# AI in Medical Imaging

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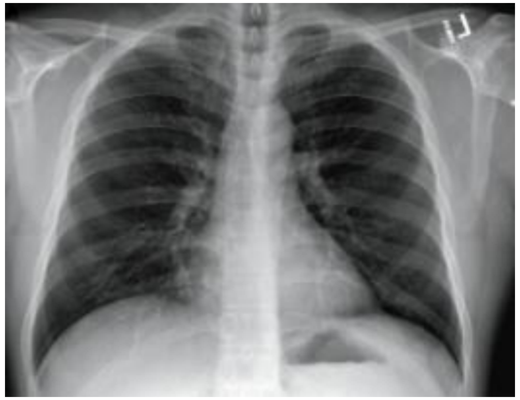
# Outline

- Background: medical imaging
- Applications of AI in Radiology
    - Real-world examples
        - Including my and colleagues' research
- Future Directions and Opportunities

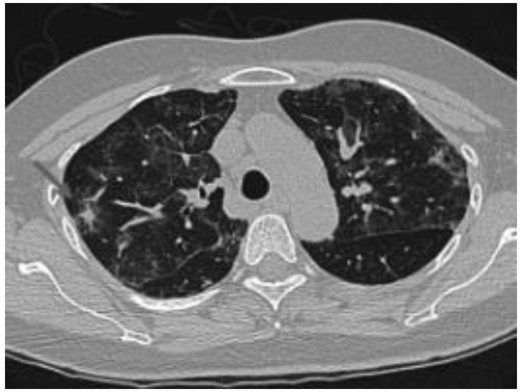
# What is medical imaging?

The process of creating visual representations of the interior of the body for clinical analysis, diagnosis, and treatment planning.

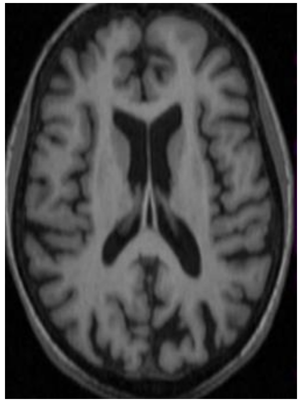
# Medical Imaging



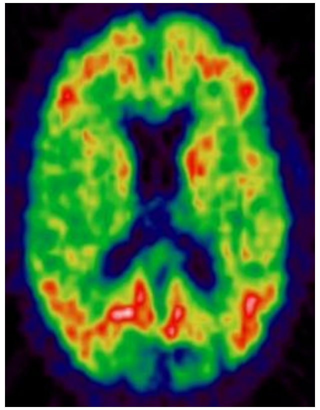
X-ray



CT



MRI



PET

Ultrasound

Medical Imaging has revolutionized healthcare, enabling earlier and more accurate disease detection.

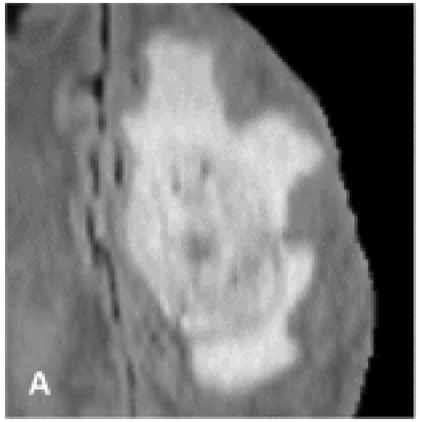
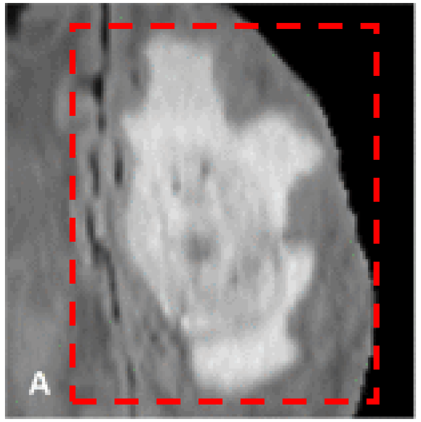
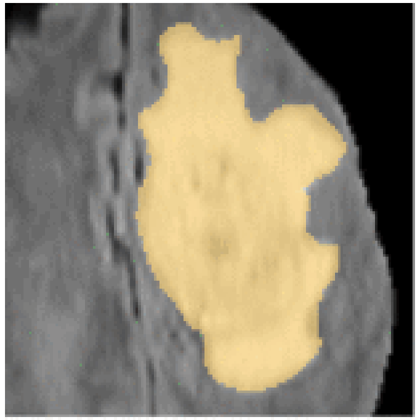
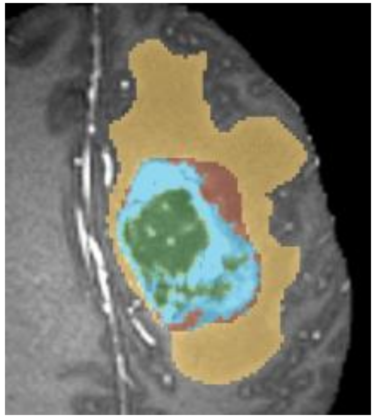
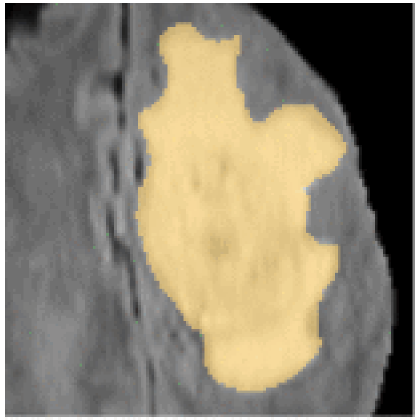
# PET

**Positron Emission Tomography (PET)**

Nuclear medicine imaging technique that provides detailed images of metabolism.


https://www.oklahomapetscan.com/pet-ct-scan/what-is-a-pet-ct-scan.php

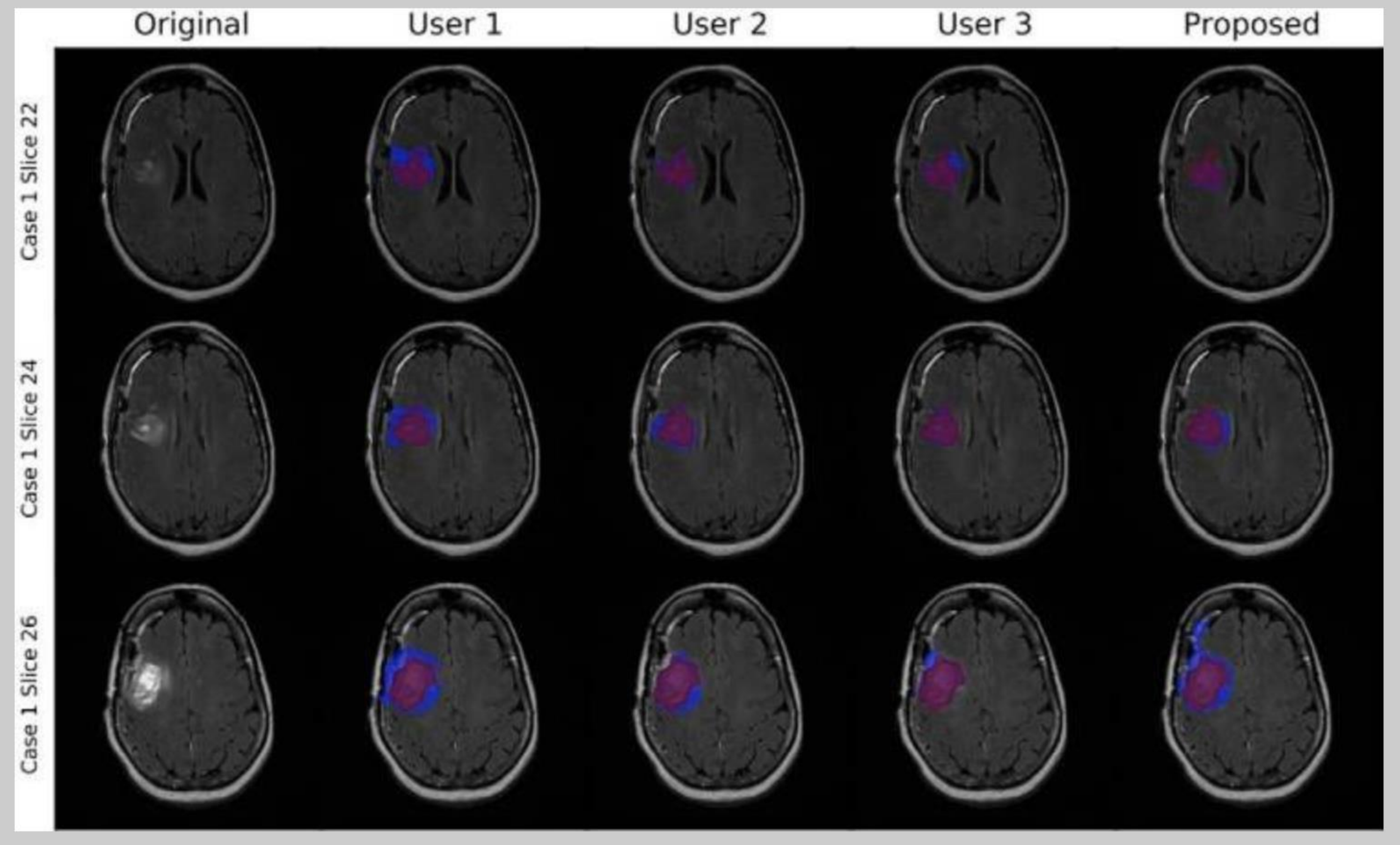
# Data Solves Medical Problems

| Classification | Detection | Segmentation | Segmentation | Regression |
|---|---|---|---|---|
|  |  |  |  |  |
| Brain tumor | | | Further Classification | Tumor volume: 7,255mm$^3$ |

**AI can help!**

Menze et al., IEEE TMI (2014)

# Tumor Segmentation (2016)



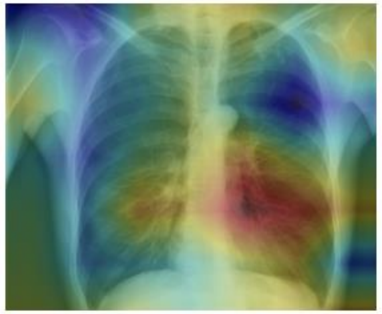

Korfiatis et al., Tomography (2016)

# CheXNet: 121-layer CNN (2017)

**Input**
Chest X-Ray Image

**CheXNet**
121-layer CNN

**Output**
Pneumonia Positive (85%)

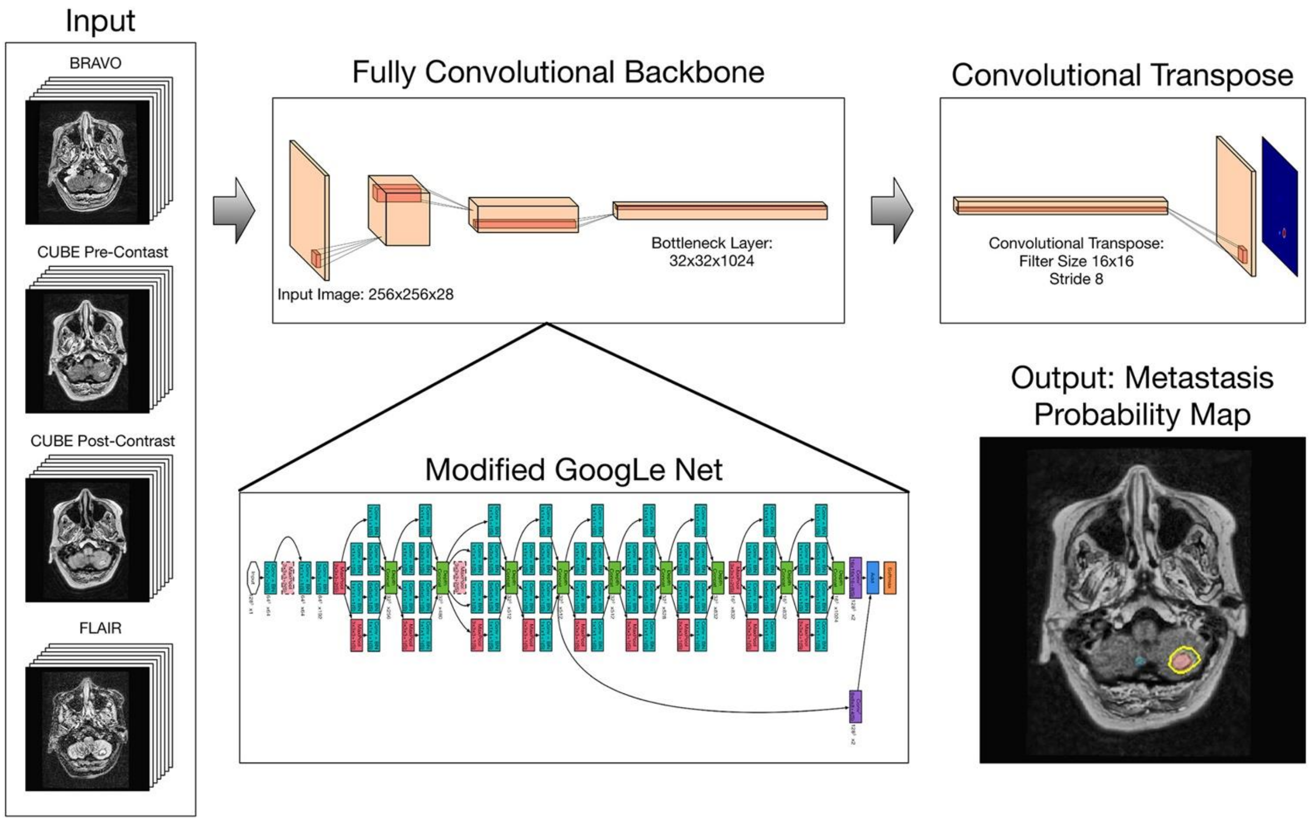


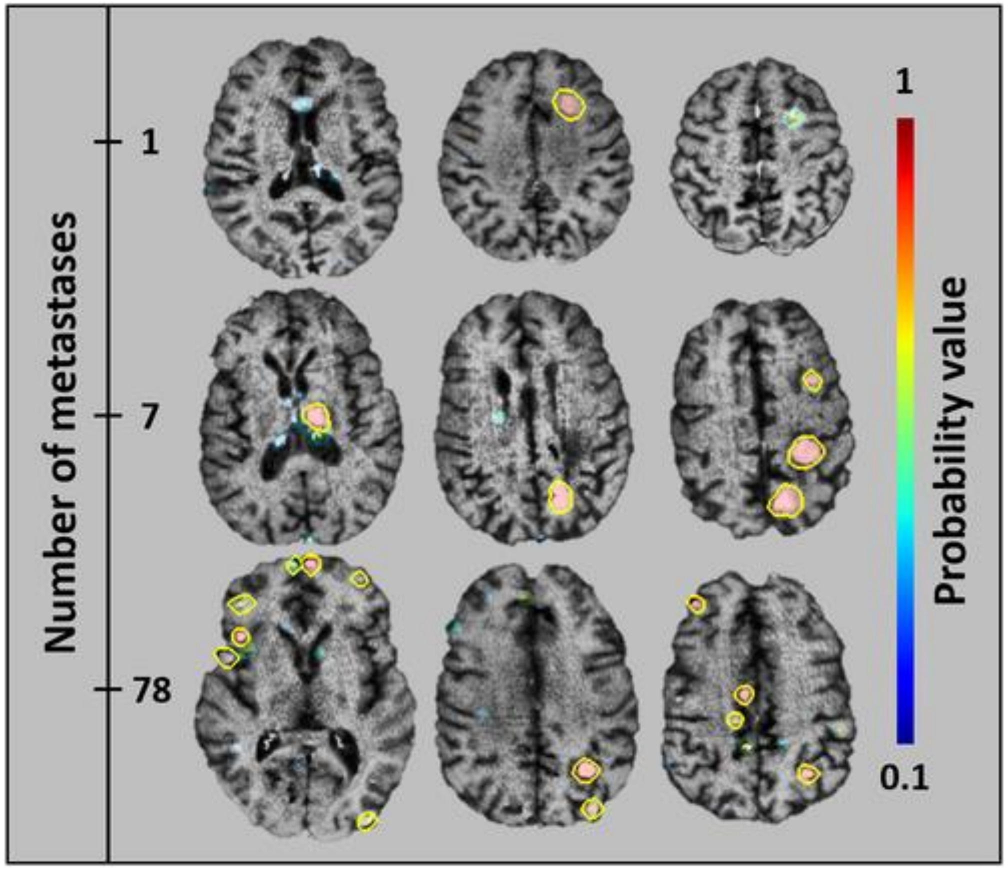
Rajpurkar, Lundgren, Ng et al.

| | F1 Score (95% CI) |
|---|---|
| Radiologist 1 | 0.383 (0.309, 0.453) |
| Radiologist 2 | 0.356 (0.282, 0.428) |
| Radiologist 3 | 0.365 (0.291, 0.435) |
| Radiologist 4 | 0.442 (0.390, 0.492) |
| Radiologist Avg. | 0.387 (0.330, 0.442) |
| CheXNet | 0.435 (0.387, 0.481) |

| Pathology | Wang et al. (2017) | Yao et al. (2017) | CheXNet (ours) |
|---|---|---|---|
| Atelectasis | 0.716 | 0.772 | **0.8094** |
| Cardiomegaly | 0.807 | 0.904 | **0.9248** |
| Effusion | 0.784 | 0.859 | **0.8638** |
| Infiltration | 0.609 | 0.695 | **0.7345** |
| Mass | 0.706 | 0.792 | **0.8676** |
| Nodule | 0.671 | 0.717 | **0.7802** |
| Pneumonia | 0.633 | 0.713 | **0.7680** |
| Pneumothorax | 0.806 | 0.841 | **0.8887** |
| Consolidation | 0.708 | 0.788 | **0.7901** |
| Edema | 0.835 | 0.882 | **0.8878** |
| Emphysema | 0.815 | 0.829 | **0.9371** |
| Fibrosis | 0.769 | 0.767 | **0.8047** |
| Pleural Thickening | 0.708 | 0.765 | **0.8062** |
| Hernia | 0.767 | 0.914 | **0.9164** |

# Brain Metastases (2019)

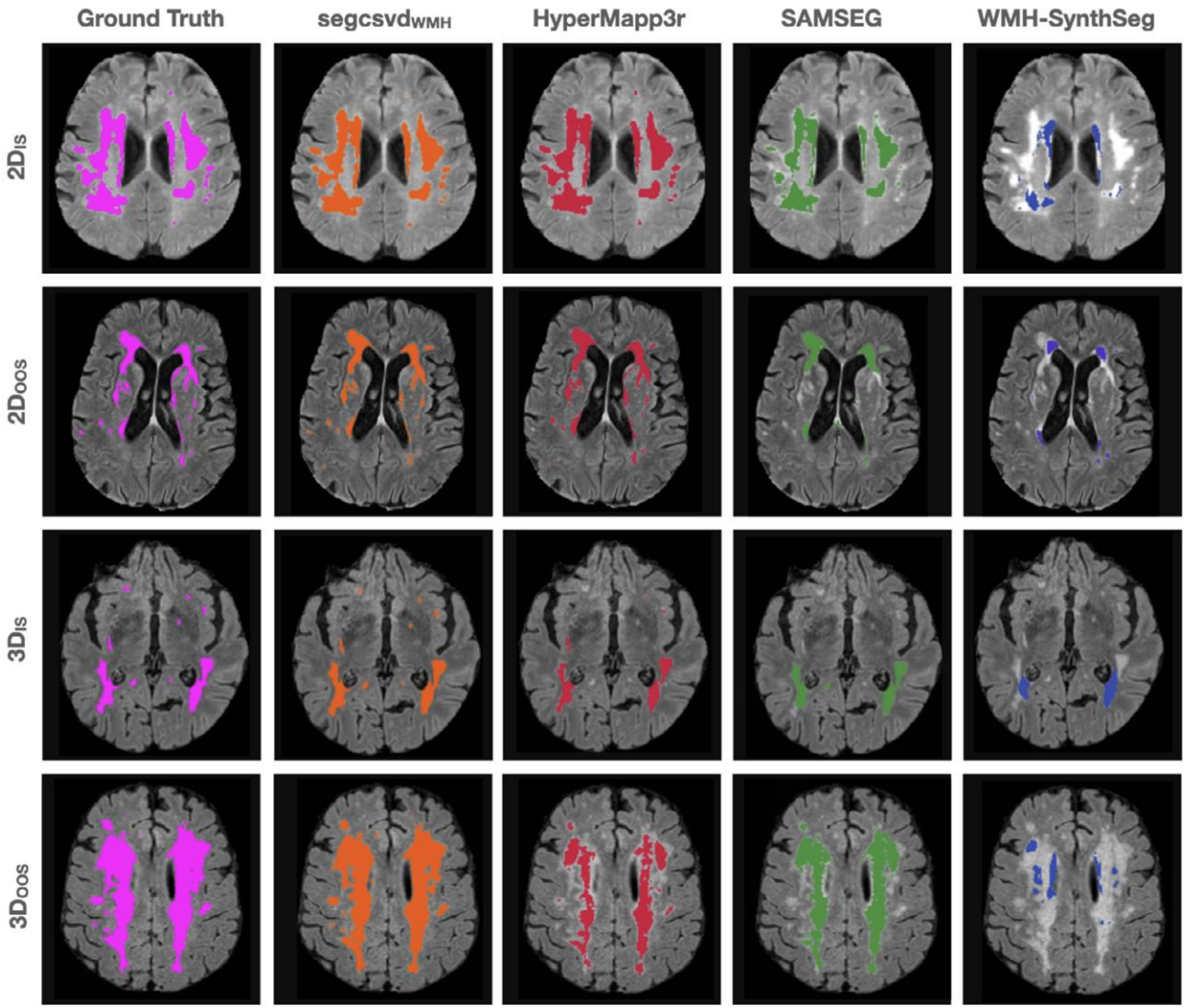





Grøvik et al., JMRI (2019)

# White Matter Hyperintensity (2024)




Gibson et al., Human Brain Mapping (2024)

# Image Enhancement

- Improve images
  - Better quality
  - Shorter scan time
  - Reduced radiation dose
- Synthesize new images

# Shorter Scan Time for MRI (2023)

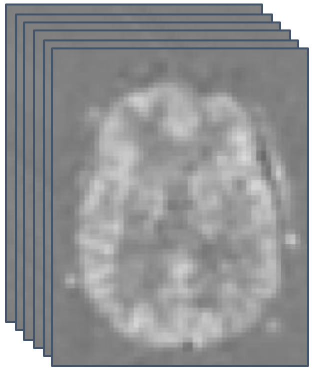
RADIOLOGICAL SCIENCES LABORATORY
STANFORD MEDICINE

MAGNETIC RESONANCE IN MEDICINE
ISMRM
ONE COMMUNITY FOR CLINICIANS AND SCIENTISTS

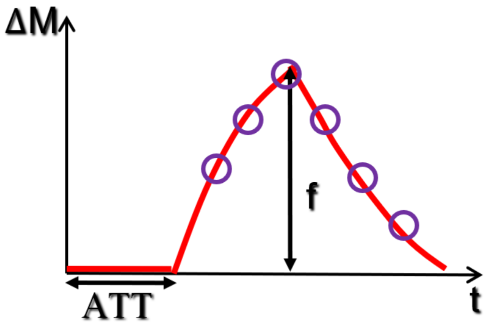
RESEARCH ARTICLE | Open Access

## Parametric cerebral blood flow and arterial transit time mapping using a 3D convolutional neural network

Donghoon Kim, Megan E. Lipford, Hongjian He, Qiuping Ding, Vladimir Ivanovic, Samuel N. Lockhart, Suzanne Craft, Christopher T. Whitlow, Youngkyoo Jung



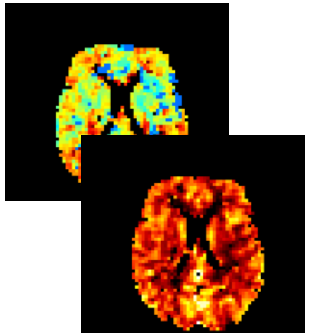
PWI



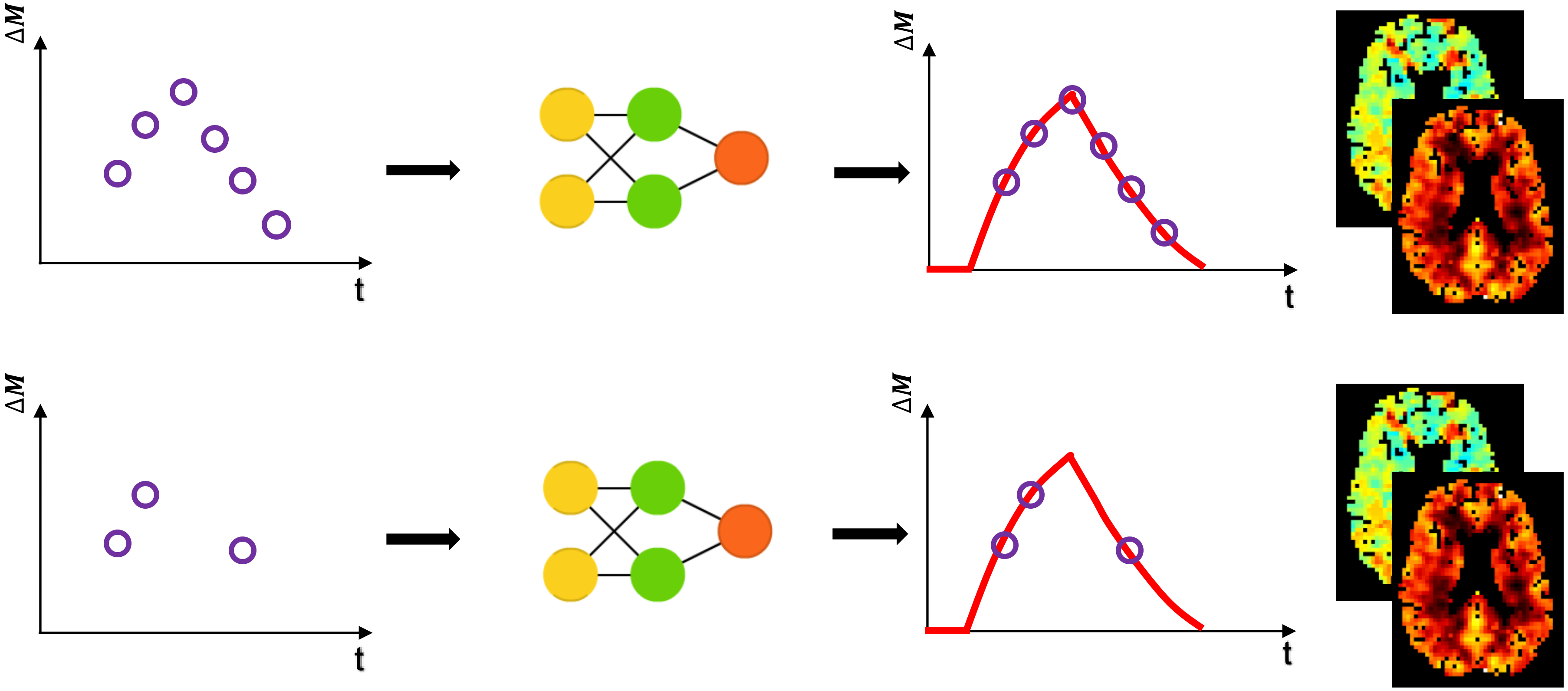

$$CBF = \Delta M / [2M_{0blood} T_{1tiss} \alpha \exp\left(-ATT/T_{1blood}\right) \cdot (1 - \exp\left(-(TI - ATT)/T_{1tiss}\right))] \quad for\ PLD < ATT$$

$$CBF = \Delta M / [2M_{0blood} T_{1tiss} \alpha \exp(-ATT/T_{1blood}) (\exp\left(-(TI - ATT - \tau)/T_{1tiss}\right))(1 - \exp\left(-\tau/T_{1tiss}\right))] \quad for\ PLD > ATT$$

**Multi-PLD PCASL Standard Model**

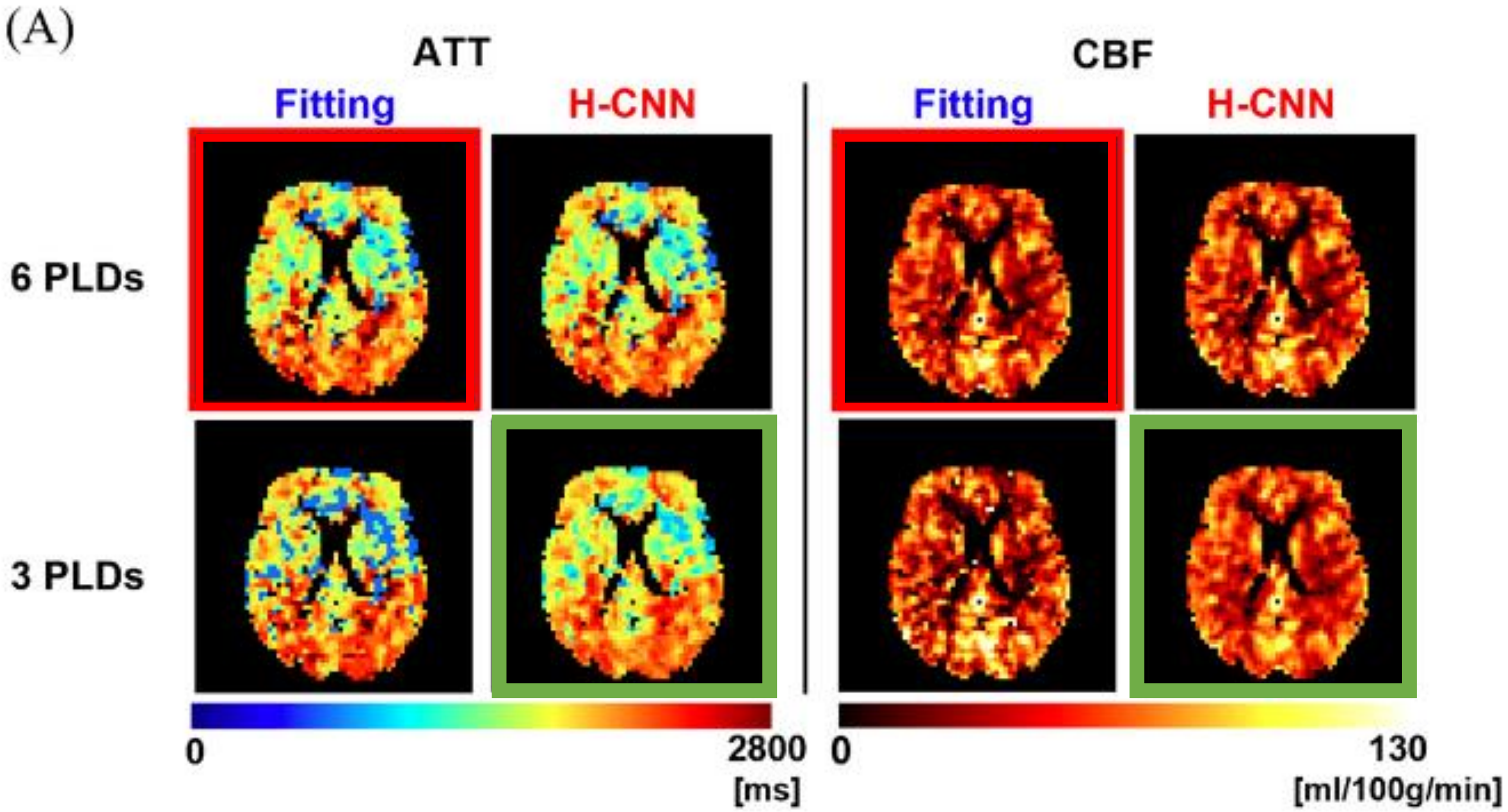


# Shorter Scan Time for MRI (2023)




**Save total scan time**

# Shorter Scan Time for MRI (2023)




**56% Time Saving**

# Industry

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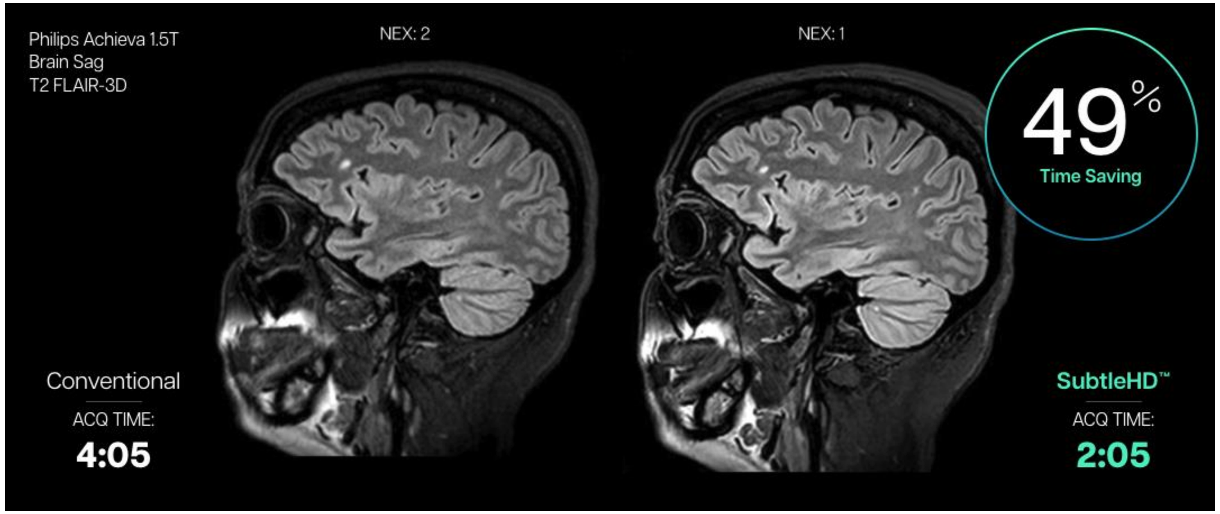
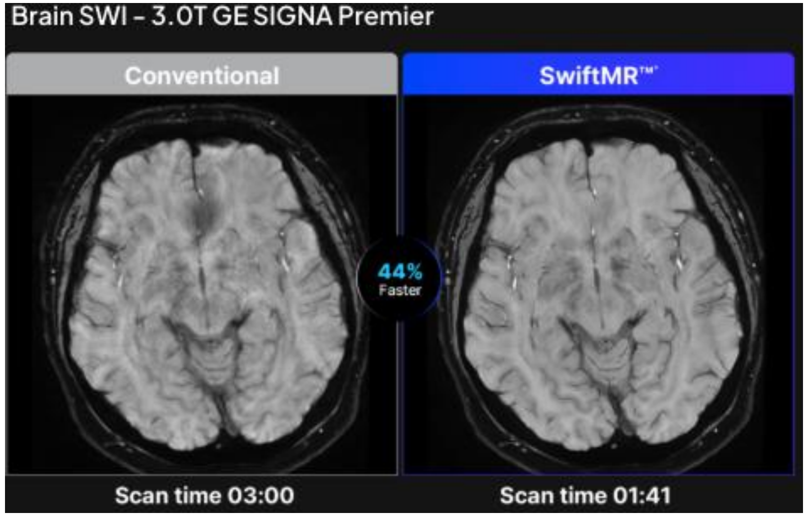
SUBTLE MEDICAL

Stanford University




AIRS MEDICAL

VERI TAS LUX MEA
서울대학교
SEOUL NATIONAL UNIVERSITY



# Reduced Radiation for PET (2023)

RSL RADIOLOGICAL SCIENCES LABORATORY
STANFORD MEDICINE

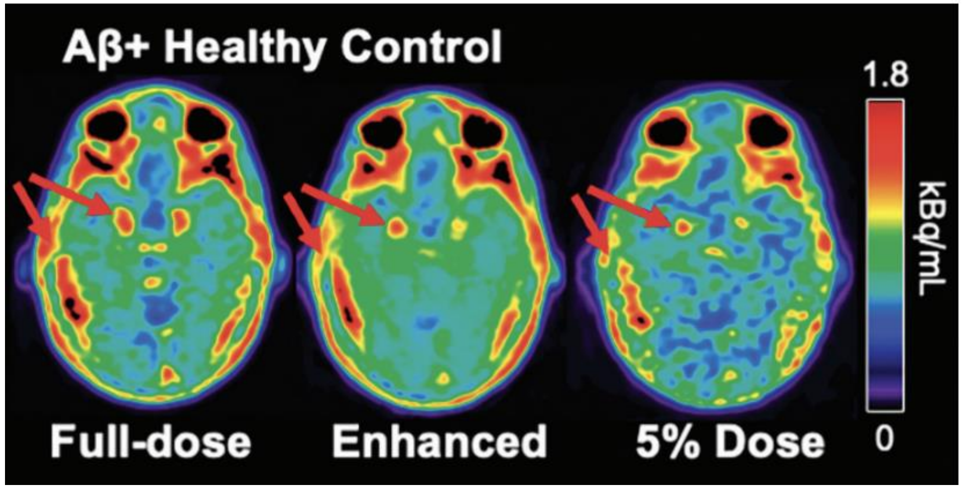
AJNR

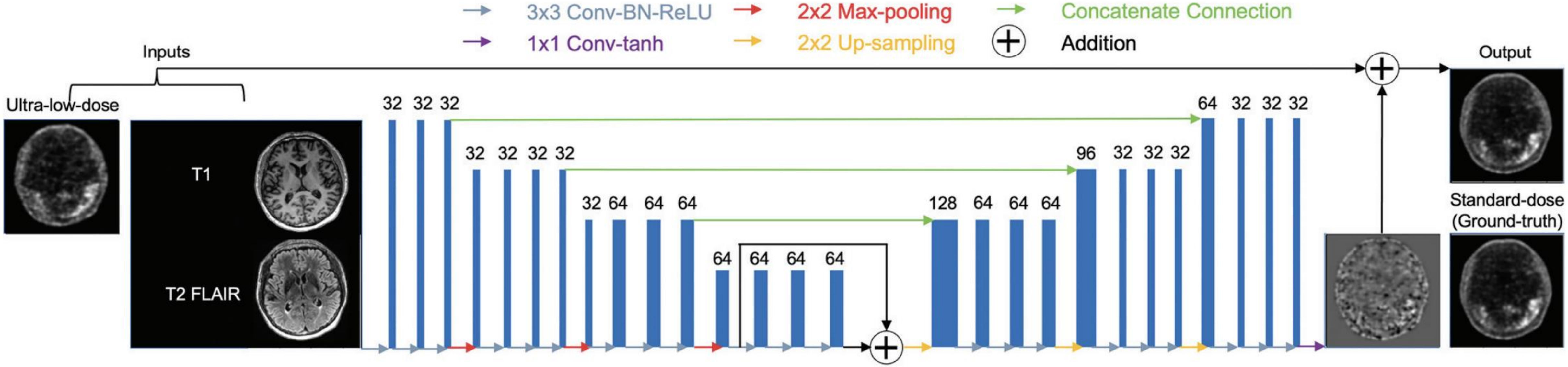
**Generative Adversarial Network–Enhanced Ultra-Low-Dose [$^{18}$F]-PI-2620 τ PET/MRI in Aging and Neurodegenerative Populations**

K.T. Chen, R. Tesfay, M.E.I. Koran, J. Ouyang, S. Shams, C.B. Young, G. Davidzon, T. Liang, M. Khalighi, E. Mormino and G. Zaharchuk

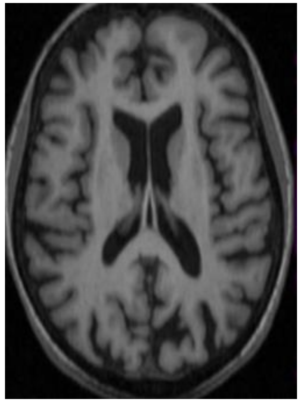
This information is current as of April 15, 2025.

*AJNR Am J Neuroradiol* 2023, 44 (9) 1012-1019
doi: https://doi.org/10.3174/ajnr.A7961
http://www.ajnr.org/content/44/9/1012



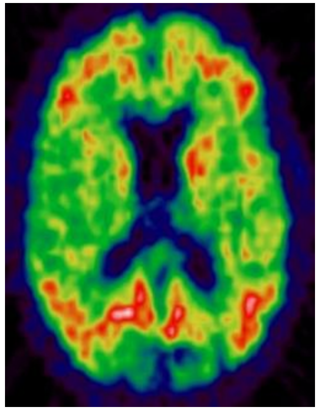
# Image Synthesis



MRI

- **Excellent** anatomical detail
- **Excellent** spatial resolution
- **Poor** molecular imaging
- Mostly non-invasive

**Synthesis**



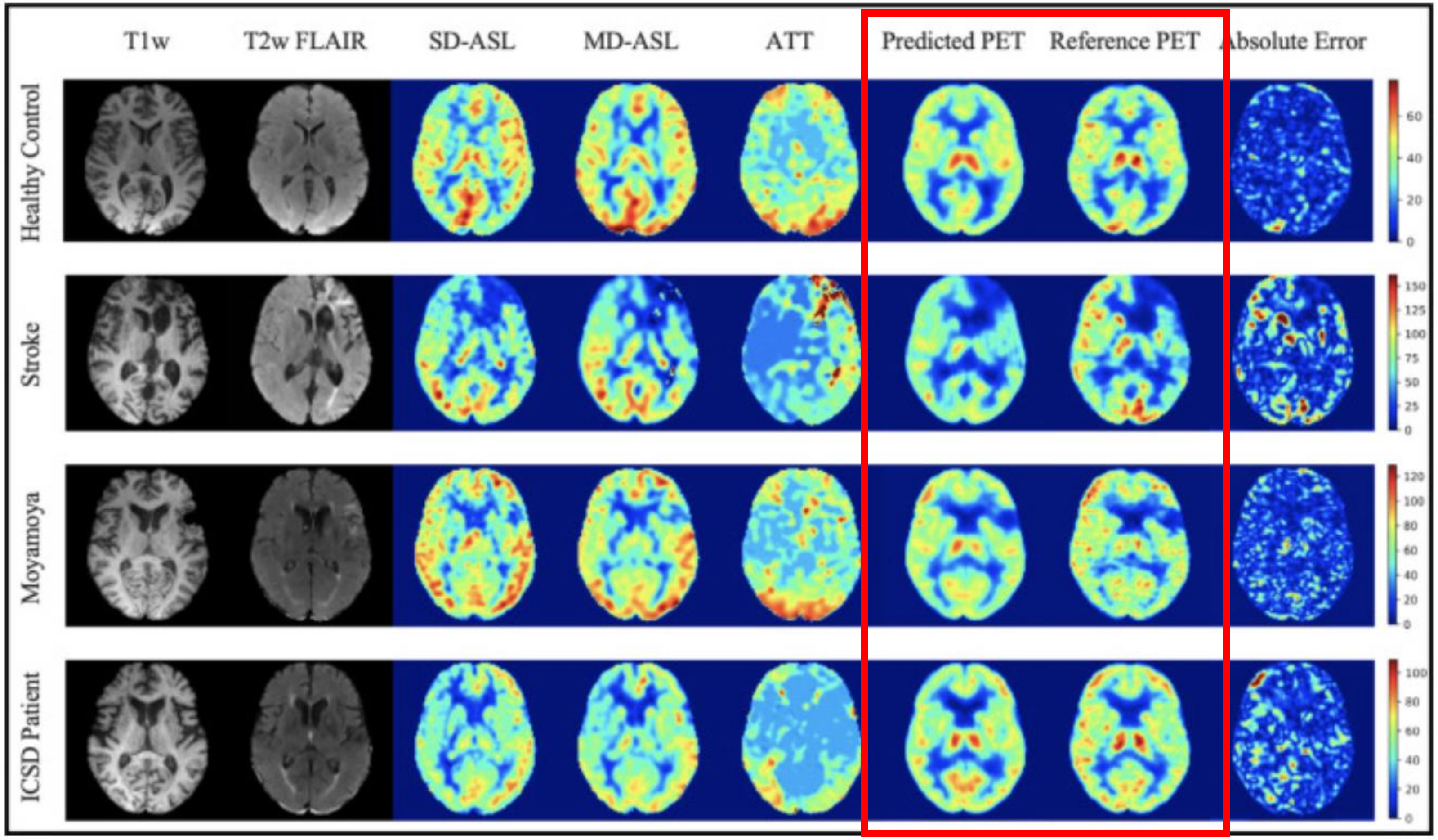
PET

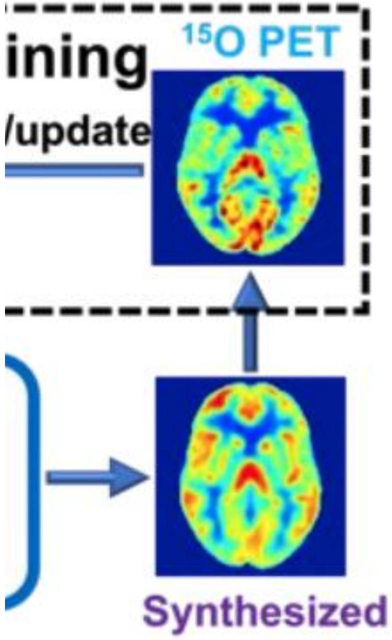
- **Poor** anatomical detail
- **Poor** spatial resolution
- **Excellent** molecular imaging
- Radioactive tracer injection

# MRI to Synthesized PET (2024)

Turning brain
water PET CBF
MRI via attent
networks

Ramy Hussein [a], David S
, Michael Moseley [a], Greg Zah




- Cross-mo
  - "Zero d

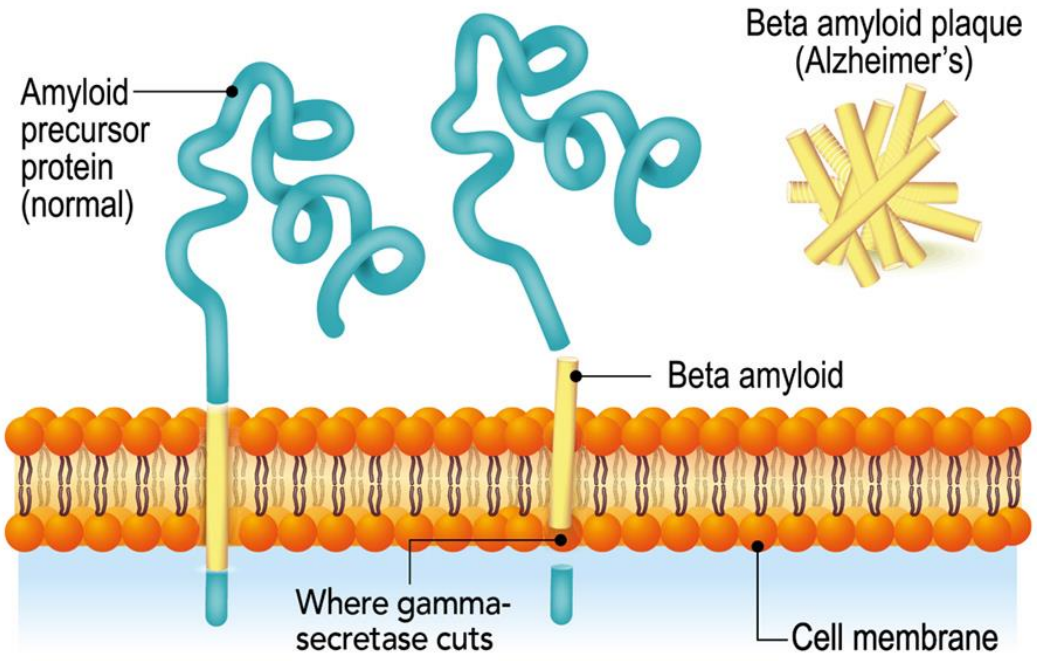
# Deep Learning-based Prediction of Amyloid Status Using Multi-Contrast MRI

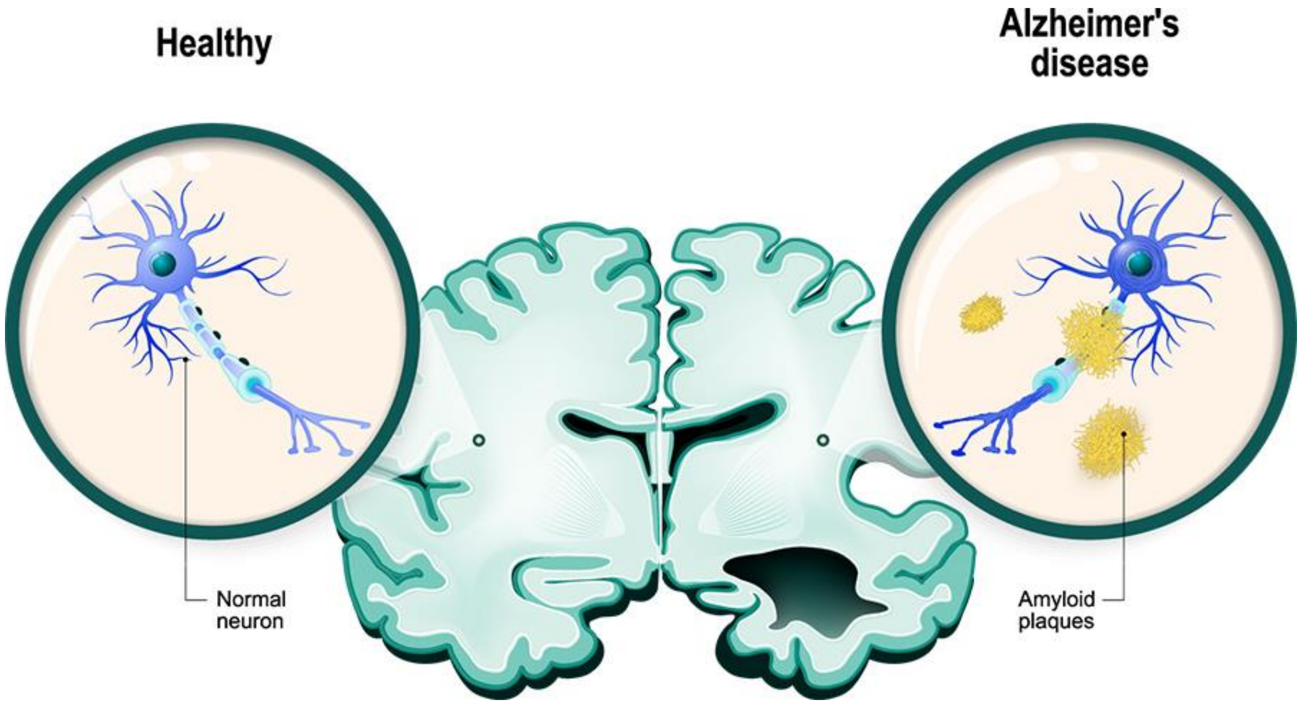
**Donghoon Kim**[1], Jon André Ottesen[1,2,3], Ashwin Kumar[1], Brandon C. Ho[1], Elsa Bismuth[1], Christina B. Young[4], Elizabeth Mormino[4], and Greg Zaharchuk[1]

1. Department of Radiology, Stanford University, Stanford, USA
2. Computational Radiology & Artificial Intelligence (CRAI) Research Group, Division of Radiology and Nuclear Medicine, Oslo University Hospital, Oslo, Norway
3. Department of Physics, Faculty of Mathematics and Natural Sciences, University of Oslo, Oslo, Norway
4. Department of Neurology and Neurological Sciences, Stanford University, Stanford, USA

# Amyloid Plaques

Amyloid-beta (Aβ) protein is formed from the breakdown of a larger protein called the amyloid precursor.



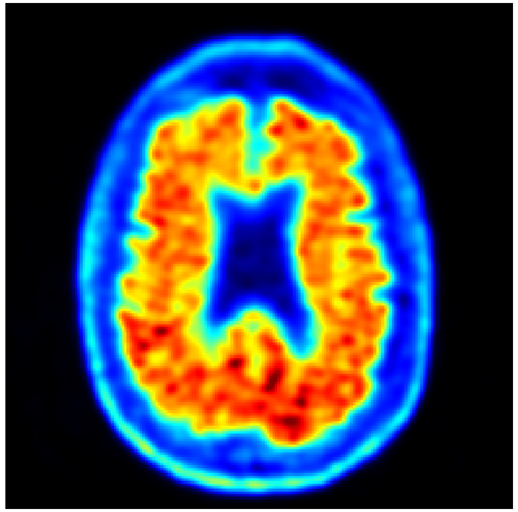




https://researchoutreach.org/articles/disruption-amyloid-β-protein-processing-drives-alzheimers/

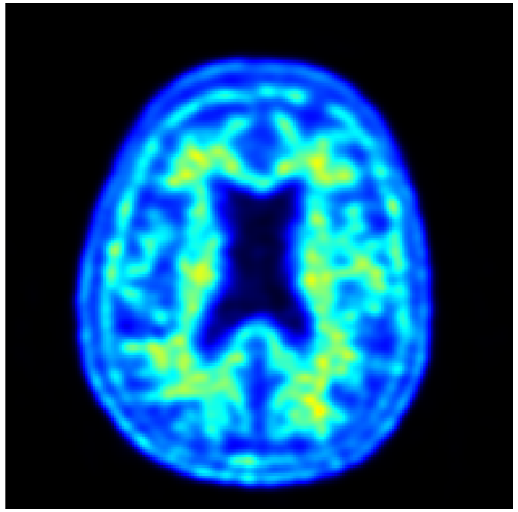
# Backgrounds

Identifying Aβ positive patients is critical.

- Only possible through PET and CSF sampling



Aβ Positive Scan

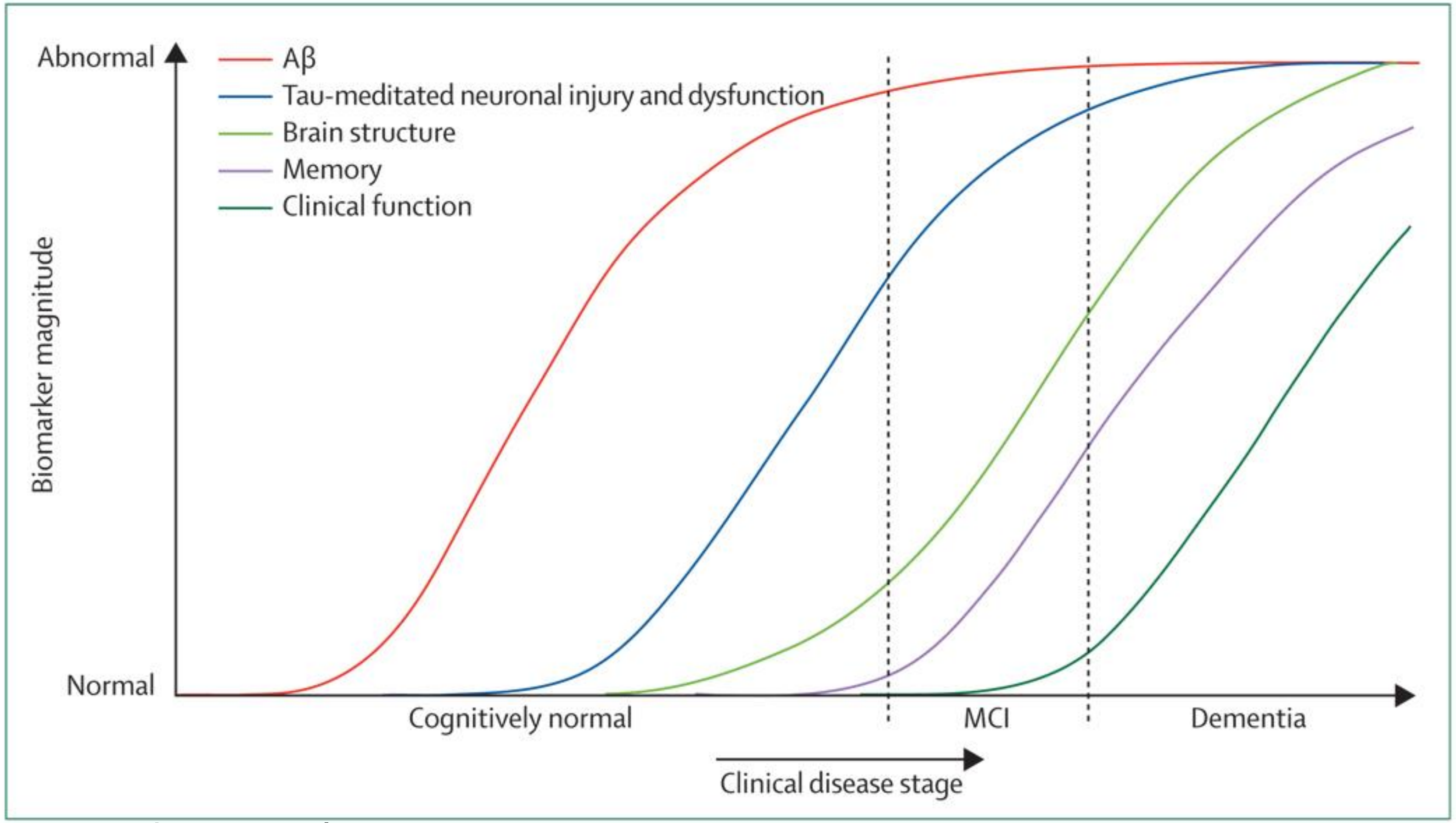


Aβ Negative Scan

# Backgrounds

## Early detection of amyloid accumulation is critical

- Early intervention

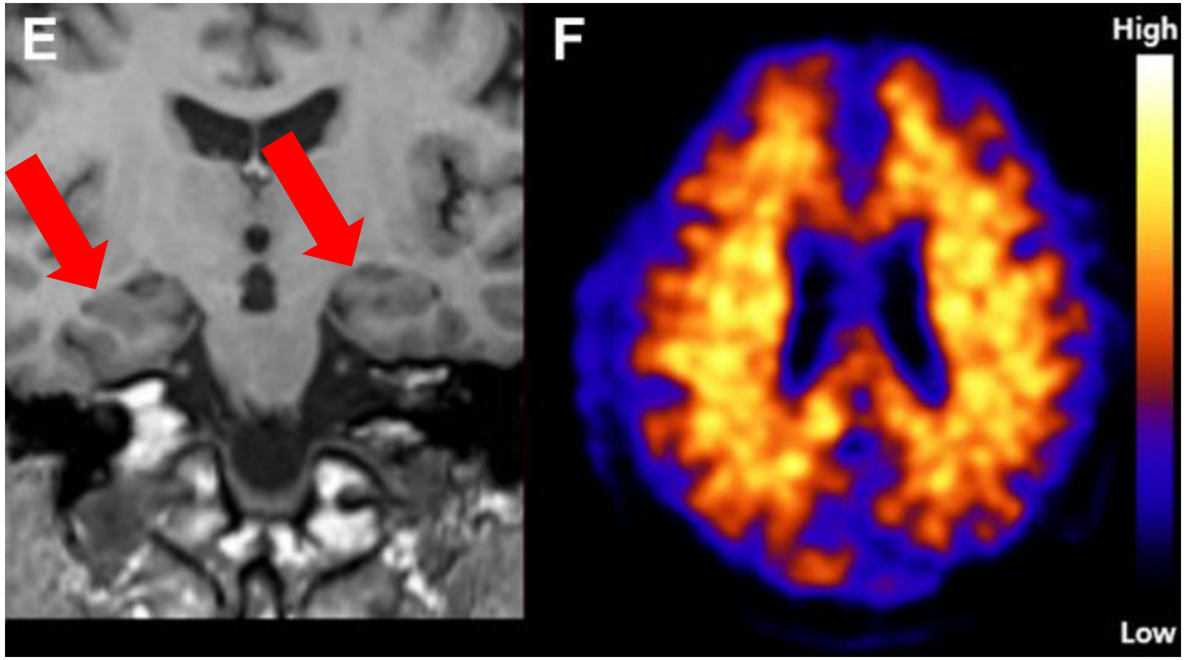



Jack Jr, CR., et al. *The Lancet Neurology* 9.1, 2010

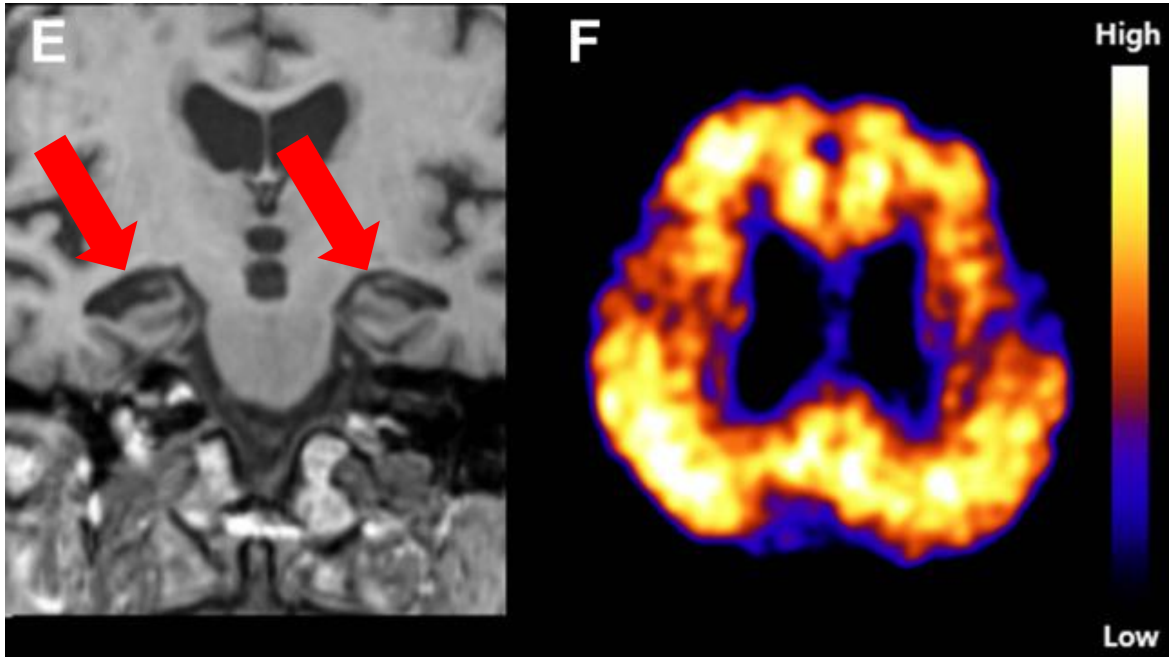
# Structural Alteration

Aβ deposition has been implicated in the structural alteration of the brain.

- Brain atrophy or hippocampal volume loss




**Aβ- Subject**




**Aβ+ Subject**

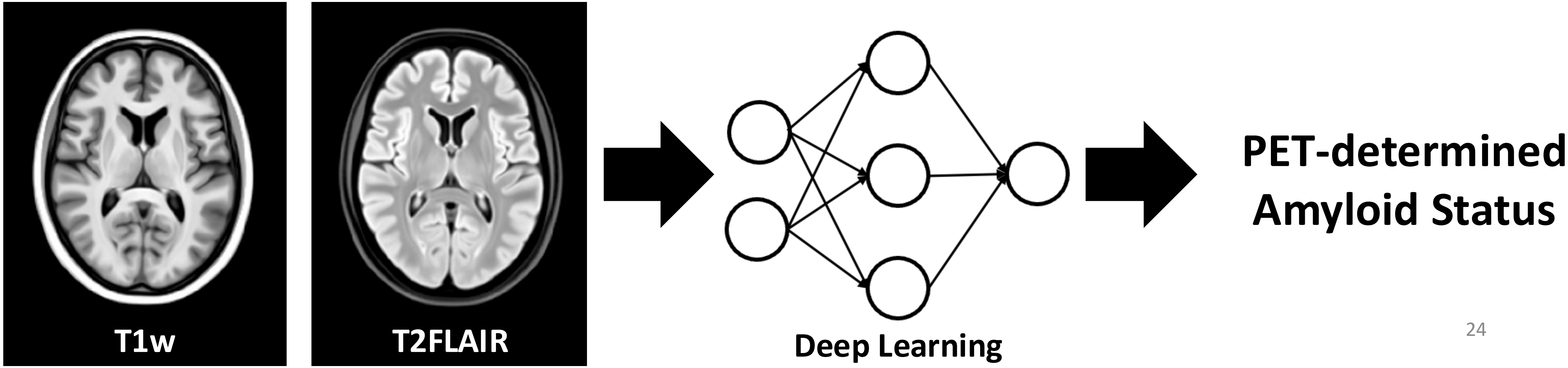
Kang KM et al., *Neuropsychiatric Disease and Treatment*, 2020

# Hypothesis and Aim

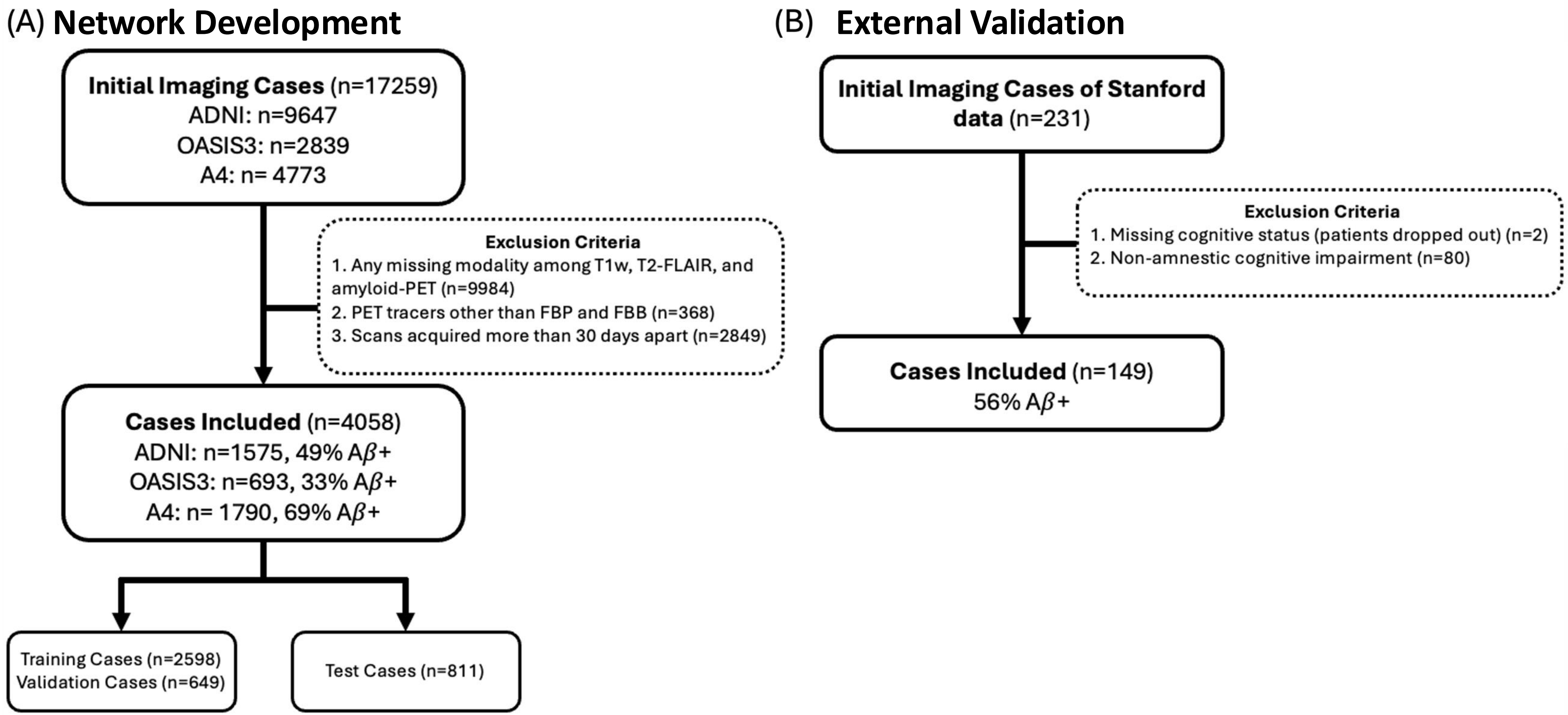


The inclusion of T2-FLAIR images would enhance the Aβ status prediction.

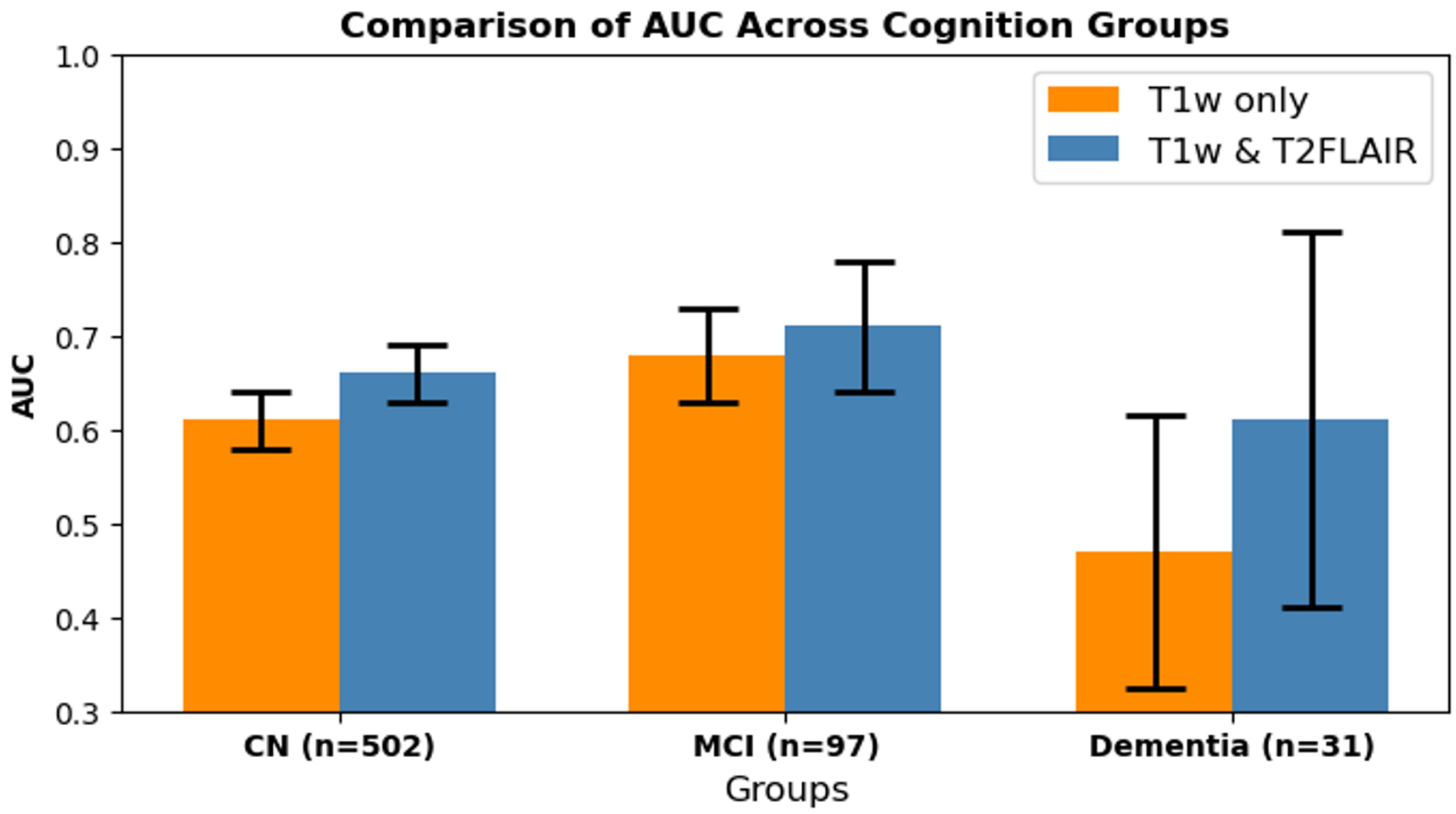
The purpose of this study was to predict Aβ status from T1 and T2-FLAIR MRIs.



# Datasets

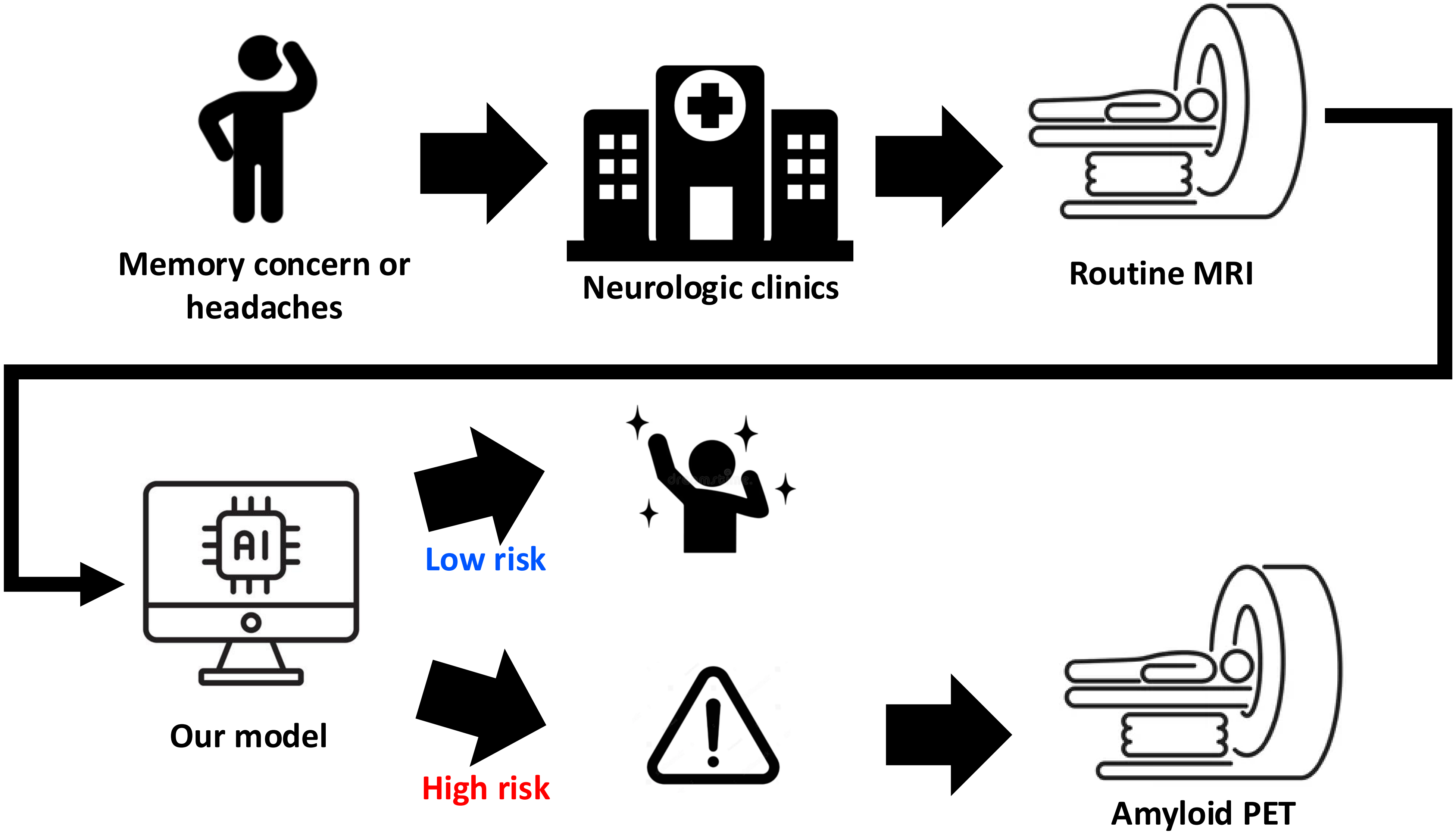

(A) Network Development
Initial Imaging Cases (n=17259)
ADNI: n=9647
OASIS3: n=2839
A4: n= 4773
Exclusion Criteria
1. Any missing modality among T1w, T2-FLAIR, and amyloid-PET (n=9984)
2. PET tracers other than FBP and FBB (n=368)
3. Scans acquired more than 30 days apart (n=2849)
Cases Included (n=4058)
ADNI: n=1575, 49% Aβ+
OASIS3: n=693, 33% Aβ+
A4: n= 1790, 69% Aβ+
Training Cases (n=2598)
Validation Cases (n=649)
Test Cases (n=811)
(B) External Validation
Initial Imaging Cases of Stanford data (n=231)
Exclusion Criteria
1. Missing cognitive status (patients dropped out) (n=2)
2. Non-amnestic cognitive impairment (n=80)
Cases Included (n=149)
56% Aβ+

# Results



Comparison of AUC Across Cognition Groups
1.0
0.9
0.8
0.7
0.6
0.5
0.4
0.3
AUC
T1w only
T1w & T2FLAIR
CN (n=502)
MCI (n=97)
Dementia (n=31)
Groups

# Impact

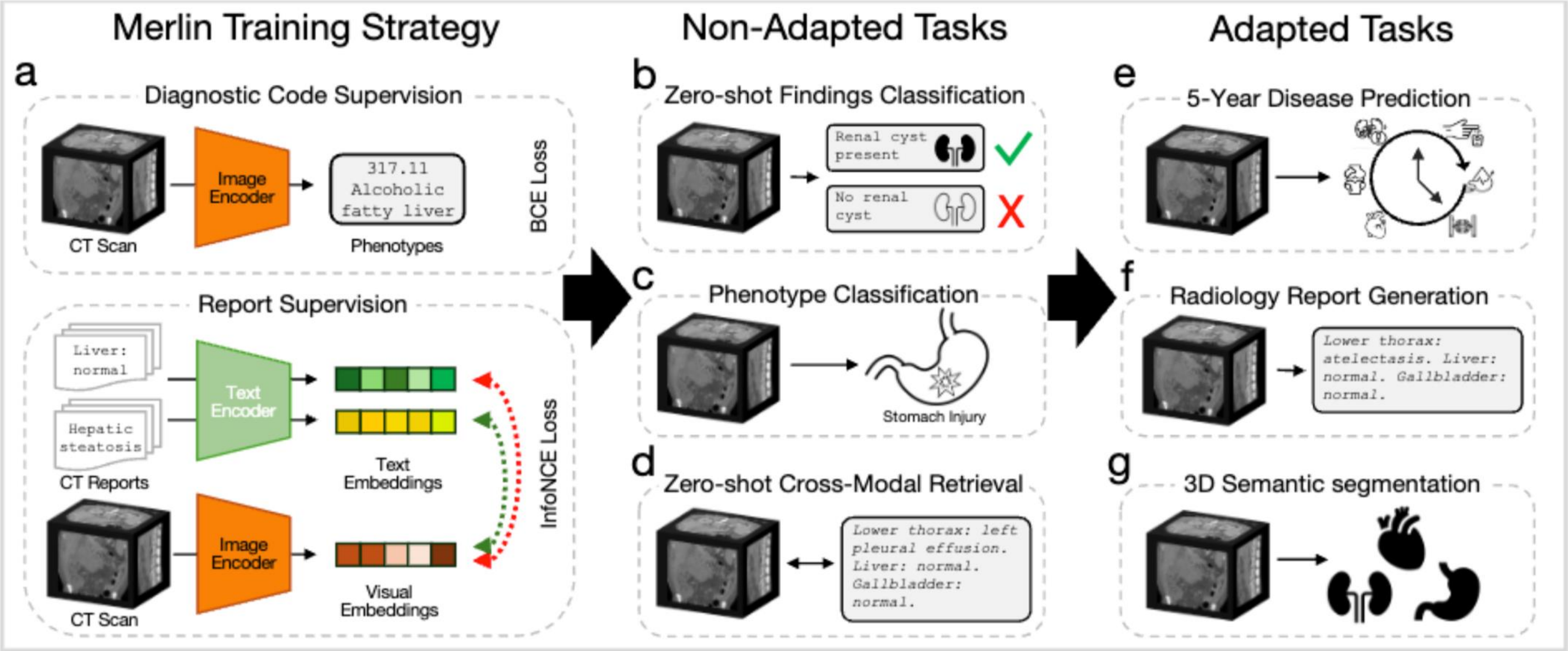

Memory concern or headaches
Neurologic clinics
Routine MRI
Our model
Low risk
High risk
Amyloid PET

# LLM and Foundation Model

- Large Language Model (LLM)
  - AI to understand and generate human language
  - GPT-4
- Foundation Model
  - Any input including language
  - Ability to fine-tune it for many specific tasks

# Vision-Language Foundation Model

- Merlin: A Vision-Language Foundation Model for 3D CT






Blankemeier/Kumar/Chaudhari et al., *under review, 2025*

# Vision-Language Foundation Model

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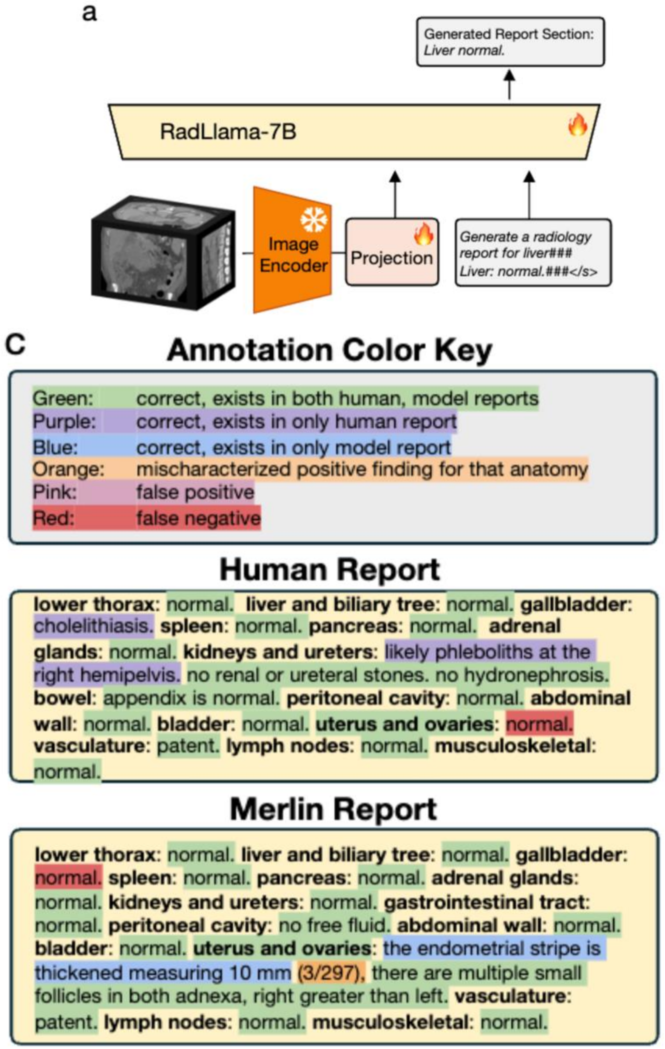
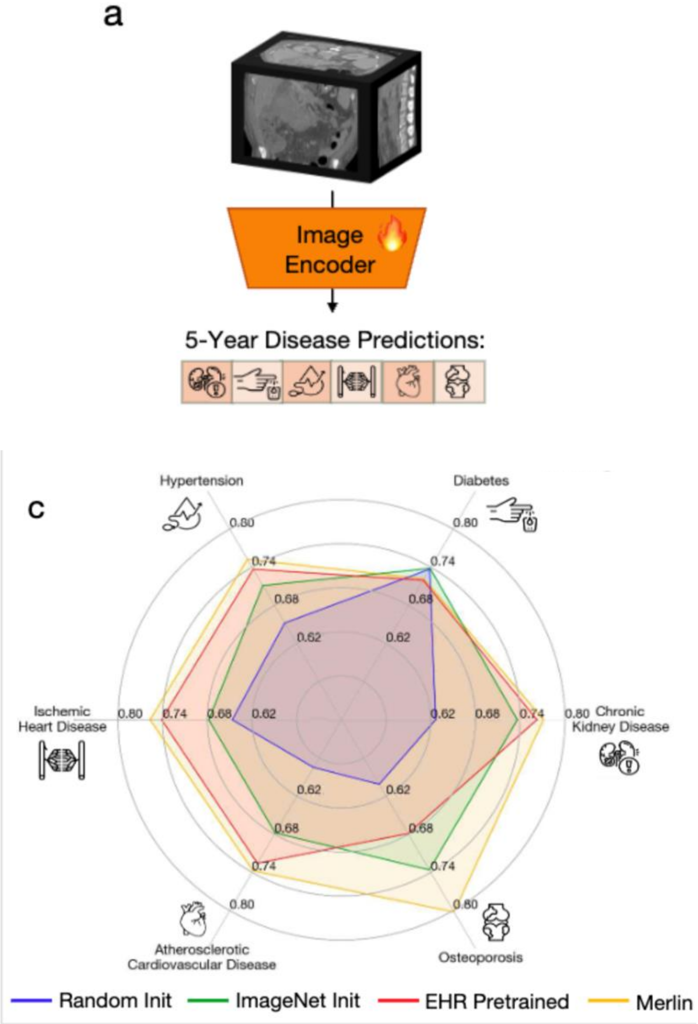
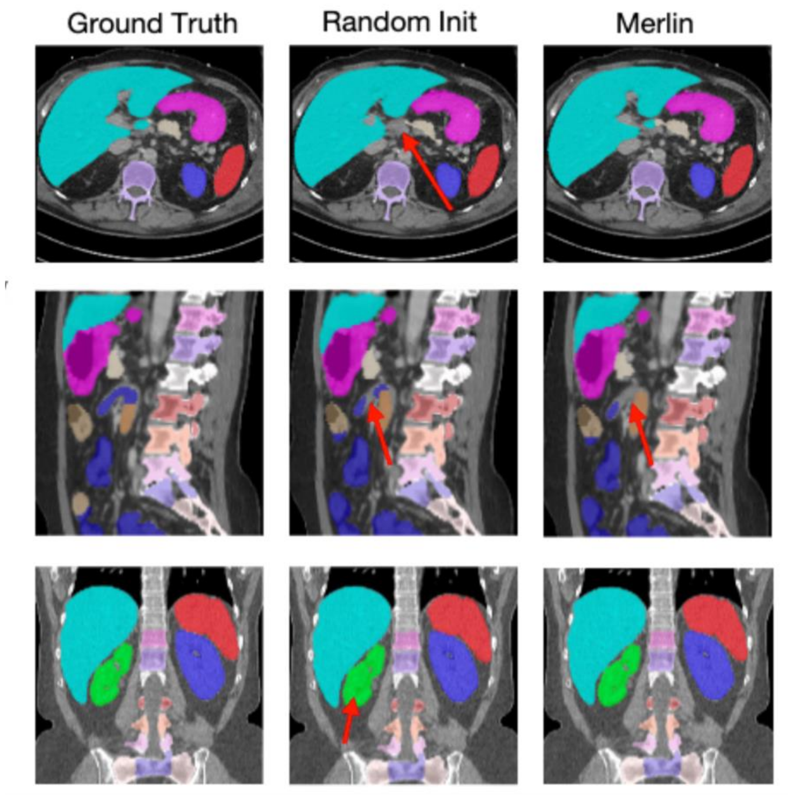
## Radiology Report Generation




## 5-Year Disease Prediction




## Segmentation



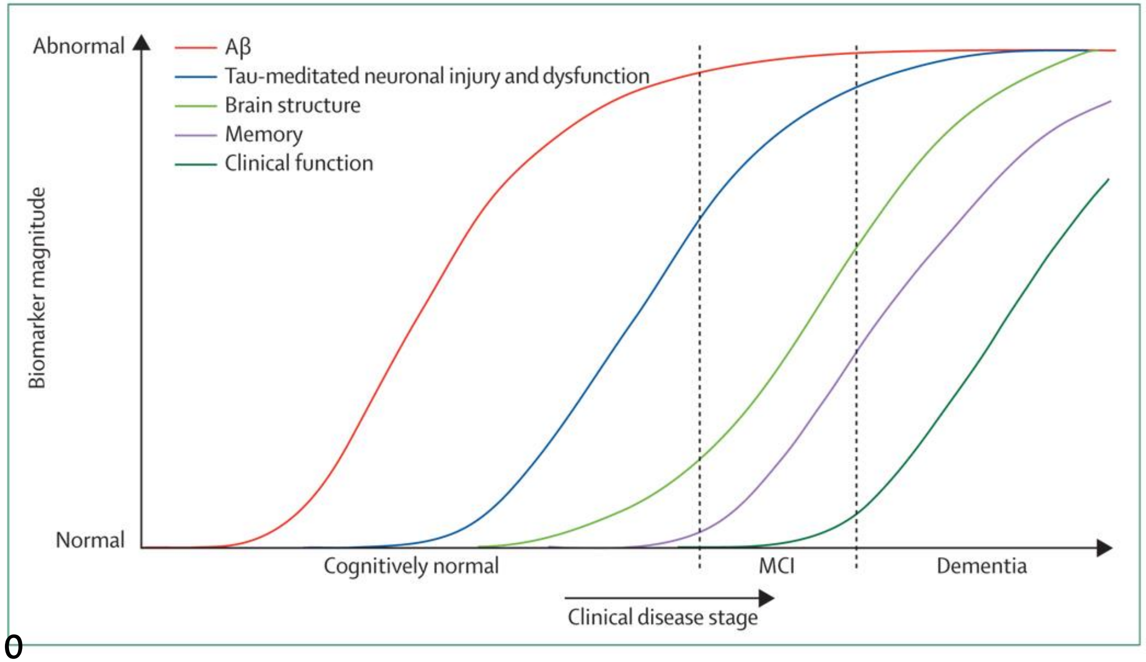
# Vision-Language Model Predicting Present and Future Tau-PET Status

# Vision-Language Foundation Model

Tau deposition is a key neuropathological hallmark of AD, strongly associated with clinical symptoms.

Tau-PET is generally inaccessible outside of major metropolitan areas.

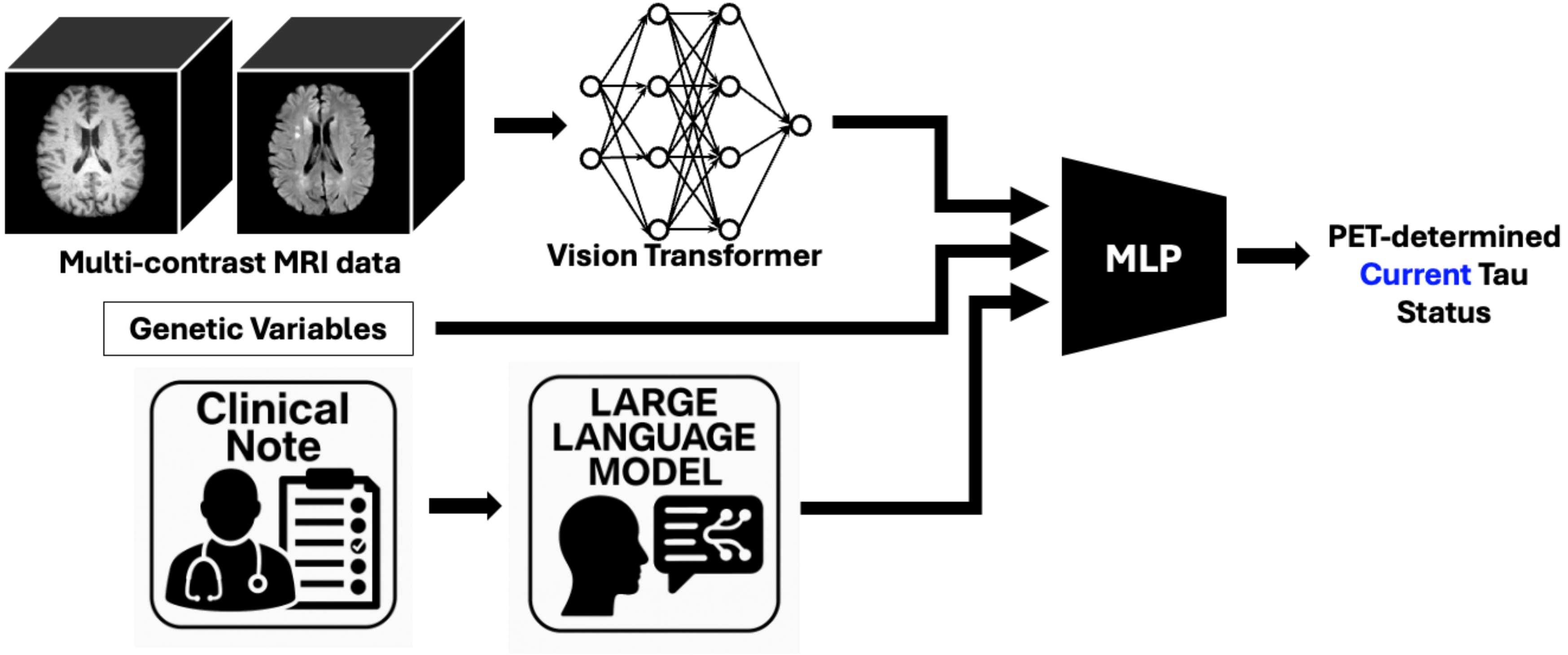
- Our previous study showed the capability predicting amyloid from MRI-only
- Tau deposition is more closely associated with structural changes




Jack Jr, CR., et al. *The Lancet Neurology* 9.1, 2010

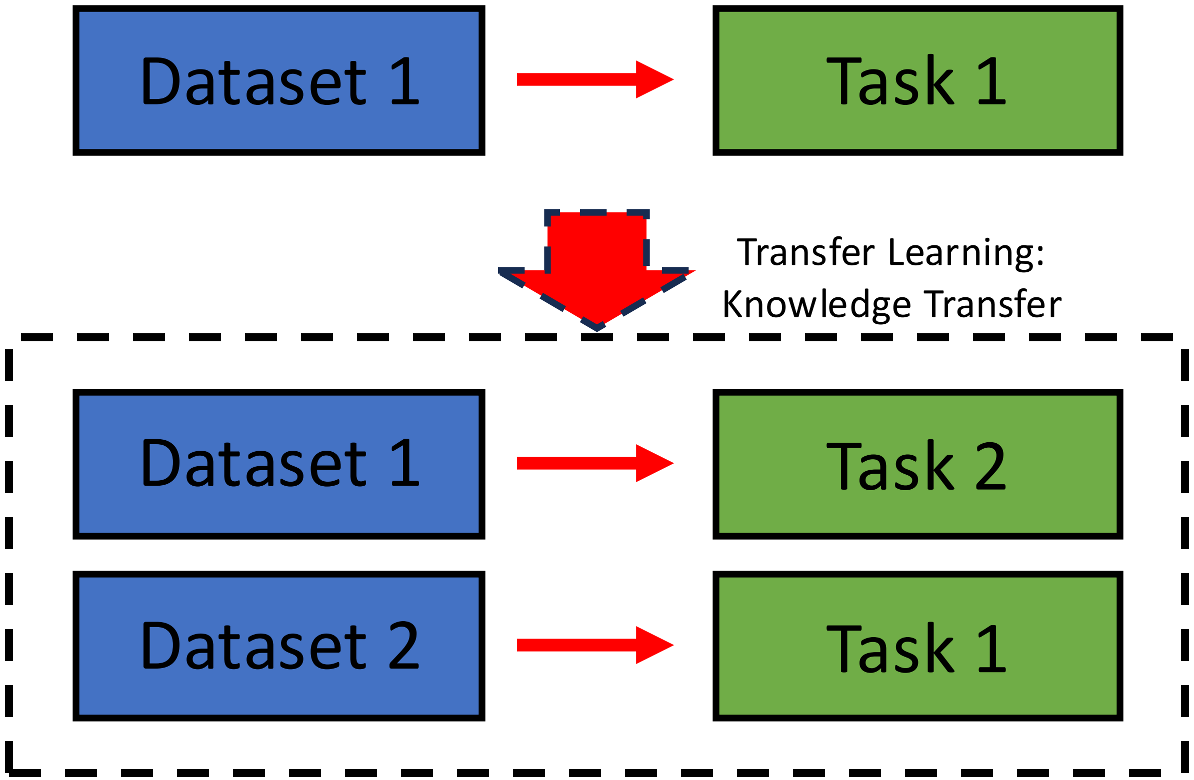
# Vision-Language Foundation Model

Vision-Language Model Predicting **Present** and **Future** Tau-PET Status



# Transfer Learning

## Knowledge Transfer



# Self-Supervised Learning

## Supervised learning

| | | |
|---|---|---|
| IM1 | IM2 | IM3 |
| IM4 | IM5 | IM6 |
| IM7 | IM8 | IM9 |

**Images**

\+

| | | |
|---|---|---|
| L1 | L2 | L3 |
| L4 | L5 | L6 |
| L7 | L8 | L9 |

**Labels**

= **Model**

# Self-Supervised Learning

## Self-Supervised learning

**Step 1:**

| | | |
|---|---|---|
| IM1 | IM2 | IM3 |
| IM4 | IM5 | IM6 |
| IM7 | IM8 | IM9 |

**Images**

**+**

| | | |
|---|---|---|
| PL1 | PL2 | PL3 |
| PL4 | PL5 | PL6 |
| PL7 | PL8 | PL9 |

**Pseudo-labels**

**= Pretrained Model**

---

**Step 2:**

| | |
|---|---|
| IM1 | IM2 |
| IM3 | IM4 |

**Images**

**+**

| | |
|---|---|
| L1 | L2 |
| L3 | L4 |

**Labels**

**= Model**

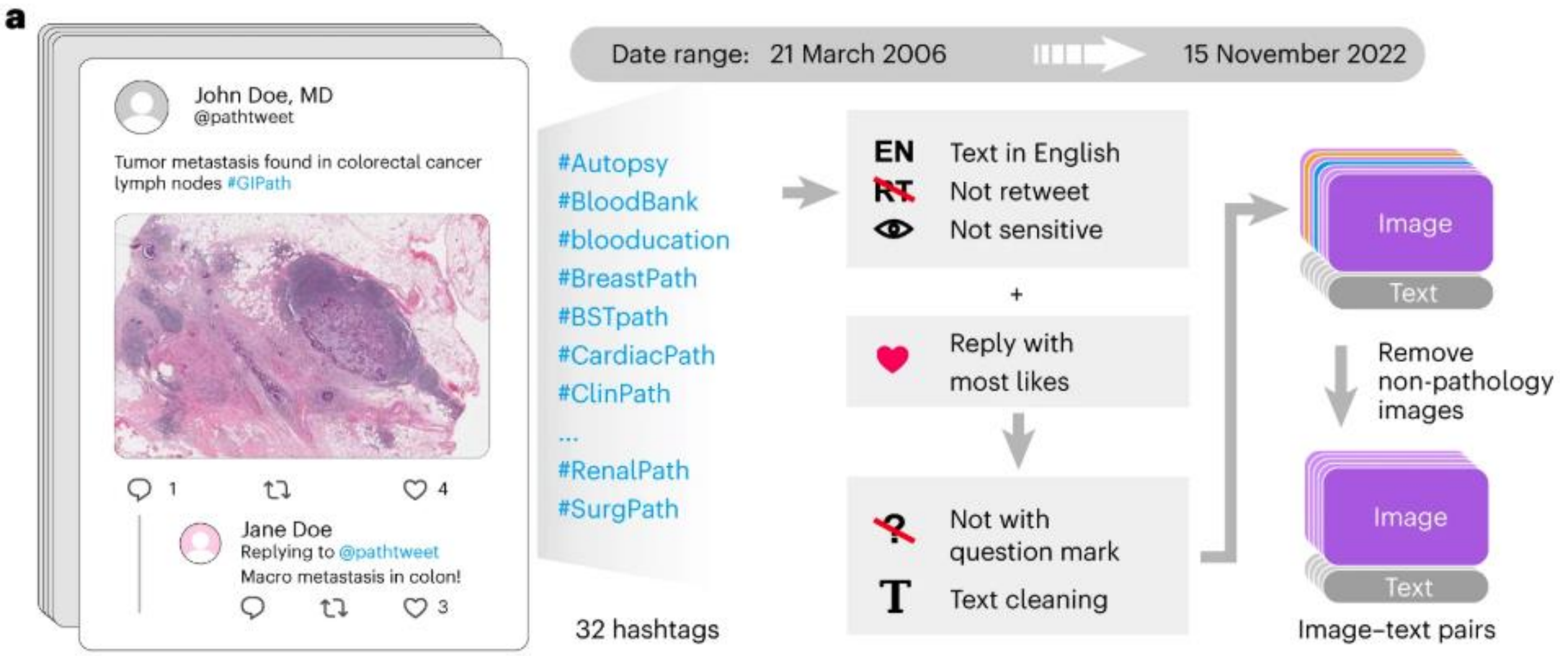
# Vision-Language Foundation Model

Article | Published: 17 August 2023

## A visual–language foundation model for pathology image analysis using medical Twitter

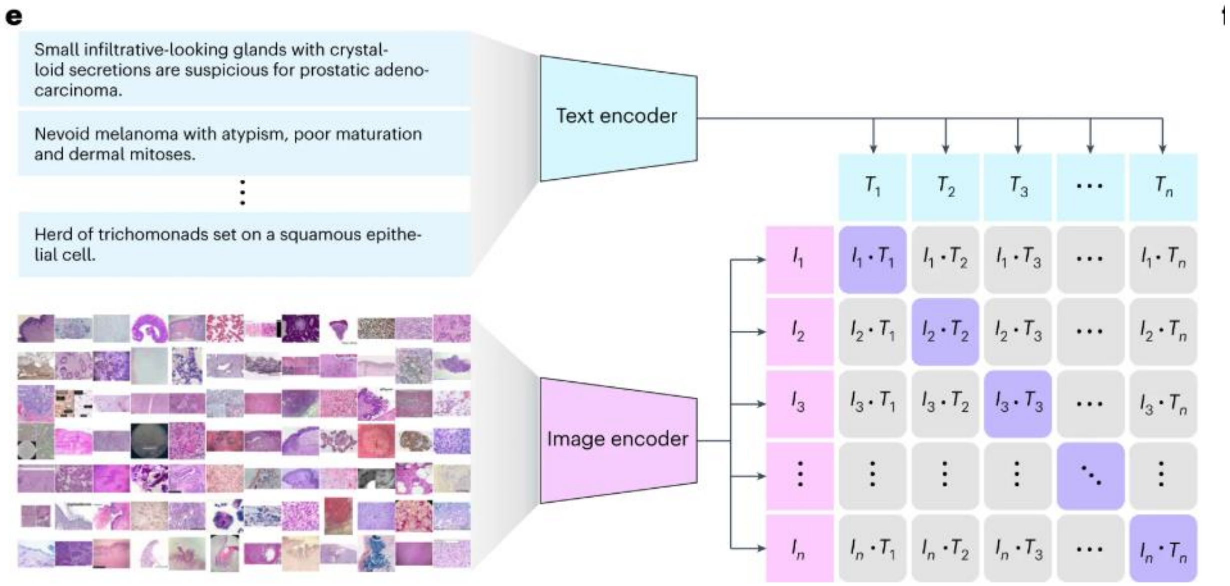
Zhi Huang, Federico Bianchi, Mert Yuksekgonul, Thomas J. Montine & James Zou

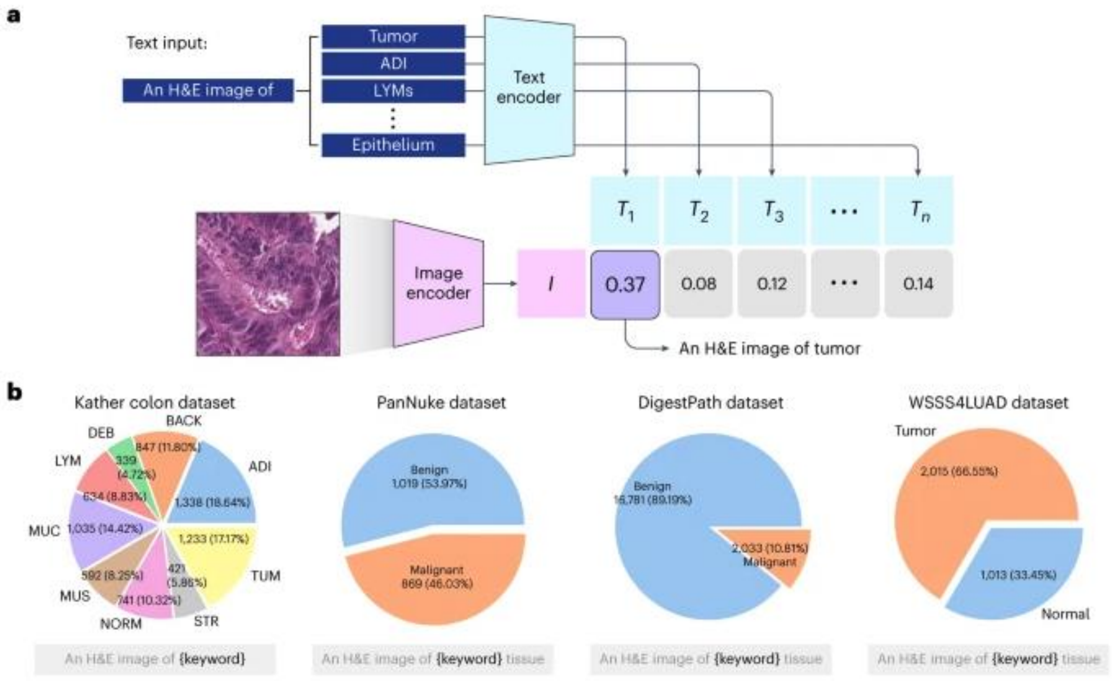
Nature Medicine **29**, 2307–2316 (2023) | Cite this article



# Vision-Language Foundation Model





# Pediatric Bone Age (2018)

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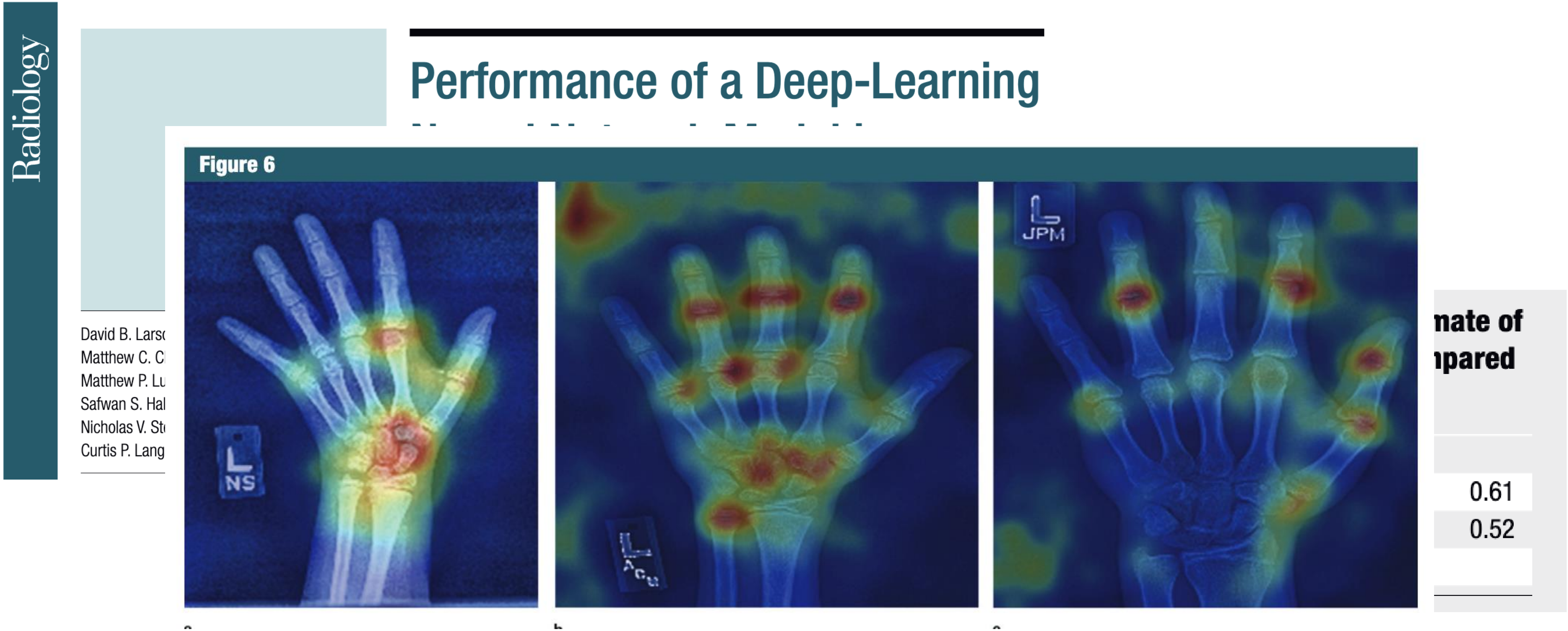
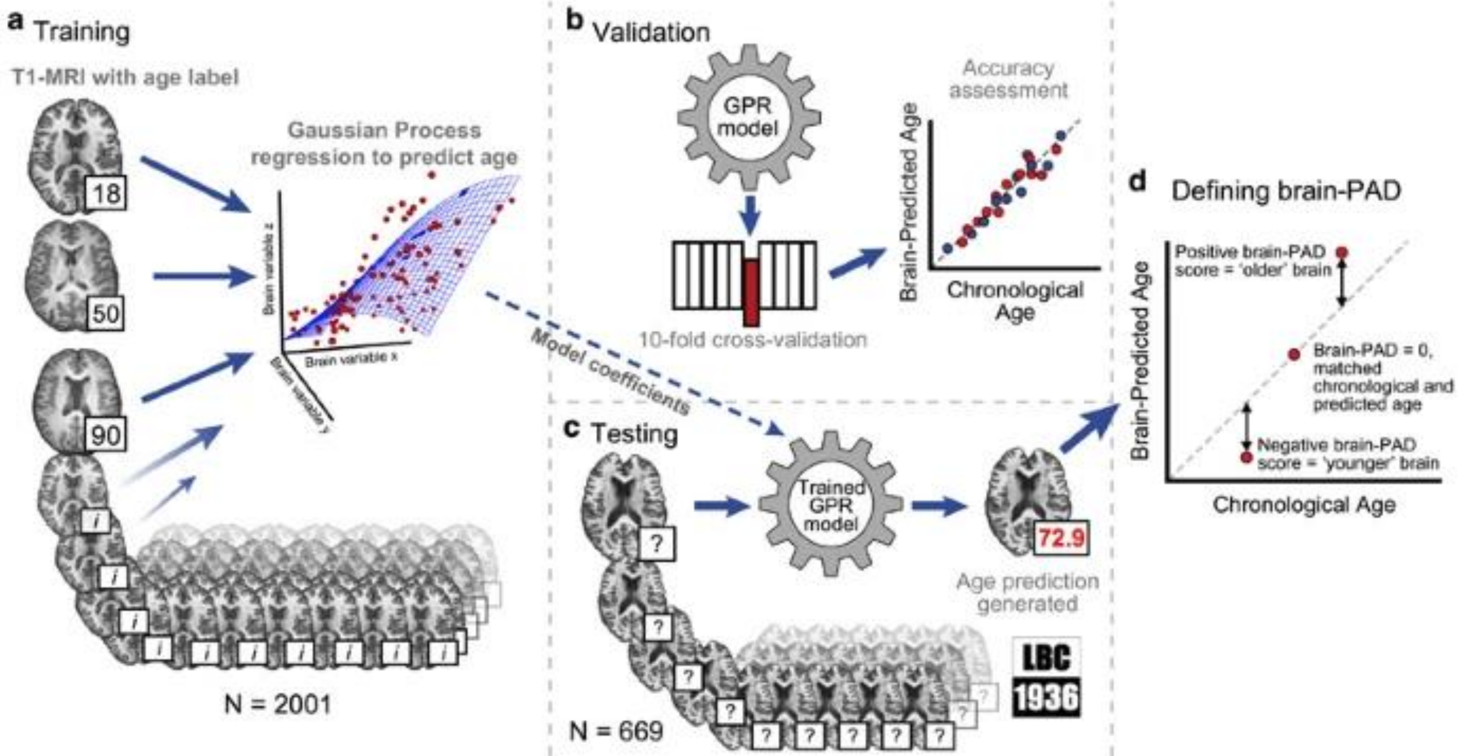


# Brain Age (2018)

## Brain age predicts mortality

J H Cole, S J Ritchie, M E Bastin, M C Valdés Hernández, S Muñoz Maniega, N Royle, J Corley, A Pattie, S E Harris, Q Zhang, N R Wray, P Redmond, R E Marioni, J M Starr, S R Cox, J M Wardlaw, D J Sharp & I J Deary

*Molecular Psychiatry* **23**, 1385–1392 (2018) | Cite this article



Original Investigation

April 14, 2025

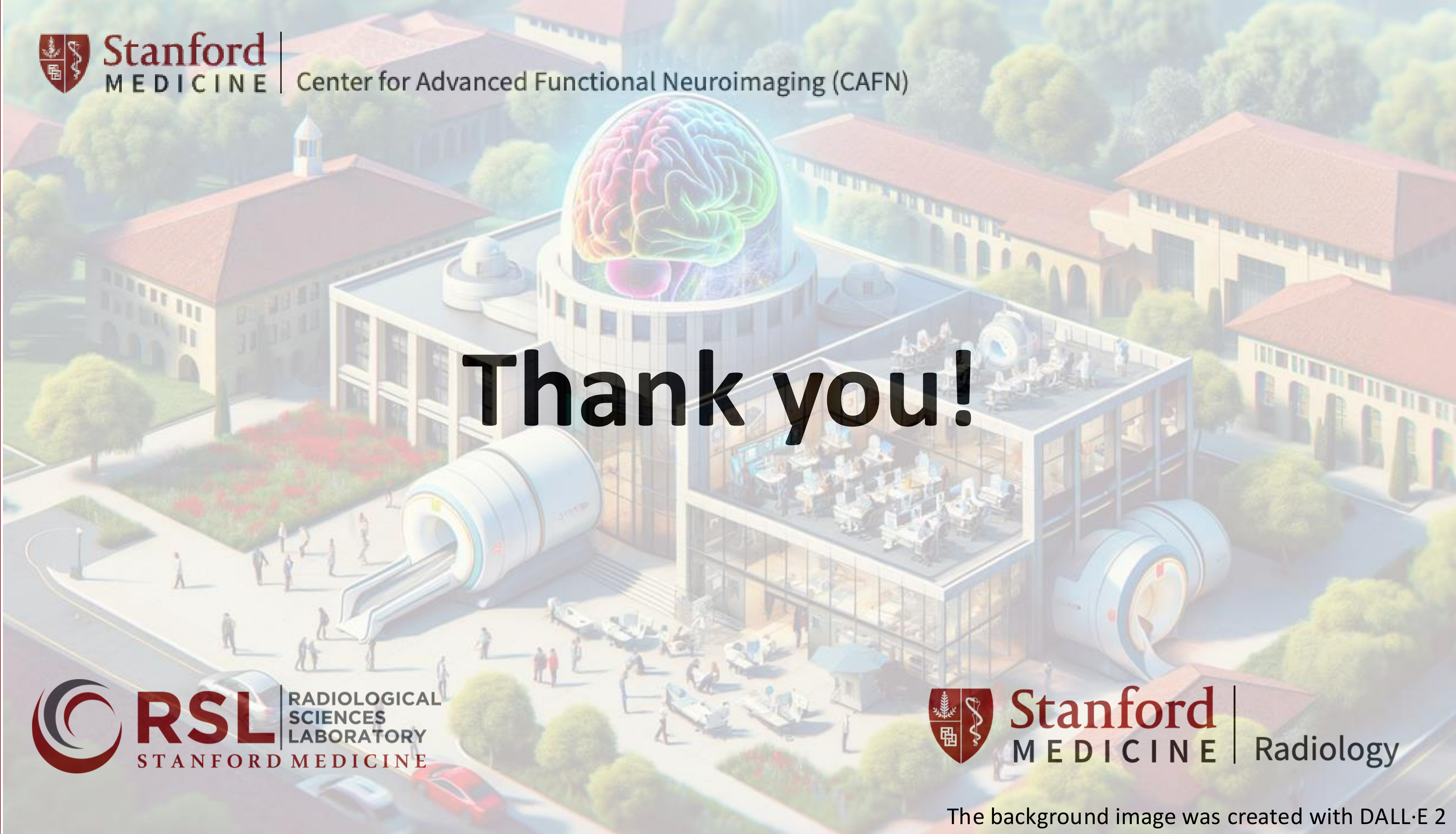
# Projected Lifetime Cancer Risks From Current Computed Tomography Imaging

Rebecca Smith-Bindman, MD[1,2,3]; Philip W. Chu, MS[1]; Hana Azman Firdaus, MPH[1]; et al

Author Affiliations | Article Information

*JAMA Intern Med.* Published online April 14, 2025. doi:10.1001/jamainternmed.2025.0505

**Conclusions and Relevance** This study found that at current utilization and radiation dose levels, CT examinations in 2023 were projected to result in approximately 103 000 future cancers over the course of the lifetime of exposed patients. If current practices persist, CT-associated cancer could eventually account for 5% of all new cancer diagnoses annually.



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# Thank you!

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The background image was created with DALL·E 2

# Deidentification

Many public neuroimaging MRI datasets are defaced to protect patient privacy