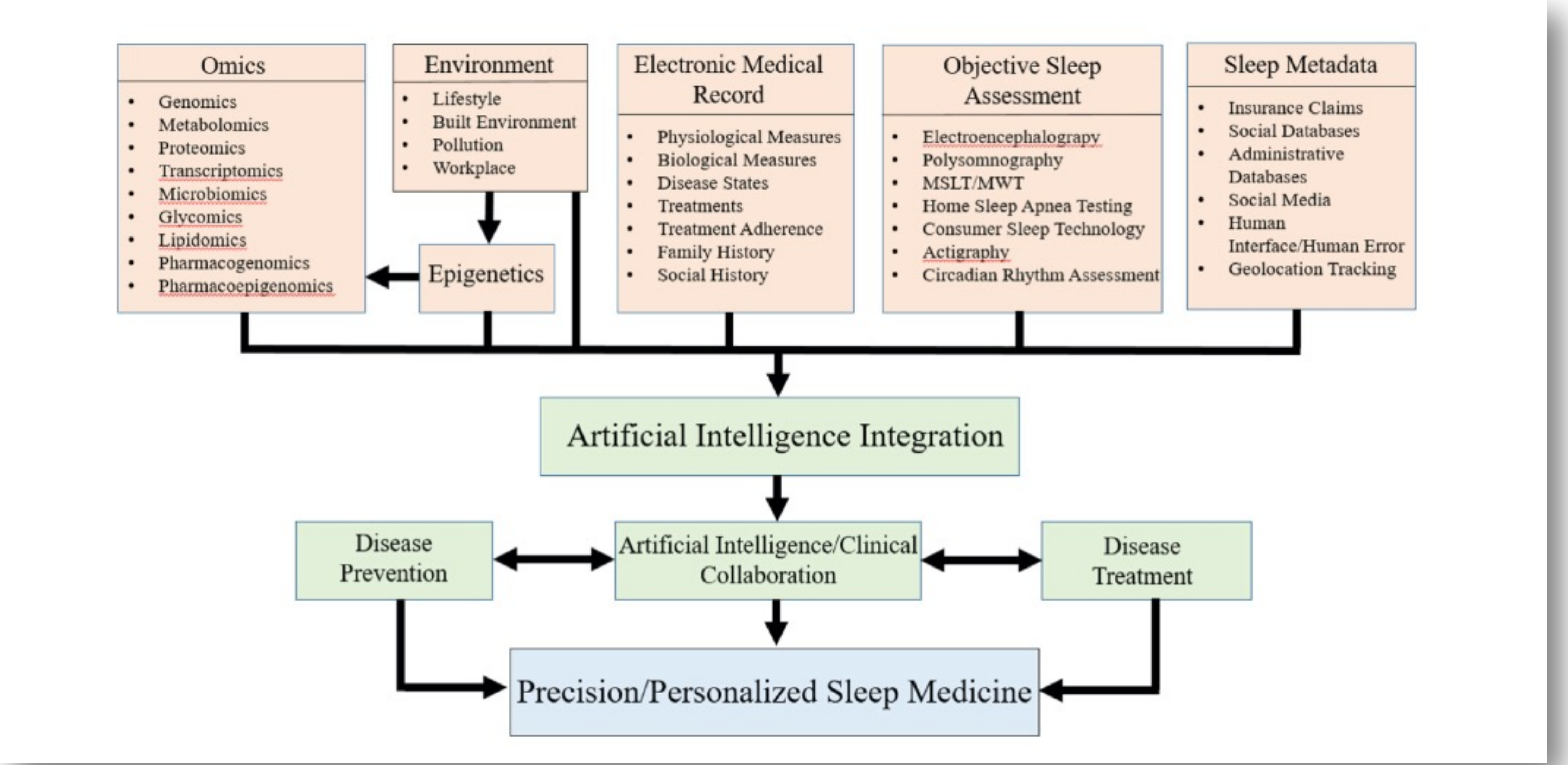
Check for updates

L’IA PRENDRA ELLE NOTRE PLACE?



L'IA PRENDRA ELLE NOTRE PLACE?

In conclusion, sleep medicine is just beginning to scratch the surface of the potential of AI to advance our understanding of sleep disorders to the benefit of our patients. Every aspect of the patient's journey will be impacted by AI, from screening to diagnosis to treatment. Endotyping of sleep disorders opens the door to targeted therapy to maximize outcomes, accelerate the time between diagnosis and optimal treatment response, and reduce unnecessary testing and trials of ineffective therapies making treatment more cost-effective. Resource deployment optimization will improve

LES ALGORYTHMES IA APPROUVES PAR LA FDA

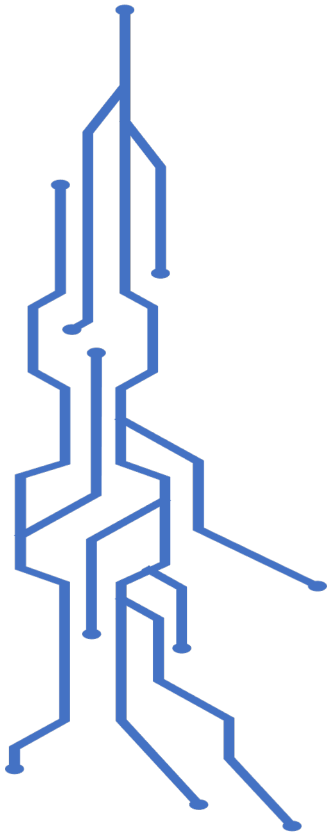
TABLE I. FDA approvals for AI-based algorithms in medicine

Date	AI-based algorithm
September 2014	Detection of atrial fibrillation (AliveCor)
March 2016	Diagnosis and treatment of ADHD (ObCheck)
July 2016	Determining insulin dosage (InPen)
October 2016	Ultrasound image diagnosis (Lumify)
November 2016	Quantification of blood glucose level (One Drop Blood Glucose)
January 2017	Memory assessment for the elderly (Cantab Mobile) Cardiac MRI analysis (Arterys)
March 2017	Diagnosis of sleep disorders (EnsoSleep)
May 2017	Analysis of thyroid nodules (AmCAD-US)
July 2017	Cancer detection (QuantX) Arrhythmia screening (Cardiologs)
November 2017	Detecting arrhythmias (Lepu Medical)
December 2017	Medical imaging platform (Subtle Medical) Detecting arrhythmias (BioFlux)
January 2018	Echocardiogram analysis (Bay Labs)
February 2018	Stroke detection on CT (Viz.ai) Liver and lung cancer diagnosis on CT and MRI (Arterys Inc) Wearable for detecting seizures (Empatica) Autism diagnosis app (Cognoa)
March 2018	Predicting blood glucose changes (Medtronic)
Apmil 2018	Detection of diabetic retinopathy (Idx) MRI brain interpretation (Icometrix)
May 2018	X-ray wrist fracture diagnosis (Imagen) Transcranial Doppler probe positioning (NeuralBot) Motion capture for the elderly (MindMotionGO)
June 2018	Managing type I diabetes (DreaMed) Blood glucose monitoring system (POGO)
July 2018	Coronary artery calcification algorithm (Zebra Medical Vision) Quantification of liver iron concentration (FerriSmart)
August 2018	Breast density via mammography (iCAD) Triage and diagnosis of time-sensitive patients (Aidoc) Detection of atrial fibrillation (PhysiQ Heart Rhythm Module)
September 2018	Detection of atrial fibrillation (Apple) Identifying visual tracking impairment (RightEye Vision System)
November 2018	Acute intracranial hemorrhage triage algorithm (MaxQ) Decision support for mammograms (ScreenPoint Medical)

CONCLUSION

- Avec l'IA :
  - Touche à toutes les pathologies
  - Du macroscopique aux different OMICS
  - Du dépistage au prognostic
  - Gain de temps
  - Economique
  - Meilleure survie
  - Traitement personnifié

NOW JUST IMAGINE…



MISSION : ERADICATE DISEASE

IN 100 % CASES

COMMON POINT IS HUMAN BEING

Solution: ERADICATE HUMANITY

THANK YOU

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