

Radiomique

Fanny Orlhac

Laboratoire d'Imagerie Translationnelle en Oncologie (LITO)

U1288 Inserm/Institut Curie, Orsay



Inserm

La science pour la santé
From science to health



2015 : Thèse en physique médicale.

Analyse de texture en imagerie TEP pour la cancérologie.



2015-2017 : 1^{er} post-doctorat.

IMIV/CEA-SHFJ & Gustave Roussy, Villejuif.



2017-2019 : 2nd post-doctorat.

Epione/Inria Sophia-Antipolis & Centre Antoine Lacassagne, Nice.

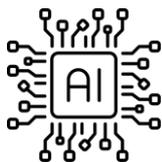


Depuis 2019 : **Chargée de Recherche Inserm.**

Laboratoire d'Imagerie Translationnelle en Oncologie - LITO, U1288 Inserm/Institut Curie, Orsay.



Mots clés : IA, TEP/TDM, cancérologie, modèles de prédiction/classification, harmonisation





Analyse des images médicales dans la pratique actuelle

Analyse des images dans la pratique actuelle



Lung-RADS™ Version 1.1

Assessment Categories Release date: 2019

Category Descriptor	Lung-RADS Score	Findings	Management	Risk of Malignancy	Est. Population Prevalence
Incomplete	0	Prior chest CT examination(s) being located for comparison Part or all of lungs cannot be evaluated	Additional lung cancer screening CT images and/or comparison to prior chest CT examinations is needed	n/a	1%
Negative No nodules and definitely benign nodules	1	No lung nodules Nodule(s) with specific calcifications: complete, central, popcorn, concentric, rings and fat containing nodules	Continue annual screening with LDCT in 12 months	≤ 1%	90%
Benign Appearance or Behavior Nodules with a very low likelihood of becoming a clinically active cancer due to size or lack of growth	2	Solid nodule(s): new < 4 mm Part solid nodule(s): < 6 mm total diameter on baseline screening Non solid nodule(s) (GGN): < 30 mm OR ≥ 30 mm and unchanged or slowly growing Category 3 or 4 nodules unchanged for ≥ 3 months			
Probably Benign Probably benign finding(s) - short term follow up suggested; includes nodules with a low likelihood of becoming a clinically active cancer	3	Solid nodule(s): ≥ 6 to < 8 mm at baseline OR new 4 mm to < 6 mm Part solid nodule(s) ≥ 6 mm total diameter with solid component < 6 mm OR new < 6 mm total diameter Non solid nodule(s) (GGN) ≥ 30 mm on baseline CT or new	6 month LDCT	1-2%	5%
Probably Suspicious Findings for which additional diagnostic testing is recommended	4A	Solid nodule(s): ≥ 8 to < 15 mm at baseline OR growing ≥ 8 mm OR new 6 to < 8 mm Part solid nodule(s): ≥ 6 mm with solid component ≥ 6 mm to < 8 mm OR with a new or growing < 4 mm solid component Endobronchial nodule	3 month LDCT; PET/CT may be used when there is a ≥ 8 mm solid component	5-15%	2%
Suspicious Findings for which additional diagnostic testing and/or tissue sampling is recommended	4B	Solid nodule(s) ≥ 15 mm OR new or growing, and ≥ 8 mm Part solid nodule(s) with: a solid component ≥ 8 mm OR a new or growing ≥ 4 mm solid component	Chest CT with or without contrast, PET/CT and/or tissue sampling depending on the "probability of malignancy and comorbidities". PET/CT may be used when there is a ≥ 8 mm solid component. For new large nodules that develop on an annual repeat screening CT, a 1 month LDCT may be recommended to address potentially infectious or inflammatory conditions	> 15%	2%
Other Clinically Significant or Potentially Clinically Significant Findings (non lung cancer)	S	Modifier - may add on to category 0-4 coding			
Volumetric measurements		1.5 mm = 1.8 mm ³ 4 mm = 33.5 mm ³ 6 mm = 113.1 mm ³ 8 mm = 268.1 mm ³			10 mm = 523.6 mm ³ 15 mm = 1767.1 mm ³ 20 mm = 4188.8 mm ³ 30 mm = 14137.2 mm ³

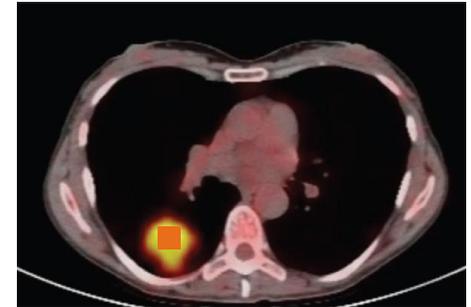
Critères RECIST



Diam. : 39 mm

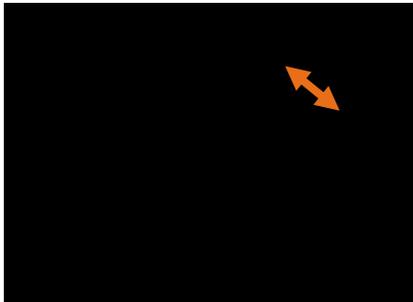


Mesures SUV



SUVmax : 15.2

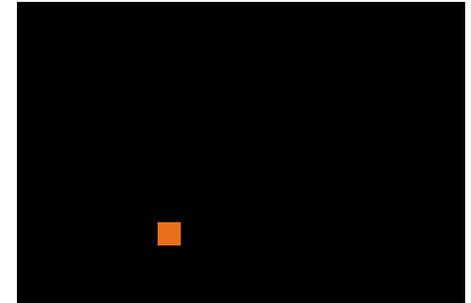
Critères RECISt



Diam. : 39 mm



Mesures SUV



SUVmax : 15.2

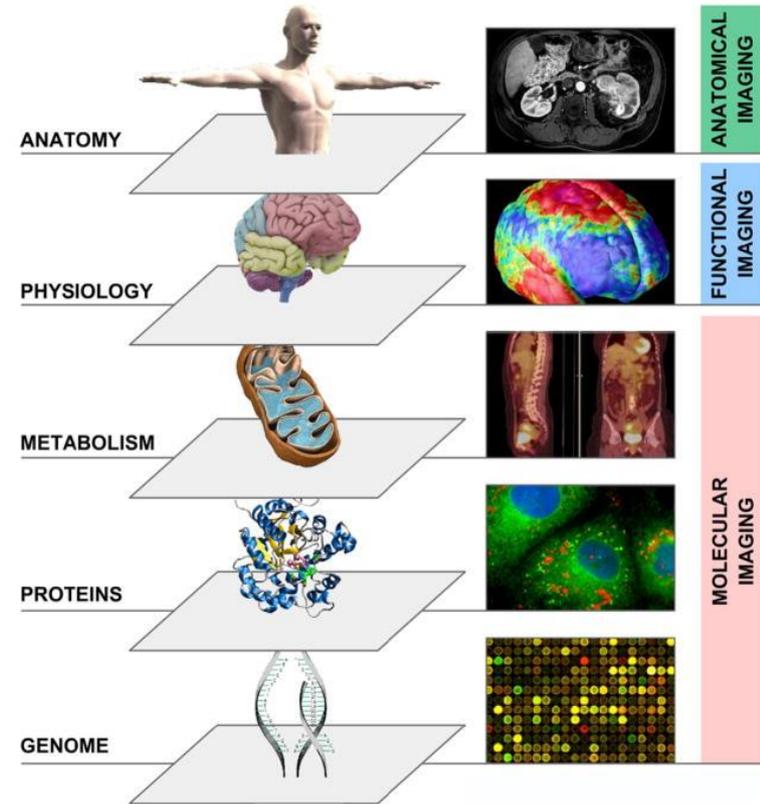
Radiomique et IA en imagerie TEP/TDM : définition



Caractéristiques macroscopiques
mesurables sur les données d'imagerie



Caractéristiques biologiques



[Lambin et al. *Eur J Cancer* 2012]

Radiomique :

Extraction automatique de paramètres issus des images médicales qui sont confrontés à des données cliniques, biologiques, ... pour :

- Améliorer la caractérisation de la maladie,
- Identifier des profils de patients,
- Etablir un lien avec le pronostic ou la réponse au traitement...



Radiology

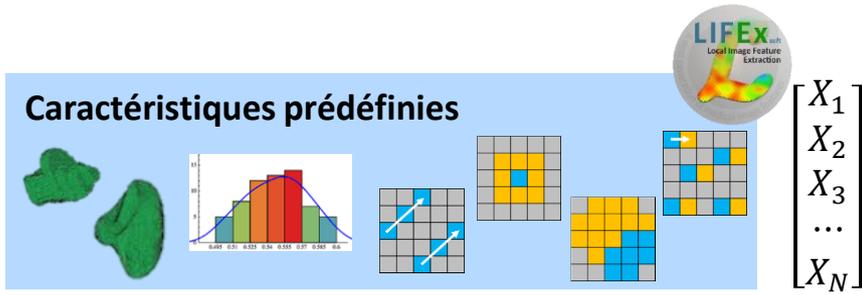
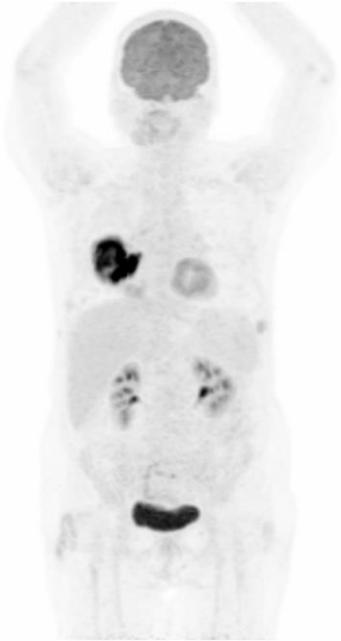
Radiomics: Images Are More than Pictures, They Are Data¹

Radiology: Volume 278: Number 2—February 2016 • radiology.rsna.org

Robert J. Gillies, PhD
Paul E. Kinahan, PhD
Helwig Hricak, MD, PhD, DrHC

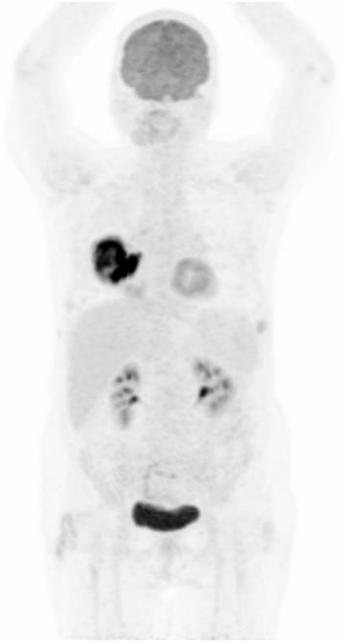
In the past decade, the field of medical image analysis has grown exponentially, with an increased number of pattern recognition tools and an increase in data set sizes. These

Radiomique : définition & historique

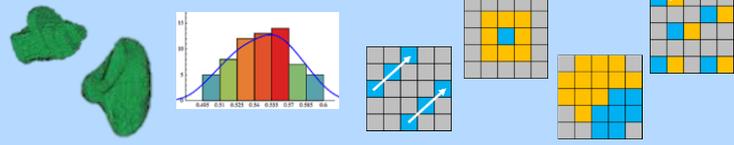


[Orlhac et al. *PET Clinics* 2022]
[Nioche et al. *Cancer Res* 2018]

Radiomique : définition & historique

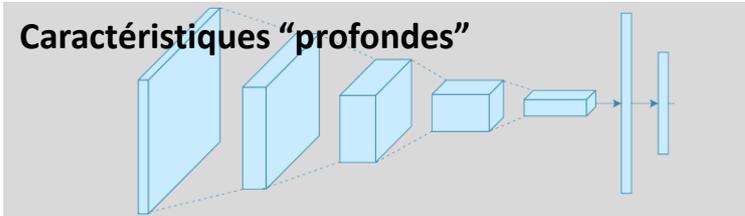


Caractéristiques prédéfinies



$$\begin{bmatrix} X_1 \\ X_2 \\ X_3 \\ \dots \\ X_N \end{bmatrix}$$

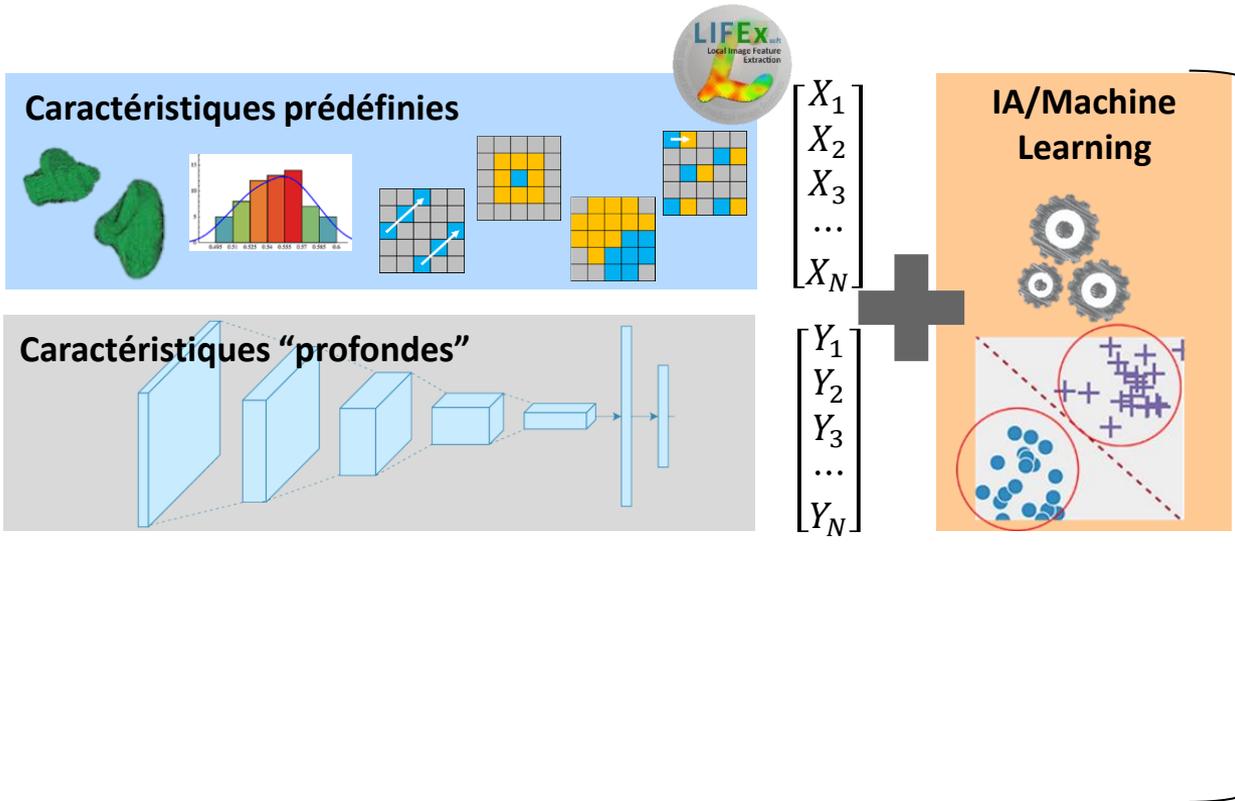
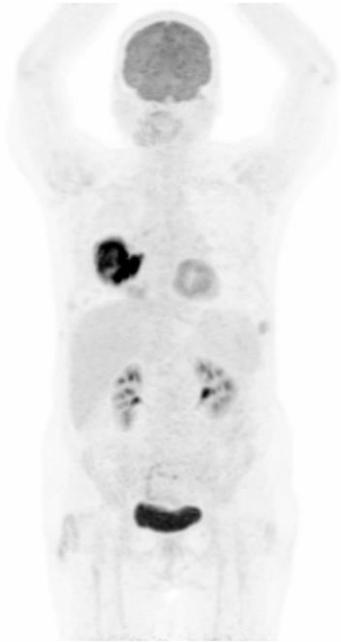
Caractéristiques "profondes"



$$\begin{bmatrix} Y_1 \\ Y_2 \\ Y_3 \\ \dots \\ Y_N \end{bmatrix}$$

[Orlhac et al. *PET Clinics* 2022]
[Nioche et al. *Cancer Res* 2018]

Radiomique : définition & historique

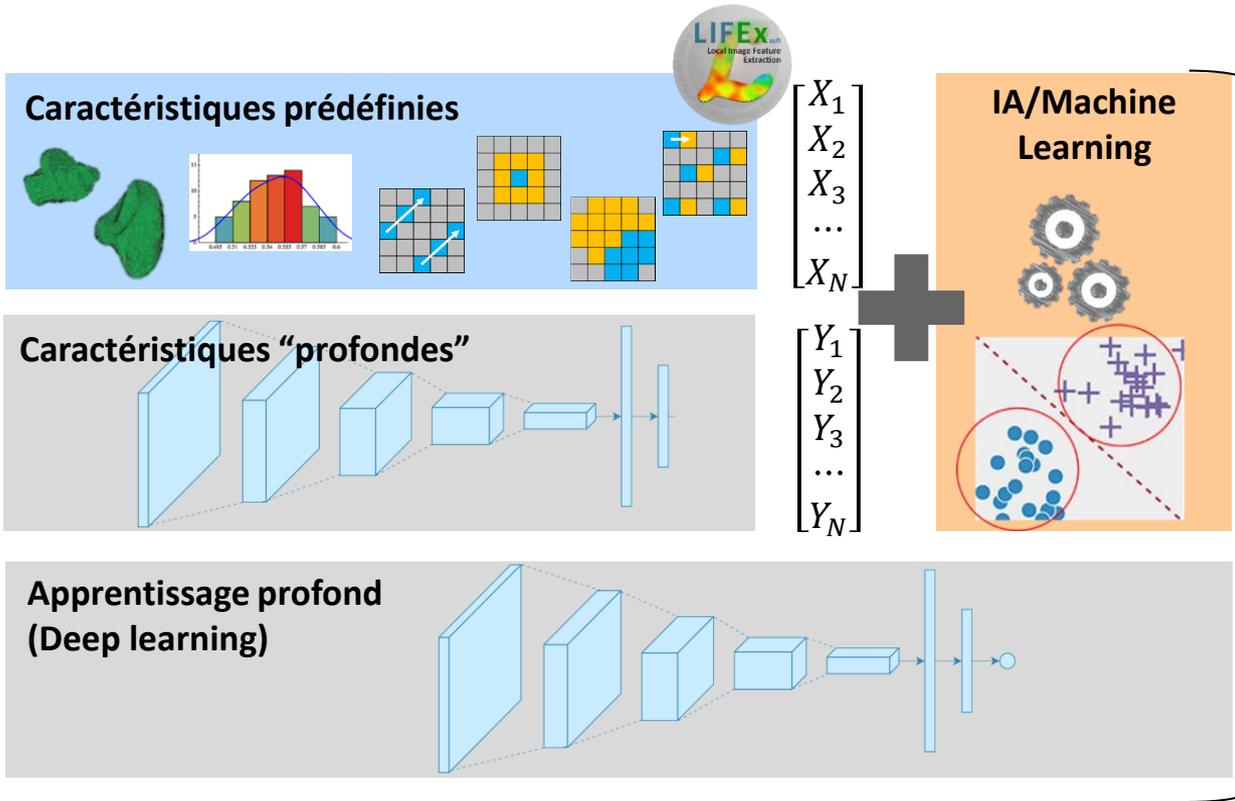
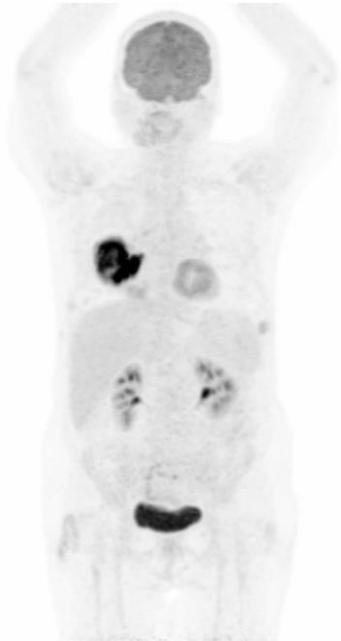


Modèles radiomiques pour prédire :

- Caractéristiques biologiques
- Réponse aux traitements
- Risque de récurrence
- Survie des patients
- ...

[Orlhac et al. *PET Clinics* 2022]
[Nioche et al. *Cancer Res* 2018]

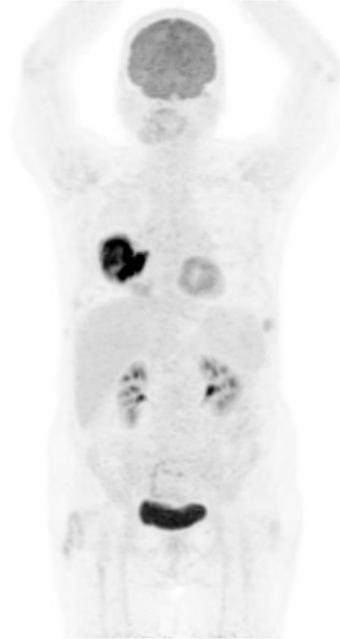
Radiomique : définition & historique



- Caractéristiques biologiques
- Réponse aux traitements
- Risque de récurrence
- Survie des patients
- ...

[Orlhac et al. *PET Clinics* 2022]
[Nioche et al. *Cancer Res* 2018]

Radiomique : définition & historique

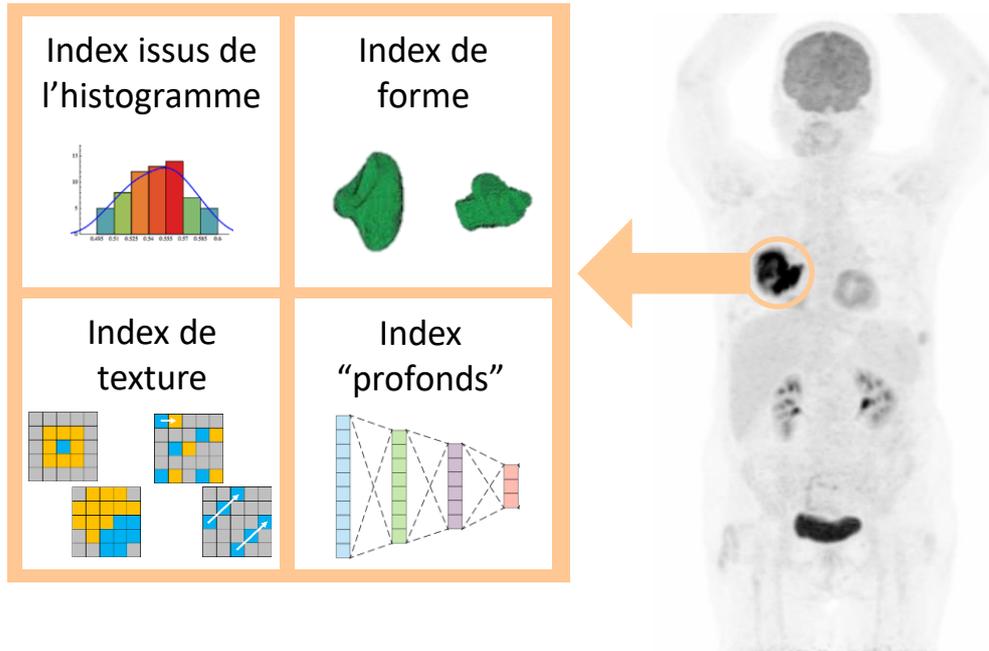


[Orlhac et al. *PET Clinics* 2022]

Radiomique : définition & historique



A l'échelle des tumeurs

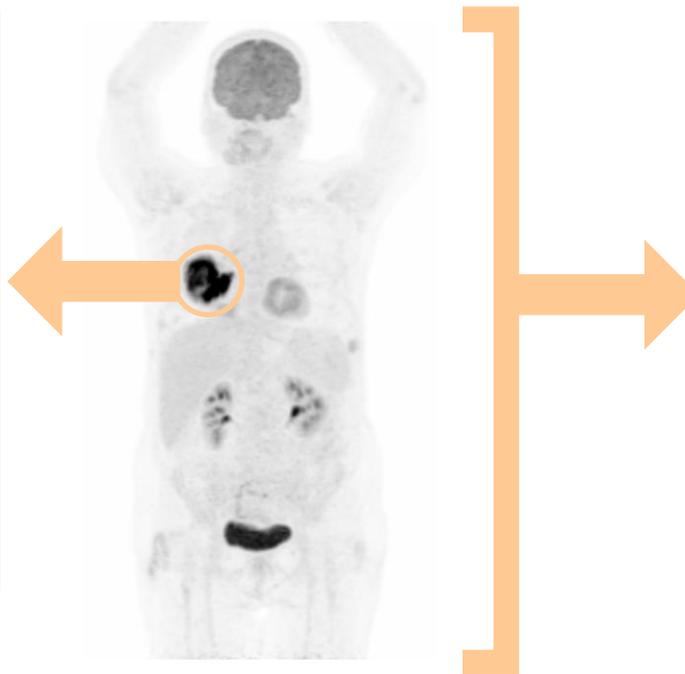
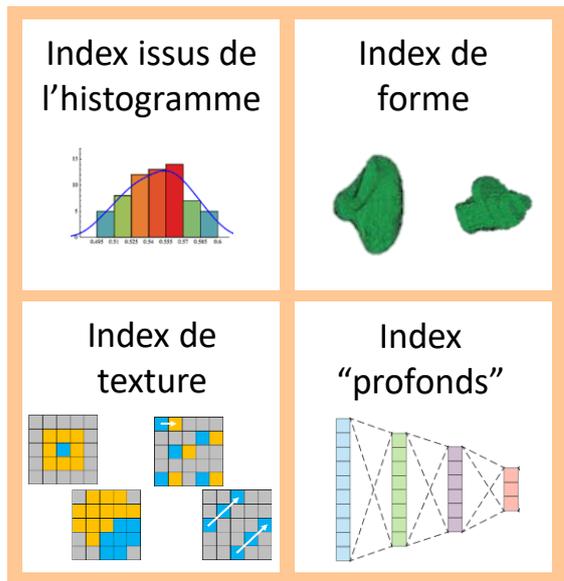


[Orlhac et al. *PET Clinics* 2022]

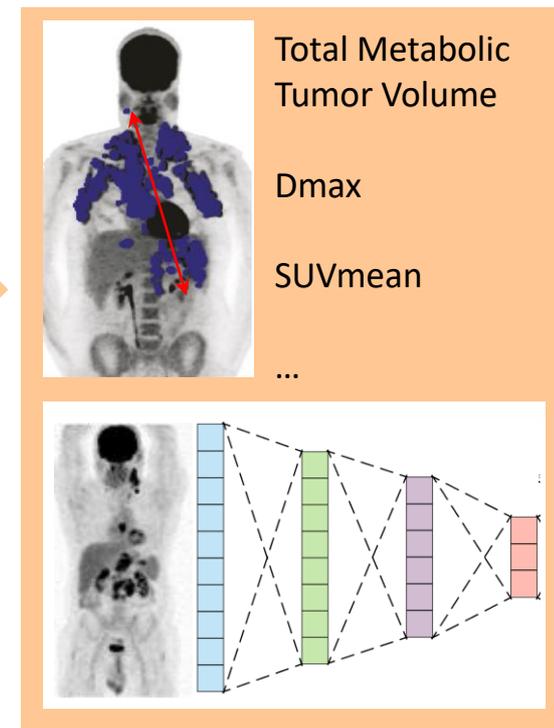
Radiomique : définition & historique



A l'échelle des tumeurs

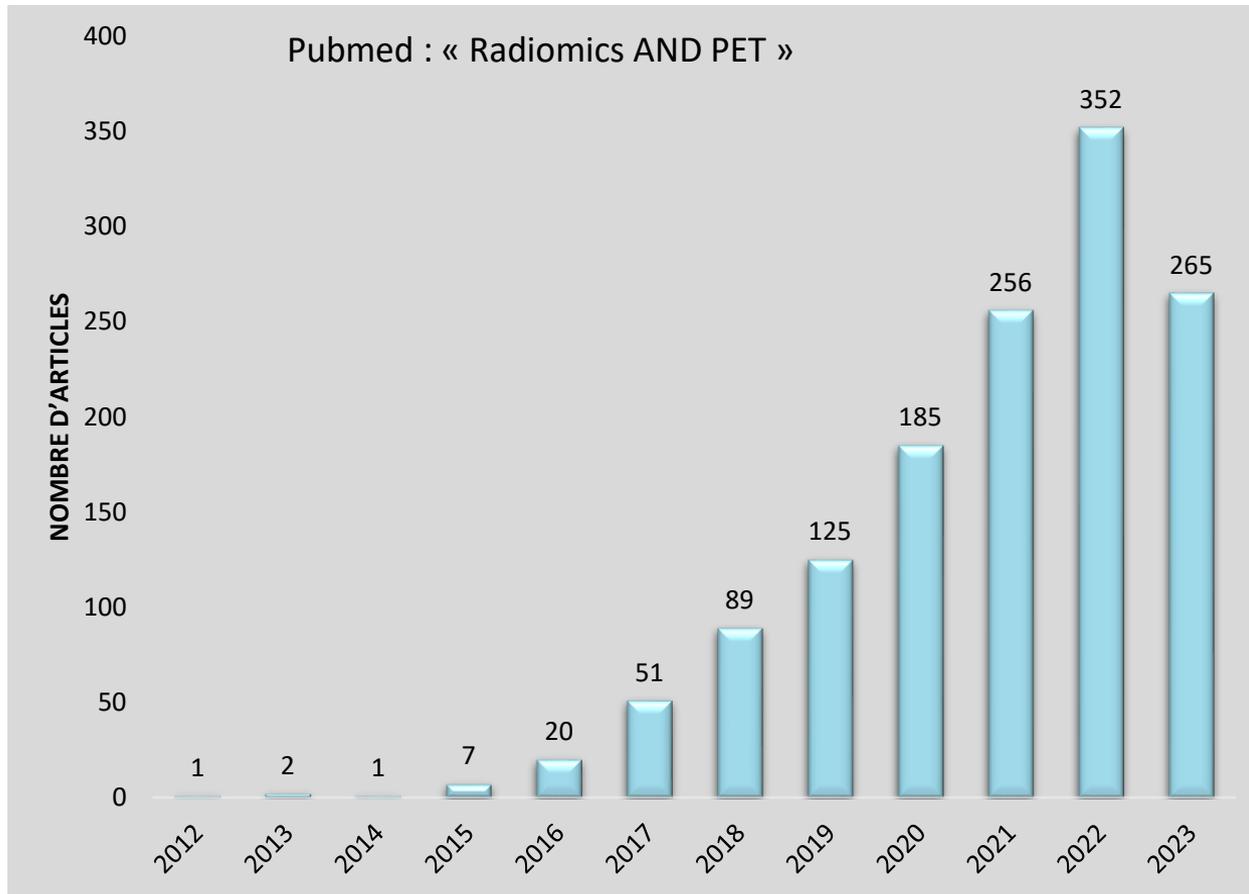


A l'échelle du patient



[Orlhac et al. *PET Clinics* 2022]

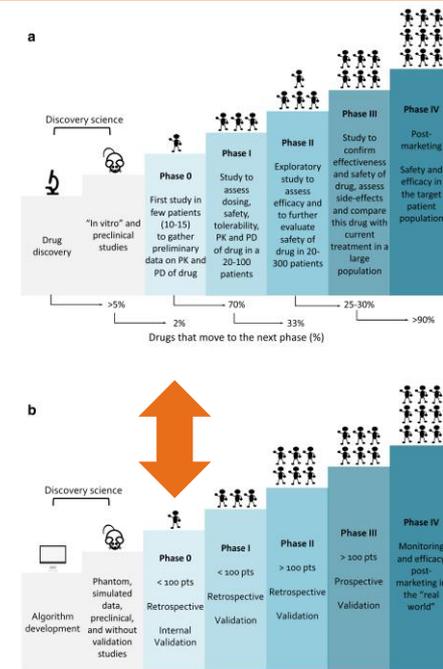
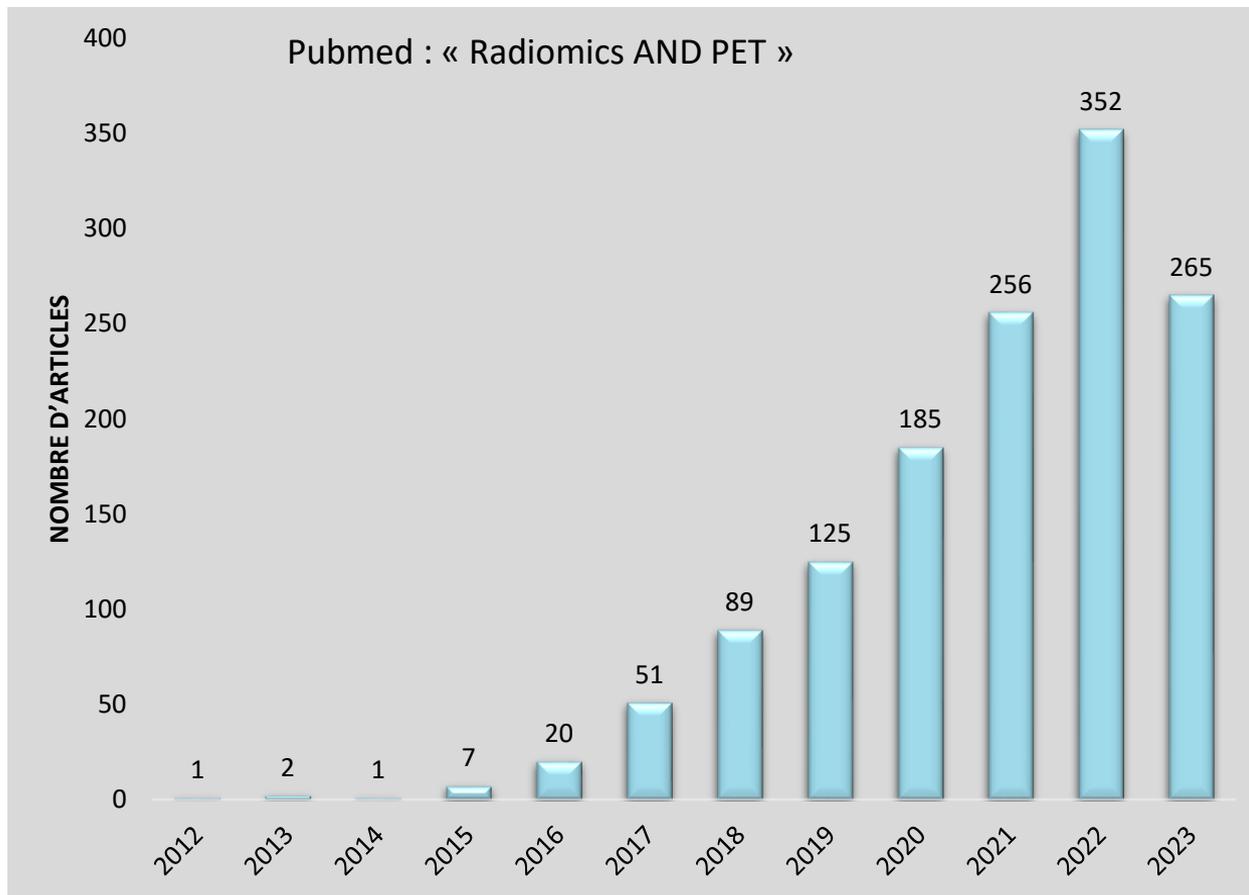
Radiomique : définition & historique



...

[Sollini et al. *Eur J Nucl Med Mol Imaging* 2019]

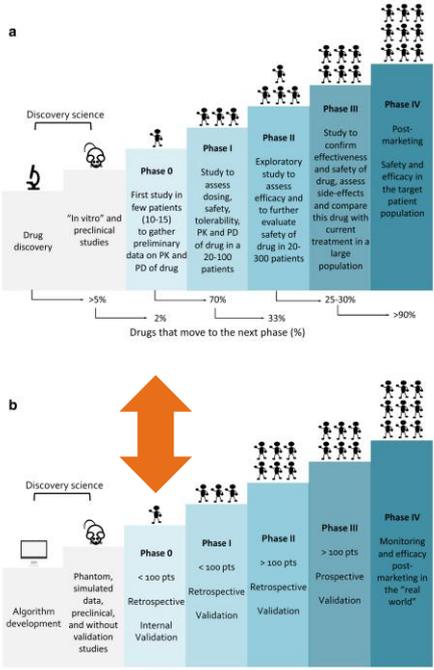
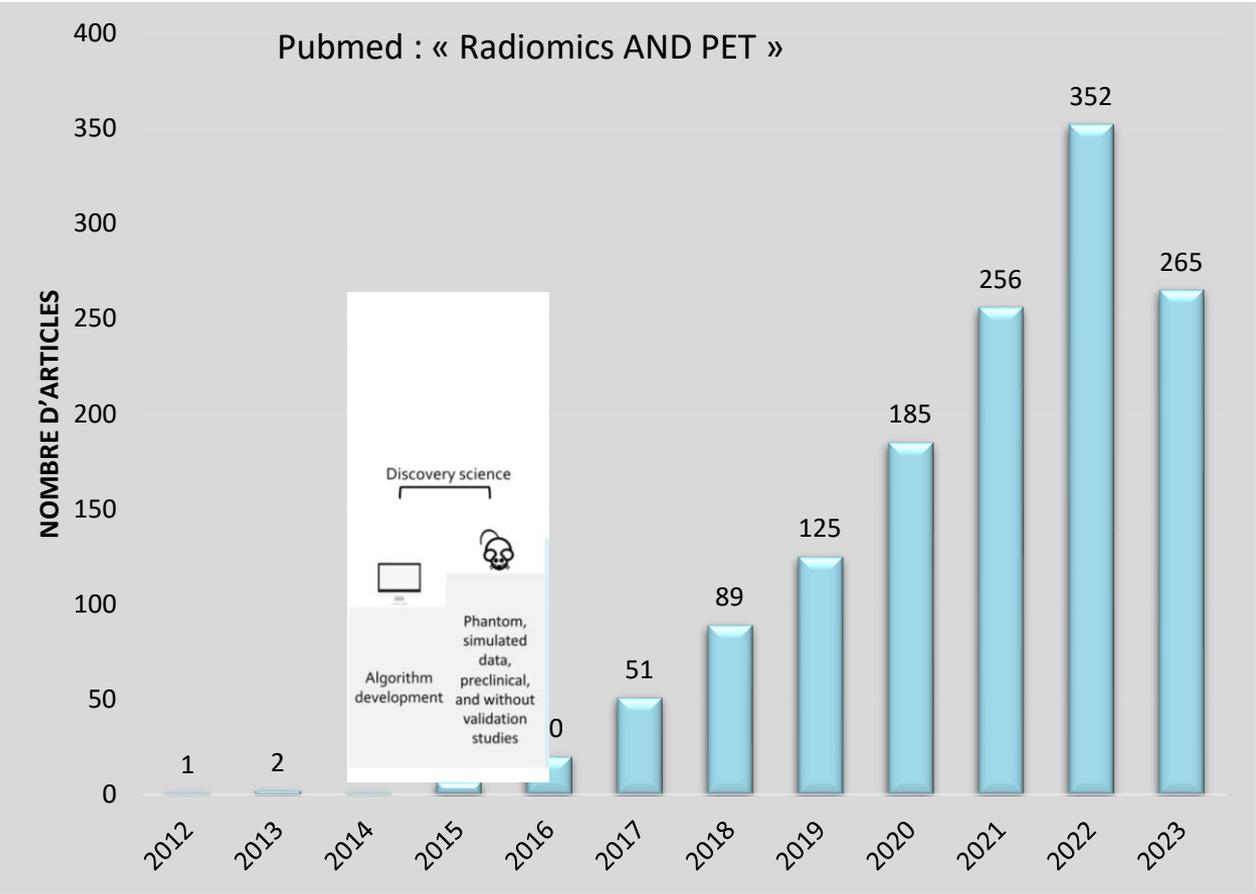
Radiomique : définition & historique



...

[Sollini et al. *Eur J Nucl Med Mol Imaging* 2019]

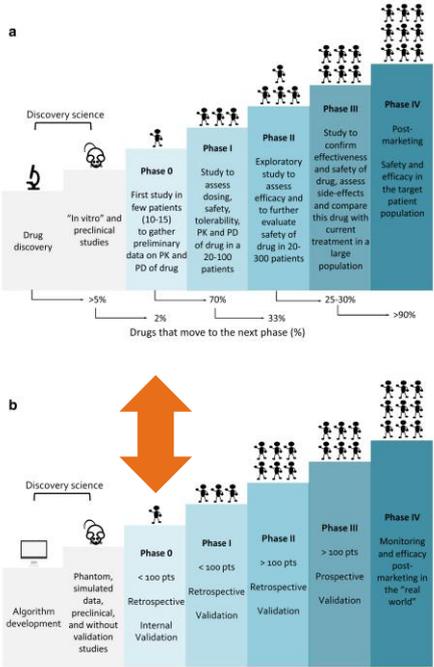
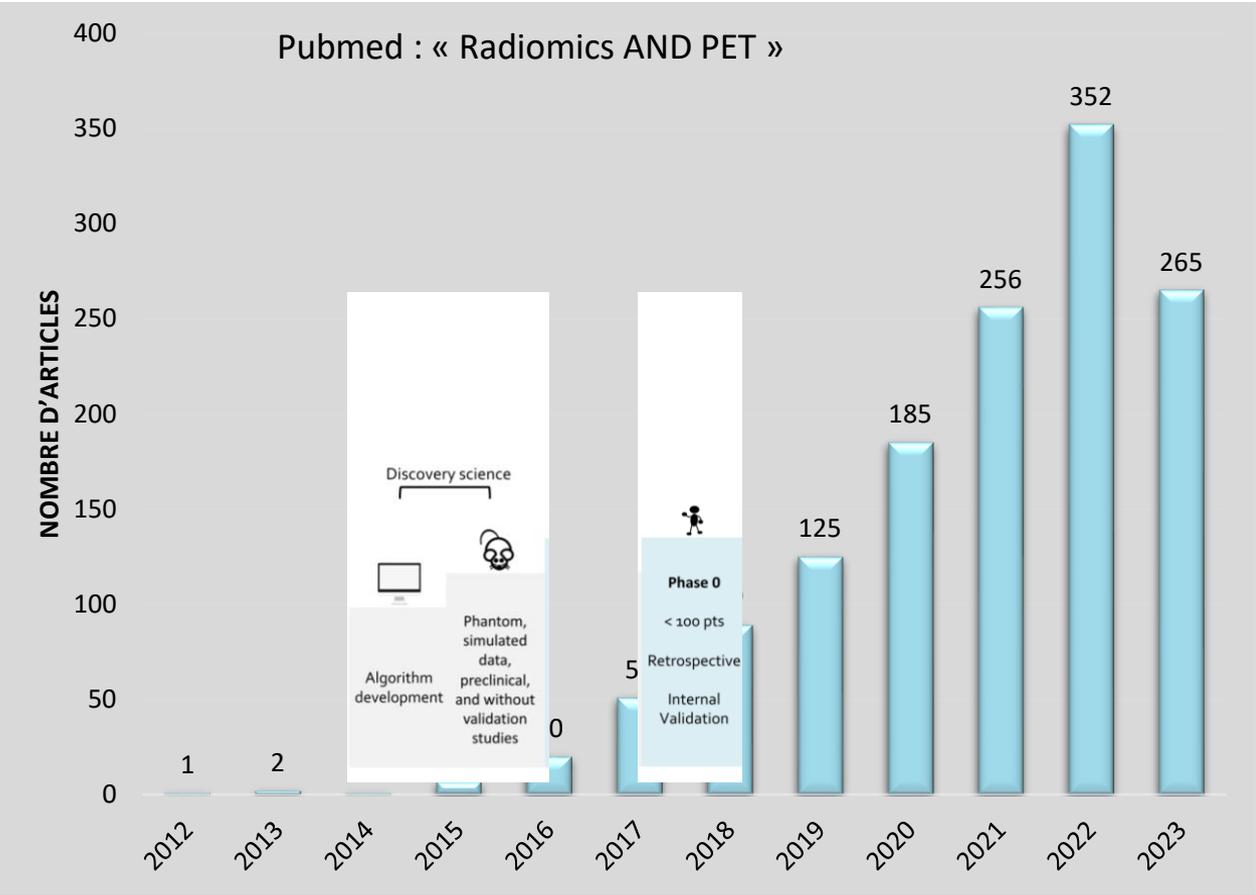
Radiomique : définition & historique



...

[Sollini et al. *Eur J Nucl Med Mol Imaging* 2019]

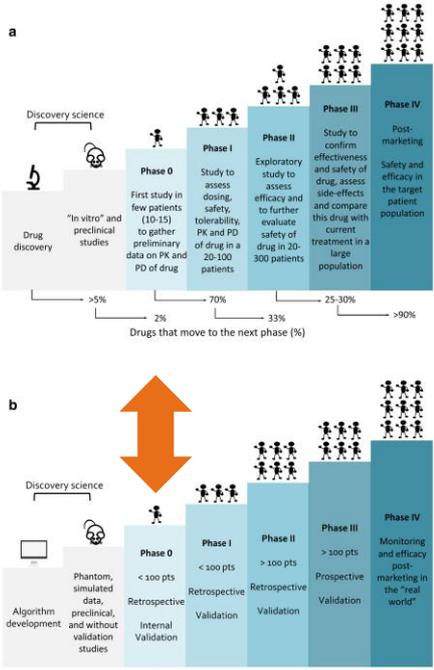
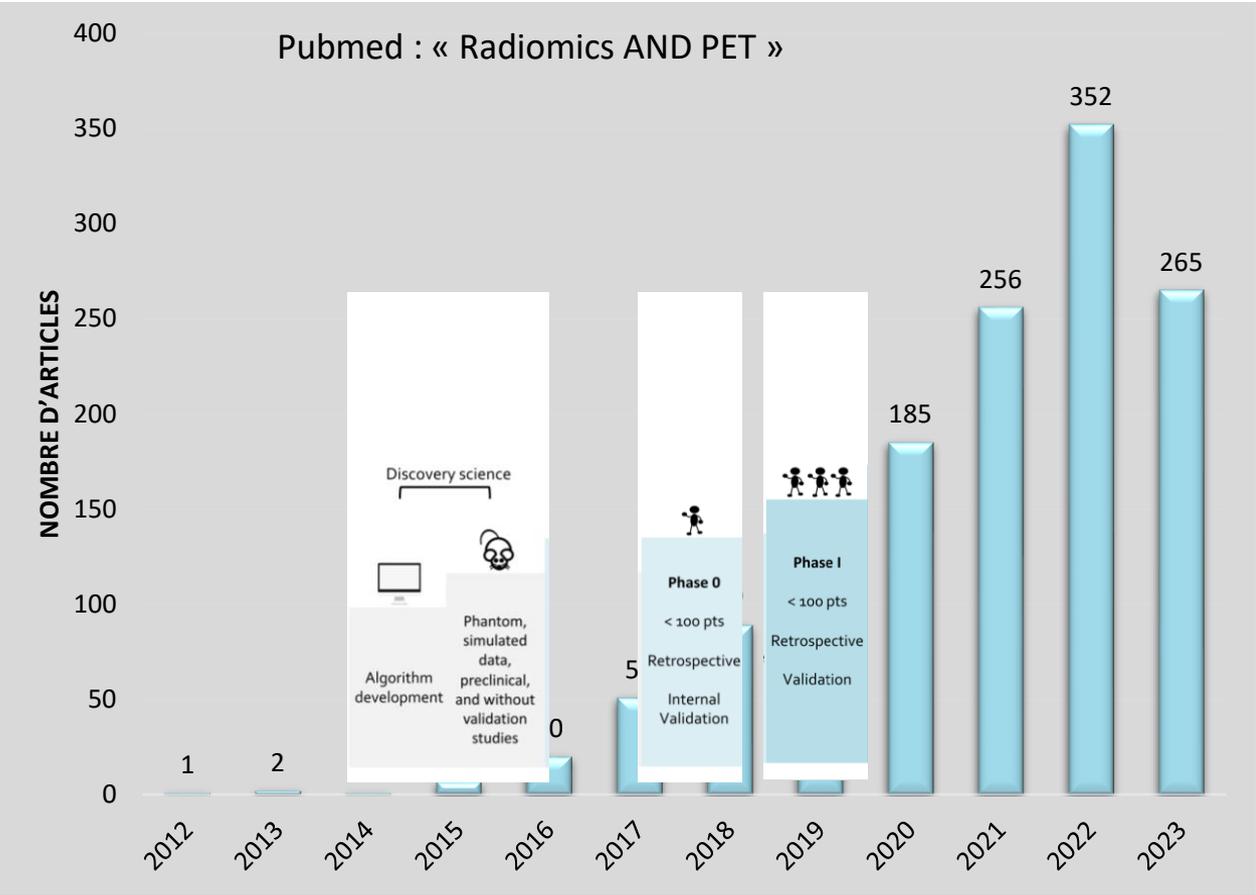
Radiomique : définition & historique



...

[Sollini et al. *Eur J Nucl Med Mol Imaging* 2019]

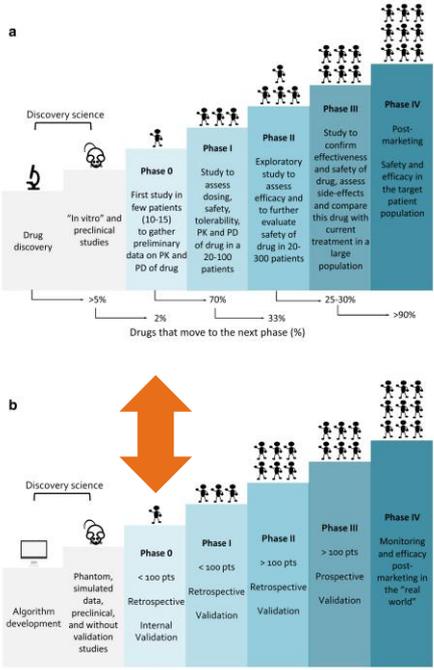
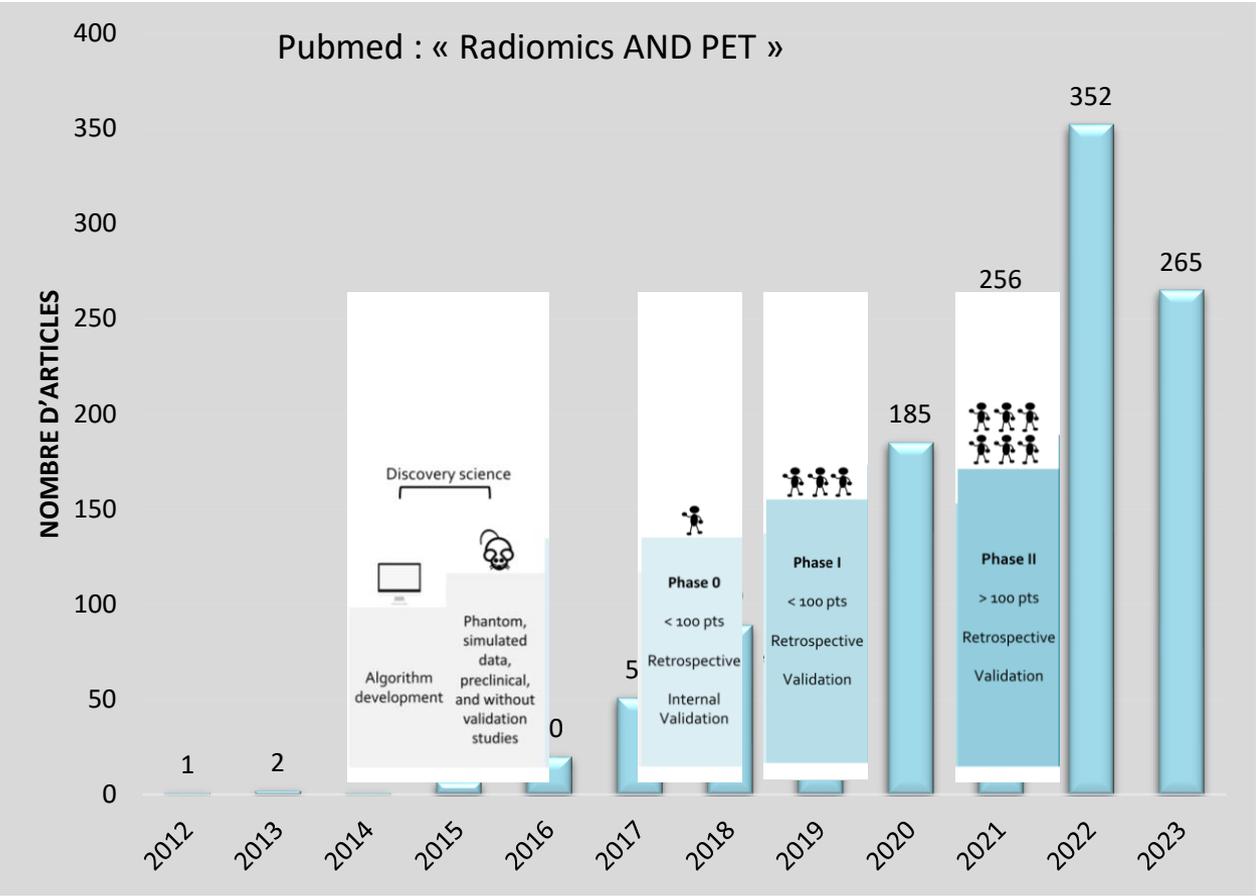
Radiomique : définition & historique



...

[Sollini et al. *Eur J Nucl Med Mol Imaging* 2019]

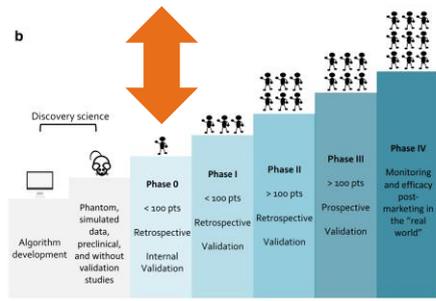
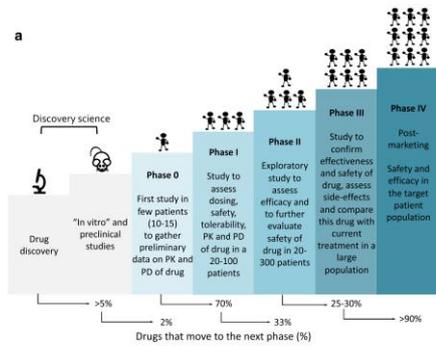
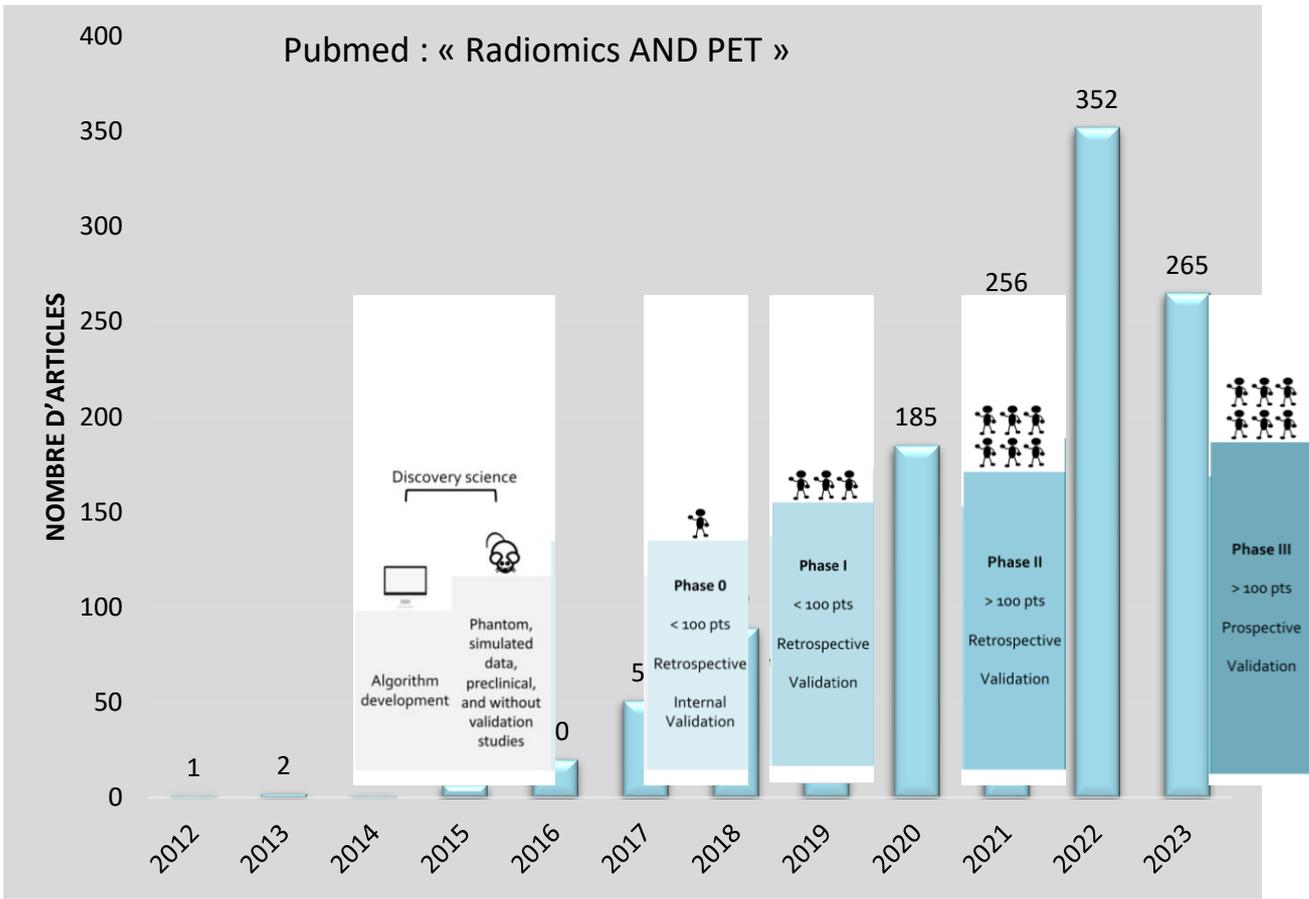
Radiomique : définition & historique



...

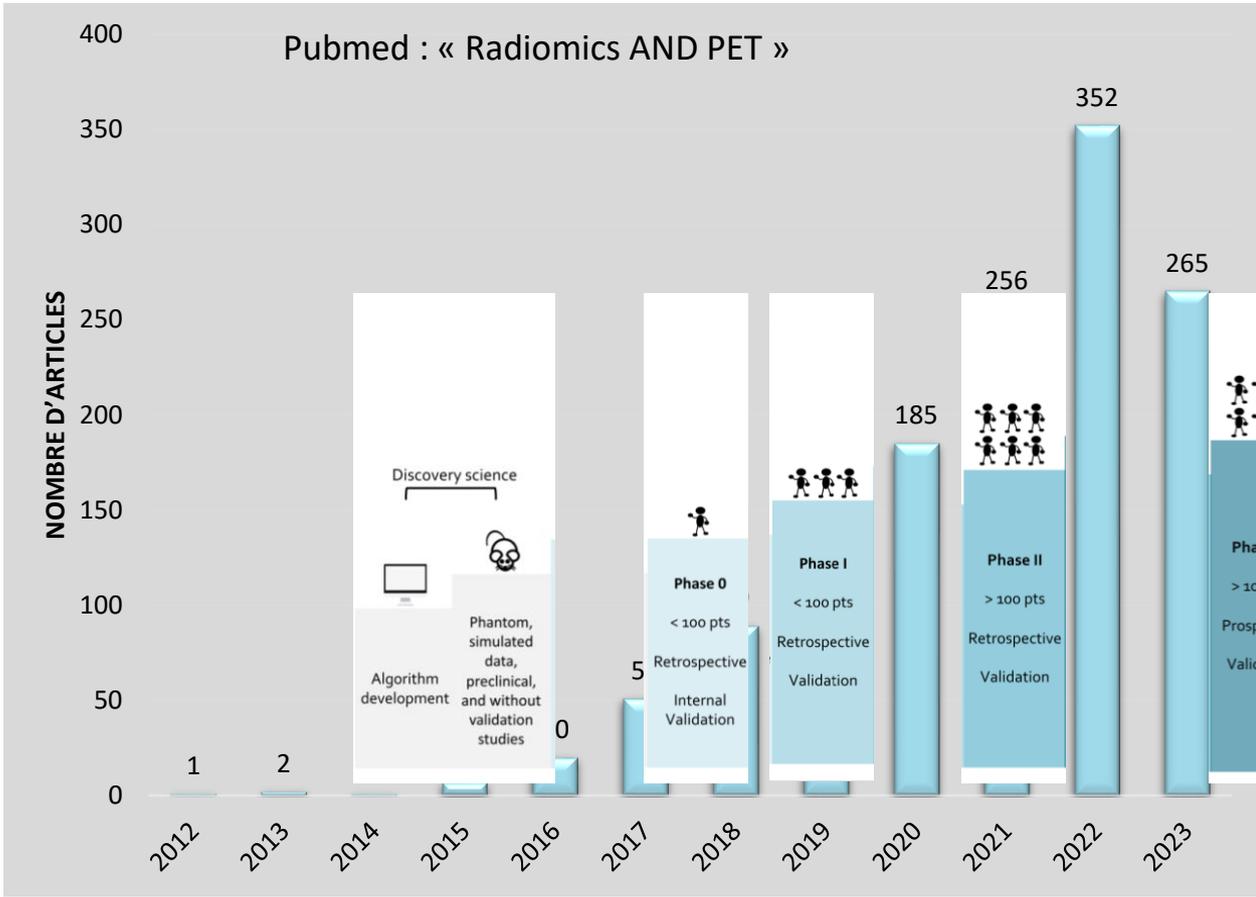
[Sollini et al. *Eur J Nucl Med Mol Imaging* 2019]

Radiomique : définition & historique

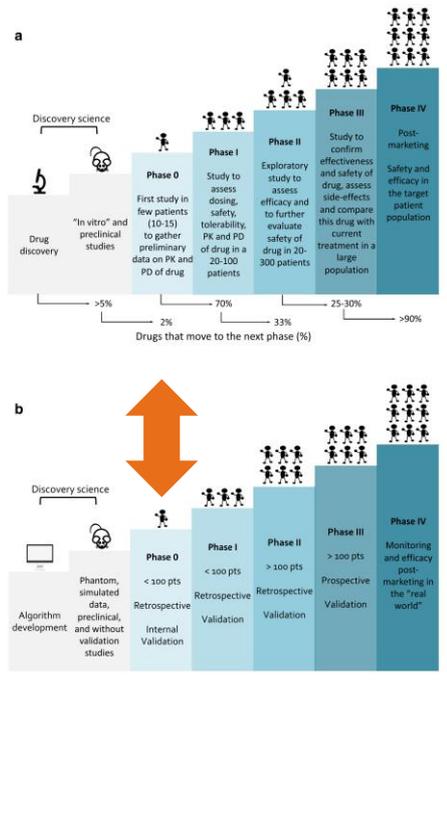


[Sollini et al. Eur J Nucl Med Mol Imaging 2019]

Radiomique : définition & historique



...



[Sollini et al. *Eur J Nucl Med Mol Imaging* 2019]



Quelques résultats...



Capturer des caractéristiques invisibles à l'œil nu



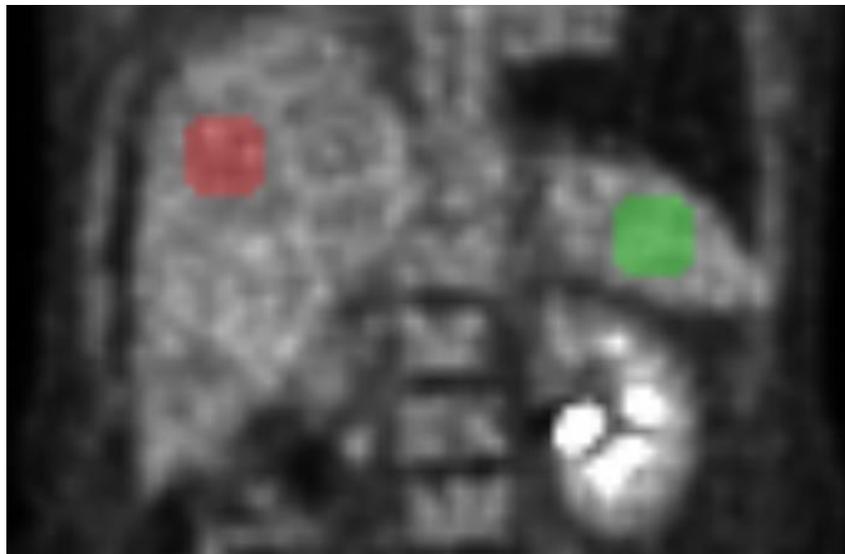
Prédire la réponse aux traitements, la survie, le risque de rechute ...



Formuler de nouvelles hypothèses



Activités métaboliques hépatiques et spléniques



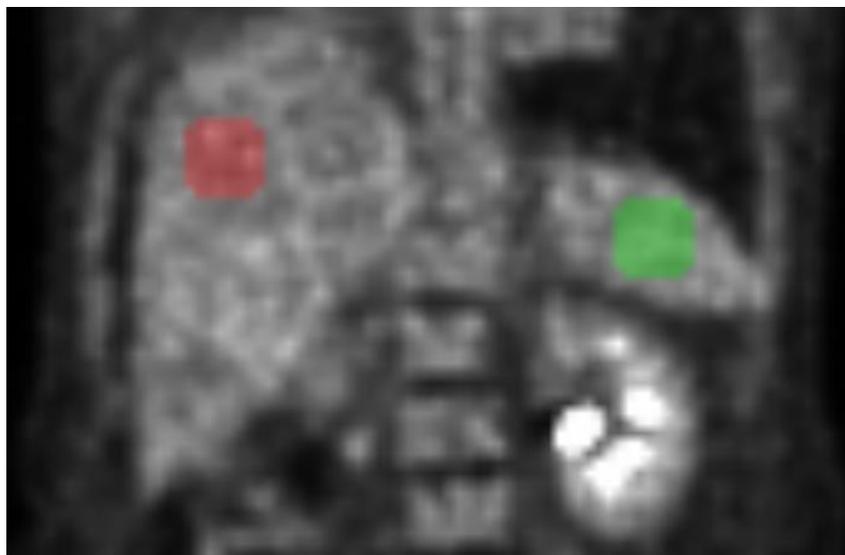
Différence de SUVmean $\leq 0,05$ SUV
Différence de SUVmax $\leq 0,05$ SUV
Régions de volume identique : 23 mL

p-value (apparié)	Foie vs Rate
Nb paires	76
SUVmean	0.059
SUVmax	0.756
Homogeneity	
Entropy	
SRE	
LRE	
LGZE	
HGZE	



Capturer des caractéristiques invisibles à l'œil nu

Activités métaboliques hépatiques et spléniques



Différence de SUVmean $\leq 0,05$ SUV
Différence de SUVmax $\leq 0,05$ SUV
Régions de volume identique : 23 mL

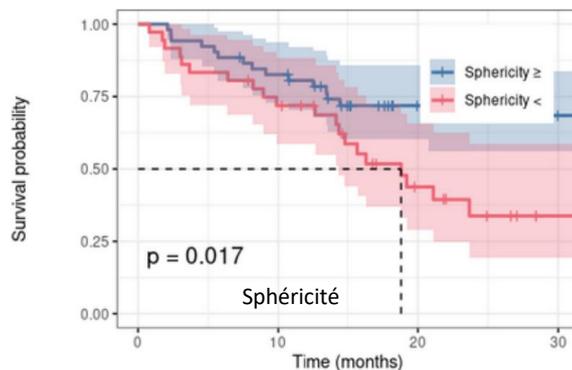
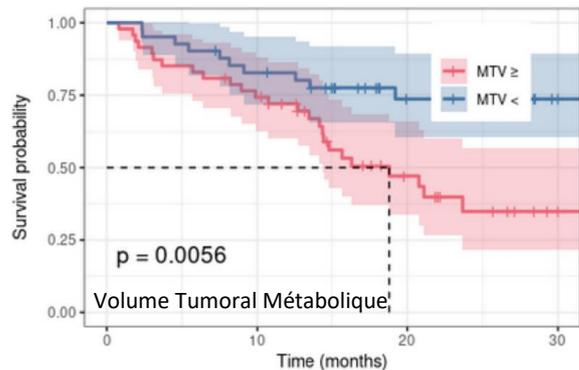
p-value (apparié)	Foie vs Rate
Nb paires	76
SUVmean	0.059
SUVmax	0.756
Homogeneity	1.70E-08
Entropy	6.89E-10
SRE	2.23E-09
LRE	1.05E-07
LGZE	7.11E-11
HGZE	5.04E-07

[Orlhac et al. *SNMMI* 2017]



Modèles de prédiction

- Biomarqueurs déjà identifiés en TEP :



Cancer pulmonaire métastatique



Immuno-chimiothérapie



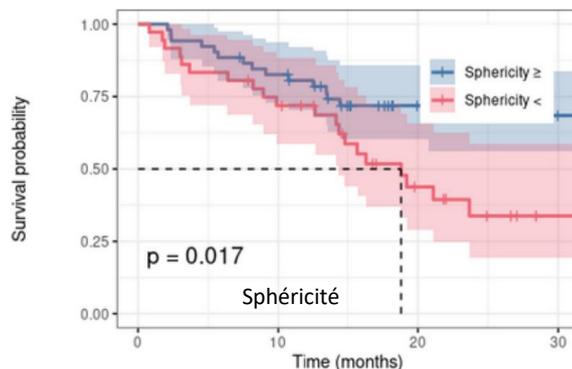
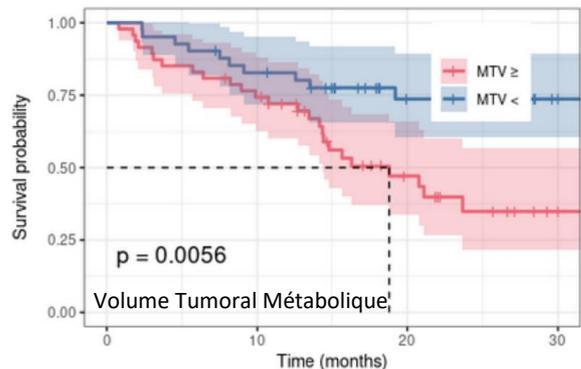
Survie globale

[Hovhannisyan et al. *J Nucl Med*, en révision]

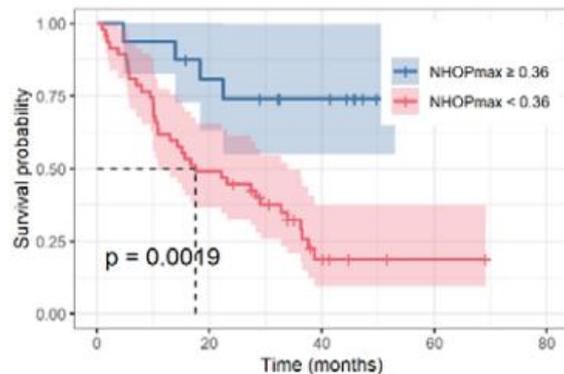
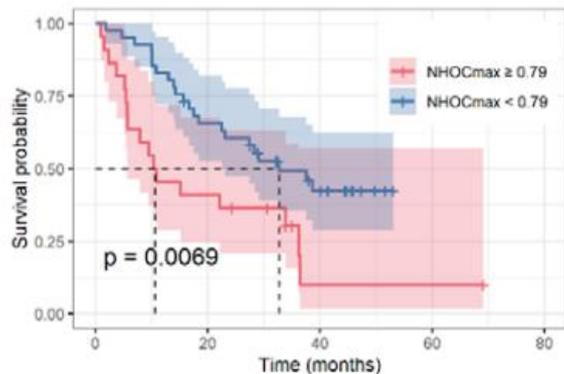


Modèles de prédiction

- Biomarqueurs déjà identifiés en TEP :



- Nouveaux biomarqueurs pronostiques en TEP :



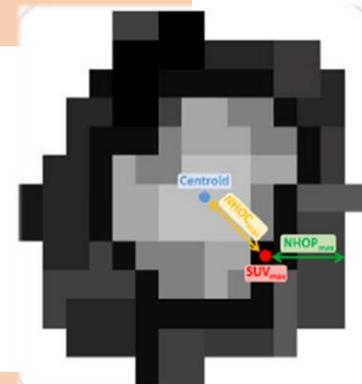
Cancer pulmonaire métastatique



Immuno-chimiothérapie



Survie globale



Cancer pulmonaire métastatique



Immunothérapie



Survie globale

[Hovhannisyan et al. *J Nucl Med*, en révision]

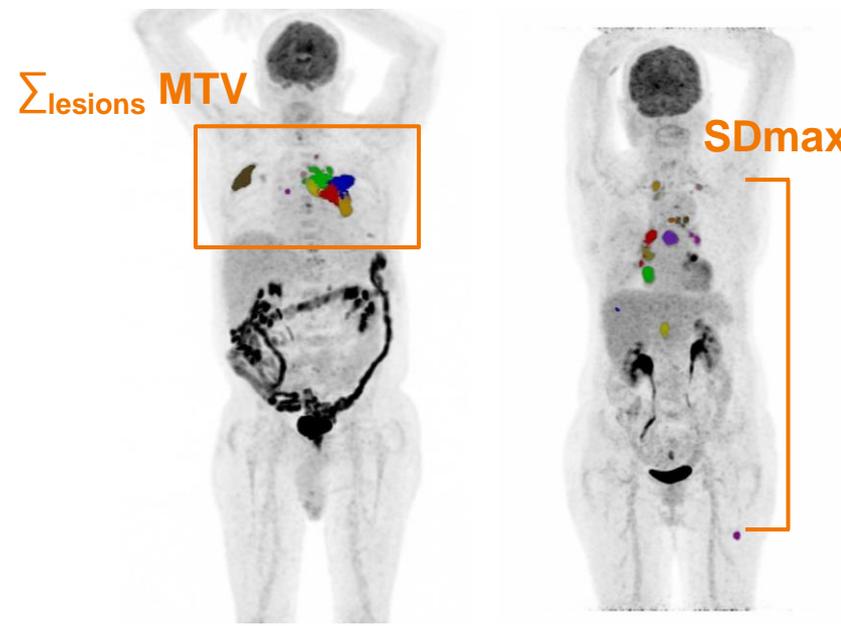
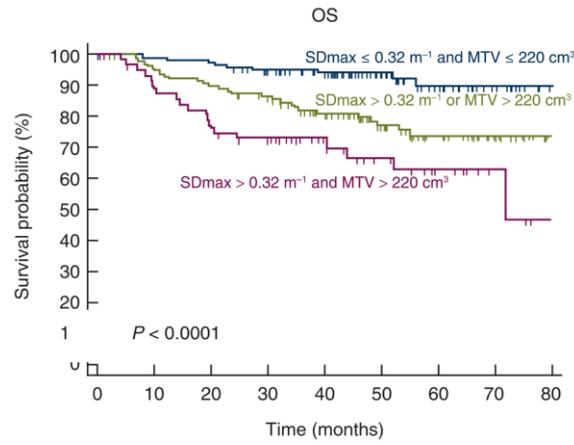
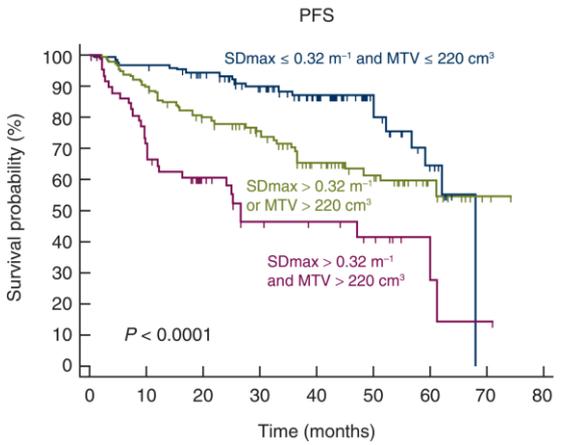


Modèles de prédiction



Lymphome diffus à grandes cellules B

Survie sans progression ou globale



[Cottreau et al. *J Nucl Med* 2020]
 [Cottreau et al. *Ann Oncol* 2021]

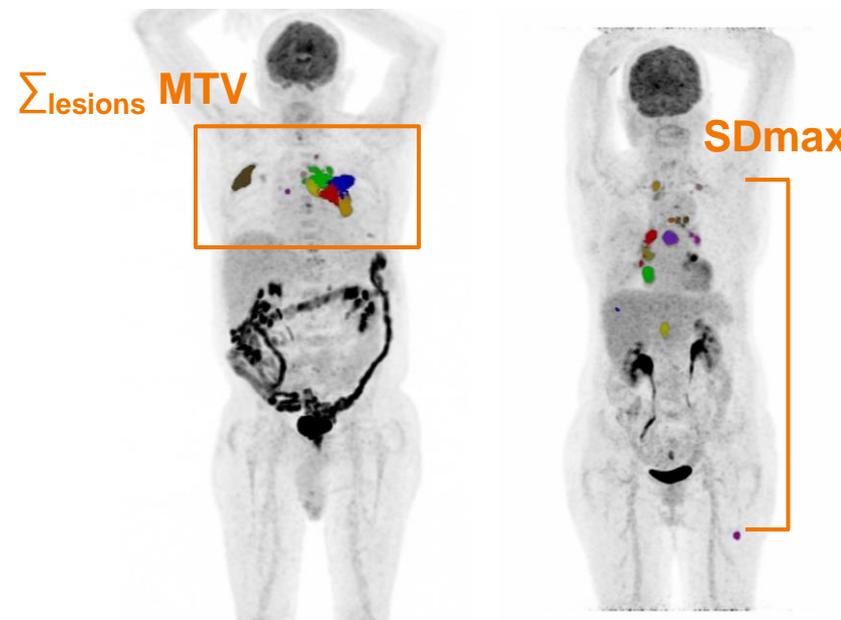
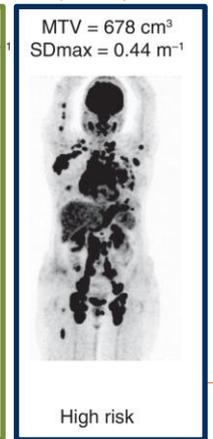
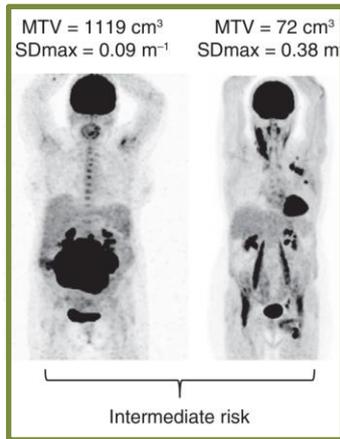
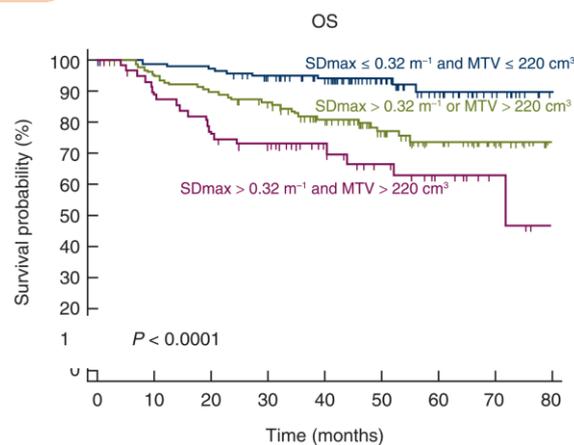
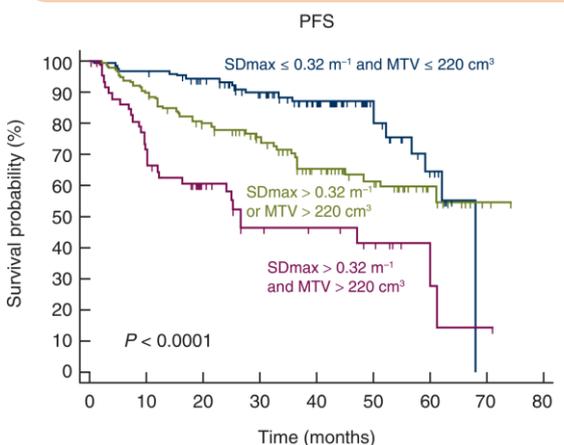


Modèles de prédiction



Lymphome diffus à grandes cellules B

Survie sans progression ou globale



[Cottreau et al. *J Nucl Med* 2020]
[Cottreau et al. *Ann Oncol* 2021]



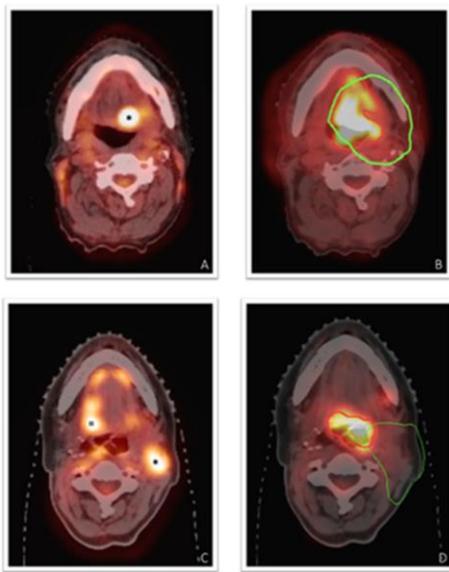
Modèles de prédiction



Cancer ORL réirradié



Risque de rechute post-réirradiation



in-field

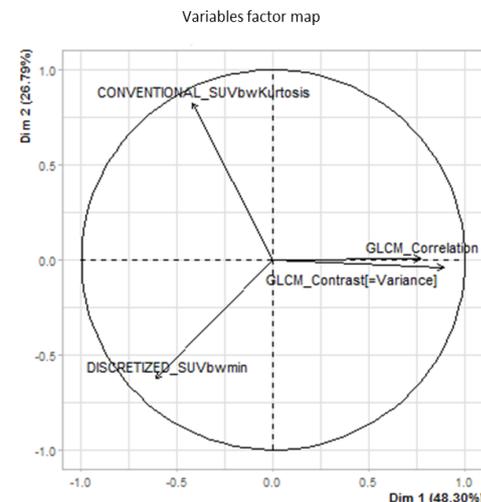
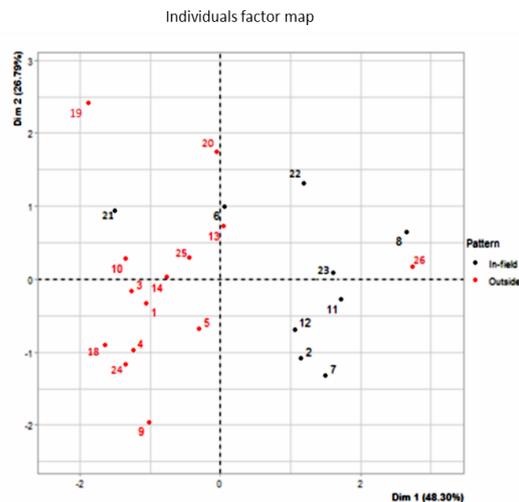
outside

Signature à 4 index :

GLCM_Contrast, GLCM_Correlation, Kurtosis, SUVmin

LOO : **bAcc = 85%** (Se = 77%, Sp = 92%)

AUC(ROC) = 0.84 (95% CI = [0.63-1])



→ Validation externe de la signature : **bAcc = 79%**
Massachusetts General hospital, Boston – 27 patients

[Beddok et al. *Eur J Nucl Med Mol Imaging* 2023]

[Beddok et al. *J Clin Oncol*, en révision]



Modèles de prédiction

- Combinaison de données de différentes sources : Radiomique + Génomique





Modèles de prédiction



- Combinaison de données de différentes sources : Radiomique + Génomique



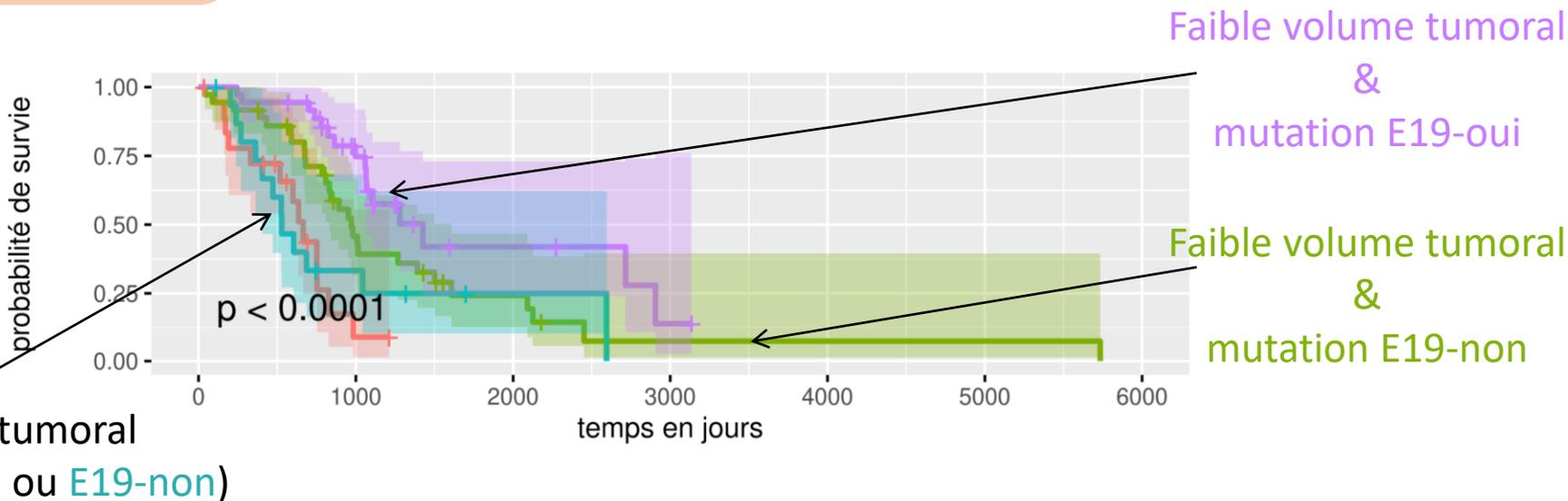
Cancer pulmonaire muté EGFR



Inhibiteur de tyrosine kinase (ITK)



Survie globale



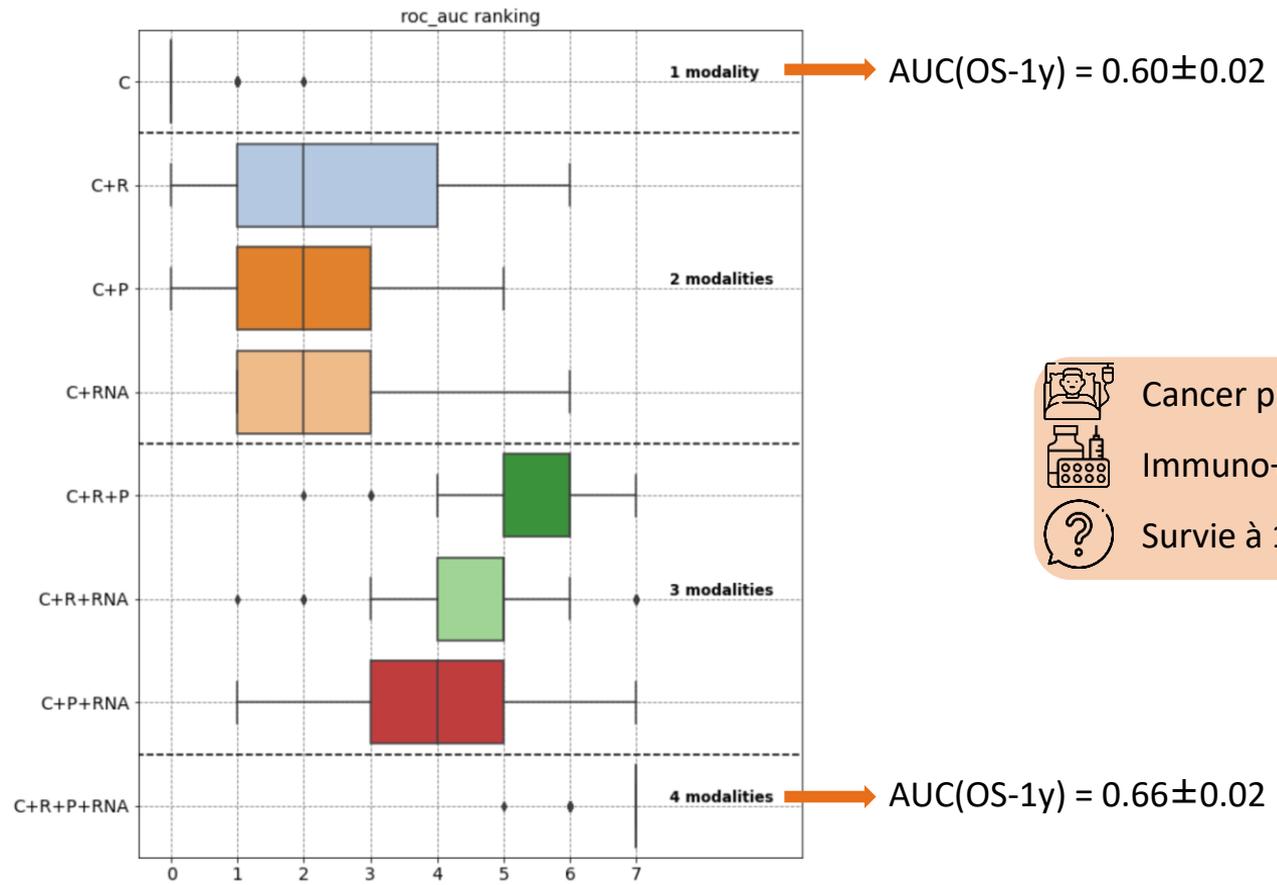


Modèles de prédiction



- Combinaison de données de différentes sources :

C : Clinique
 R : Radiomique
 P : Pathomique
 RNA : Génomique



Cancer pulmonaire métastatique
 Immuno+/-chimiothérapie
 Survie à 1 an

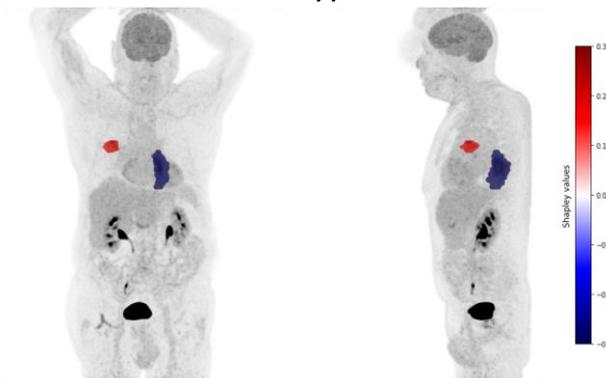
[Captier et al. *ARC Sign'it* 2023]

Formuler de nouvelles hypothèses

Quel est le sous-type de cancer ?

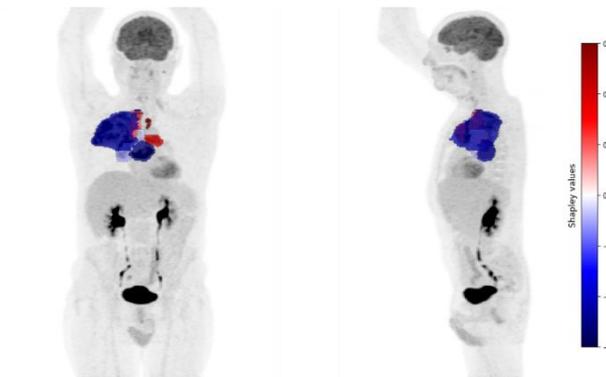
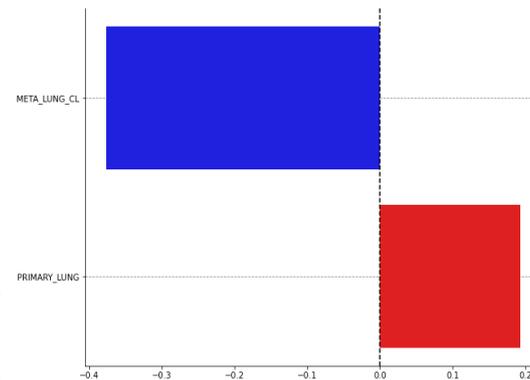
Quelles lésions contribuent le plus à une classification correcte ?

Label : autre sous-type

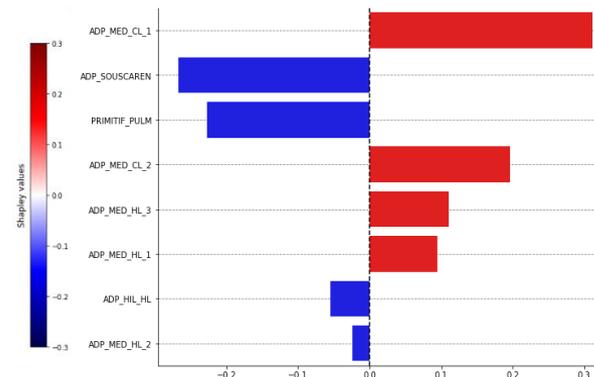


Autre sous-type

Adénocarcinome



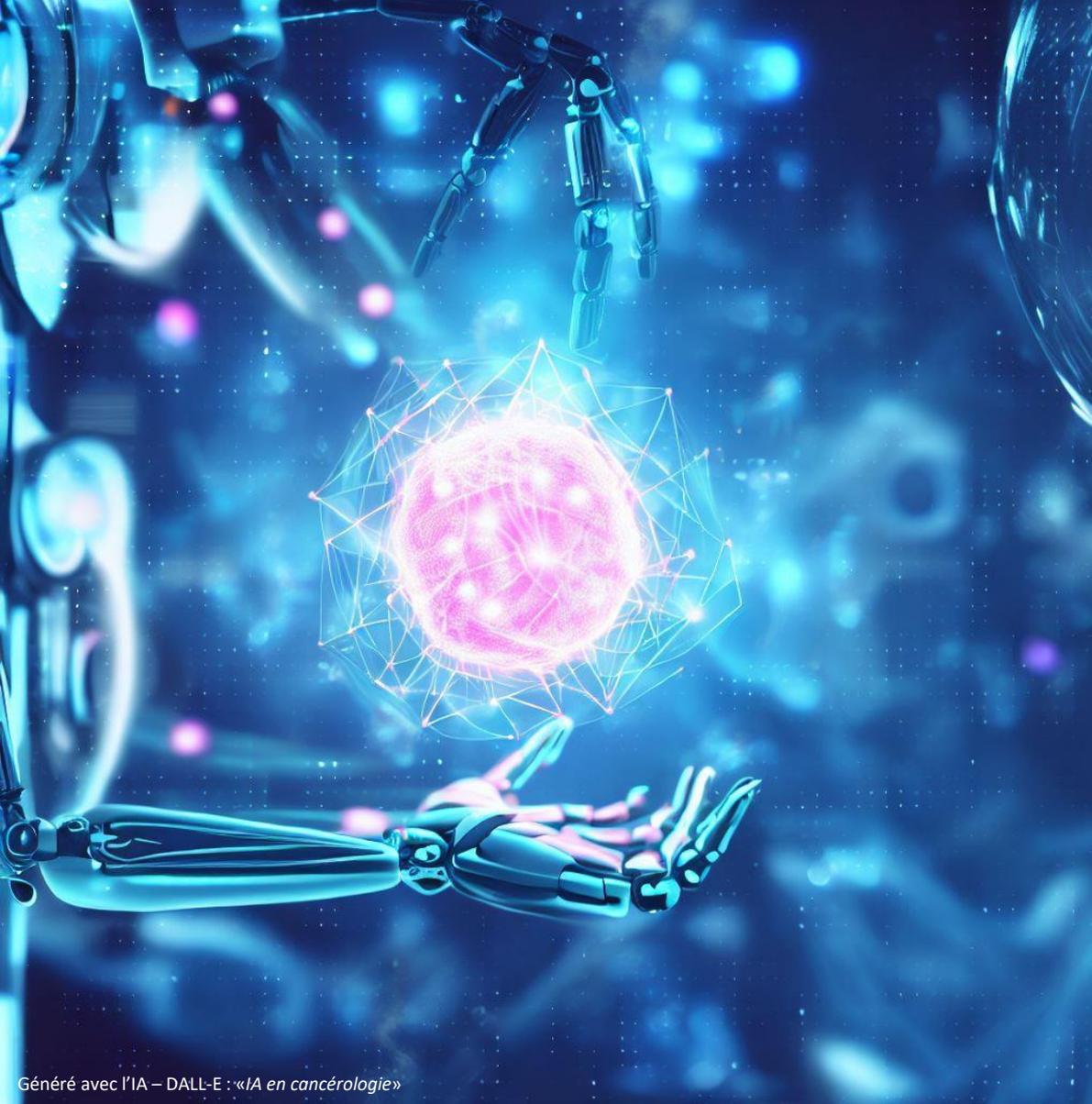
Label : adénocarcinome



[Captier et al. *Radiology: AI*, soumis]

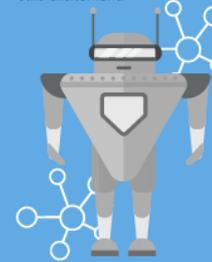
IA ?

Deep learning ?



ARTIFICIAL INTELLIGENCE

Early artificial intelligence stirs excitement.



MACHINE LEARNING

Machine learning begins to flourish.



DEEP LEARNING

Deep learning breakthroughs drive AI boom.



1950's 1960's 1970's 1980's 1990's 2000's 2010's

Since an early flush of optimism in the 1950's, smaller subsets of artificial intelligence - first machine learning, then deep learning, a subset of machine learning - have created ever larger disruptions.



Améliorer la reconstruction d'images

Diminuer le temps d'acquisition

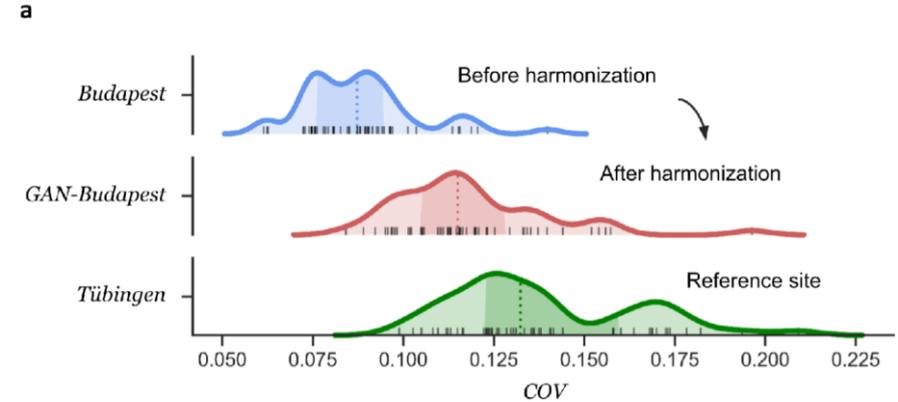
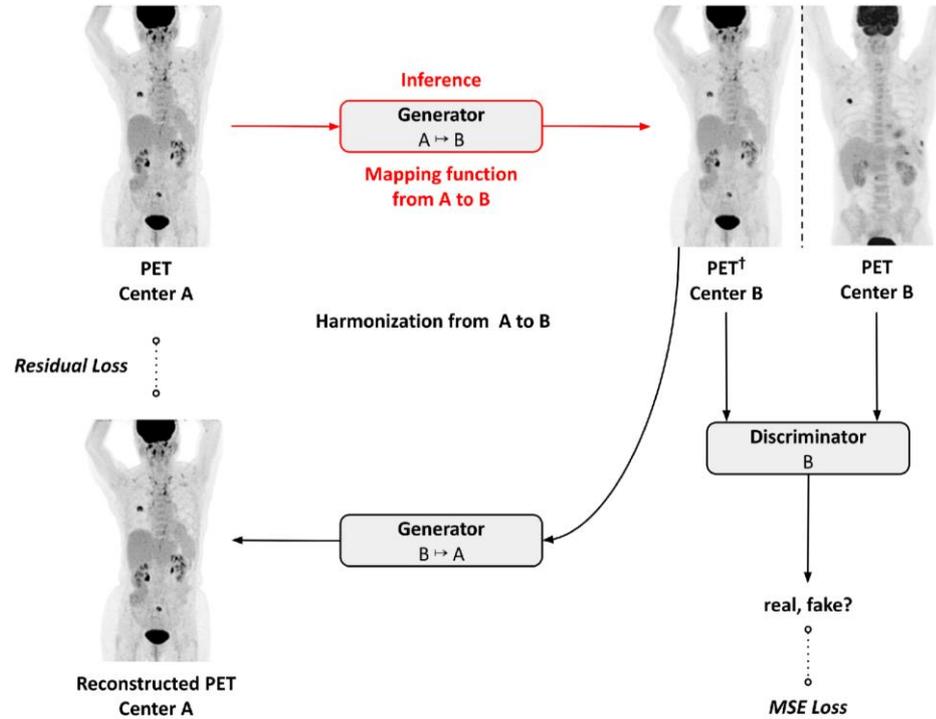
Réduire la dose

...

Cf. présentation de David Sarrut



Harmoniser les qualités d'images



[Haberl et al. *Radiology: AI*, en révision]



Standardiser des comptes rendus

Q1, Dr. Weber: Hello. Could you please write a PET/CT report for a patient with suspected lung cancer? The scan shows a hypermetabolic mass in the right upper lobe and hypermetabolic lymph nodes in the right hilar and left lower paratracheal region. Please include the TNM stage.



Wolfgang Weber,
MD, PhD



Standardiser des comptes rendus

Q1, Dr. Weber: Hello. Could you please write a PET/CT report for a patient with suspected lung cancer? The scan shows a hypermetabolic mass in the right upper lobe and hypermetabolic lymph nodes in the right hilar and left lower paratracheal region. Please include the TNM stage.



Wolfgang Weber,
MD, PhD

Commentary, Drs. Buvat and Weber: This quite impressive response was given within a few seconds! ChatGPT uses the typical language of radiology reports and provides SUV_{max} values that are consistent with high metabolic activity. It also gets the TNM stage almost right. It interprets the left paratracheal nodes as “contralateral mediastinal nodes” and assigns the correct N2 stage. Interestingly, it uses the slightly outdated 7th edition of lung cancer TNM staging, which defines T3 as a tumor with a diameter of >7 cm. The current 8th edition defines T3 by a tumor diameter between 5 and 7 cm.

ChatGPT:

Patient: [Patient Name] Date of Exam: [Date].

Indication: Evaluation of suspected lung cancer.

Technique: Whole body PET/CT scan was performed with the administration of [dose] of FDG.

Findings:

- 1. Hypermetabolic mass is identified in the right upper lobe (SUV max 8.2) with an associated spiculated margin, consistent with a primary lung malignancy.
- 2. Hypermetabolic lymph nodes are identified in the right hilar (SUV max 6.5) and left lower paratracheal (SUV max 6.7) regions, consistent with nodal involvement by lung cancer.
- 3. CT scan of the chest also confirms the above-mentioned findings and also shows no evidence of distant metastasis.

TNM stage: T3N2M0 (The tumor is located in the right upper lobe, it is larger than 7cm and there is nodal involvement in the right hilar and left lower paratracheal region, no evidence of distant metastasis).

Impression: Hypermetabolic mass in the right upper lobe with associated spiculated margin and hypermetabolic lymph nodes in the right hilar and left lower paratracheal region consistent with lung cancer. Recommend further workup and histopathological correlation, including biopsy of the primary tumor and involved lymph nodes.





Répondre aux questions des patients



ChatGPT responses to 25 questions about [¹⁸F]FDG-PET/CT and PET/CT reports were ...

- ✓ **appropriate** (92% of items)
- ✓ **helpful** (96% of items)
- ... but some were inconsistent (16%)

ChatGPT could substitute advice given to patients by nuclear medicine staff about [¹⁸F]FDG-PET/CT.

TABLE 2
All 25 Tasks Submitted to ChatGPT and Majority Rating

Question/report	Description	Appropriate	Helpful	Inconsistent
Q1	How long does a PET scan take?	1	1	2
Q2	Is a PET scan harmful?	1	1	1
Q3	How should I prepare for a PET scan?	1	1	2
Q4	I'm a caregiver to a toddler. Are there any precautionary measures after a PET scan?	3*	3*	3*
Q5	Can I take a PET scan as a diabetic?	1	1	1
Q6	Is a PET scan recommended for lung cancer before surgery?	2	2	2
Q7	Why is a PET scan needed for Hodgkin lymphoma?	1	1	1
Q8	How accurate is a PET scan for lung cancer?	1	2	1
Q9	Is a PET scan better than a CT scan for lung cancer?	2	1	1
Q10	Does negative on PET mean that a lung nodule is benign?	2	1	1
Q11	Does a hypermetabolic lung nodule on PET mean that I have lung cancer?	1	1	1
Q12	My PET scan showed a hypermetabolic lung nodule. Should I have it removed?	1	1	2
Q13	What does "Deauville 5" mean in a PET report?	1	1	1
R1	Hodgkin lymphoma: initial staging	1	1	2
R1Q1	What's my lymphoma stage?	3*	2	3*
R2	Hodgkin lymphoma: response assessment	1	1	2
R3	NSCLC: initial staging (early stage)	1	1	1
R3Q1	How should my lung cancer be treated?	2	2	3*
R4	NSCLC: initial staging (locally advanced)	1	1	1
R4Q1	What's my cancer stage?	2	1	3*
R4Q2	How should my lung cancer be treated?	1	2	2
R5	NSCLC: initial staging (stage IV)	1	1	1
R5Q1	What's my life expectancy?	1	1	2
R6	Solitary pulmonary nodule (PET-negative)	1	1	1
R6Q1	Should the lung nodule be removed?	1	1	1

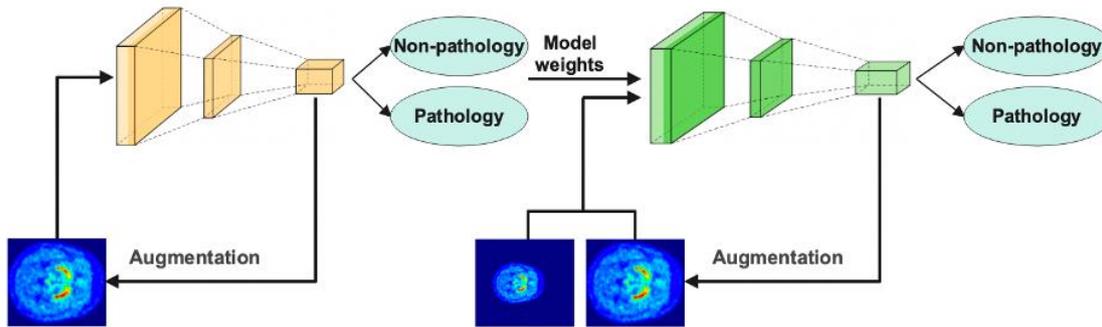
*Negative rating (category 3 or 4).
Inconsistent = only 1 rater.

Rating categories are explained in Table 1. In 5 of 6 PET/CT reports, follow-up questions were raised.



Classifier automatiquement les images

Exemple : *identification du syndrome parkinsonien à partir des images TEP à la 18F-FDopa*

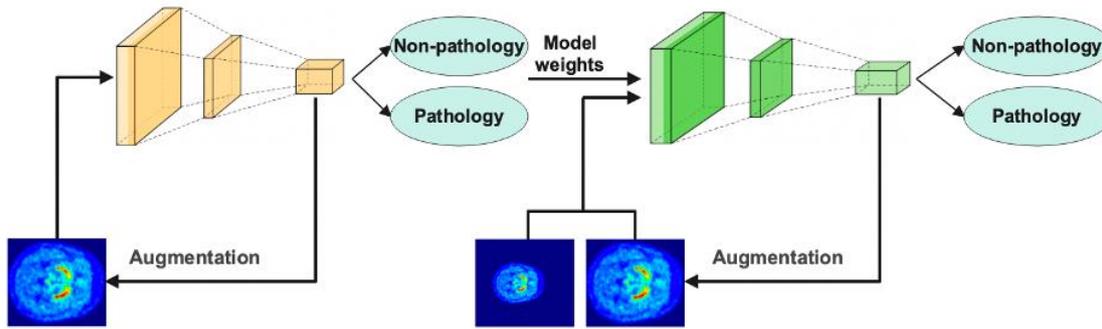


	3D-CNN model		
	bAcc (%)	Spe (%)	Sen (%)
Validation set C_1 (5-folds) Mean \pm std 417 pts	92.0 \pm 1.8	95.4 \pm 2.9	88.6 \pm 4.2
Internal test set C_2 - 100 pts	99.2	98.4 (60/61)	100 (39/39)



Classifier automatiquement les images

Exemple : *identification du syndrome parkinsonien à partir des images TEP à la 18F-FDopa*



	3D-CNN model		
	bAcc (%)	Spe (%)	Sen (%)
Validation set C_1 (5-folds) Mean \pm std 417 pts	92.0 \pm 1.8	95.4 \pm 2.9	88.6 \pm 4.2
Internal test set C_2 - 100 pts	99.2	98.4 (60/61)	100 (39/39)

→ Hôpital non-expert – 170 patients : modèle 3D-CNN a permis de reclassifier correctement 10 patients par rapport au diagnostic initial du médecin nucléaire





Identifier des lésions & segmenter

Set d'entraînement/validation : **287 patients**
Set de test : 95 patients

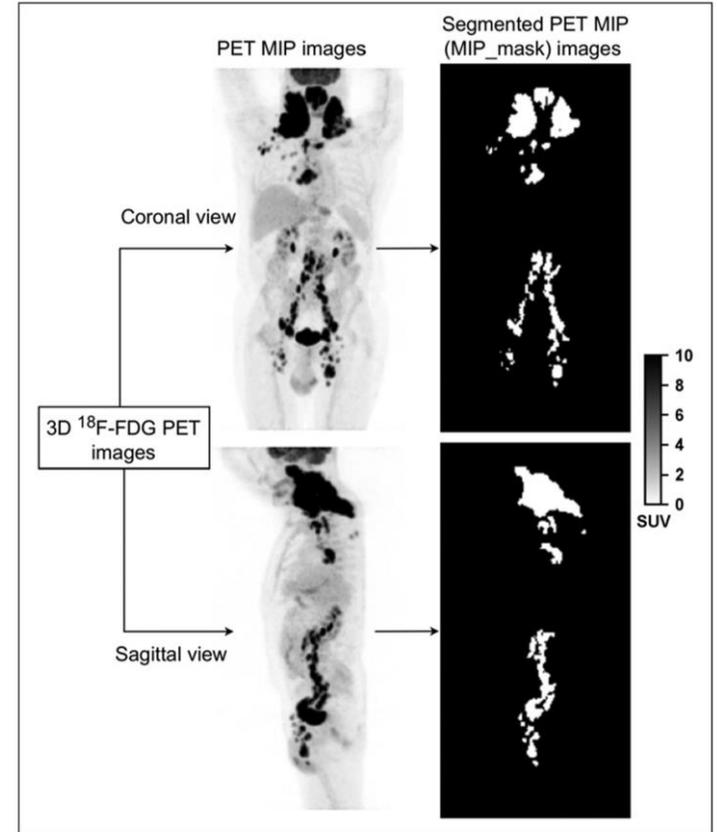
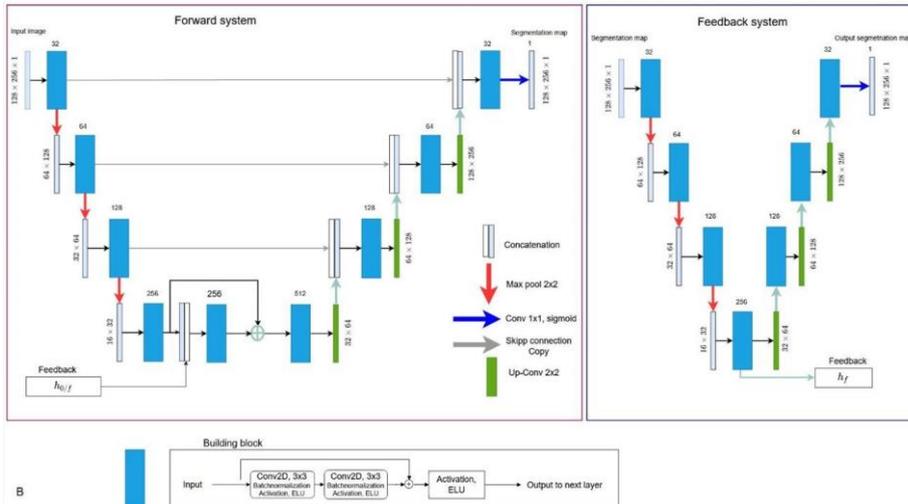


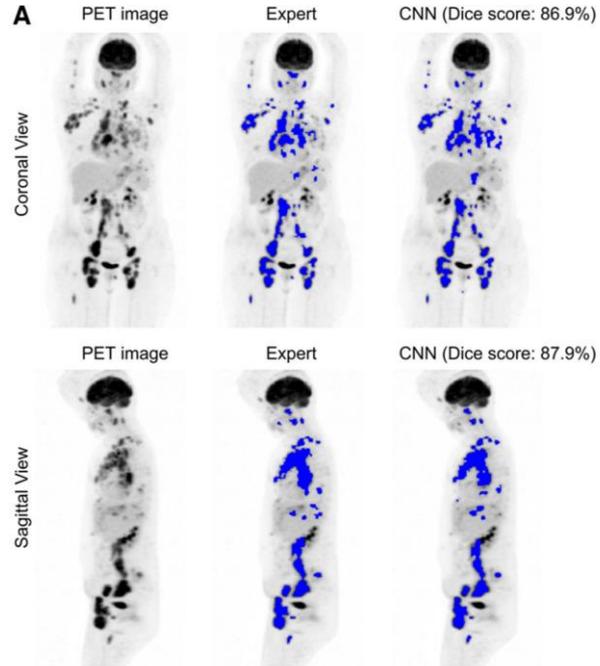
FIGURE 2. Example of ^{18}F -FDG PET MIP images (left) and associated lymphoma regions (right) based on expert delineation of the 3D ^{18}F -FDG PET images.

[Girum et al. *J Nucl Med* 2022]

Deep learning/apprentissage profond pour...



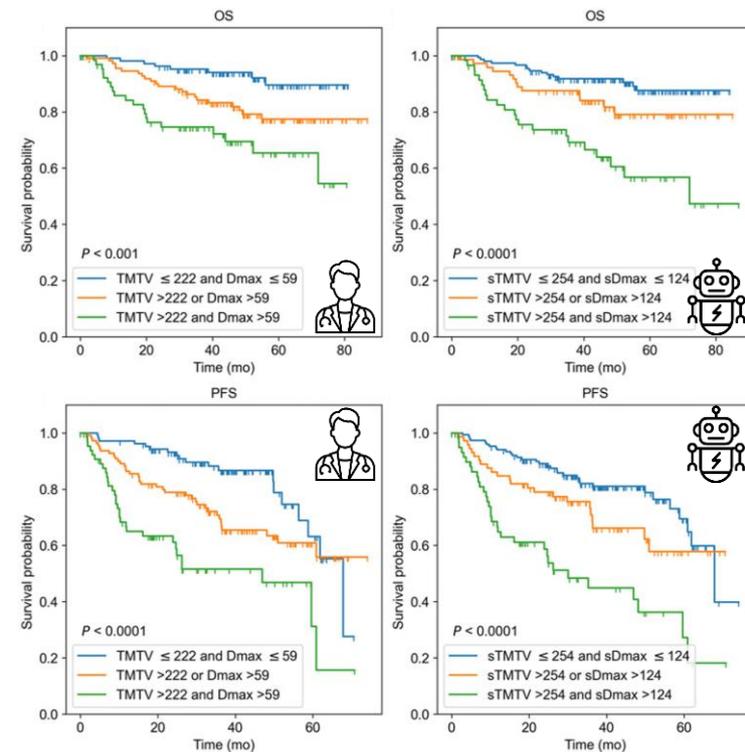
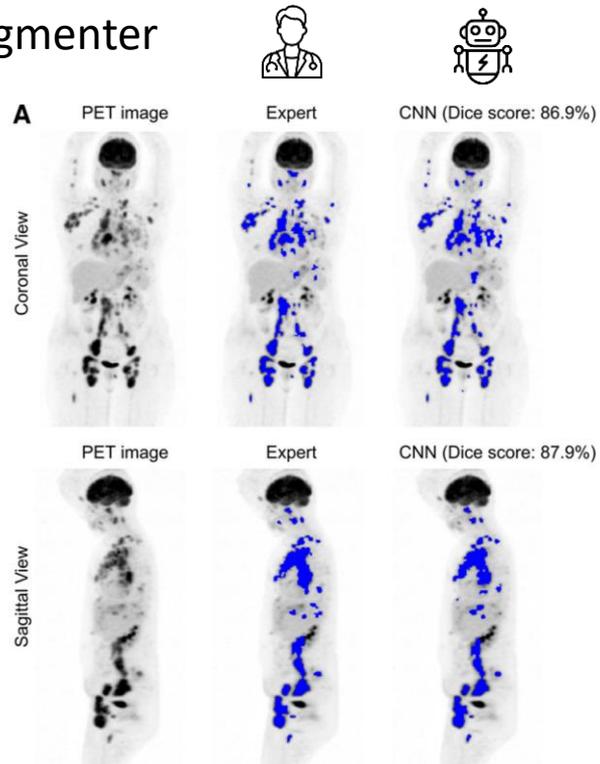
Identifier des lésions & segmenter



[Girum et al. *J Nucl Med* 2022]



Identifier des lésions & segmenter



→ Calcul automatique de biomarqueurs de la masse tumorale et de la dispersion aussi informatifs que ceux des experts

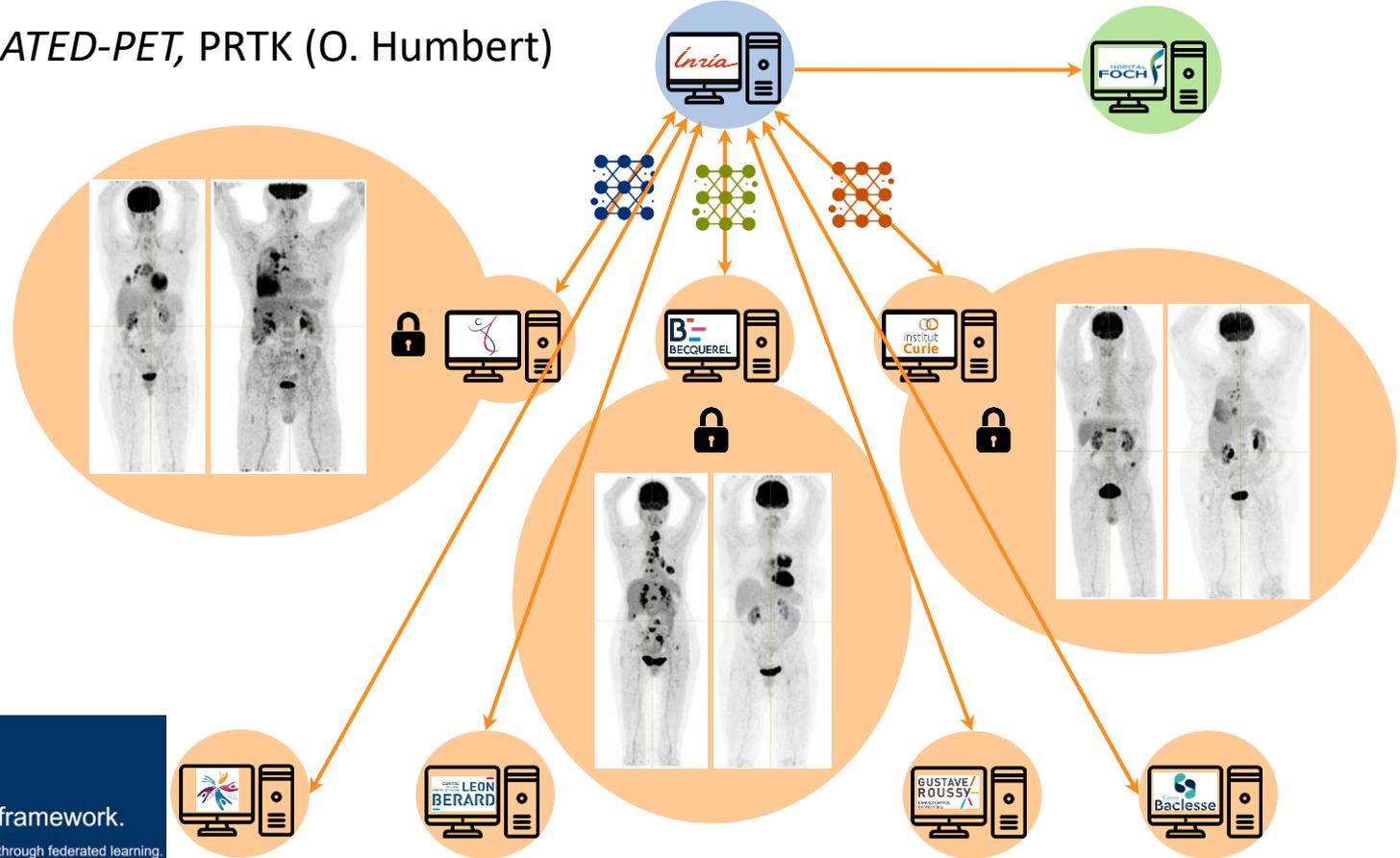


[Girum et al. *J Nucl Med* 2022]

Deep learning/apprentissage profond pour...

Apprendre sur de grands jeux de données : apprentissage fédéré

Exemple : *projet FEDERATED-PET, PRTK* (O. Humbert)



Inria



Fed-BioMed

An open-source federated learning framework.

Open source project focused on empowering biomedical research through federated learning.

LITO

Les défis



Algorithmes spécifiques pour chaque tâche



Dépendance aux données d'entraînement (patients & images)



Manque de validations externes ET indépendantes



Les défis



Algorithmes spécifiques pour chaque tâche



Dépendance aux données d'entraînement (patients & images)



Manque de validations externes ET indépendantes

Quelques pistes



Conditions d'utilisation à lister



Mises à jour régulières



Score de confiance



Décryptage de l'algo



Robustesse

Saison des champignons : attention aux applications de reconnaissance sur smartphone

Par Anne-Sophie Tassart le 04.09.2023 à 13h00

🕒 Lecture 3 min.

A cause de l'humidité, la saison des champignons est en avance et les intoxications se multiplient. L'Agence nationale de sécurité sanitaire met en garde contre les applications d'identification, responsables de plusieurs cas en 2022.



Récolte de Cèpes d'été (*Boletus reticulatus*) en Lorraine, France
© ANDRE SIMON / BIODSGARDEN / BIOSPHOTO VIA AFP



Risque élevé d'erreurs

Sauf que leur fiabilité est sérieusement remise en question, à commencer par l'Office national des forêts qui, dans un communiqué publié début octobre, recommande aux chasseurs de champignons de « ne pas faire confiance aux applications sur [leur] téléphone pour identifier les champignons », car elles « se trompent dans la moitié des cas ».

La Dépêche
Évreux

Les défis



Algorithmes spécifiques pour chaque tâche



Dépendance aux données d'entraînement (patients & images)

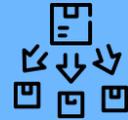


Manque de validations externes **ET** indépendantes

Quelques pistes



Standardisation
des
biomarqueurs



Partage
des outils



[Zwanenburg et al. *Radiology* 2020]

Conclusion



- Extraction automatique/semi-auto de bien plus de caractéristiques des images que les métriques disponibles actuellement
- Littérature : résultats encourageants en Radiomique
- Deep learning/IA : résultats très satisfaisants en segmentation, en classification et prédiction (quand les bases de données sont importantes)... → 2ème lecteur ?



- Extraction automatique/semi-auto de bien plus de caractéristiques des images que les métriques disponibles actuellement
- Littérature : résultats encourageants en Radiomique
- Deep learning/IA : résultats très satisfaisants en segmentation, en classification et prédiction (quand les bases de données sont importantes)... → 2ème lecteur ?



- Manque de validations externes ET indépendantes
- Besoin de mise à disposition des outils/algorithmes +++

Laboratoire d'Imagerie Translationnelle en Oncologie (LITO)

U1288 Inserm/Institut Curie, Orsay-Paris-St Cloud



Julie Auriac

Irène Buvat

Nicolas Captier

Hornella Fokem-Fosso

Kibrom Girum

Narinée Hovhannisyan

Marie Luporsi

Christophe Nioche

...