



Multidisciplinary Approaches to Cancer Symposium

Artificial Intelligence and the Future of Imaging

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Vice Chair of Education, Department of Radiology

Neuroradiology Section Chief

City of Hope

Disclosures

- I do not have any relevant financial relationships.

This presentation and/or comments will provide a balanced, non-promotional, and evidence-based approach to all diagnostic, therapeutic and/or research related content.

Cultural Linguistic Competency (CLC) & Implicit Bias (IB)

STATE LAW:

The California legislature has passed Assembly Bill (AB) 1195, which states that as of July 1, 2006, all Category 1 CME activities that relate to patient care must include a cultural diversity/linguistics component. It has also passed AB 241, which states that as of January 1, 2022, all continuing education courses for a physician and surgeon **must** contain curriculum that includes specified instruction in the understanding of implicit bias in medical treatment.

The cultural and linguistic competency (CLC) and implicit bias (IB) definitions reiterate how patients' diverse backgrounds may impact their access to care.

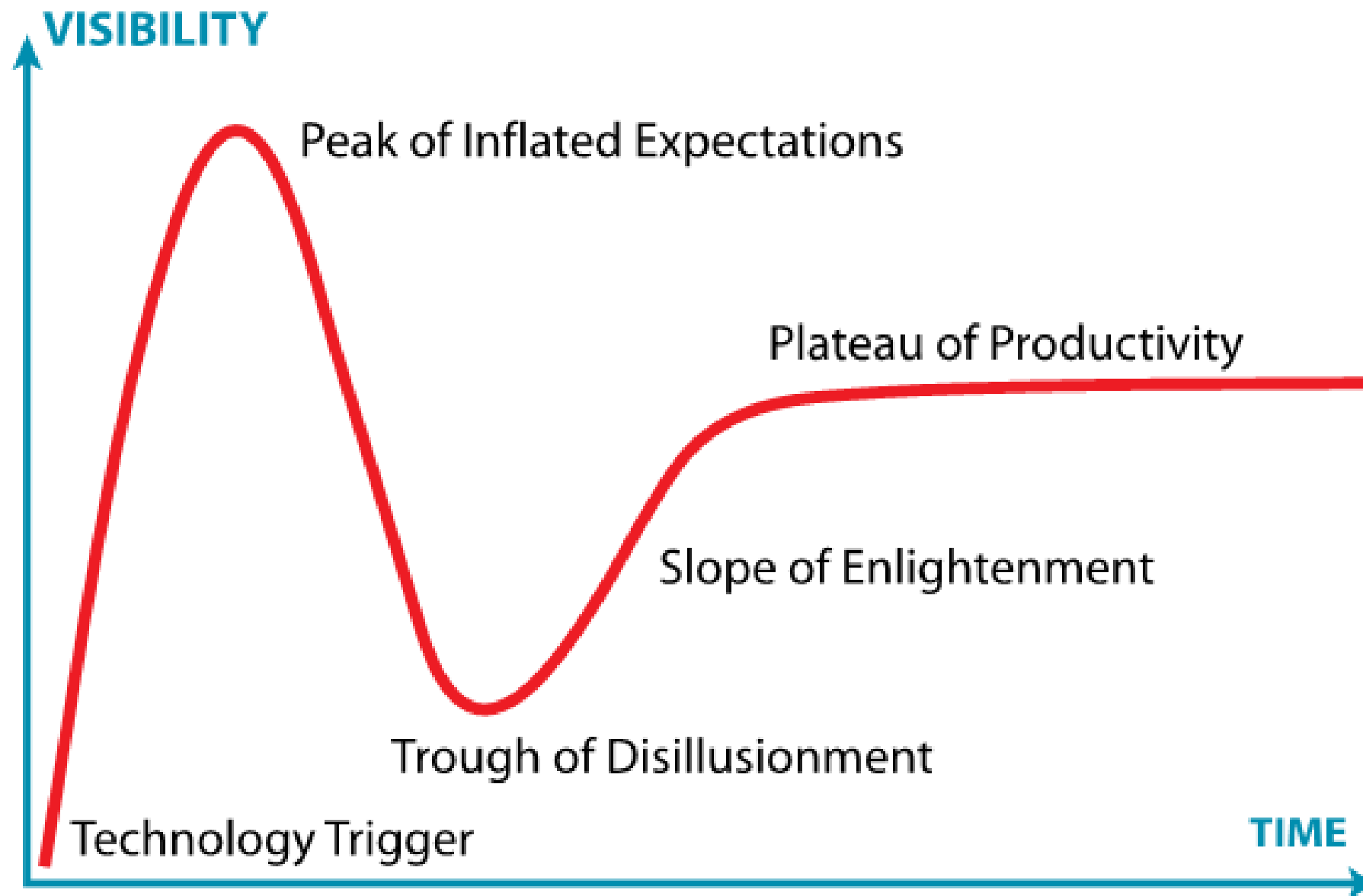
EXEMPTION:

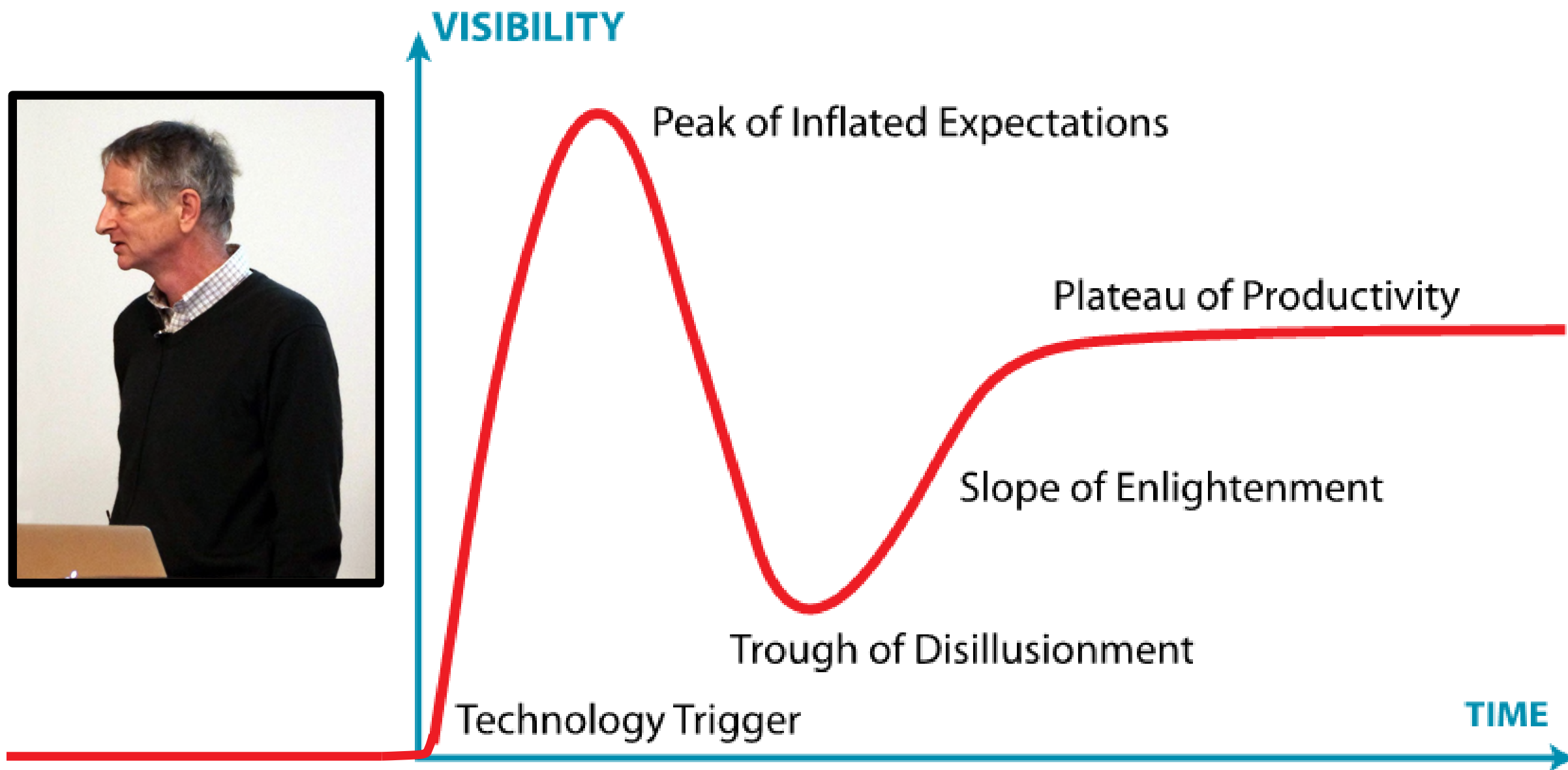
Business and Professions Code 2190.1 exempts activities which are dedicated solely to research or other issues that do not contain a direct patient care component.

The following CLC & IB components will be addressed in this presentation:

- *Discuss unknown confounders in data set used to train imaging algorithms in various patient groups and potential affects on model performance.*
- *Address implicit bias in adoption of AI models for imaging care of patients based on current concepts of standard of care from viewpoints of various stakeholders in chain of healthcare imaging decision making.*









VISIBILITY

Peak of Inflated Expectations

Plateau of Productivity

Slope of Enlightenment

Trough of Disillusionment

Technology Trigger

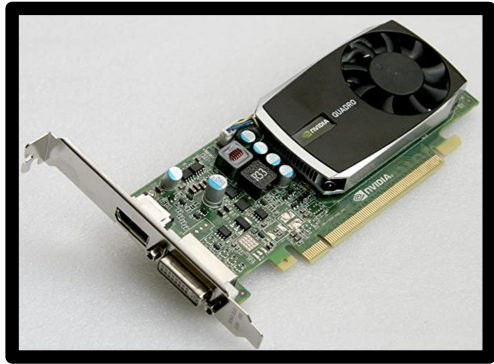
TIME

1987

University of Toronto – AI, Robotics, and Society



+



2012

VISIBILITY



Technology Trigger

Peak of Inflated Expectations

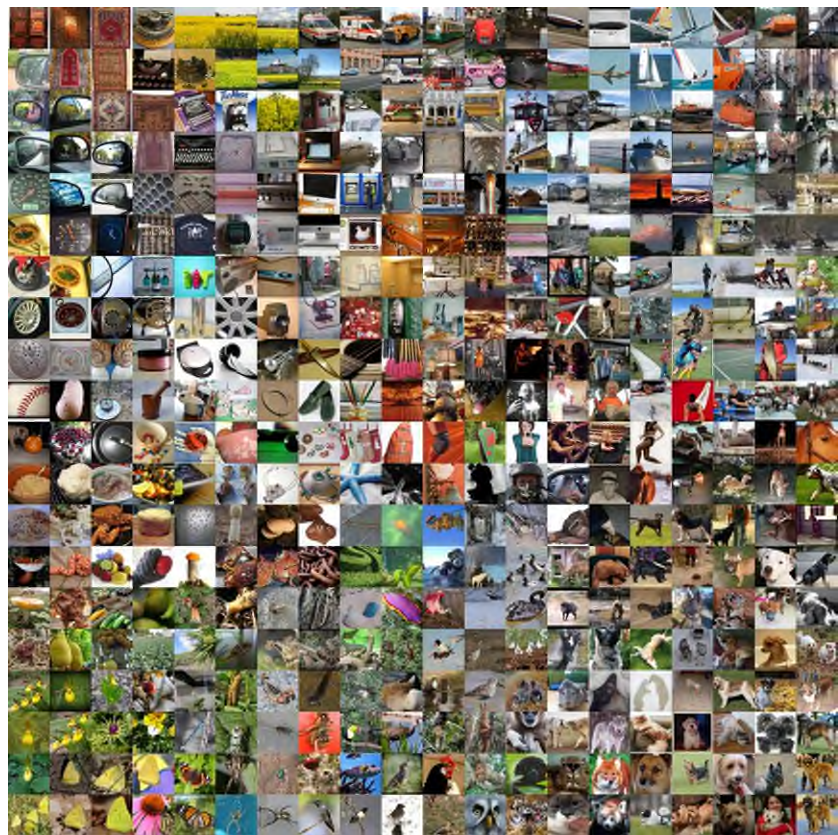
Plateau of Productivity

Slope of Enlightenment

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TIME

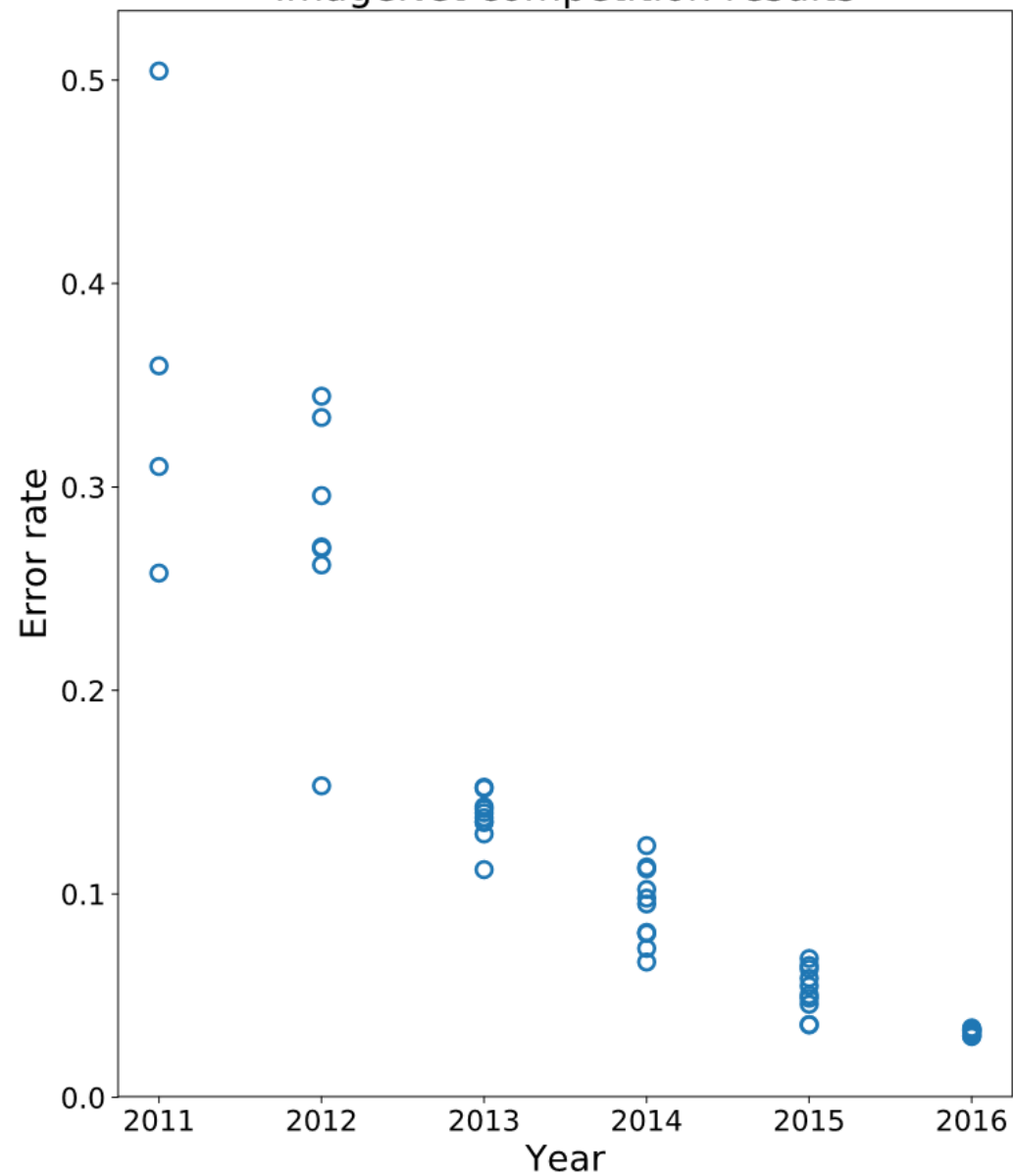


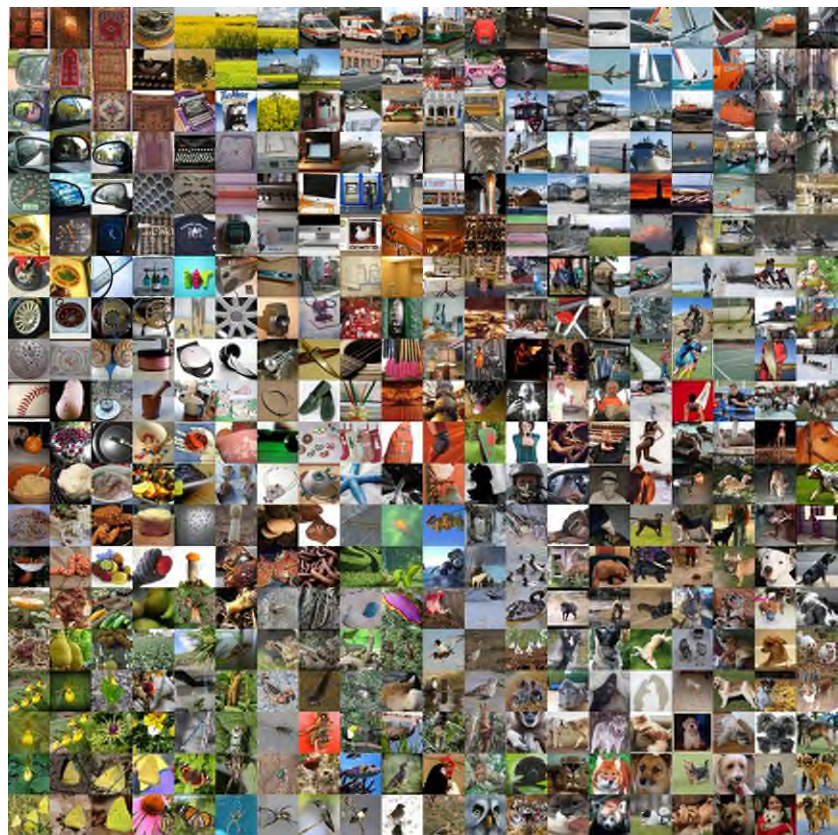


ImageNet – 14m images, 22k categories



ImageNet competition results

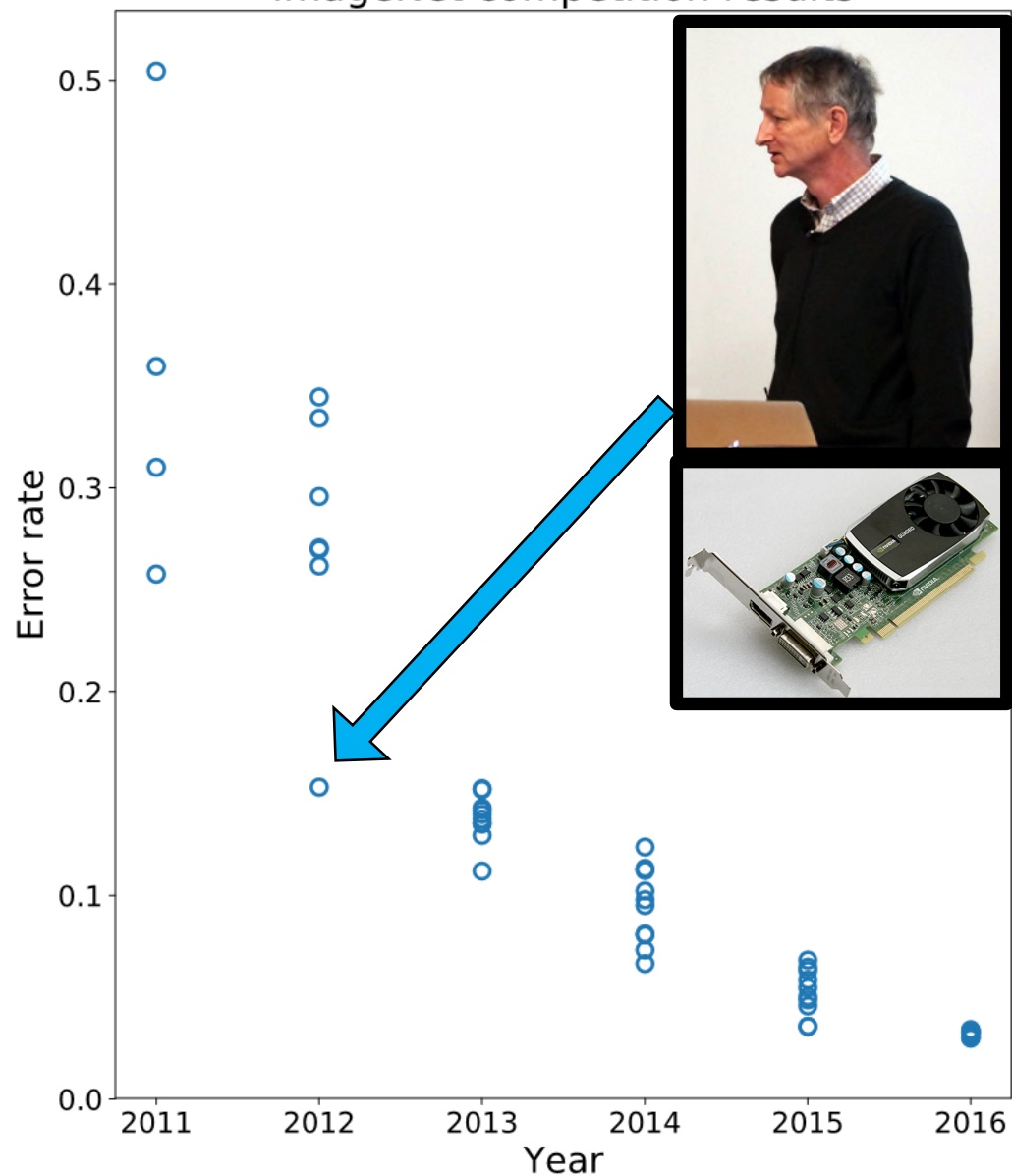


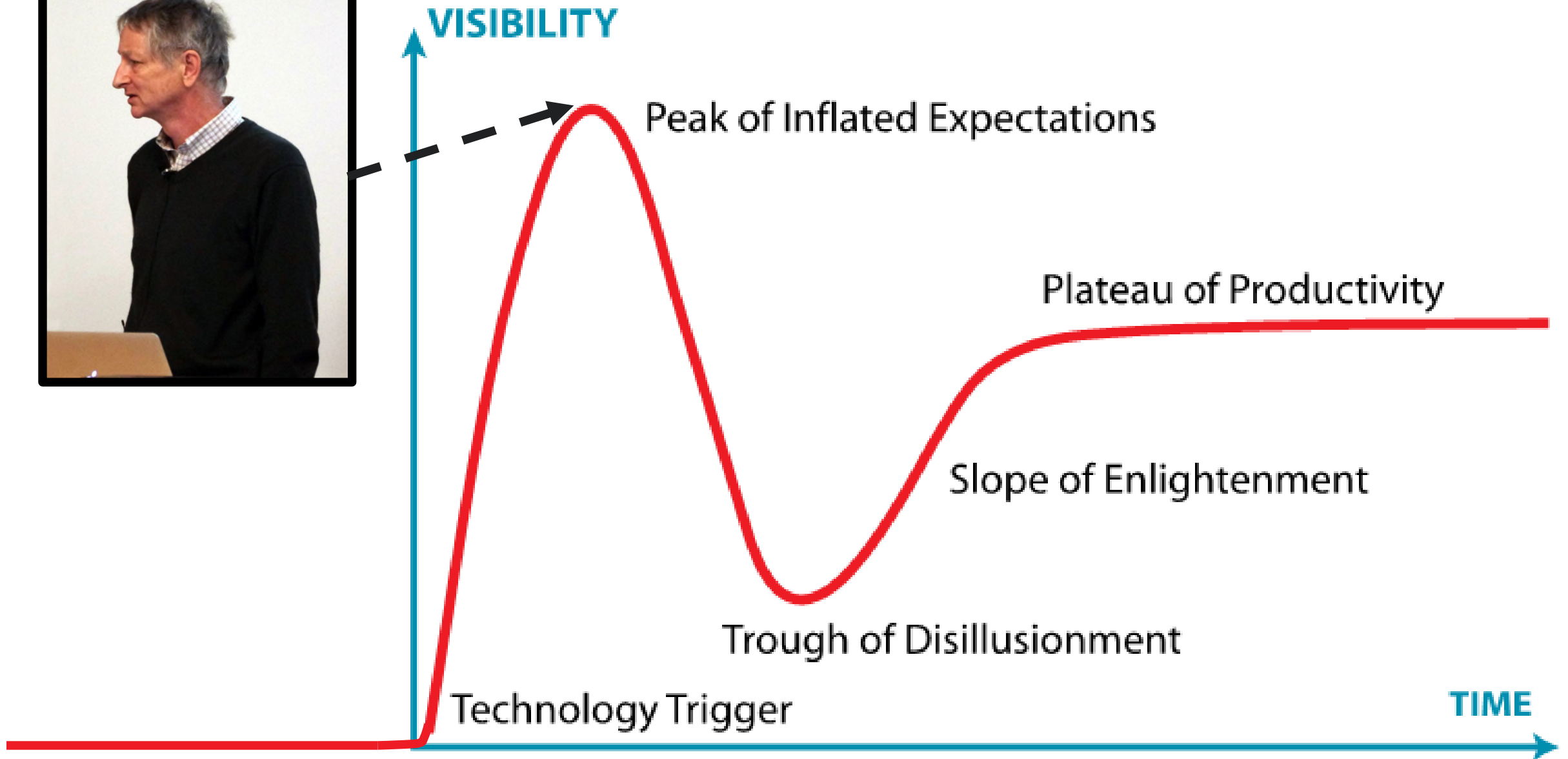


ImageNet – 14m images, 22k categories



ImageNet competition results







VISIBILITY

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TIME

“I think if you **work as a radiologist**, you’re like the coyote that’s **already over the edge of the cliff** but hasn’t yet looked down, so doesn’t know there’s **no ground underneath him...**”

Geoffrey Hinton, 2016

<https://www.youtube.com/watch?v=2HMPRXstSvQ>



“People should **stop training radiologists now.**

It's just completely obvious that **within five years**, deep learning is going to do **better than radiologists.”**

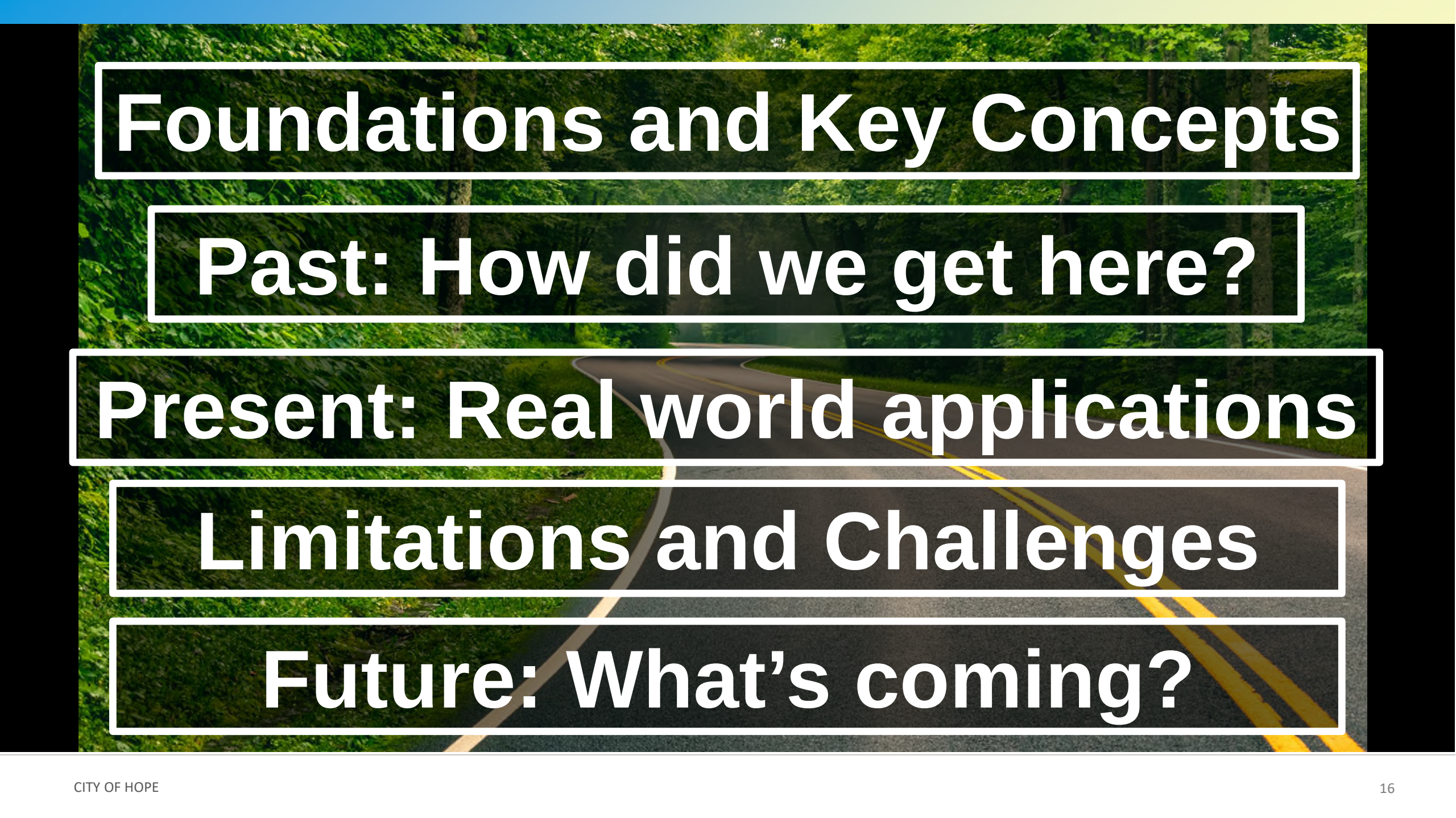
Geoffrey Hinton, 2016

<https://www.youtube.com/watch?v=2HMPRXstSvQ>





"Geoffrey Hinton speaking about radiology" Dall-E 2021



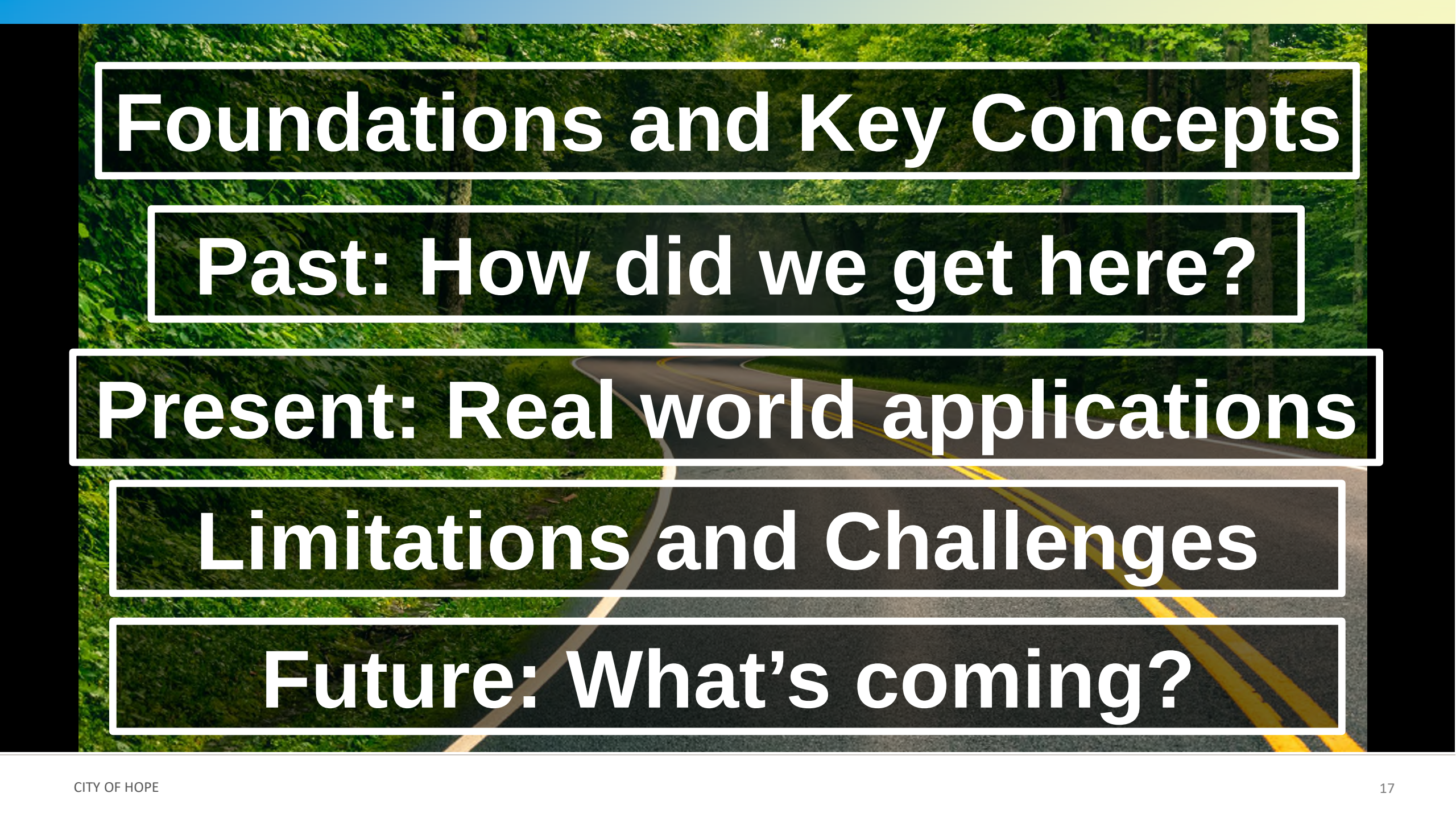
Foundations and Key Concepts

Past: How did we get here?

Present: Real world applications

Limitations and Challenges

Future: What's coming?



Foundations and Key Concepts

Past: How did we get here?

Present: Real world applications

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Future: What's coming?

Foundations & Key Concepts

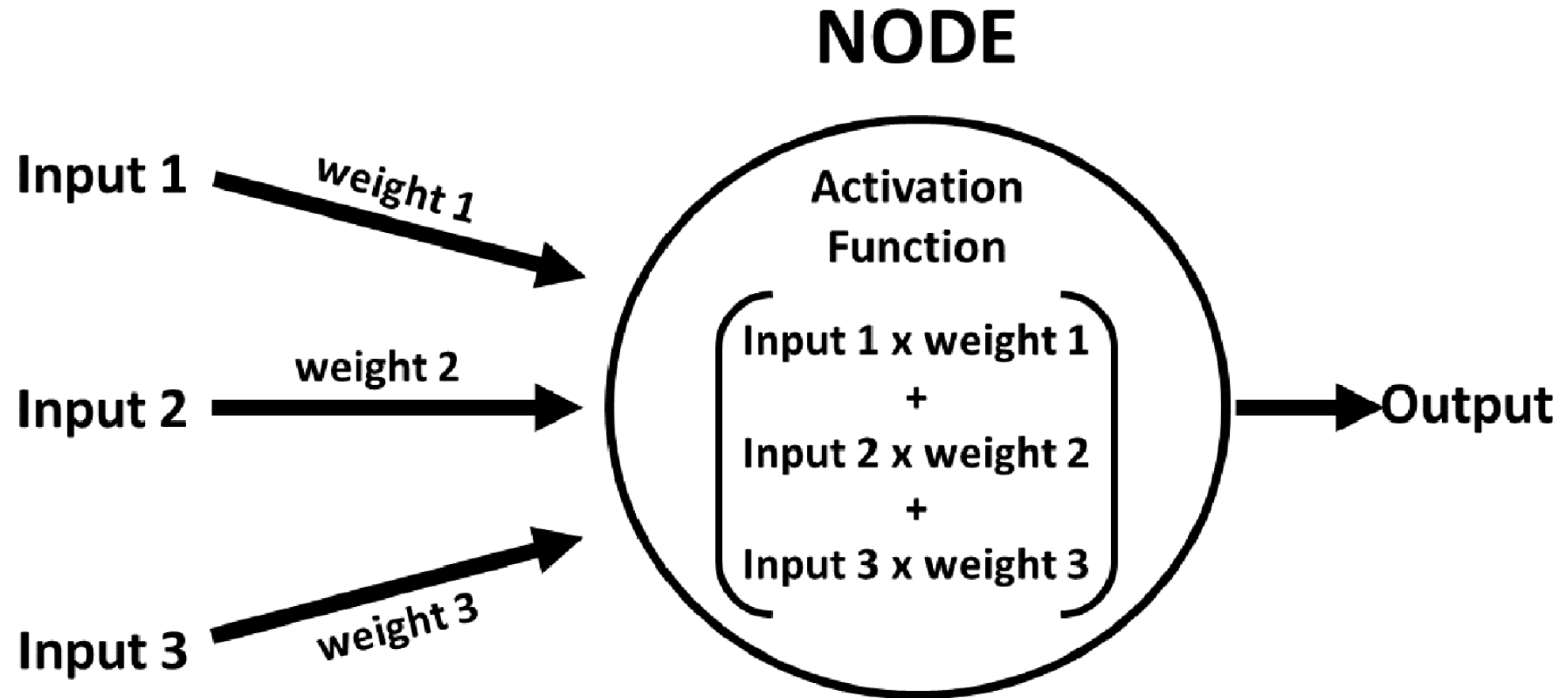
ARTIFICIAL INTELLIGENCE

MACHINE LEARNING

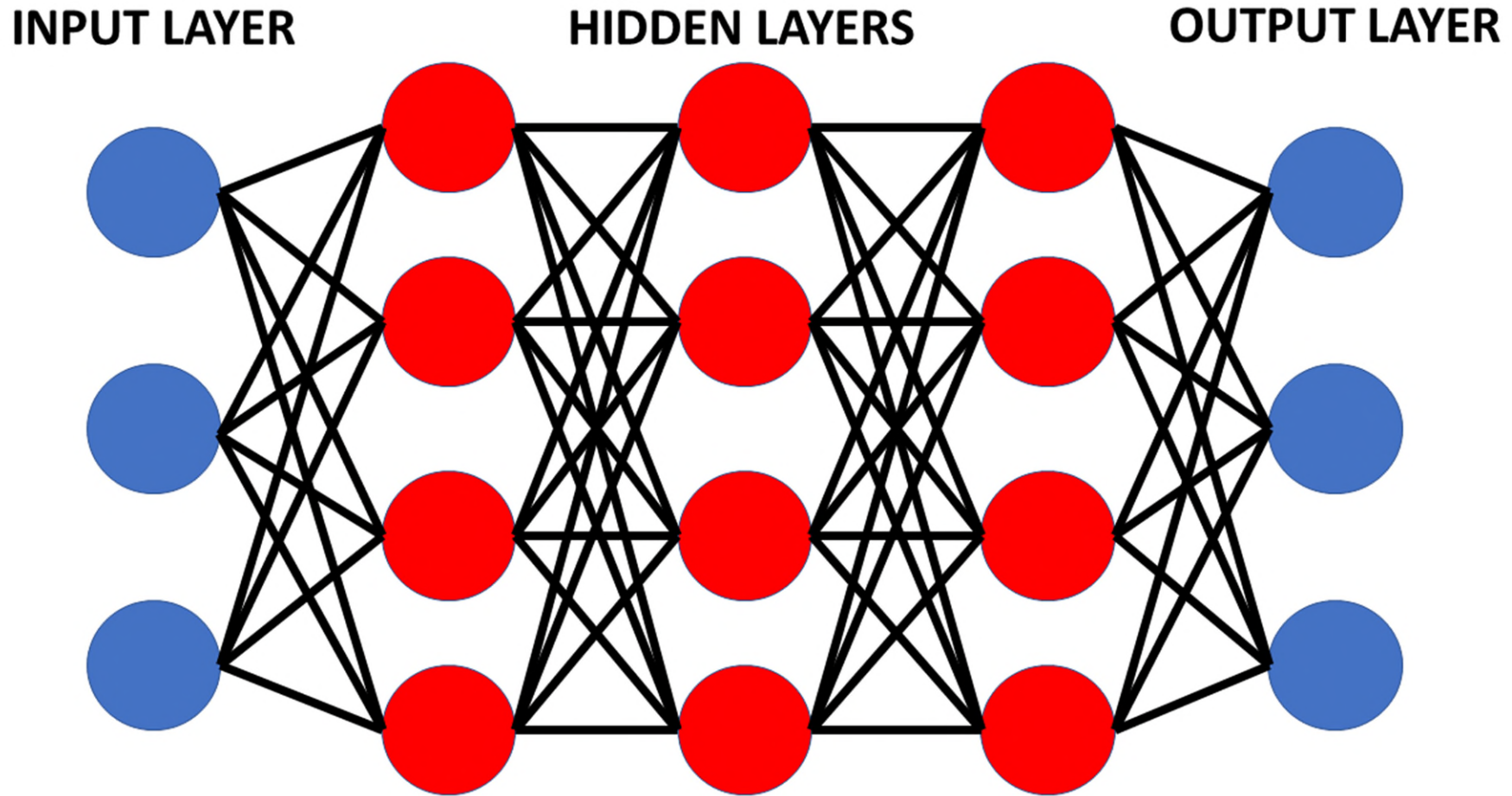
NEURAL NETWORK

DEEP LEARNING

Neural Network



Neural Network



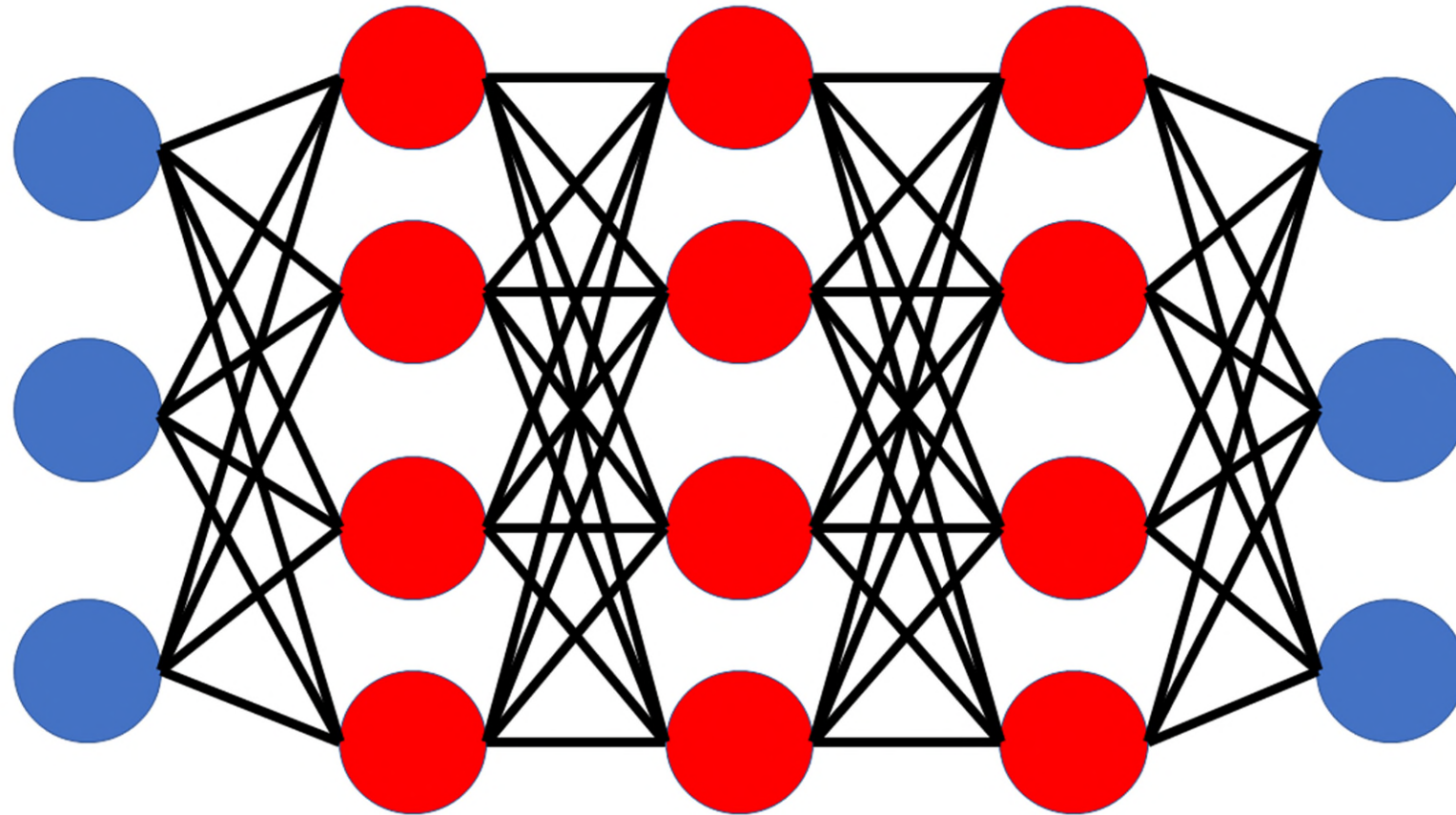
Neural Network

Deep Learning

INPUT LAYER

HIDDEN LAYERS

OUTPUT LAYER



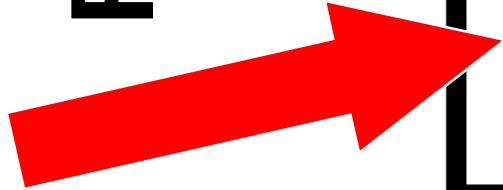
Foundations & Key Concepts

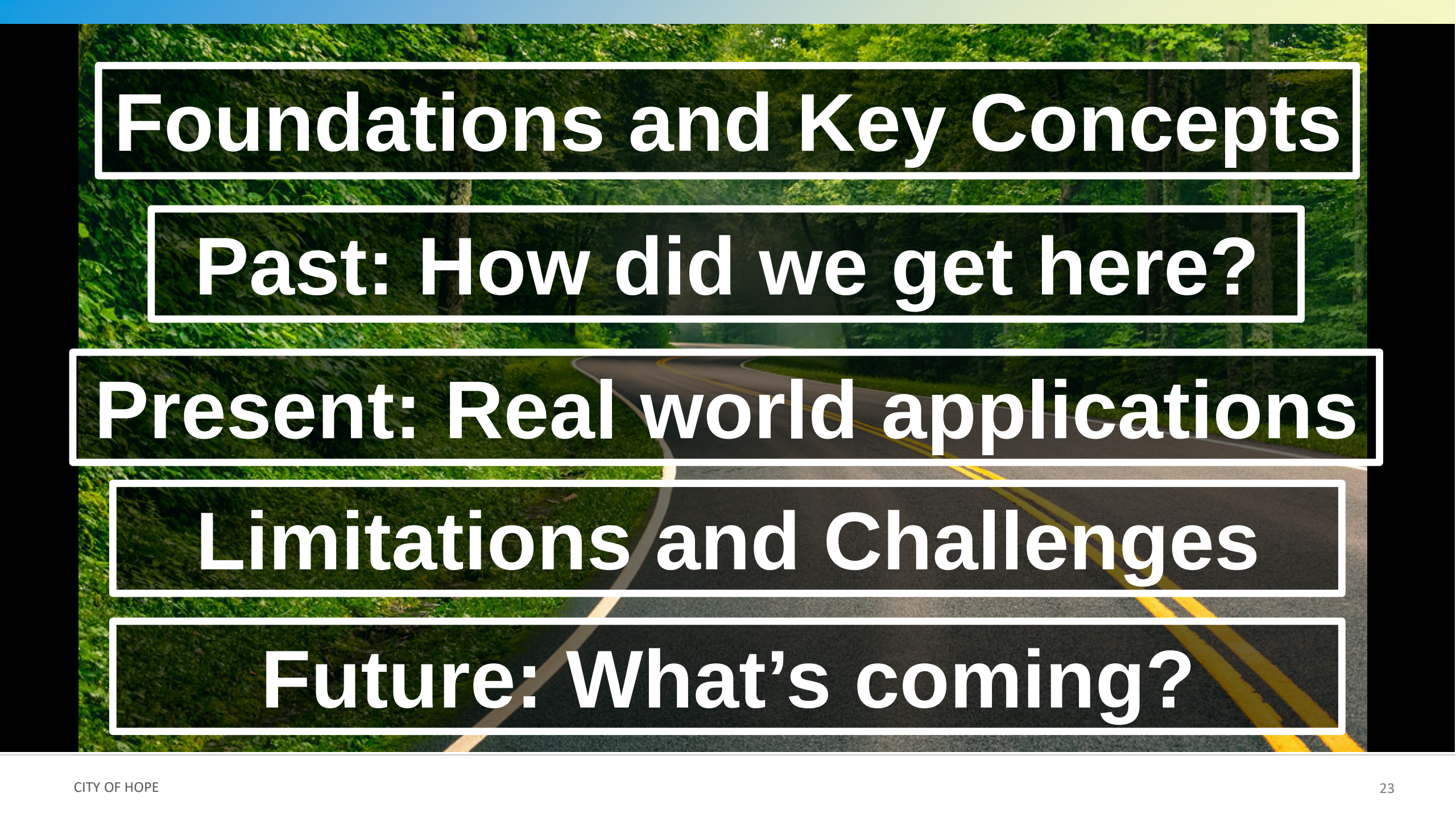
ARTIFICIAL INTELLIGENCE

MACHINE LEARNING

NEURAL NETWORK

DEEP LEARNING





Foundations and Key Concepts

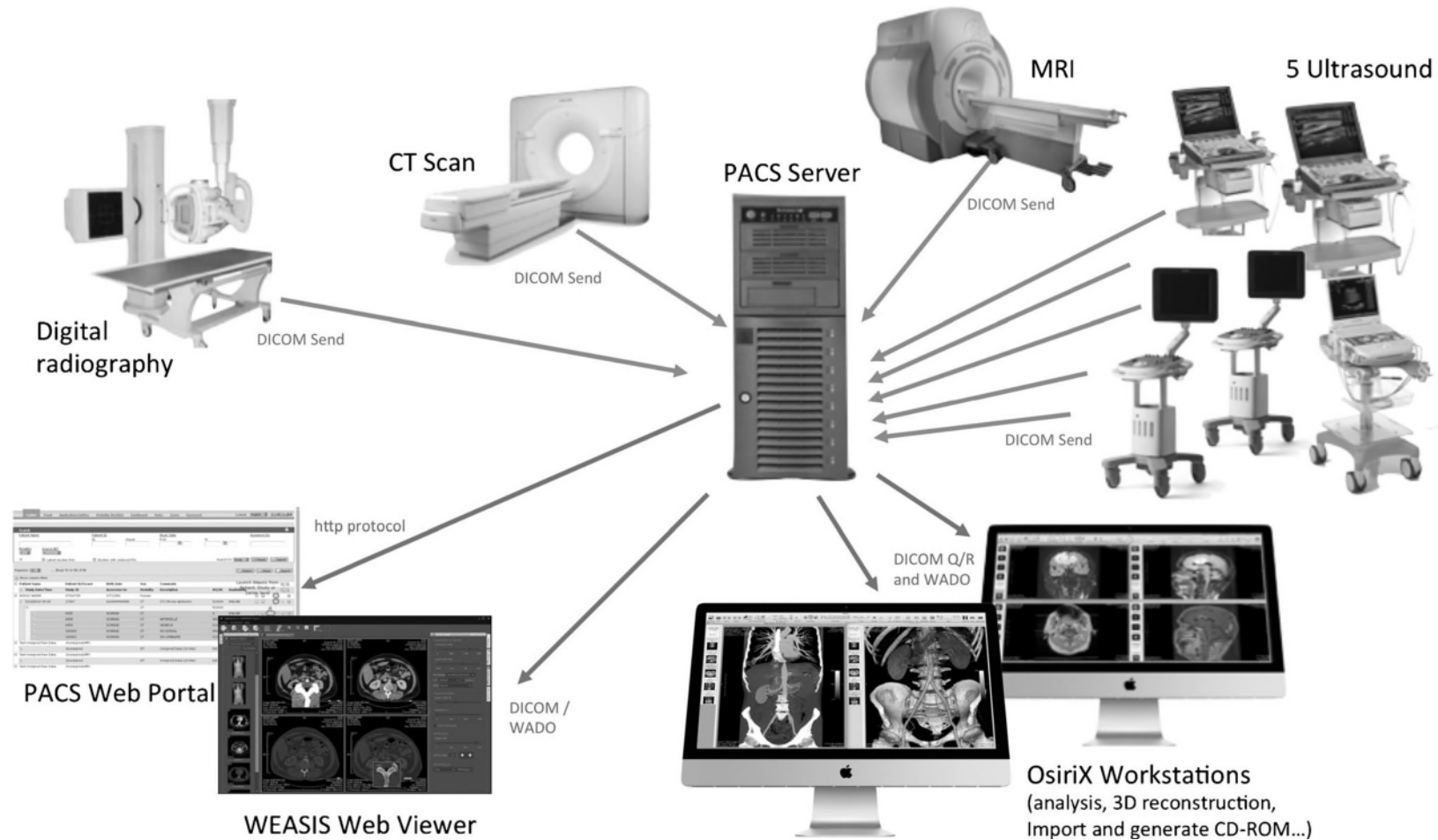
Past: How did we get here?

Present: Real world applications

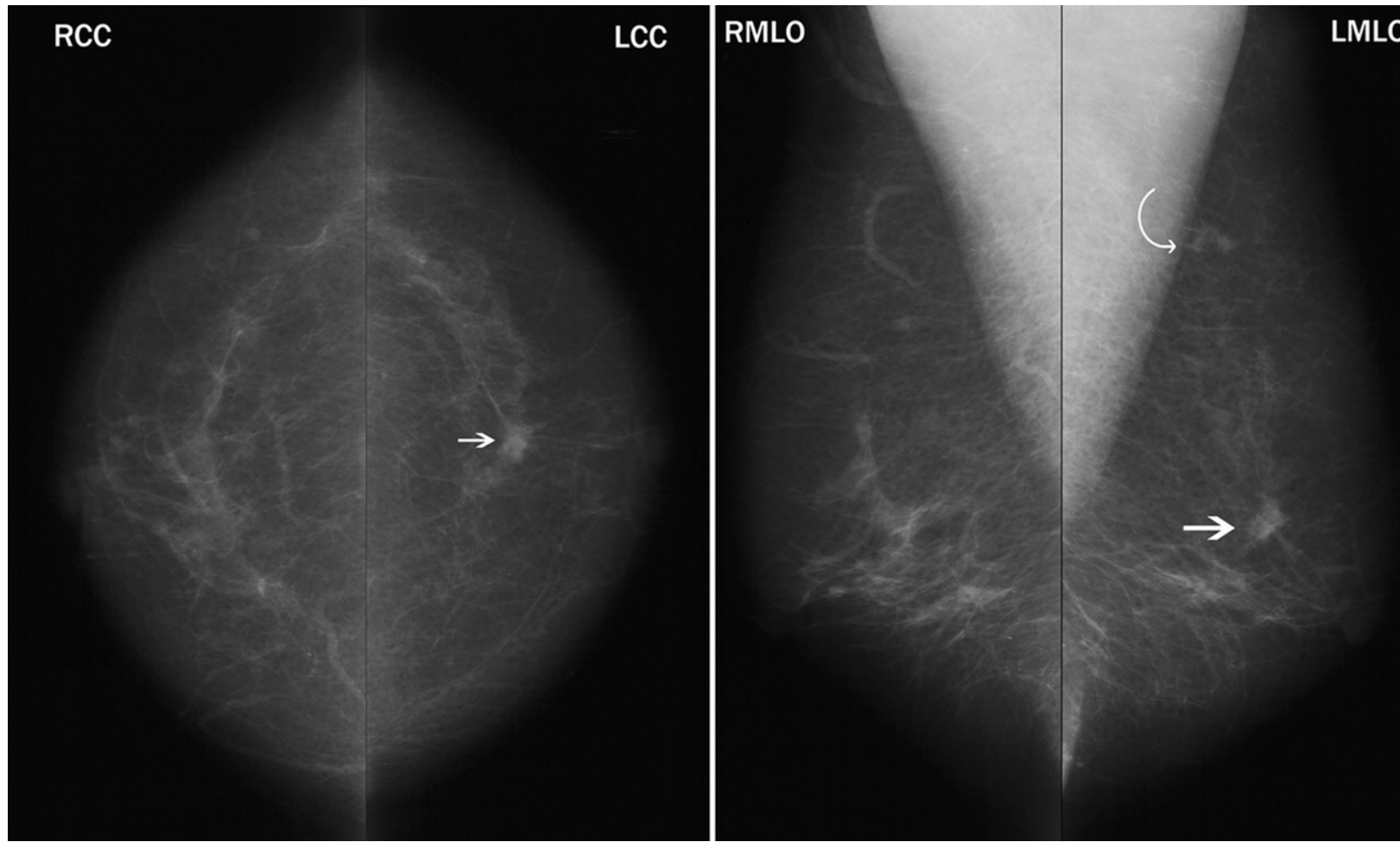
Limitations and Challenges

Future: What's coming?

The Past: Early CAD & Historical Lessons



The Past: Early CAD & Historical Lessons



1998
FDA approval

2002
CMS pay

2000 – 2008
Proliferation of
PACS

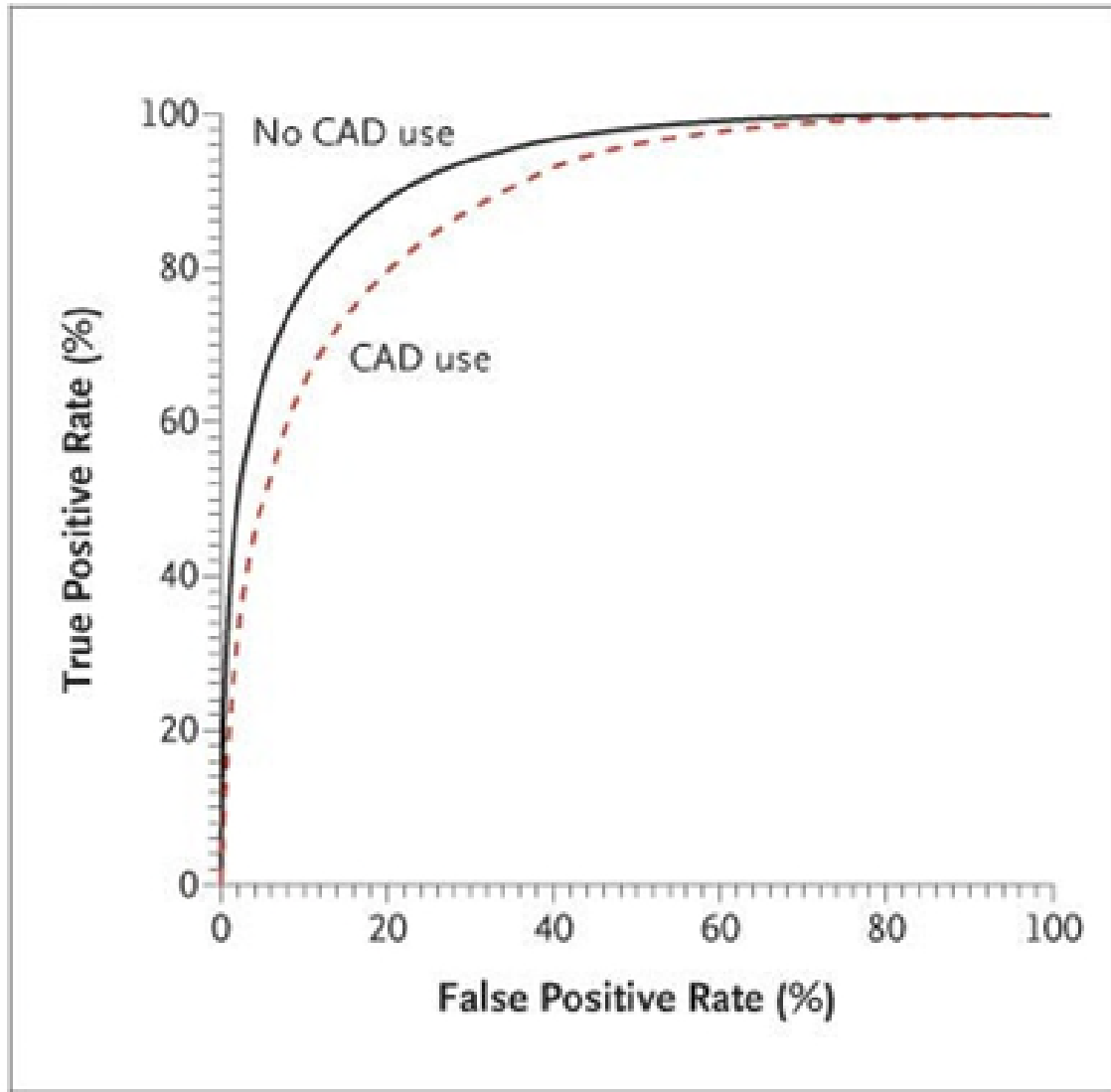
Morton et al. Screening Mammograms: Interpretation with Computer-aided Detection—Prospective Evaluation. Radiology 2005

The Past: Early CAD & Historical Lessons

Early studies show small increase in detection rates (2-10%) and earlier detection (2 months)

All small second reader studies

No outcomes evidence



2007

Fenton, et al – large multi-institutional study showed increase in FP and potential overdiagnosis

2016

92% of imaging facilities used CAD

2018

Medicare ceased add-on payments for CAD

Fenton JJ, et al. Influence of computer-aided detection on performance of screening mammography. N Engl J Med. 2007 Apr 5;356(14):1399-409.

Why did CAD fail?

"Second reader" - not all readers are the same!

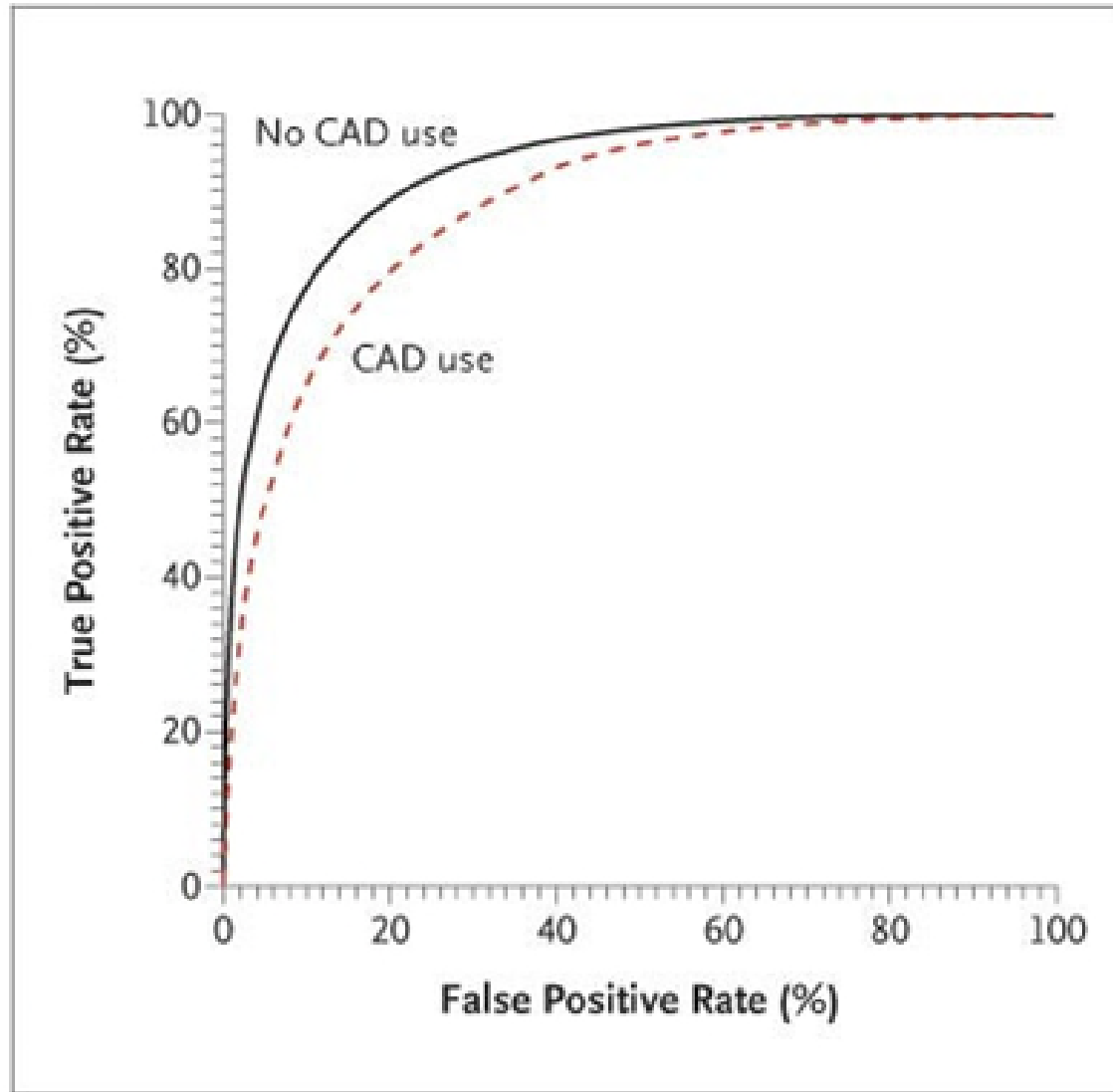
True positives < False positives

False sense of security

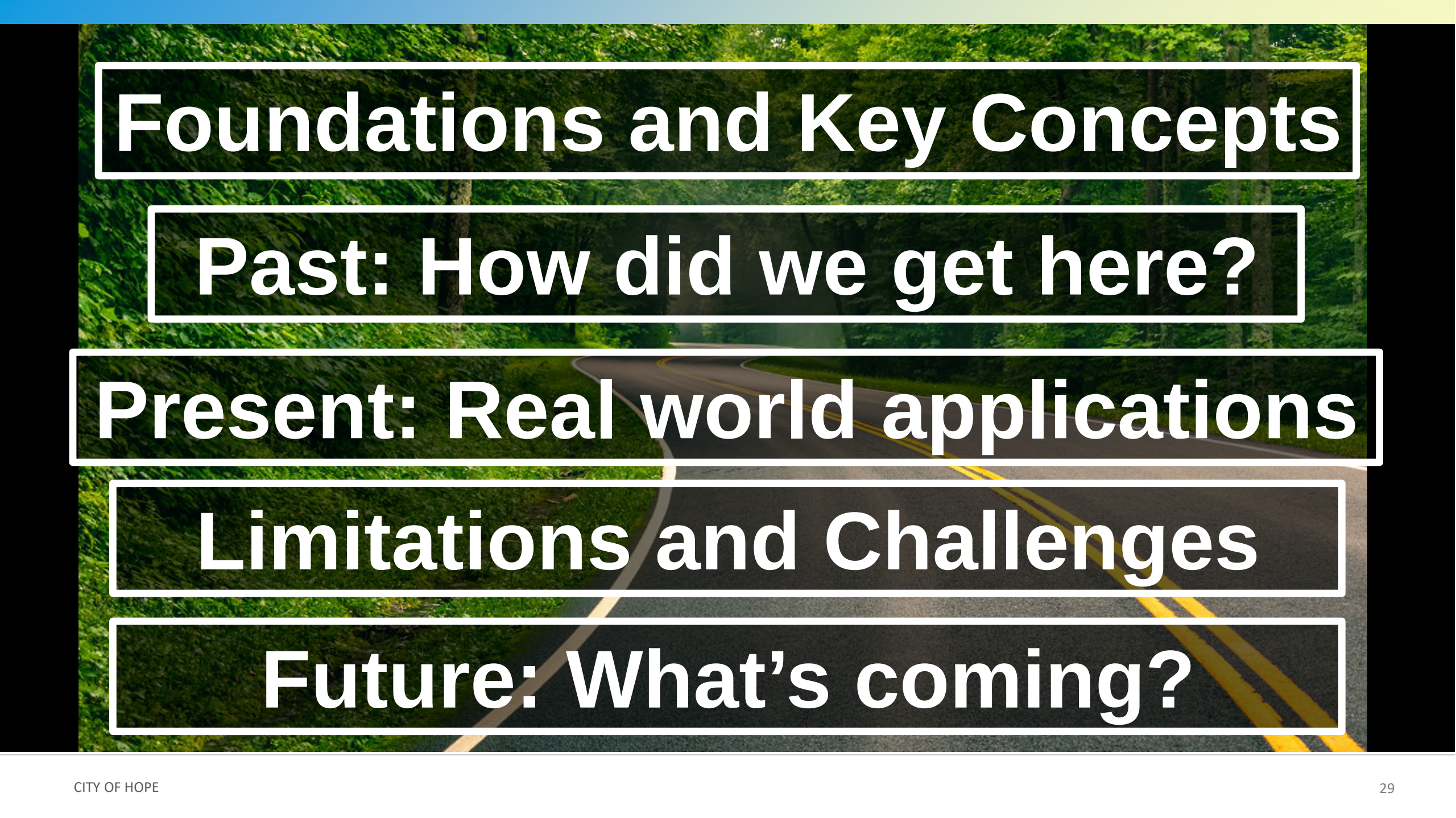
Trained supervision of algorithms

Lack of processing power

Cost without improved outcomes



Fenton JJ, et al. Influence of computer-aided detection on performance of screening mammography. N Engl J Med. 2007 Apr 5;356(14):1399-409.



Foundations and Key Concepts

Past: How did we get here?

Present: Real world applications

Limitations and Challenges

Future: What's coming?

The Present: Real-World Applications

1,247 FDA approved clinical AI algorithms

***as of May 30, 2025**

The Present: Real-World Applications

1,247 FDA approved clinical AI algorithms

>1000 Related to medical imaging

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The Present: Real-World Applications

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956 Radiology-based

***as of May 30, 2025**

The Present: Real-World Application

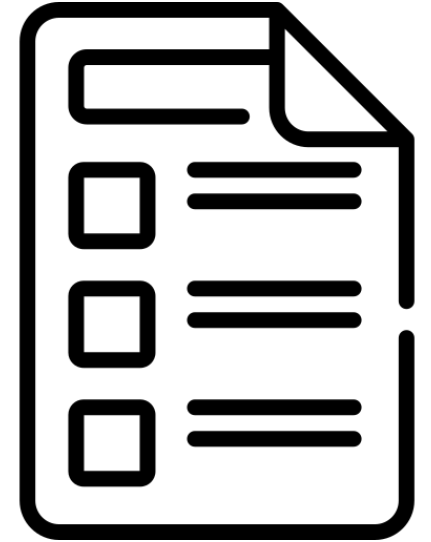
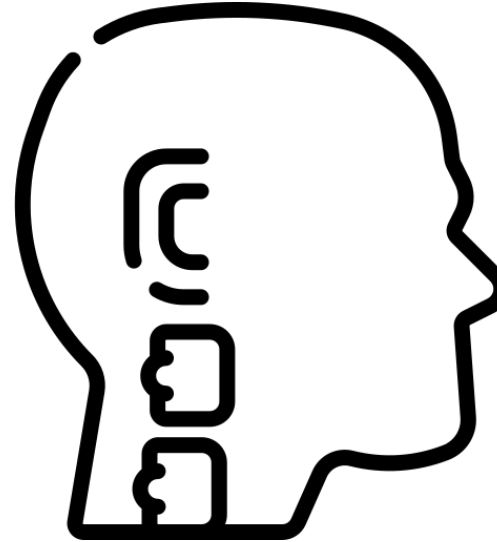
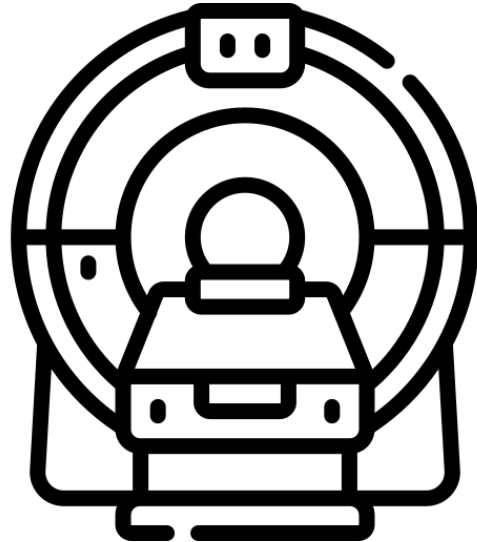
1,247 FDA approved algorithms

>1000 Deep Learning Imaging

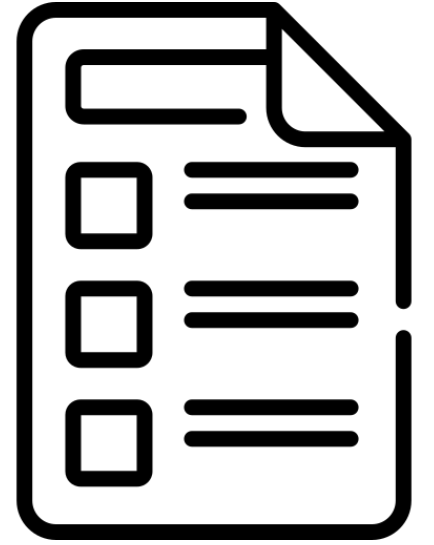
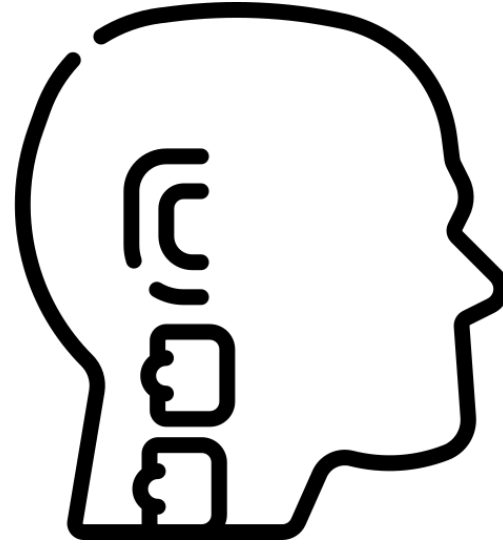
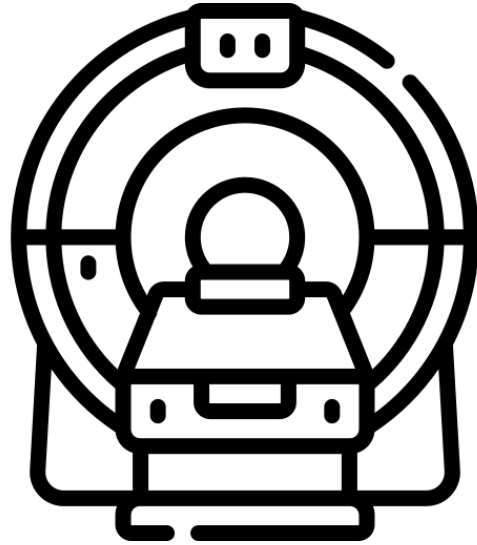
95% AI-based

Lack of CPT codes –
limited or no funding

*as of May 30, 2025



Radiology Workflow Pipeline



Imaging Order

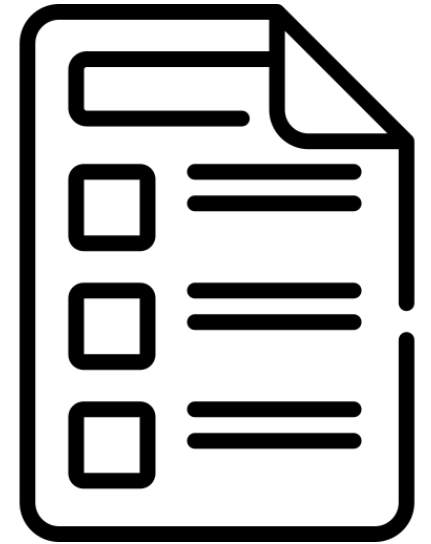
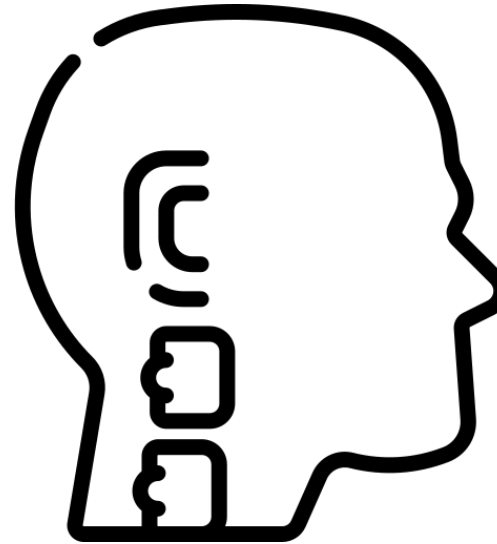
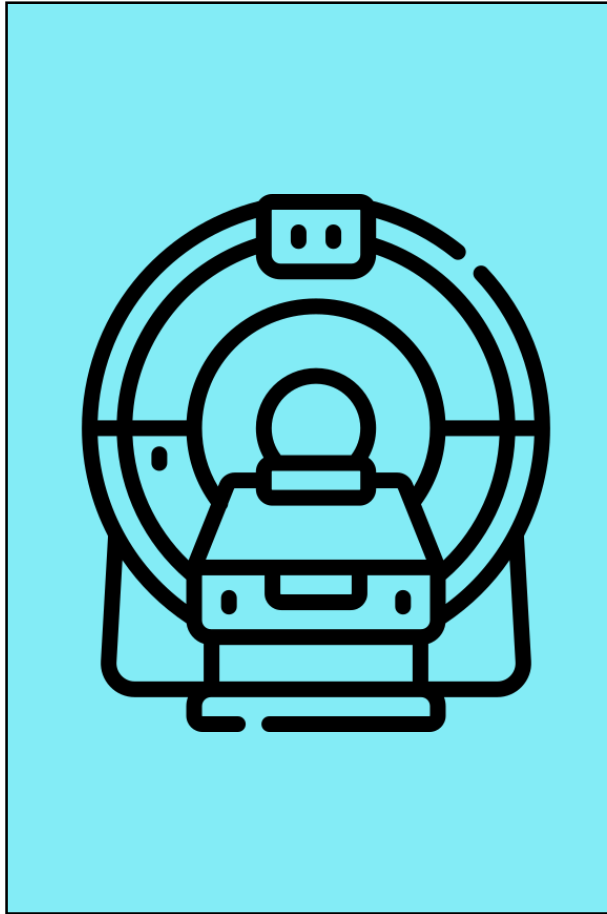


Image Acquisition

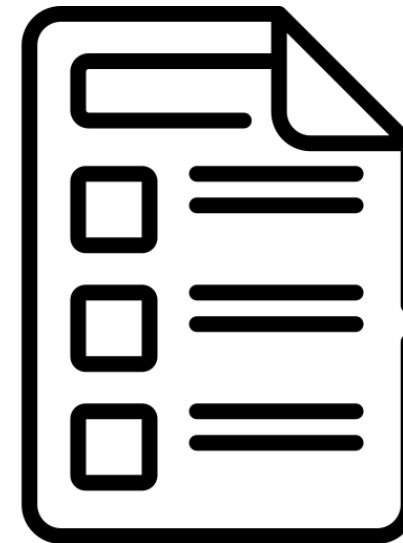
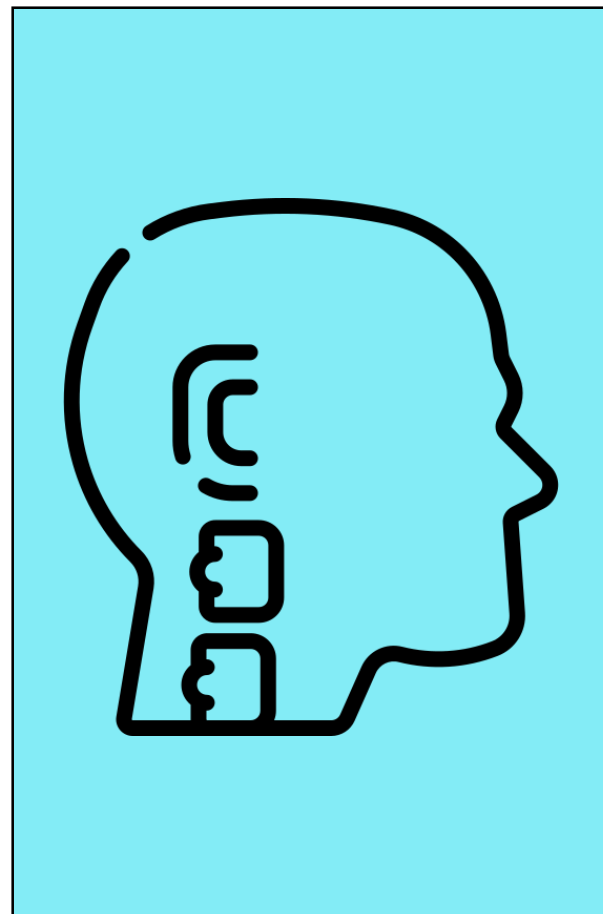
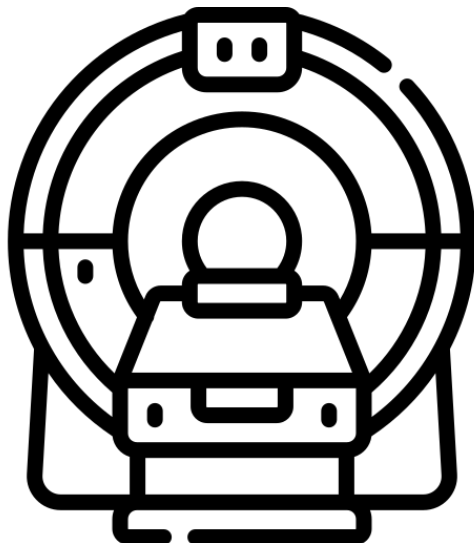
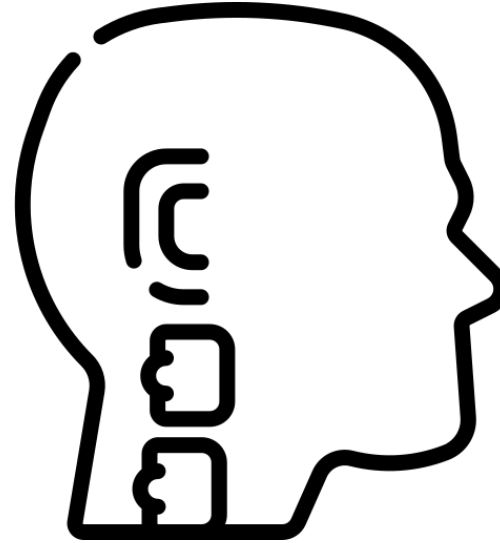
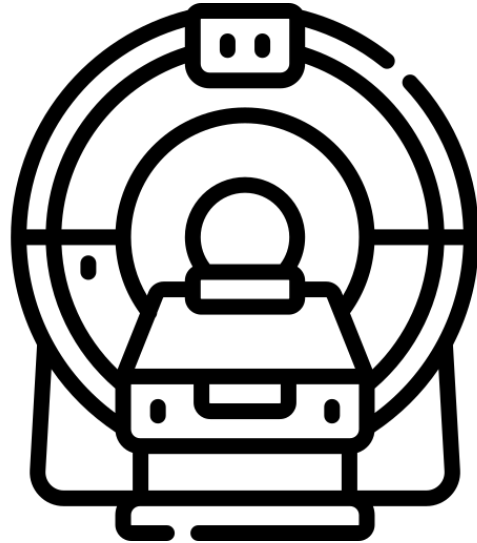
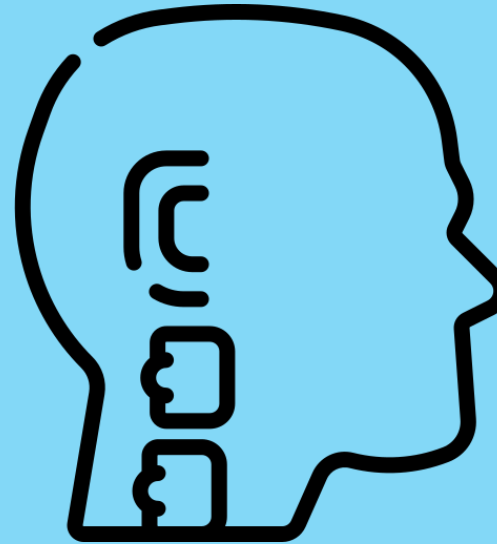
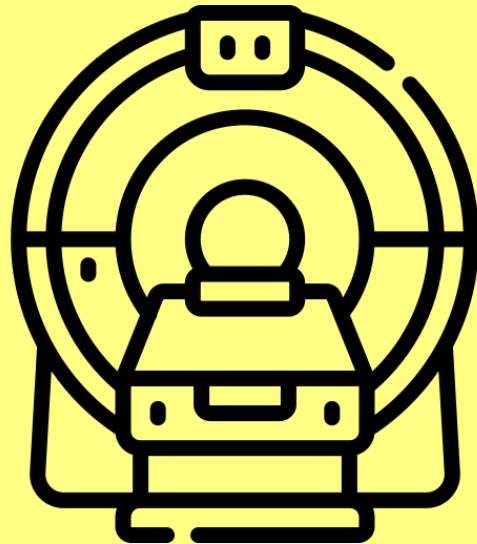


Image Interpretation

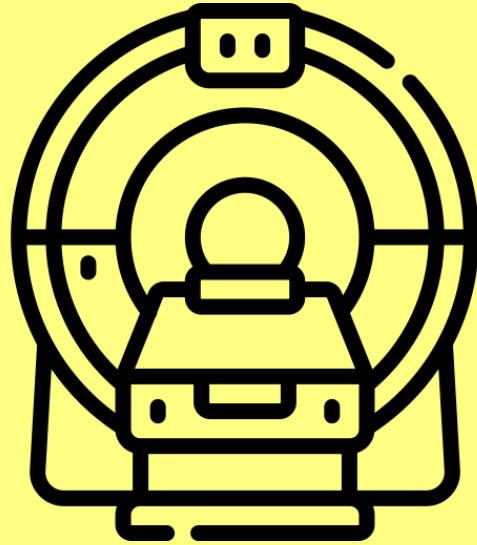


Report Generation



Upstream Processes

Downstream Processes



Upstream Processes

Clinical decision support

Scheduling

Protocols

Acquisition guidance

Quality standardization

Image optimization

Post processing

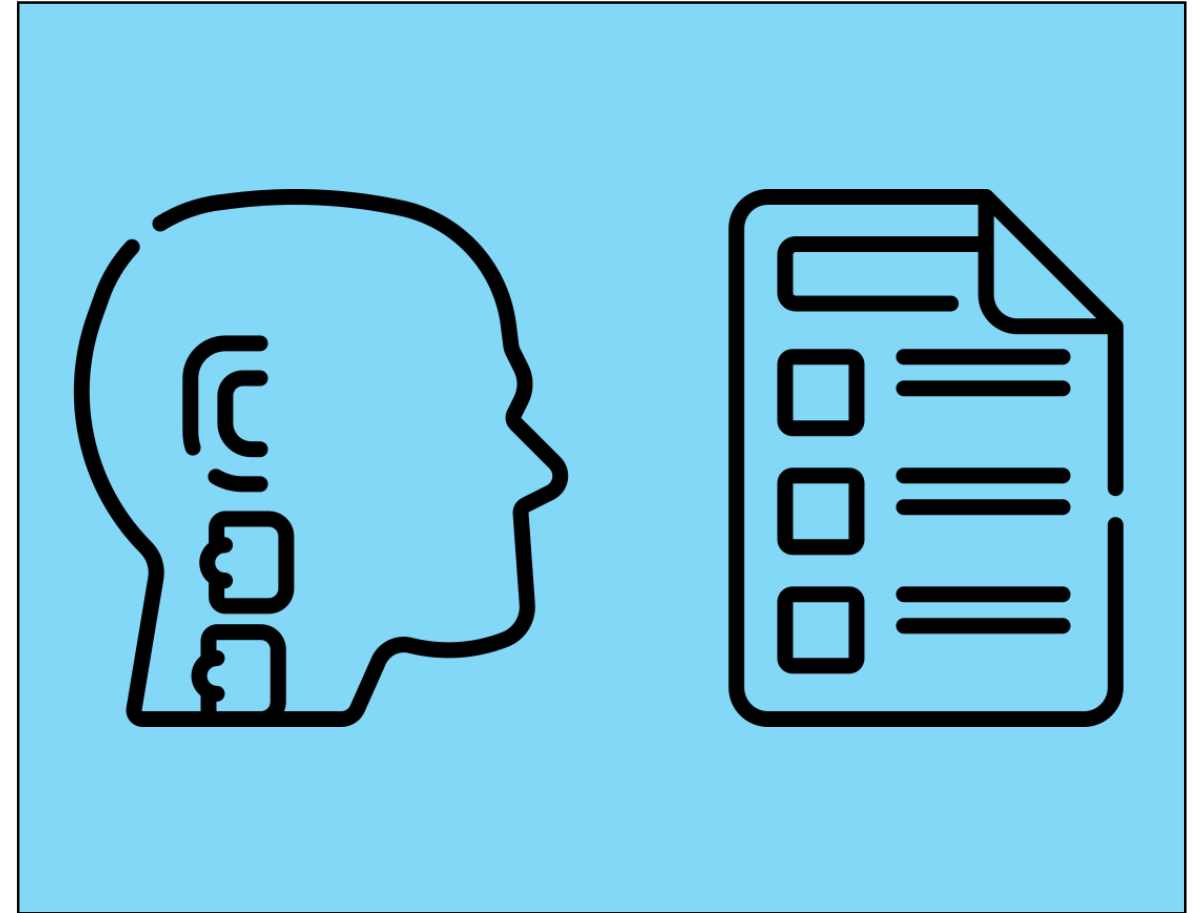
Worklist optimization

Segmentation

Treatment planning

Radiomics

**Natural language
processing**



Downstream Processes

**Right study at the right
time**

**Increased regulatory focus
on 'quality'**

**Increase high value
imaging, decrease low
value imaging**

Clinical decision support

Scheduling

Protocols

Acquisition guidance

Quality standardization

Image optimization

Post processing

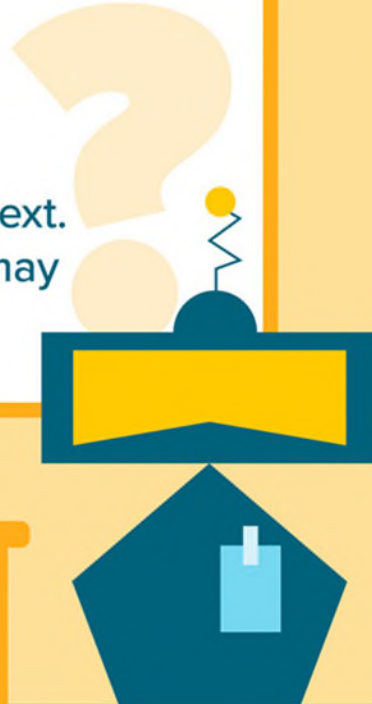
Worklist optimization

Can an AI clinical decision support (CDS) tool improve the rate of structured indication entries and scored orders?

Shreve LA, Fried JG, Liu F, et al. *J Am Coll Radiol*. 2023;20

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Imaging CDS needs structured indications to score orders, yet providers prefer free text. Artificial intelligence may offer a solution.



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Recorded and assessed outpatient advanced imaging orders, before and after implementation:

CDS SCORE

- Not appropriate
- Maybe appropriate
- Appropriate
- Unscored

INDICATION TYPE

- Structured
- Free-text
- Both
- None

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Significant increases in proportion of orders with:

STRUCTURED INDICATION

34.5% → 67.2%

SCORED ORDERS

29.8% → 52.2%



47.8% of orders remained unscored due to:

- INFRASTRUCTURE (37.3%)
- PROVIDER BEHAVIOR (19.2%)
- MIXED (43.4%)

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Though an AI tool embedded in CDS nearly doubled the rate of structured imaging order entries, nearly half of orders remained unscored.

Shreve LA, Fried JG, Liu F, et al. *J Am Coll Radiol*. 2023;20

American College of Radiology

ACR AC Portal

Explore by scenario

Explore by topic

Explore by procedure

Panel

Sex

Age

Body Area

Priority Clinical Areas

All

All

All

All

All

Search

Clear

Search

Panel	Scenario	Sex	Age	Body Area	Priority Clinical Areas
Breast	3110141 Axillary adenopathy, breast cancer suspected	Male Only	18 - 150	Breast	
Breast	3194817 Axillary lump, palpable, new, bilateral, initial axilla imaging	Female Only	18 - 150	Breast	
Breast	3194815 Axillary lump, palpable, new, unilateral, initial axilla imaging	Female Only	18 - 150	Breast	
Breast	3194837 Axillary node, suspicious on imaging, not mammo or US, next imaging study	Female Only	18 - 150	Breast	
Breast	3194835 Axillary node, suspicious on mammo or US, next imaging study	Female Only	18 - 150	Breast	
Breast	3199337 Breast abscess suspected, pregnant, initial imaging	Female Only	10 - 60	Breast	
Breast	3197142 Breast cancer screening, >=20-25% estimated lifetime risk	Female Only	30 - 150	Breast	
Breast	3199408 Breast cancer screening, >=20-25% estimated lifetime risk	Female Only	18 - 29	Breast	
Breast	3197137 Breast cancer screening, 15-20% estimated lifetime risk	Female Only	30 - 150	Breast	
Breast	3199194 Breast cancer screening, ashkenazi descent	Male Only	25 - 150	Breast	
Breast	3199207 Breast cancer screening, ashkenazi descent	Male Only	18 - 24	Breast	
Breast	3199209 Breast cancer screening, average risk	Male Only	25 - 150	Breast	

Total Records: 3890

ACR Appropriateness Criteria® Brain Tumors. [Variants 1 to 6](#) and [Table 1](#) and [2](#).

Variant 1. Adult. Primary brain tumor screening. Genetic risk factors.		
Procedure	Appropriateness Category	Relative Radiation Level
MRI head without and with IV contrast	Usually Appropriate	O
MRI complete spine without and with IV contrast	May Be Appropriate	O
MRI head without IV contrast	May Be Appropriate	O
MR spectroscopy head without IV contrast	Usually Not Appropriate	O
MRI complete spine with IV contrast	Usually Not Appropriate	O
MRI complete spine without IV contrast	Usually Not Appropriate	O
MRI functional (fMRI) head without IV contrast	Usually Not Appropriate	O
MRI head perfusion with IV contrast	Usually Not Appropriate	O
MRI head perfusion without IV contrast	Usually Not Appropriate	O
MRI head with IV contrast	Usually Not Appropriate	O
MRI head without IV contrast with DTI	Usually Not Appropriate	O
CT head with IV contrast	Usually Not Appropriate	⚠⚠⚠
CT head without and with IV contrast	Usually Not Appropriate	⚠⚠⚠
CT head without IV contrast	Usually Not Appropriate	⚠⚠⚠
DOTATATE PET/CT brain	Usually Not Appropriate	⚠⚠⚠
DOTATATE PET/MRI brain	Usually Not Appropriate	⚠⚠⚠
FDG-PET/CT brain	Usually Not Appropriate	⚠⚠⚠
FDG-PET/MRI brain	Usually Not Appropriate	⚠⚠⚠
Fluciclovine PET/MRI brain	Usually Not Appropriate	⚠⚠⚠
Fluciclovine PET/CT brain	Usually Not Appropriate	⚠⚠⚠⚠

ACR Appropriateness Criteria® Brain Tumors. Variants 1 to 6 and Table 1 and 2.

Variant 1. Adult. Primary brain tumor screening. Genetic risk factors.

Procedure	Appropriateness Category	Relative Radiation Level
MRI head without and with IV contrast	Usually Appropriate	0
MRI complete spine without and with IV contrast	May Be Appropriate	0
MRI head without IV contrast	May Be Appropriate	0
MR spectroscopy head without IV contrast	Usually Not Appropriate	0
MRI complete spine with IV contrast	Usually Not Appropriate	0
MRI complete spine without IV contrast	Usually Not Appropriate	0
MRI functional (fMRI) head without IV contrast	Usually Not Appropriate	0
MRI head perfusion with IV contrast	Usually Not Appropriate	0
MRI head perfusion without IV contrast	Usually Not Appropriate	0
MRI head with IV contrast	Usually Not Appropriate	0
MRI head without IV contrast with DTI	Usually Not Appropriate	0
CT head with IV contrast	Usually Not Appropriate	⚠⚠⚠
CT head without and with IV contrast	Usually Not Appropriate	⚠⚠⚠
CT head without IV contrast	Usually Not Appropriate	⚠⚠⚠
DOTATATE PET/CT brain	Usually Not Appropriate	⚠⚠⚠
DOTATATE PET/MRI brain	Usually Not Appropriate	⚠⚠⚠
FDG-PET/CT brain	Usually Not Appropriate	⚠⚠⚠
FDG-PET/MRI brain	Usually Not Appropriate	⚠⚠⚠
Fluciclovine PET/MRI brain	Usually Not Appropriate	⚠⚠⚠
Fluciclovine PET/CT brain	Usually Not Appropriate	⚠⚠⚠⚠

Noise reduction

Raw data reconstruction

**Synthetic image
generation**

**Personalized scanning
protocols**

Clinical decision support

Scheduling

Protocols

Acquisition guidance

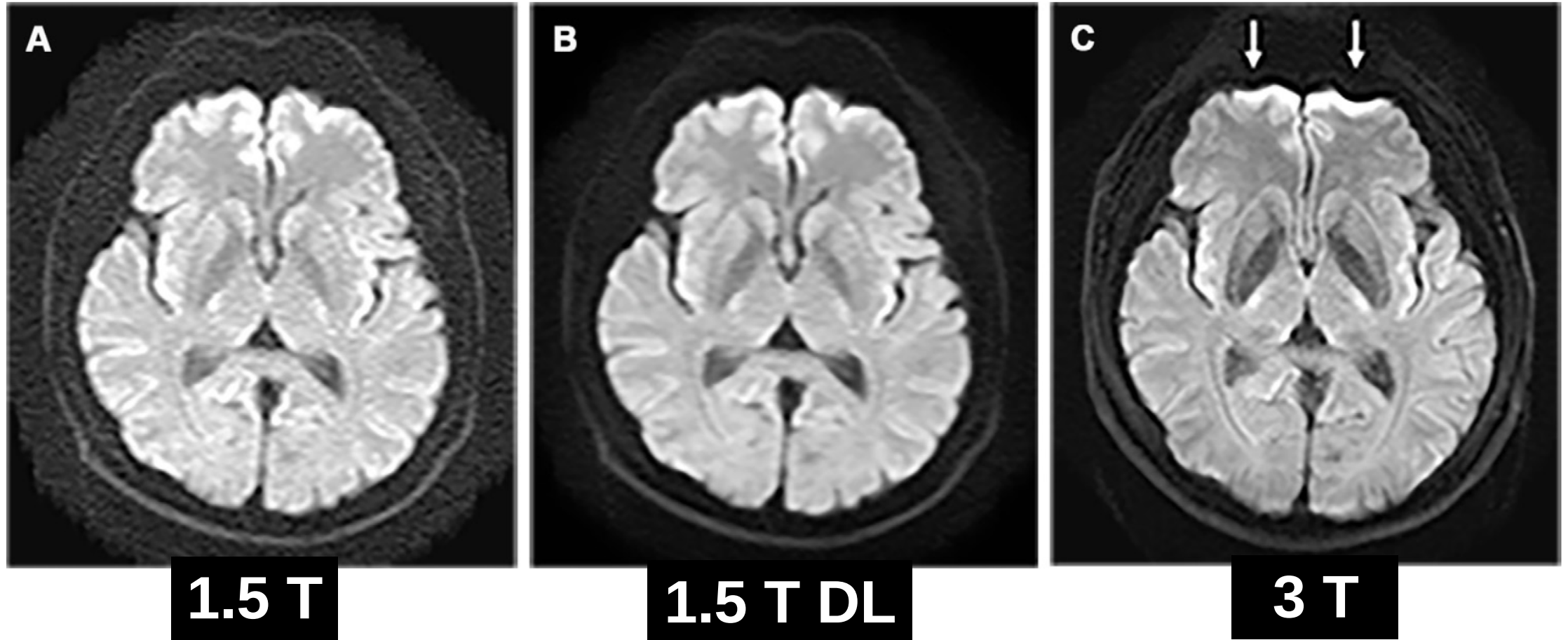
Quality standardization

Image optimization

Post processing

Worklist optimization

Image Quality: DL Denoising

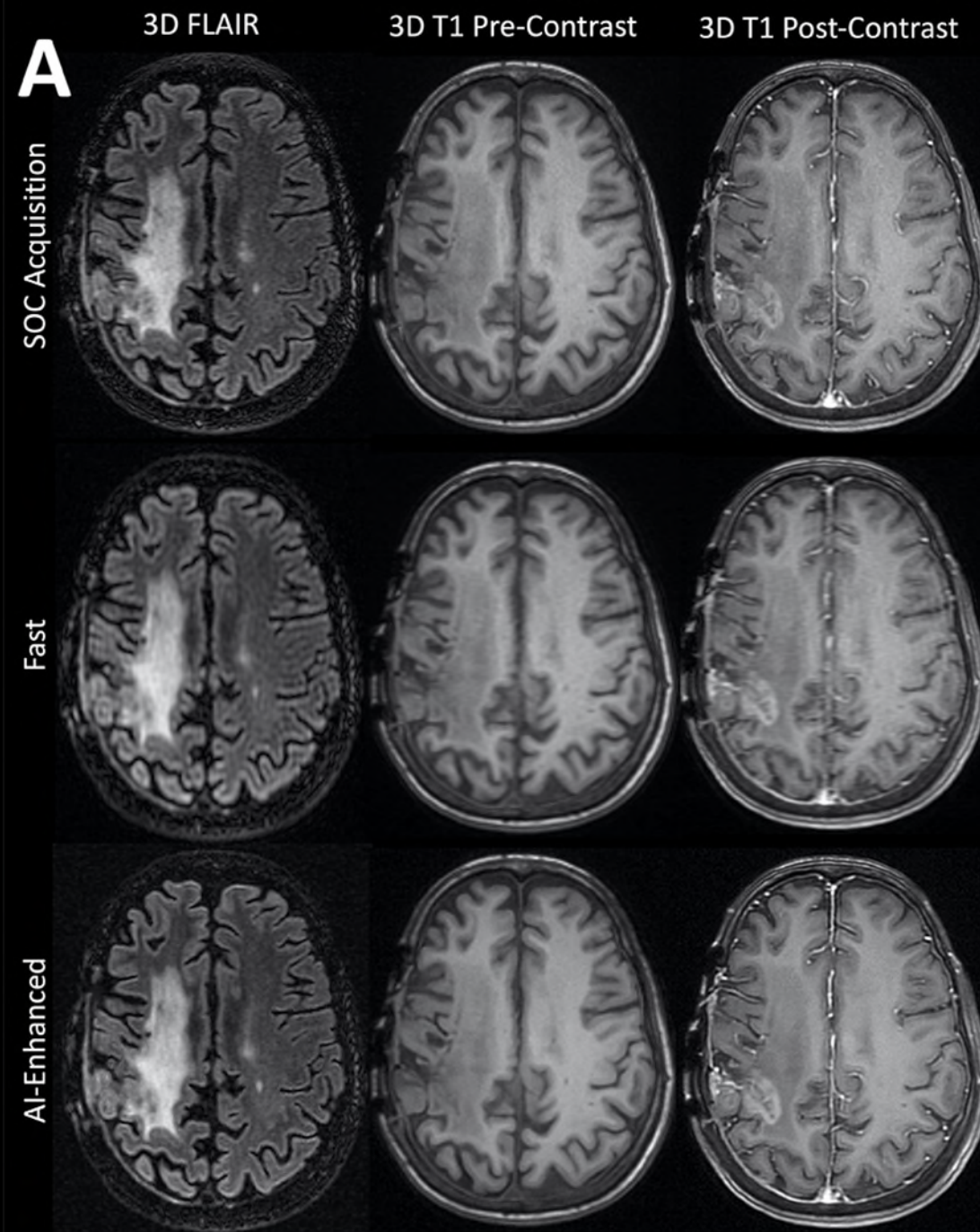


1. Kiryu S, Akai H, Yasaka K, et al. Clinical Impact of Deep Learning Reconstruction in MRI. *RadioGraphics*. 2023;43(6):e220133. doi:10.1148/rg.220133

Image Quality: DL Acceleration

Imaging Parameter	Sequence					
	3D T1 Precontrast		3D T2 FLAIR		3D T1 Postcontrast	
	SOC	Faster	SOC	Faster	SOC	Faster
Acquisition plane	Axial	Axial	Sagittal	Sagittal	Axial	Axial
TR (msec)	8	8	5500	5500	8	8
TE (msec)	3	3	160	160	3	3
Flip angle (degrees)	15	15	90	90	15	15
Section thickness (mm)	1.4	1.4	1.4	1.4	1.4	1.4
Acquisition matrix	256 × 256	256 × 128	256 × 256	256 × 128	256 × 256	256 × 128
Acquisition time (sec)	175	96	344	190	175	96
Time reduction (%)		45.1		44.7		45.1

Rudie JD, Gleason T, Barkovich MJ, et al. Clinical Assessment of Deep Learning–based Super-Resolution for 3D Volumetric Brain MRI. *Radiol: Artif Intell.* 2022;4(2):e210059.



Rudie JD, et al *Radiol: Artif Intell.* 2022

Noise reduction

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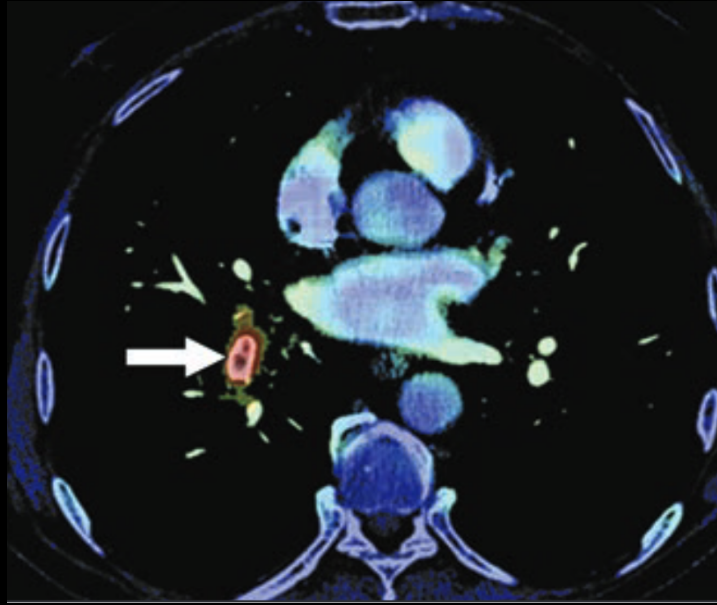
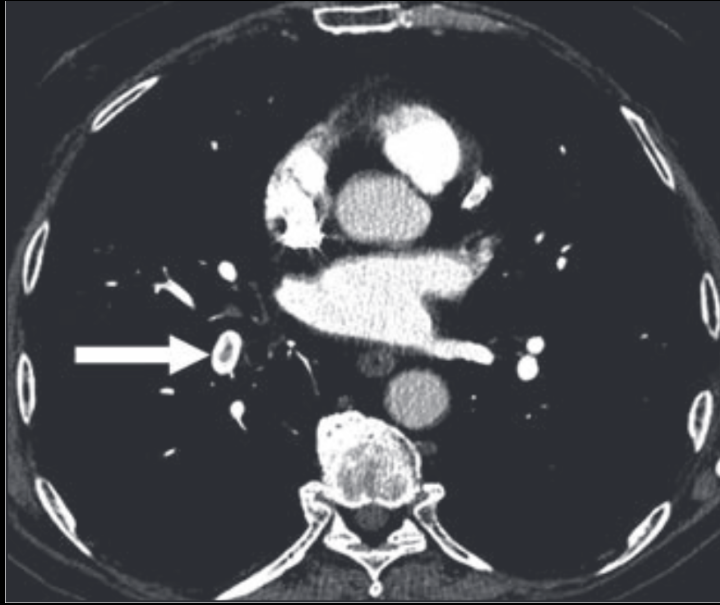
Acquisition guidance

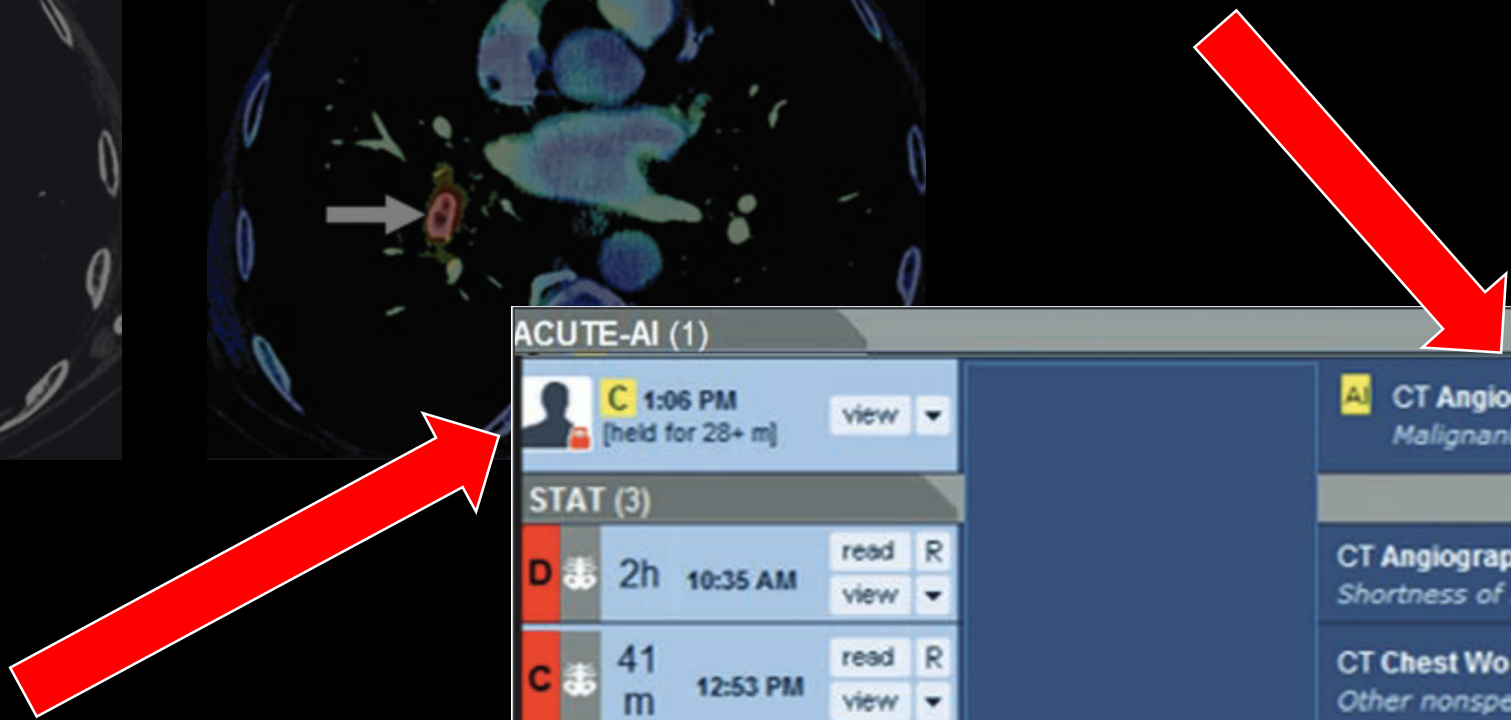
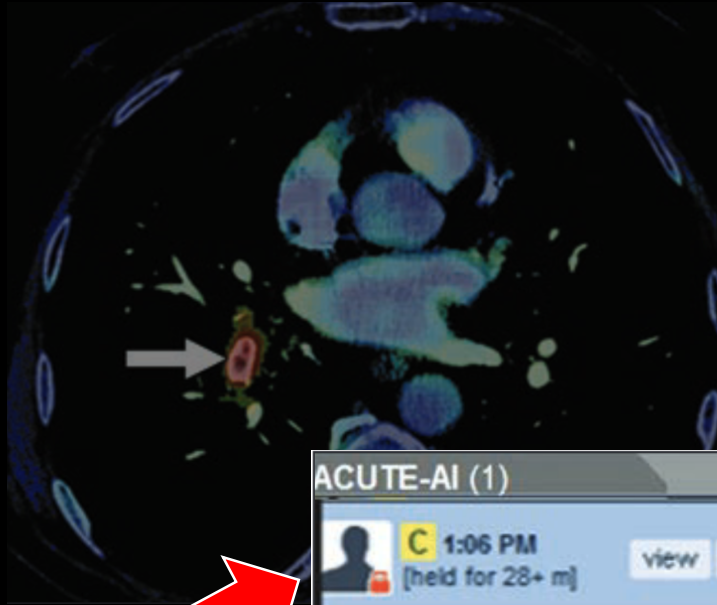
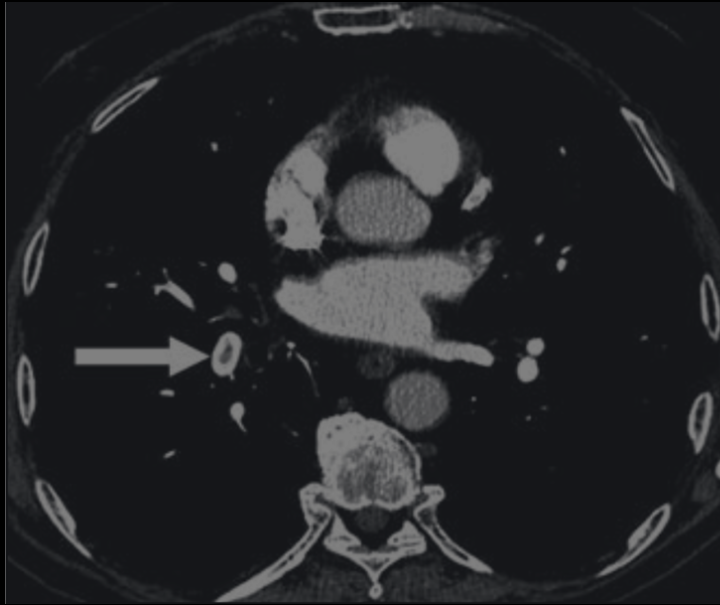
Quality standardization

Image optimization

Post processing

Worklist optimization





ACUTE-AI (1)

C 1:06 PM [held for 28+ m] [view](#) ▼

STAT (3)

D		2h	10:35 AM	read	R
				view	▼
C		41 m	12:53 PM	read	R
				view	▼
C		9m	1:25 PM	read	R
				view	▼

URGENT (7)

C		1d	12:10 PM	read	R
				view	▼
C		21h	4:10 PM	read	R
				view	▼

AI **CT Angiography Chest Pulmonary**
Malignant neoplasm of overlapping

CT Angiography Chest Pulmonary Arte
Shortness of breath(R06.02)

CT Chest Wo Iv Contrast
Other nonspecific abnormal finding ...

CT Chest Wo Iv Contrast
Solitary pulmonary nodule(R91.1)

CT Chest W Iv Contrast
Malignant neoplasm of upper lobe, l...

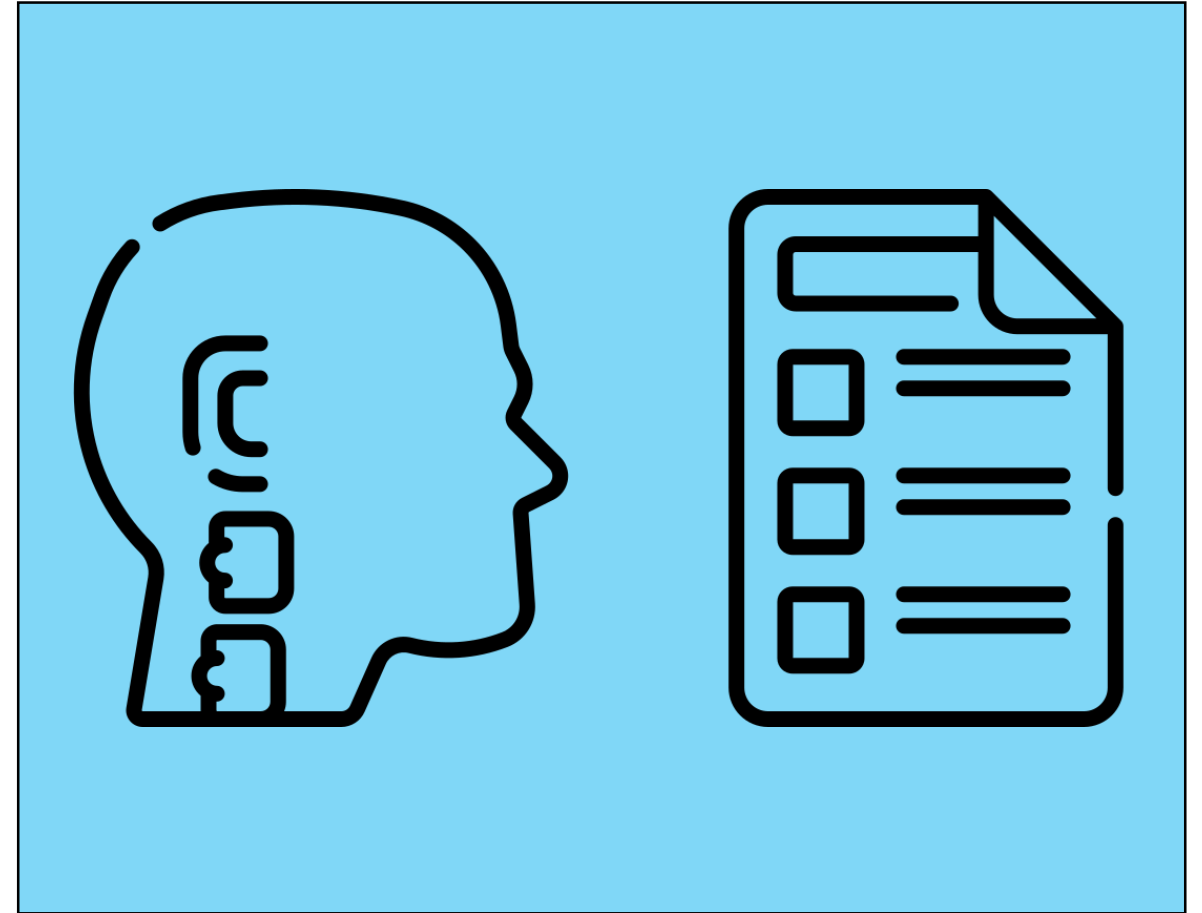
CT Chest Wo Iv Contrast
Bronchiectasis, uncomplicated () (J...*

Segmentation

Treatment planning

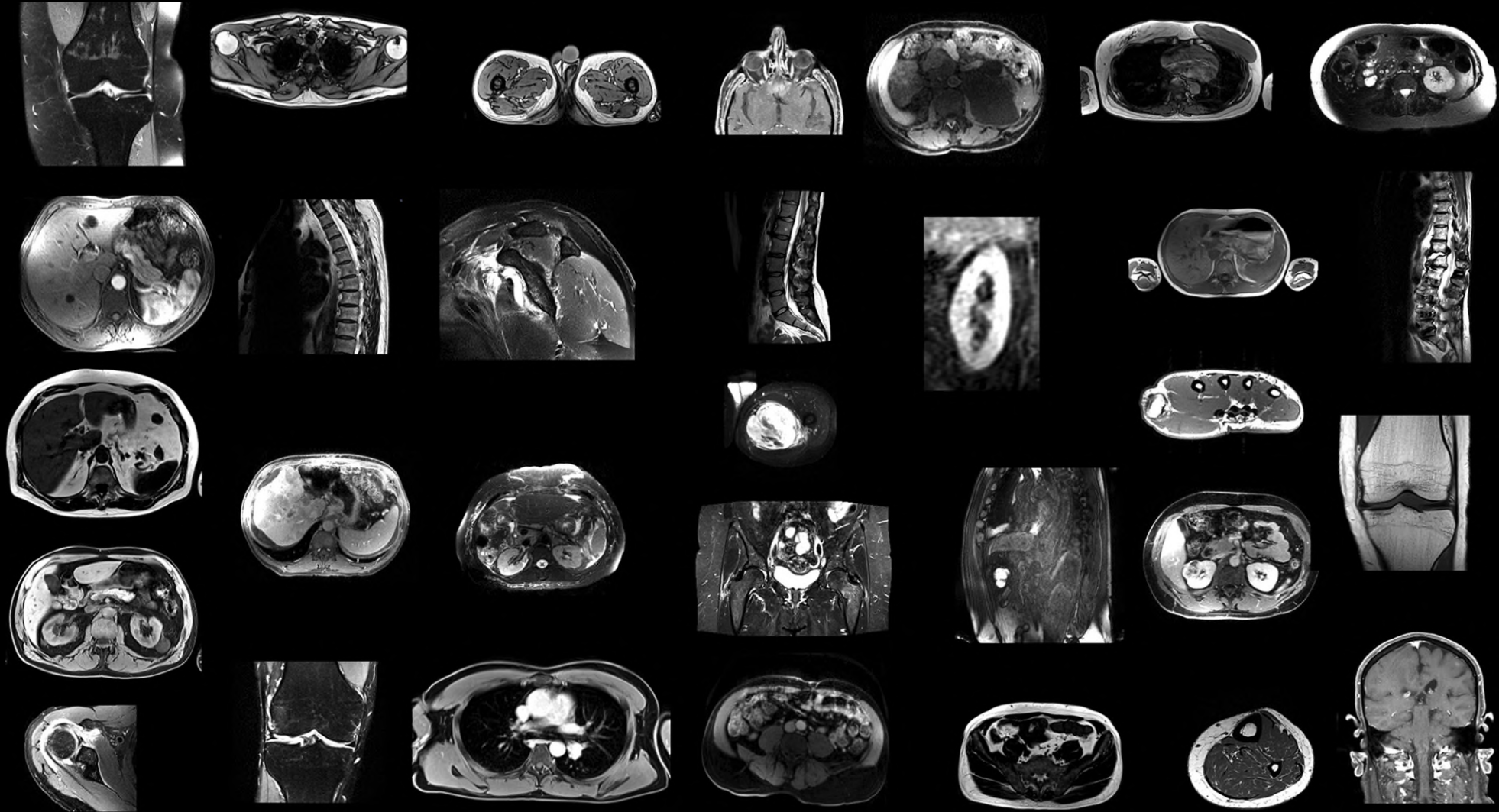
Radiomics

**Natural language
processing**

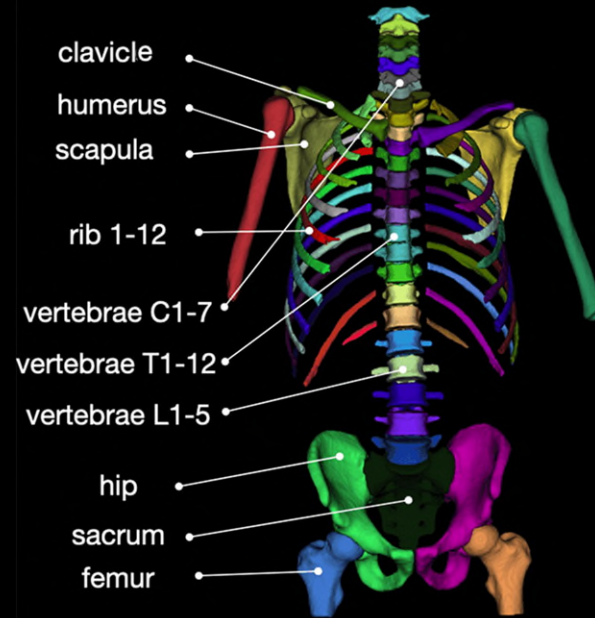


Downstream Processes

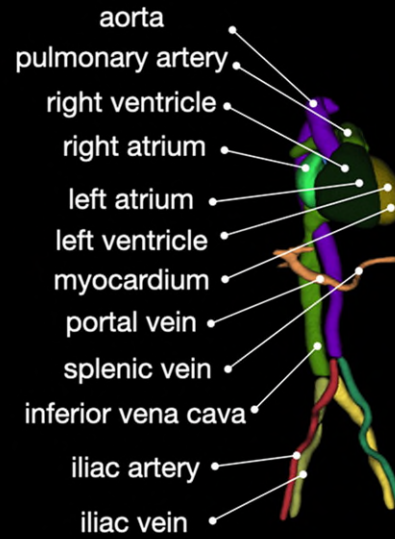
Downstream Processes - Segmentation



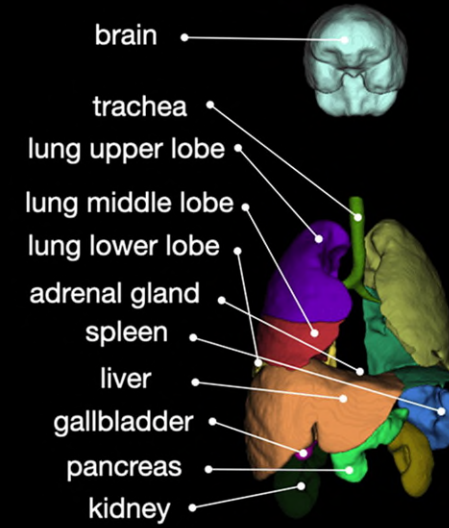
Skeleton



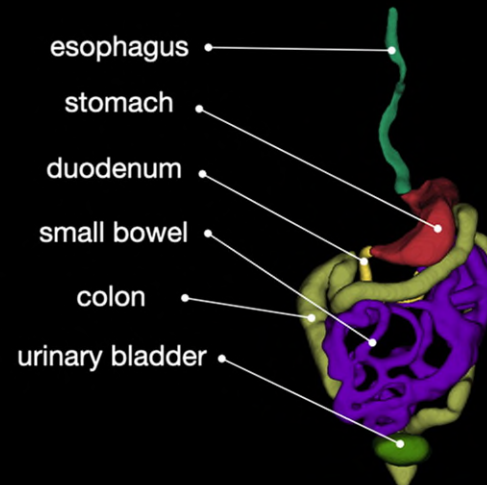
Cardiovascular System



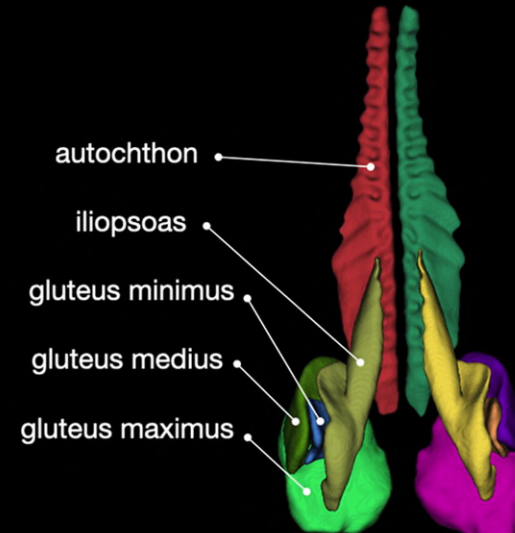
Other organs



Gastrointestinal Tract



Muscles



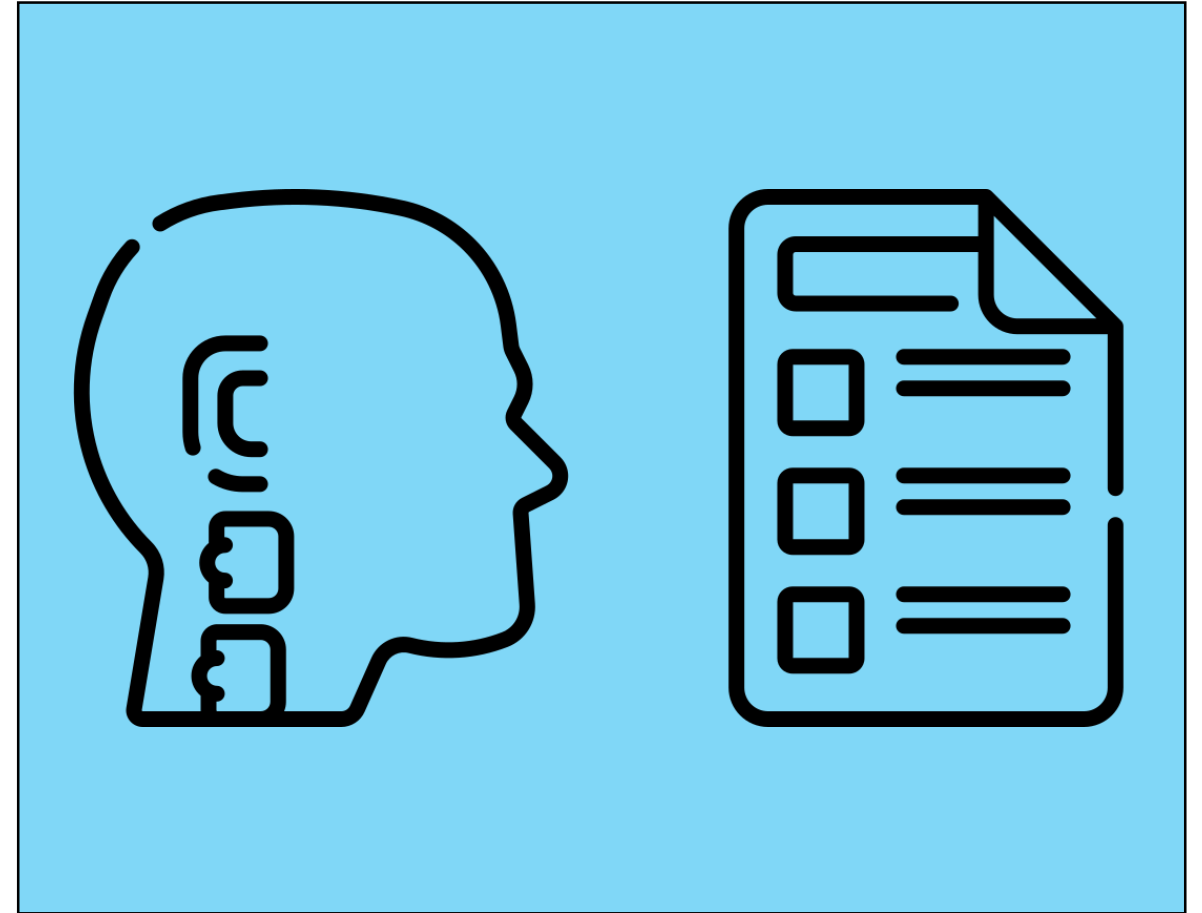
D'Antonoli TA, et al. *Radiology*. 2025.

Segmentation

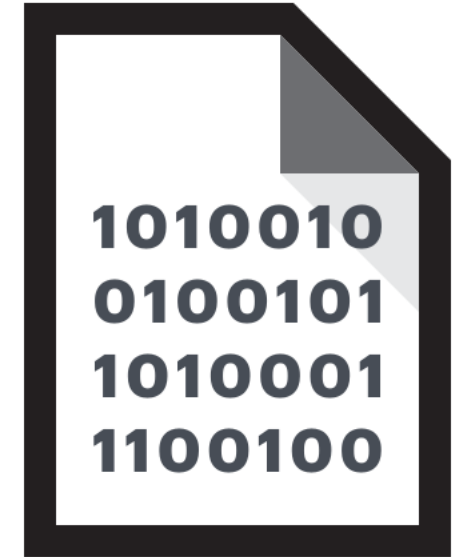
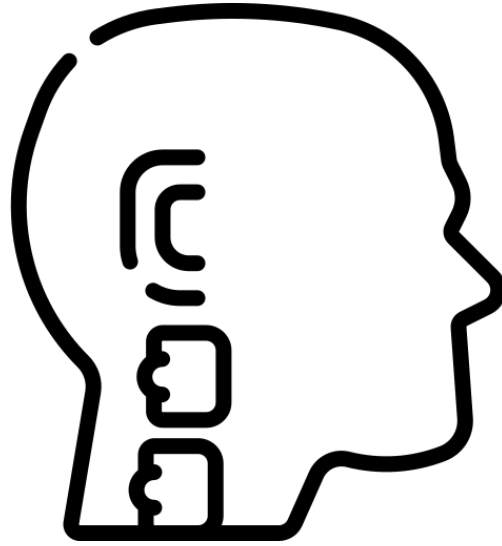
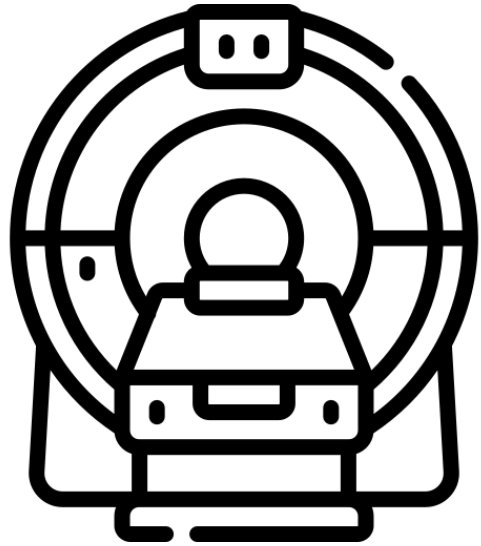
Treatment planning

Radiomics

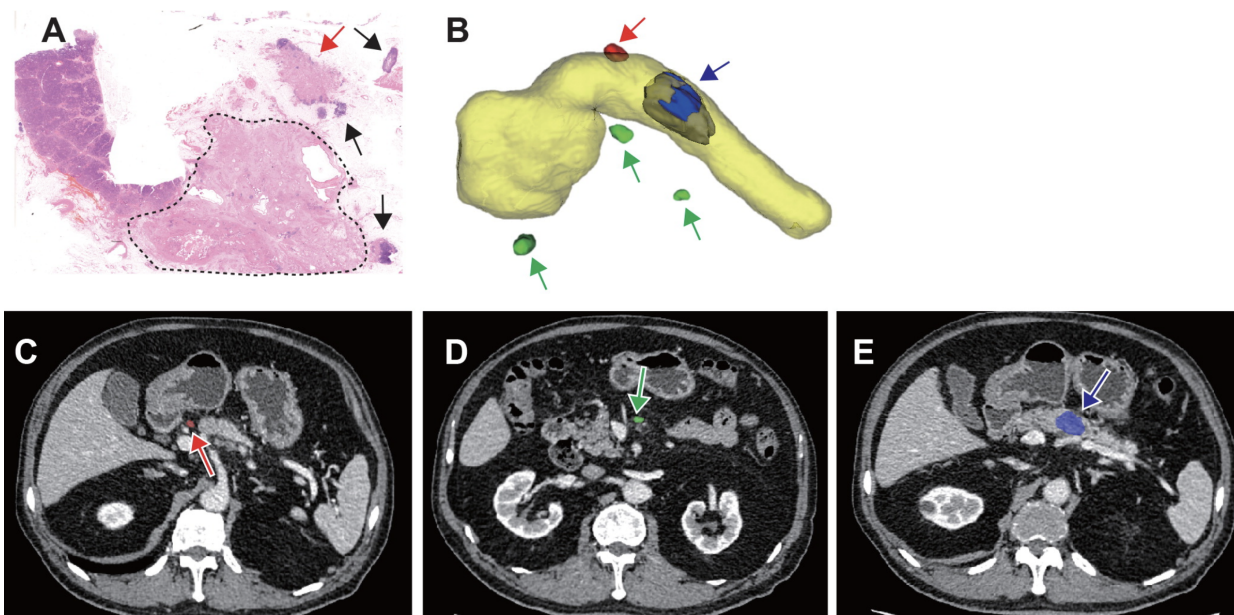
**Natural language
processing**



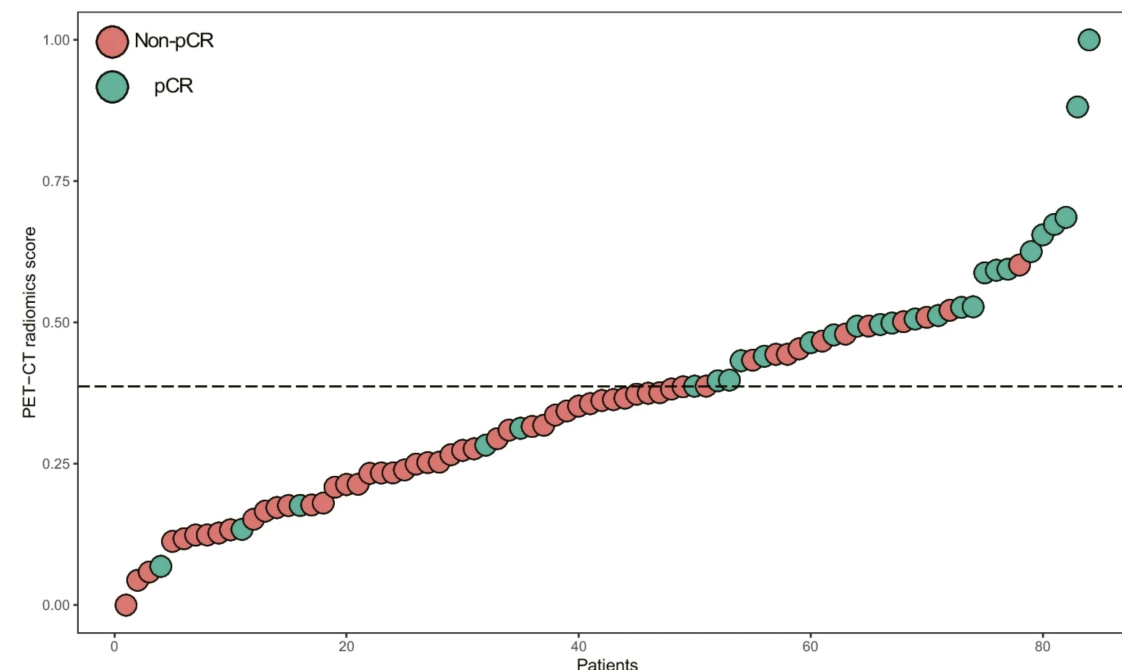
Downstream Processes



Radiomics



Bian Y, et al. *Radiology*. 2023.



Yang M, et al. *European Radiology*. 2024.

Diagnosis & classification

Treatment prediction

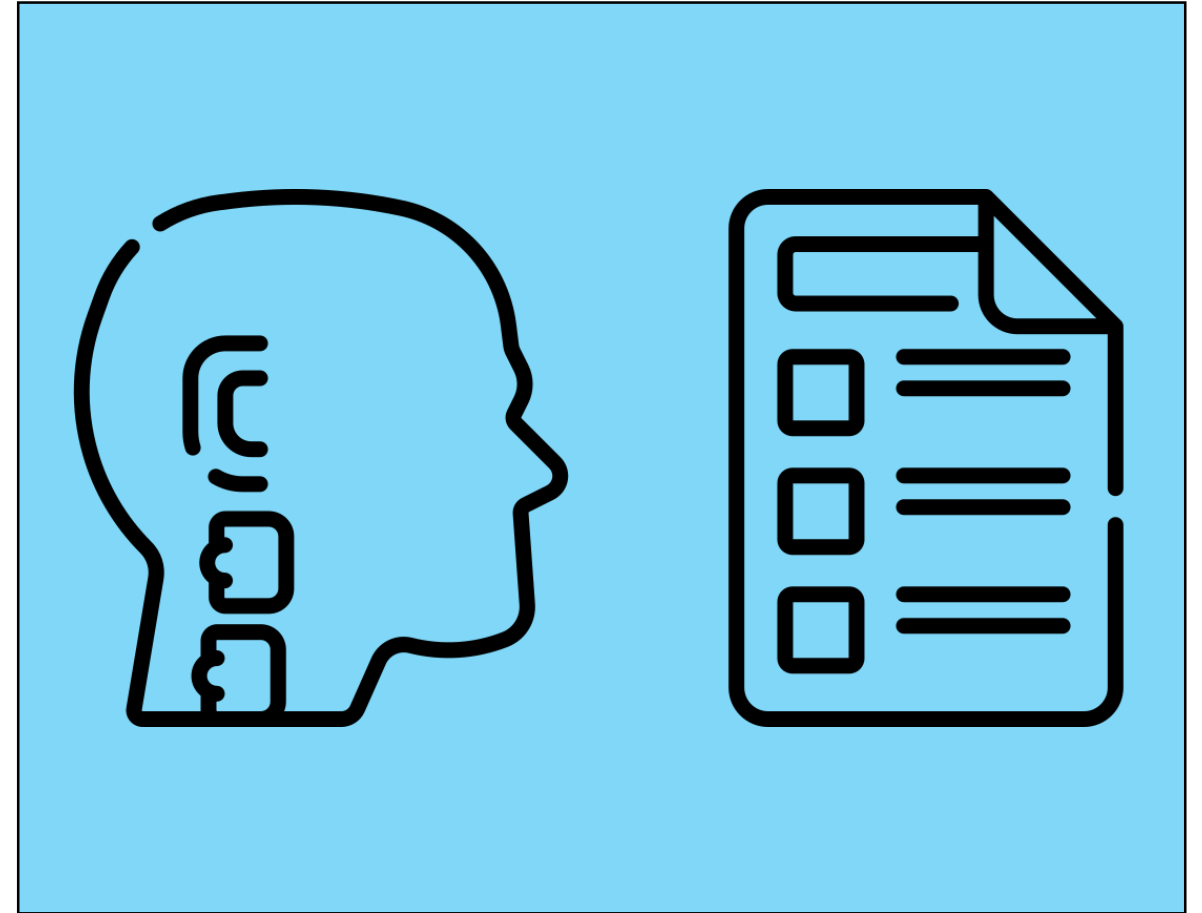
Radiomics

Segmentation

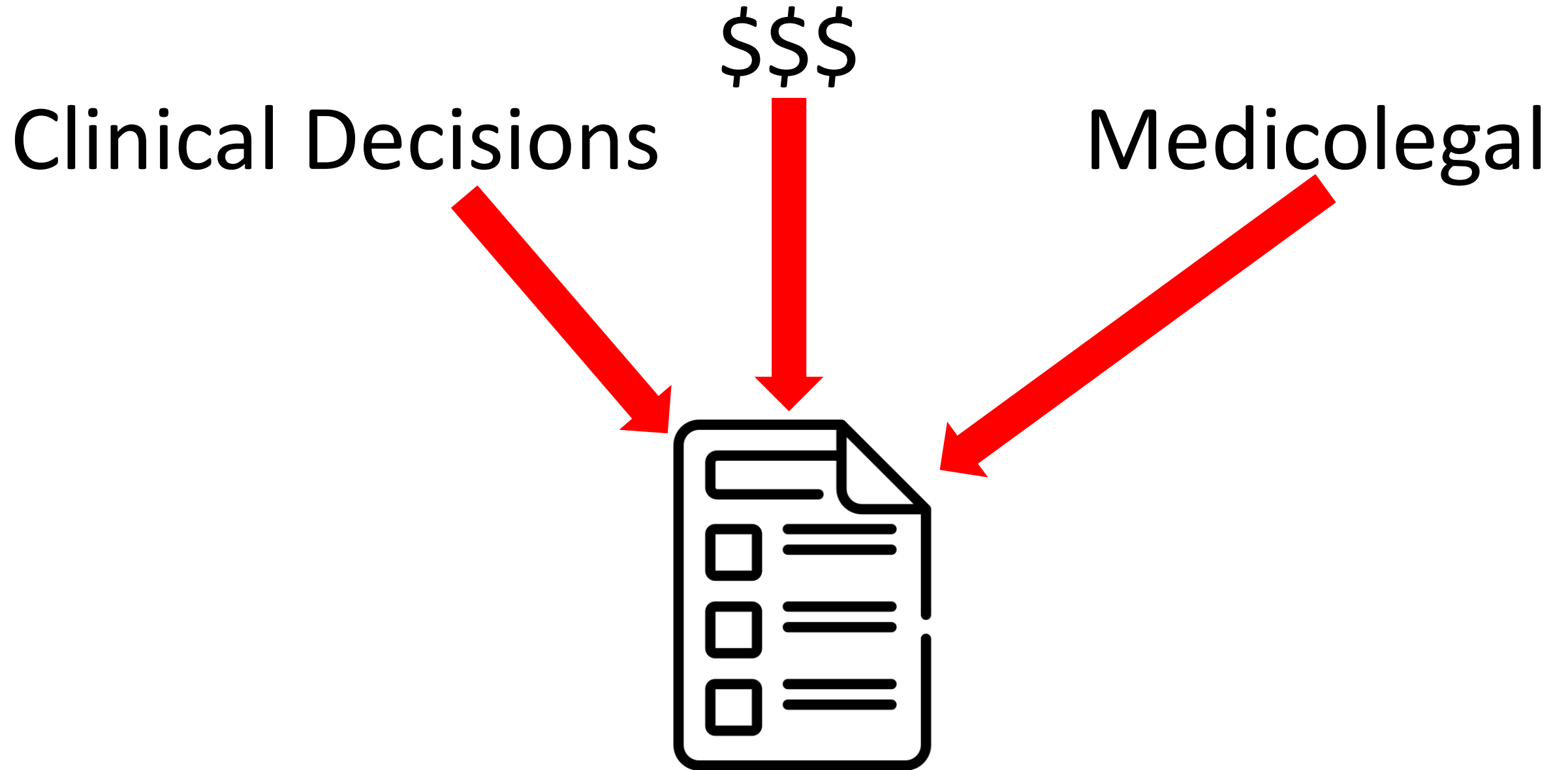
Treatment planning

Radiomics

**Natural language
processing**



Downstream Processes



FINDINGS:

NECK:

Parotid glands: The parotid glands are stable in appearance.

Submandibular glands: The submandibular glands are stable in appearance.

Thyroid gland: The thyroid gland is stable in appearance and heterogeneous in attenuation with suggestion of heterogeneous nodules, such as the approximately 6 mm heterogeneous nodule within the right thyroid lobe on series 11, image 96. The thyroid gland would be better evaluated with ultrasound.

Oral cavity: Evaluation of the oral cavity is limited due to streak artifact from dental amalgam.

Pharynx/larynx: There is persistent asymmetric soft tissue fullness within the right greater than left oropharynx (including the right greater than left base of tongue extending into the vallecula). There is persistent asymmetric soft tissue fullness within the left greater than right hypopharynx. There are right tonsilloliths.

Lymph nodes: No significant change in the prominent bilateral cervical and supraclavicular lymph nodes, such as the left level 2 lymph node measuring approximately 14 mm x 9 mm on series 11, image 60.

Paranasal sinuses: Scattered paranasal sinus mucosal thickening. Polypoid densities within the right maxillary sinus.

Mastoid air cells: Visualized mastoid air cells are clear. Soft tissue attenuating material within the bilateral external auditory canals, which is non-specific but may potentially represent cerumen.

Nasal cavity: Polypoid mucosal thickening within the bilateral nasal cavity. Narrowing of the bilateral middle meatus due to mucosal thickening.

Vessels: The left vertebral artery is asymmetrically smaller than the right vertebral artery, not significantly changed.

Globes are intact. Persistent features suggestive of bilateral enophthalmos. Suggestion of mild thickening within the bilateral periorbital regions, which is non-specific.

CHEST:

Axilla: No significant change in the prominent axillary lymph nodes with preservation of a fatty hilum.

Mediastinum/hilum/heart: No significant change in the ill-defined soft tissue density within the anterior mediastinum, which is nonspecific but may potentially represent thymic tissue. No significant change in the scattered prominent mediastinal lymph nodes, such as the precarinal lymph node measuring approximately 13 mm x 5 mm on series 4, image 61. No significant change in the prominent hilar lymph nodes, such as the approximately 9 mm x 5 mm right hilar lymph node on series 4, image 71. Heart size is stable and mildly enlarged. Small pericardial effusion. Small hiatal hernia. Features suggestive of esophageal wall thickening, which is nonspecific. Cardiophrenic lymph nodes measure subcentimeter in short axis, not significant by CT size criteria.

Lungs: Scarring within the bilateral lung apices. Mild bilateral peribronchial thickening. Atelectasis within the bilateral lower lungs. There are ill-defined groundglass densities and septal thickening within the bilateral lower lungs, which are nonspecific. Possible trace bilateral pleural effusions. There is bilateral posterior pleural nodularity, which is nonspecific. There are scattered subcentimeter nodules, which are nonspecific. There are scattered subcentimeter nodules, which are nonspecific. There are scattered subcentimeter nodules, which are nonspecific.

ABDOMEN/PELVIS:

Liver: The liver is mildly enlarged measuring approximately 16.2 cm in SI dimension. No significant change in the approximately 3 cm hypodense lesion within the right hepatic lobe on series 4, image 166, which is nonspecific but may potentially be related to local fat.

Spleen: The spleen is at the upper limits of normal in size measuring approximately 9.4 cm in SI dimension.

Gallbladder and Biliary Tree: Suggestion of mild gallbladder wall thickening, which is nonspecific.

Pancreas: The pancreas is stable in appearance. Persistent prominence of the main pancreatic duct.

Adrenal Glands: Stable nodular thickening of the adrenal glands.

Kidneys: The kidneys enhance symmetrically. There is no hydronephrosis. Low-density lesions within the kidneys, too small to characterize. Persistent region of cortical thinning and scarring within the left kidney.

Vasculature: There is heterogeneity within the portal vein, which is nonspecific but may be related to contrast mixing artifact.

Bladder: The urinary bladder is distended. There is mild circumferential bladder wall thickening, which is nonspecific.

Pelvic Organs: Persistent heterogeneous appearance of the uterus.

Bowel and Peritoneum: There is no evidence of bowel obstruction. Suggestion mild wall thickening of the rectum and distal colon, which is nonspecific. Suggestion of mild wall thickening of the stomach and proximal duodenum, which is not specific. No significant change in the mesenteric and mesocolic fat, which are nonspecific.

Abdominal and Pelvic Lymphadenopathy: Scattered upper abdominal, mesenteric, retroperitoneal, inguinal, and pelvic lymph nodes that measure subcentimeter in short axis, not significant by CT size criteria.

Abdominal Wall: There are scattered areas of haziness and stranding within the soft tissues of the abdominal and pelvic wall, which are nonspecific.

BONES:

No significant change in the bony structures. There is no significant change in scattered lytic and sclerotic bony lesions. Representative lesions are shown below.

-There is no significant change in the mixed lytic/sclerotic lesion within the right iliac bone with associated cortical disruption and soft tissue components measuring approximately 31 mm x 22 mm on series 4, image 260.

-No significant change in the sclerotic lesion measuring approximately 4 mm within the posterior left fourth rib on series 4, image 336.

-No significant change in the heterogeneous sclerotic lesion within the posterior T2 vertebral body on series 4, image 25 measuring approximately 4 mm.

Degenerative changes within the spine. Mild vertebral height loss at multiple levels within the spine. Incidental note is made of torus mandibularis.

IMPRESSION:

1. Persistent asymmetric soft tissue fullness within the right greater than left oropharynx (including the right greater than left base of tongue extending into vallecula). Persistent asymmetric soft tissue fullness within the left greater than right hypopharynx. Findings are nonspecific. Clinical correlation is recommended.

2. No significant change in the prominent bilateral cervical and supraclavicular lymph nodes.

3. Scattered subcentimeter lung nodules, stable. These are nonspecific.

4. No significant change in the scattered lytic and sclerotic bony lesions, such as the mixed lytic and sclerotic lesion within the right iliac bone with associated cortical disruption and soft tissue components.

5. The thyroid gland is heterogeneous in attenuation with suggestion of heterogeneous nodules, such as the approximately 6 mm heterogeneous nodule within the right thyroid lobe. The thyroid gland would be better evaluated with ultrasound.

6. Mild hepatomegaly. No significant change in the approximately 13 mm hypodense lesion within the right hepatic lobe, which is nonspecific.

Extraction of data labels

Patient friendly translations

Smart recommendations

Improved critical findings

communication

Smart Impression

Clinical decision support

Scheduling

Protocols

Acquisition guidance

Quality standardization

Image optimization

Post processing

Worklist optimization

Upstream Processes

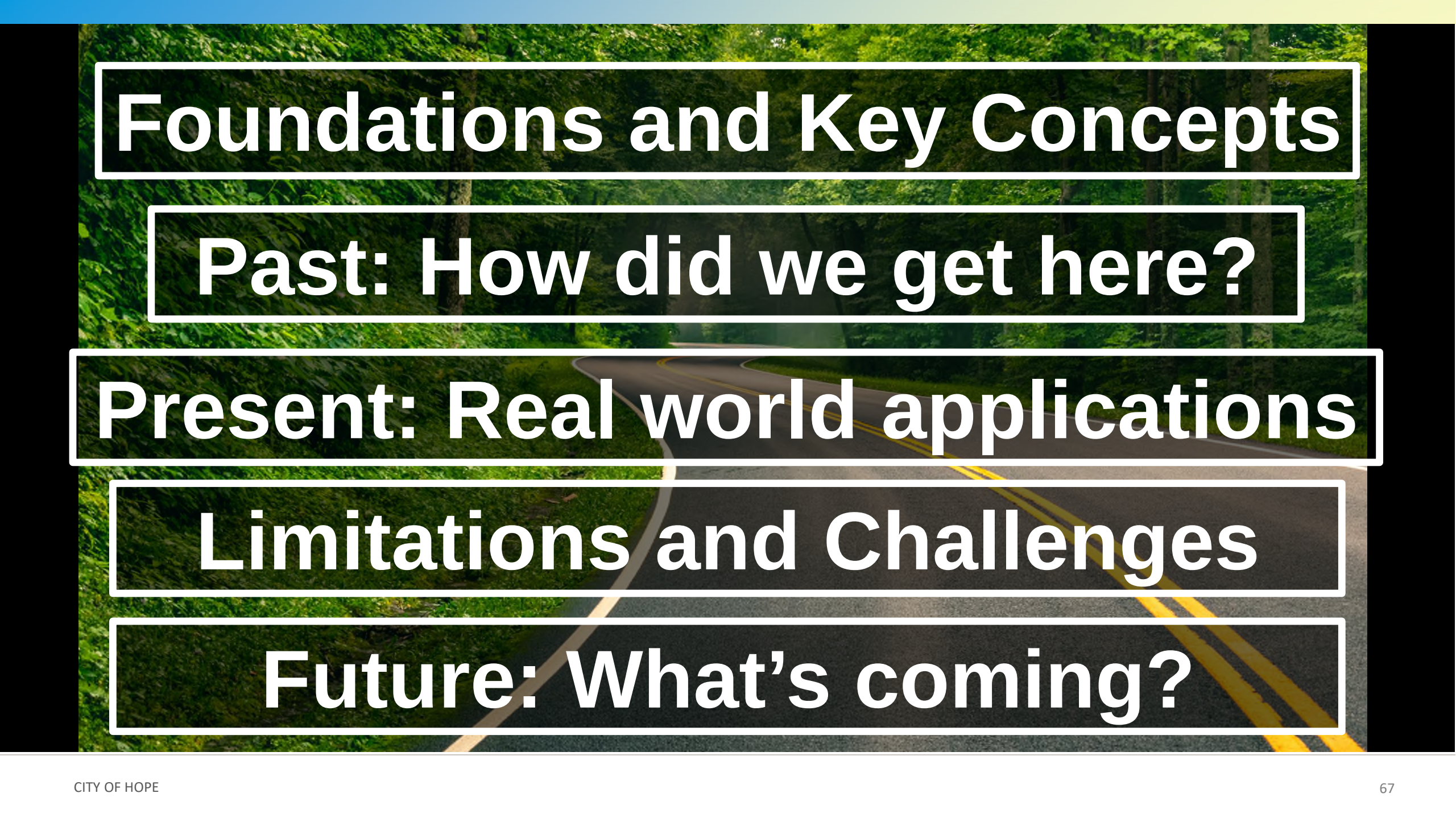
Segmentation

Treatment planning

Radiomics

**Natural language
processing**

Downstream Processes



Foundations and Key Concepts

Past: How did we get here?

Present: Real world applications

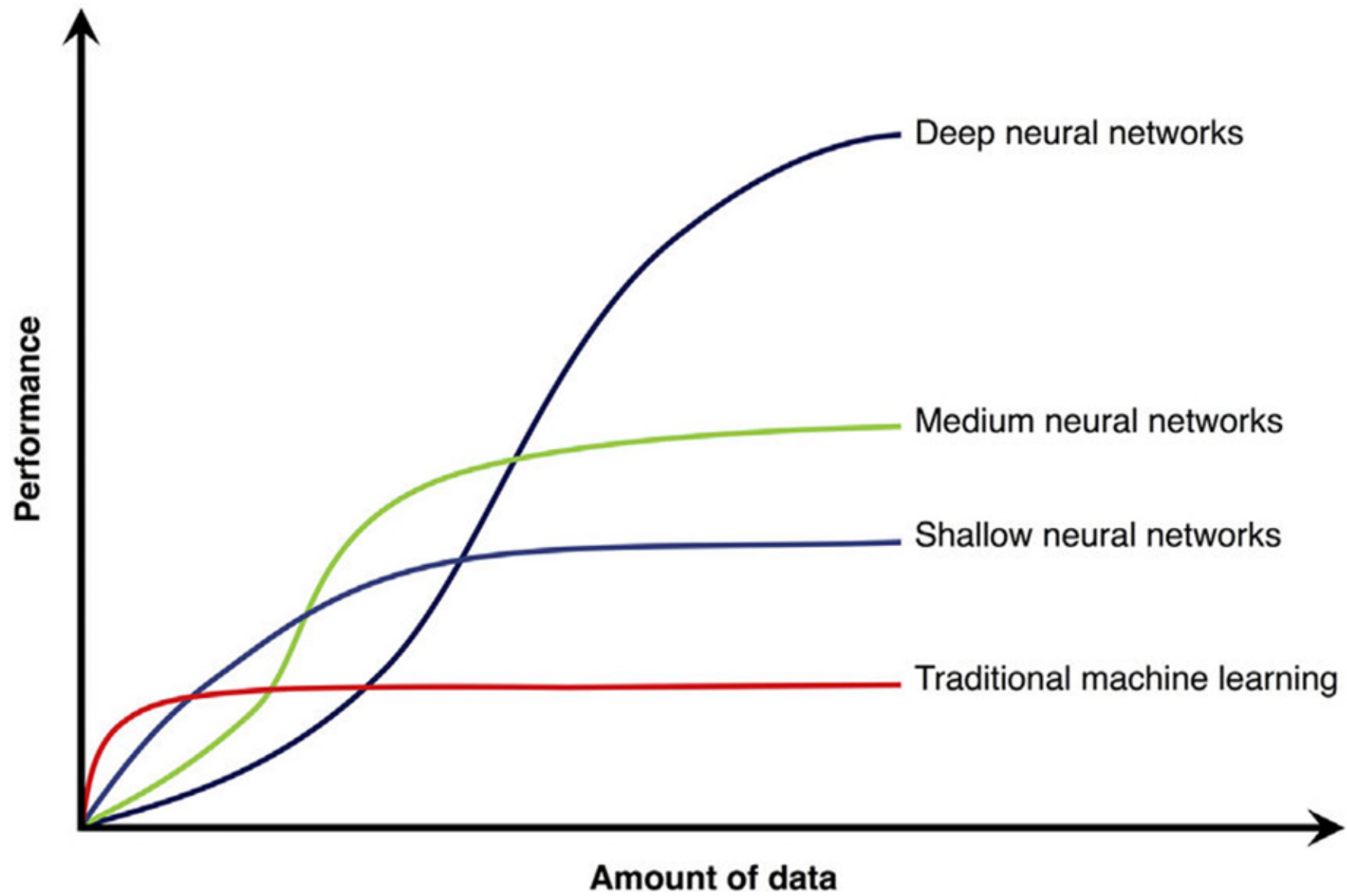
Limitations and Challenges

Future: What's coming?



Limitations and Bias

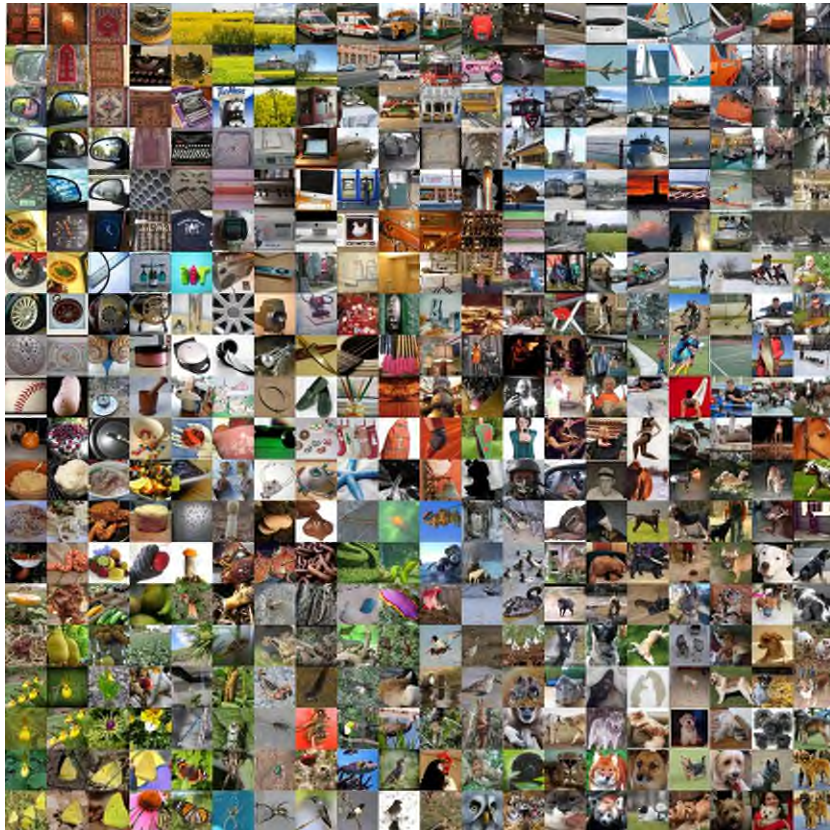
DATA



Tang, An et al. Canadian Association of Radiologists Journal. 2018.

Imaging data sets (artificial intelligence)

Assoc Prof Frank Gaillard  and Andrew Murphy  et al.

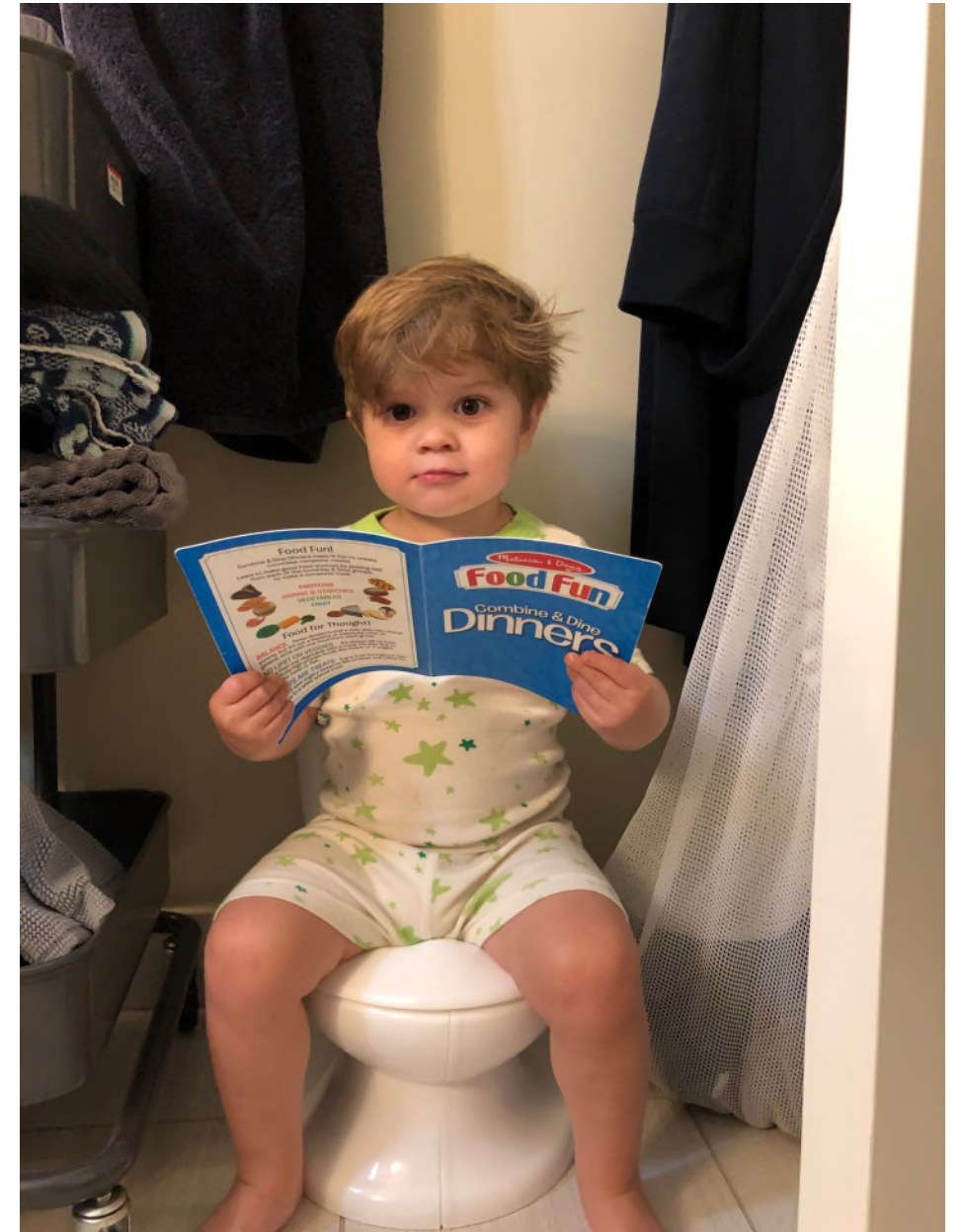


ImageNet – 14m images, 22k categories

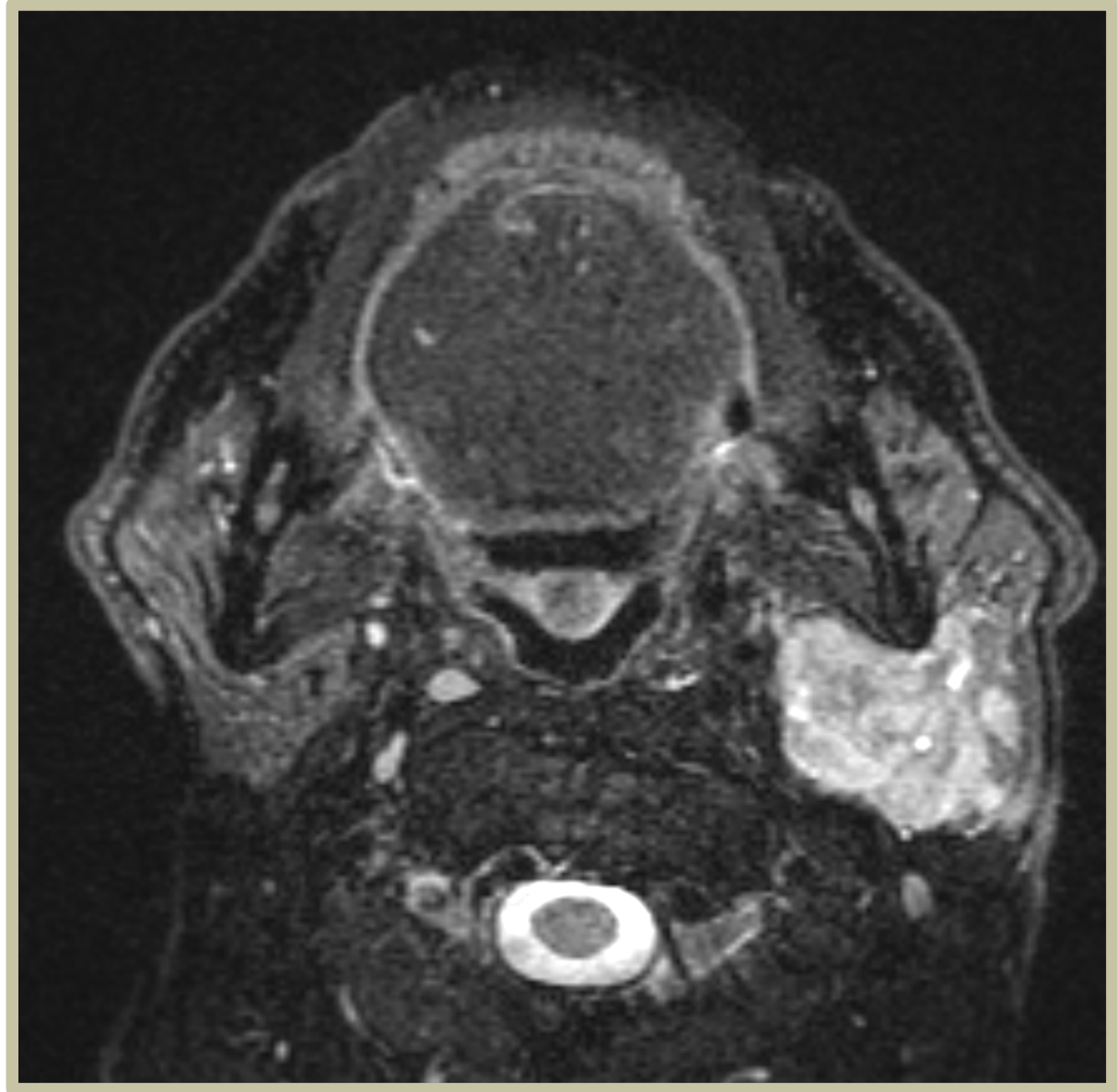
- [1000 Functional Connectomes Project](#): over 1000 functional MRI exams collected from sites across the globe
- [ACR Data Science](#): list of ~20 data sets
- [CheXpert](#): 224,316 chest radiographs
- [Computed Tomography Emphysema Database](#) small images specifically for texture analysis
- [Johns Hopkins University Data Archive](#) contains a data set of head CT scans
- [The Medical Image Bank of Valencia](#)
- [MD.ai](#): a collection of public projects
- [OpenI - The Open Access Biomedical Image Search Engine](#): data sets search engine, API (application programmer interface) to create customized data sets available at [MedPix](#)
- [OpenNeuro](#): list of over 200 neuro data sets
- [OASIS](#): open access neuro data sets
- [Spineweb](#) 16 spinal imaging data sets
- [UCLH Stroke EIT Dataset](#)
- [MRNet](#): 1,370 annotated knee MRI examinations
- [MURA](#): a large dataset of musculoskeletal radiographs
- [MIMIC-CXR Database](#): 377,110 chest radiographs with free-text radiology reports
- [PADCHEST](#): 160,000 chest X-rays with multiple labels on images
- [TB Portals](#)
- [UC Irvine Machine Learning Repository](#): various radiological and nuclear medicine data sets among other types of data sets
- [York Cardiac MRI Dataset](#) cardiac MRIs
- [Zenodo](#) searchable projects

Ground truth?

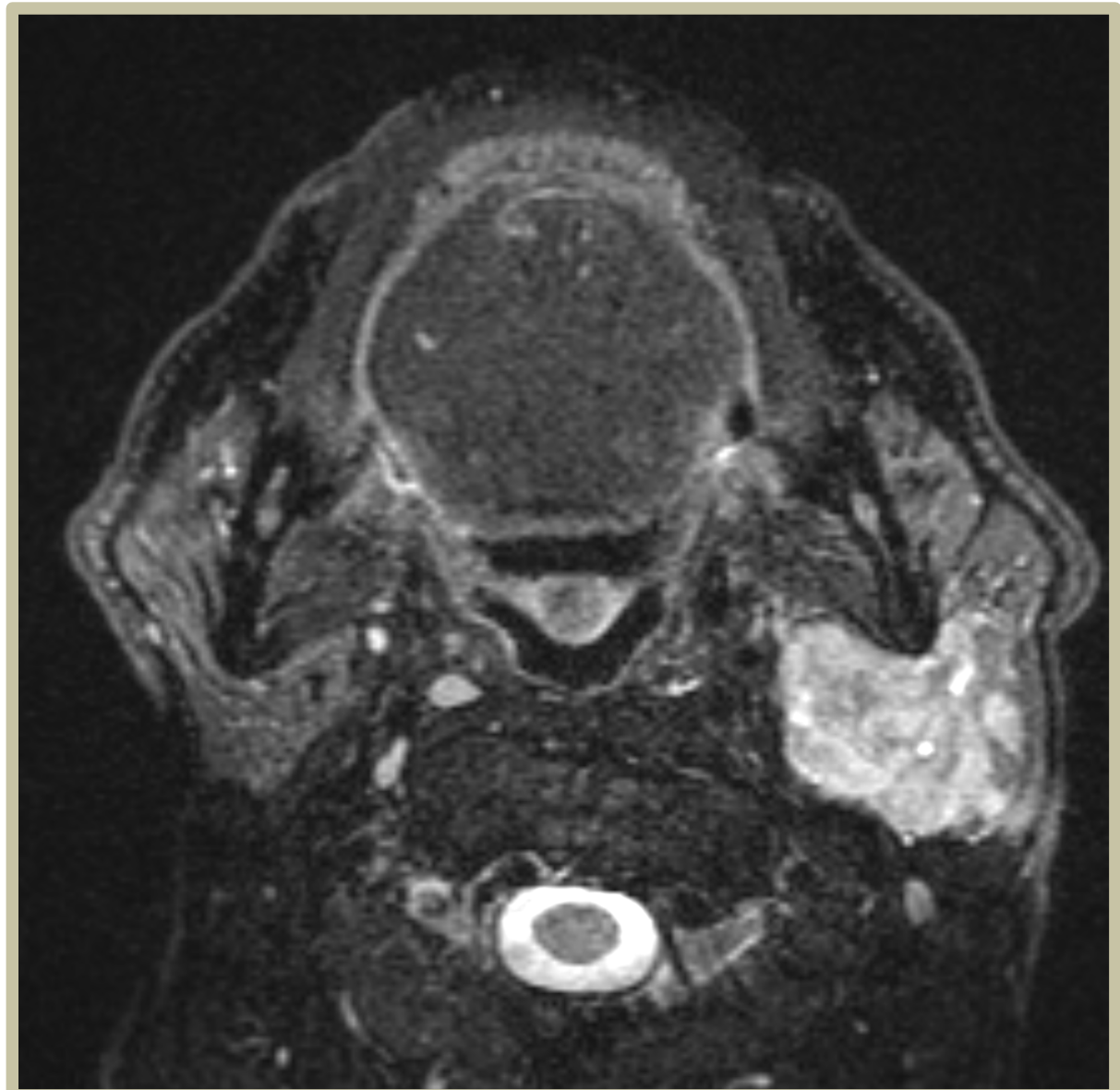
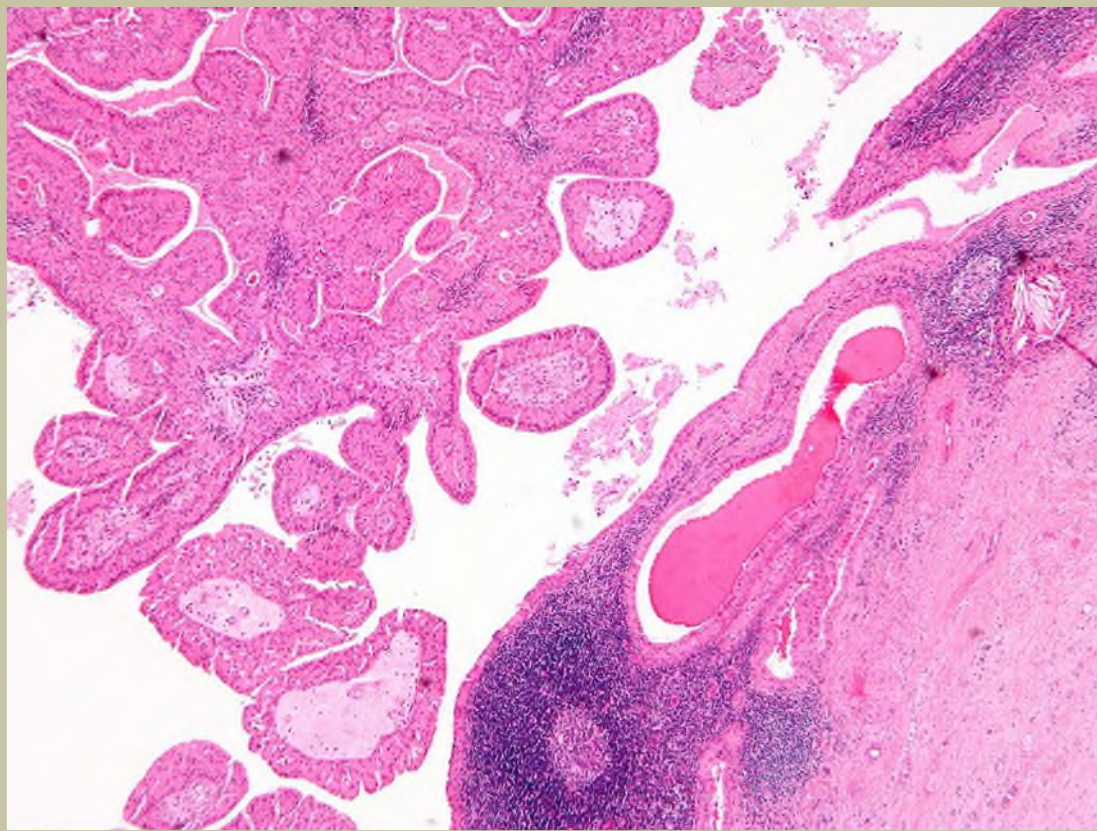
- **Cat**
- **Dog**
- **Boy**
- **Truck**



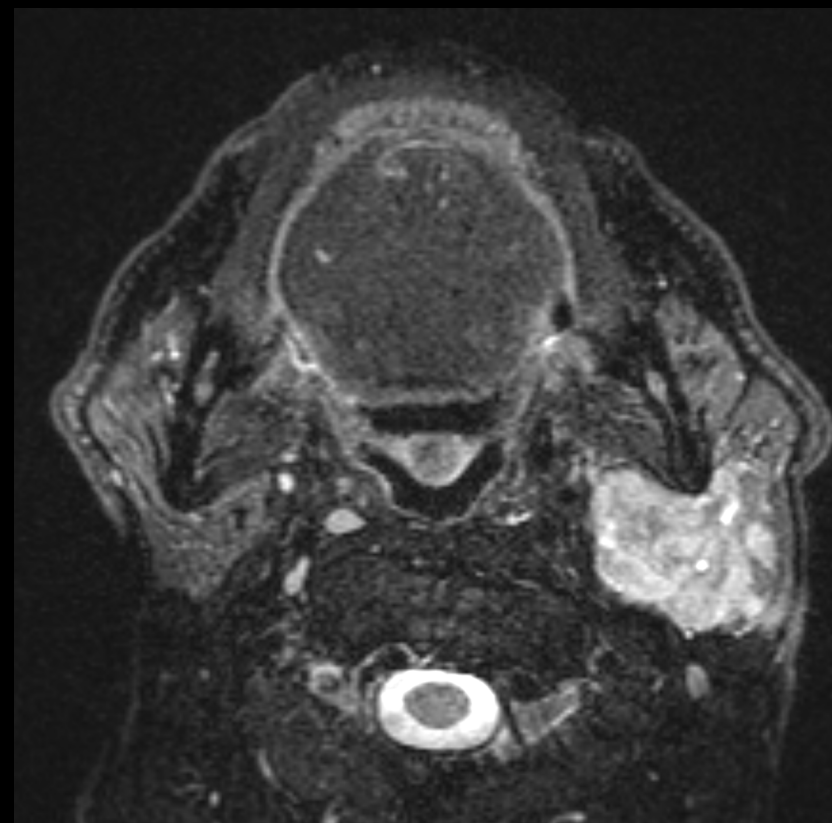
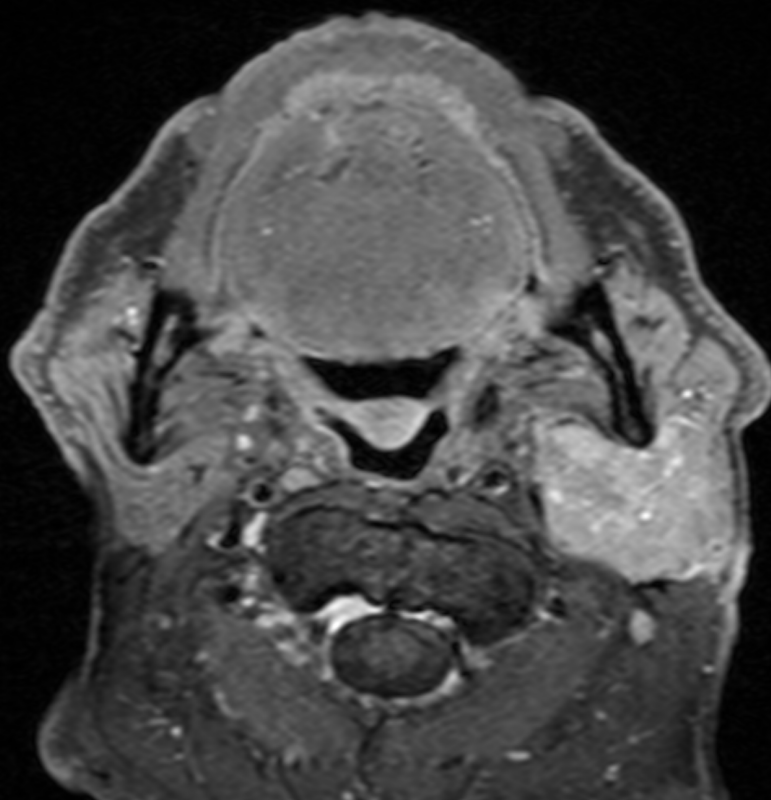
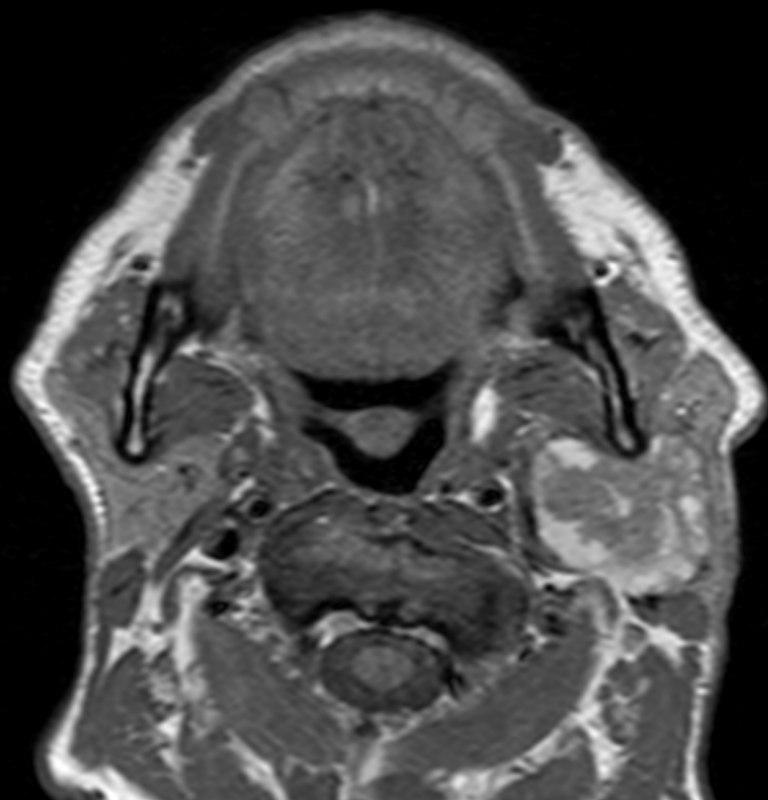
Ground truth?

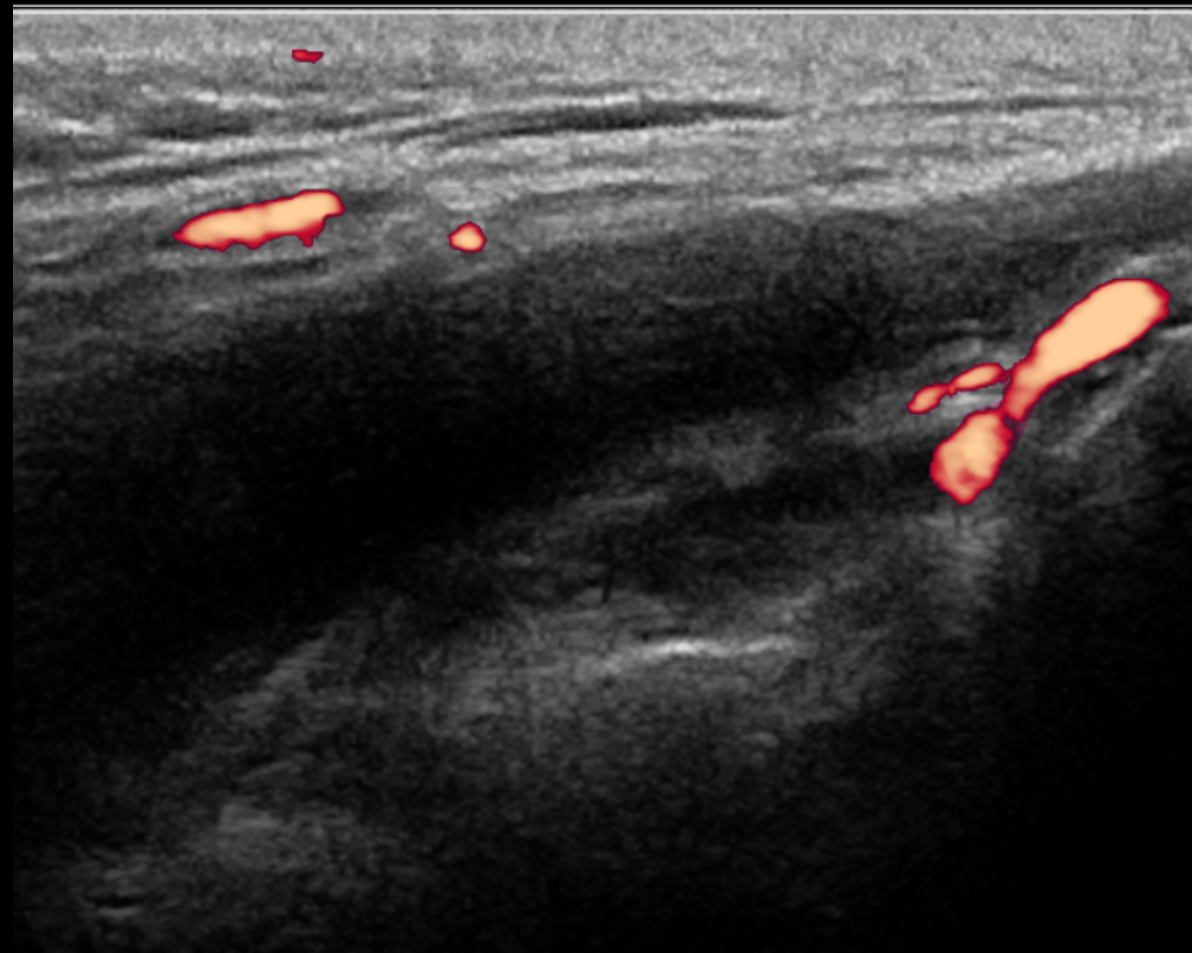
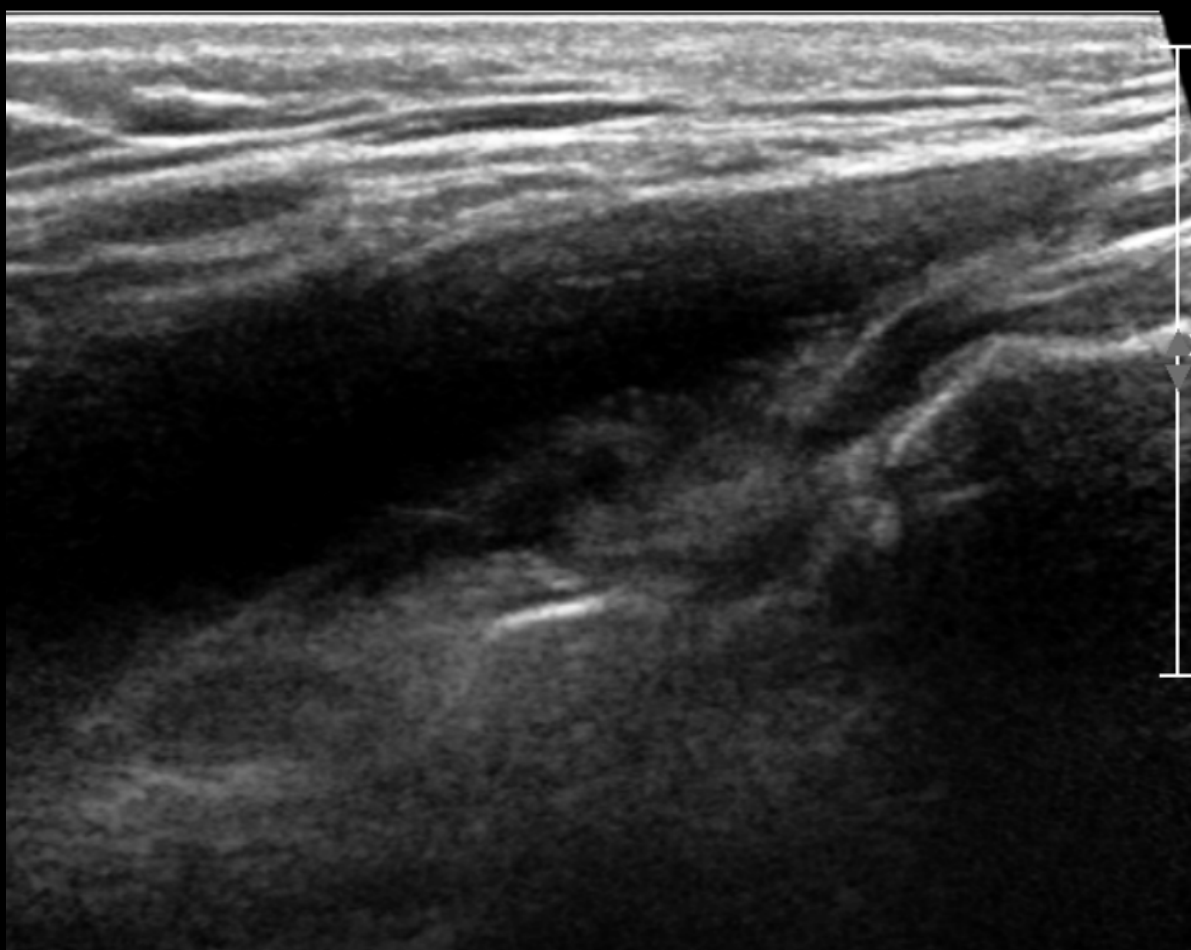


Ground truth?









Complex, Layered Data



**When you hear hoofbeats behind you,
don't expect to see a zebra**

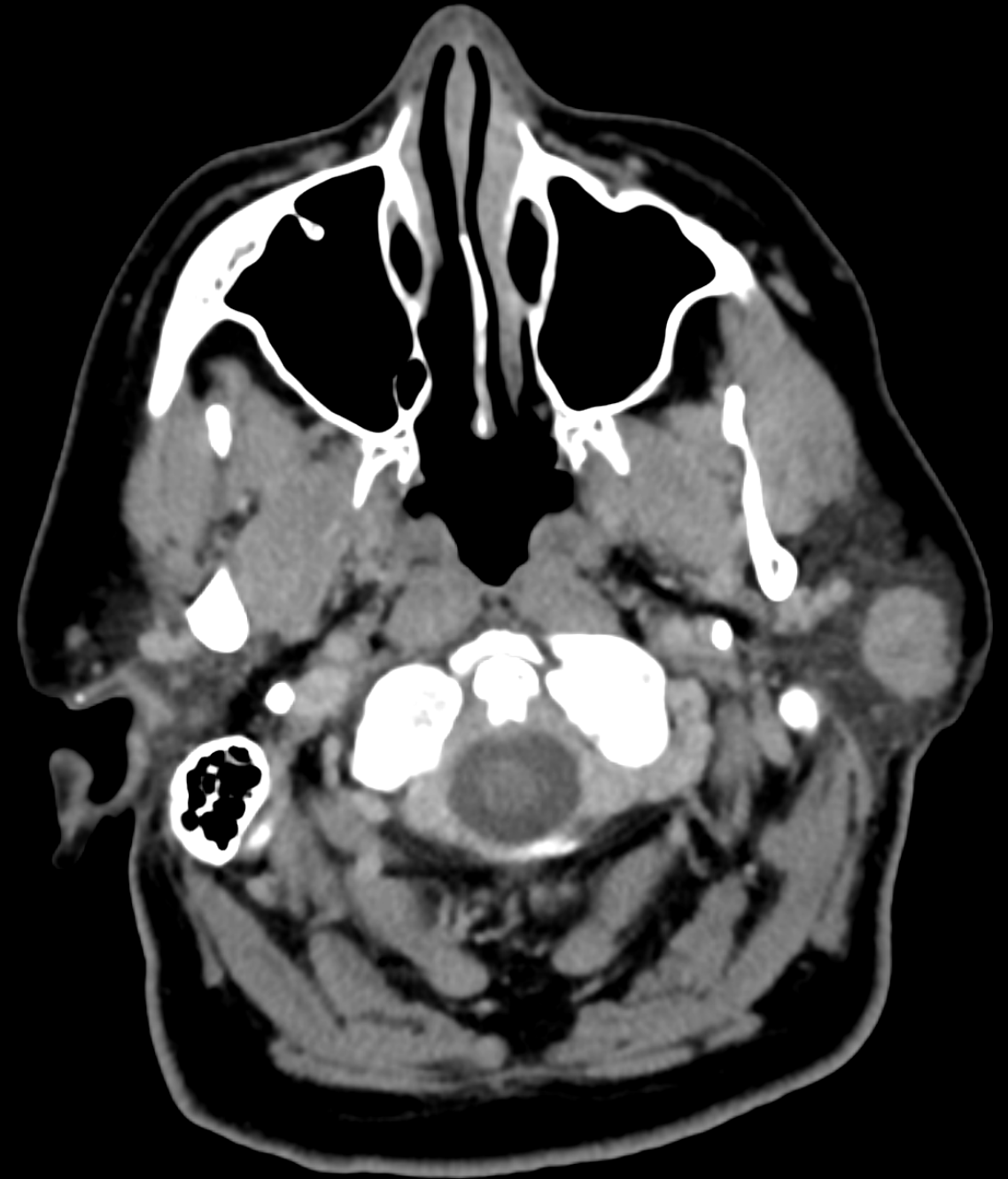
BMT

Warthin

Adenoid Cystic

Mucoep

Met LN



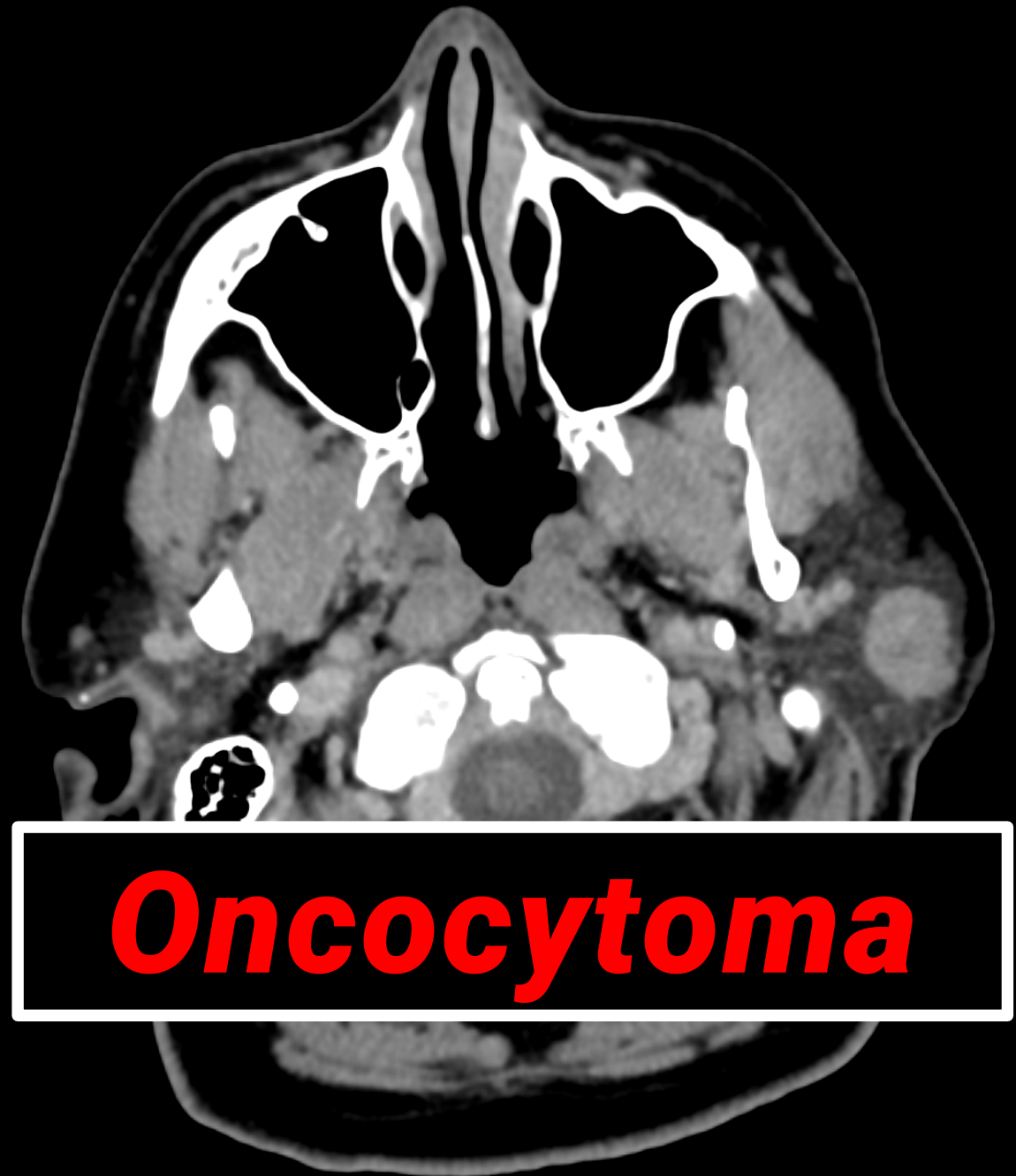
~~BMT~~

~~Warthin~~

~~Adenoid Cystic~~

~~Mucoep~~

~~Met LN~~



Oncocytoma

~~BMT~~

~~Warthin~~

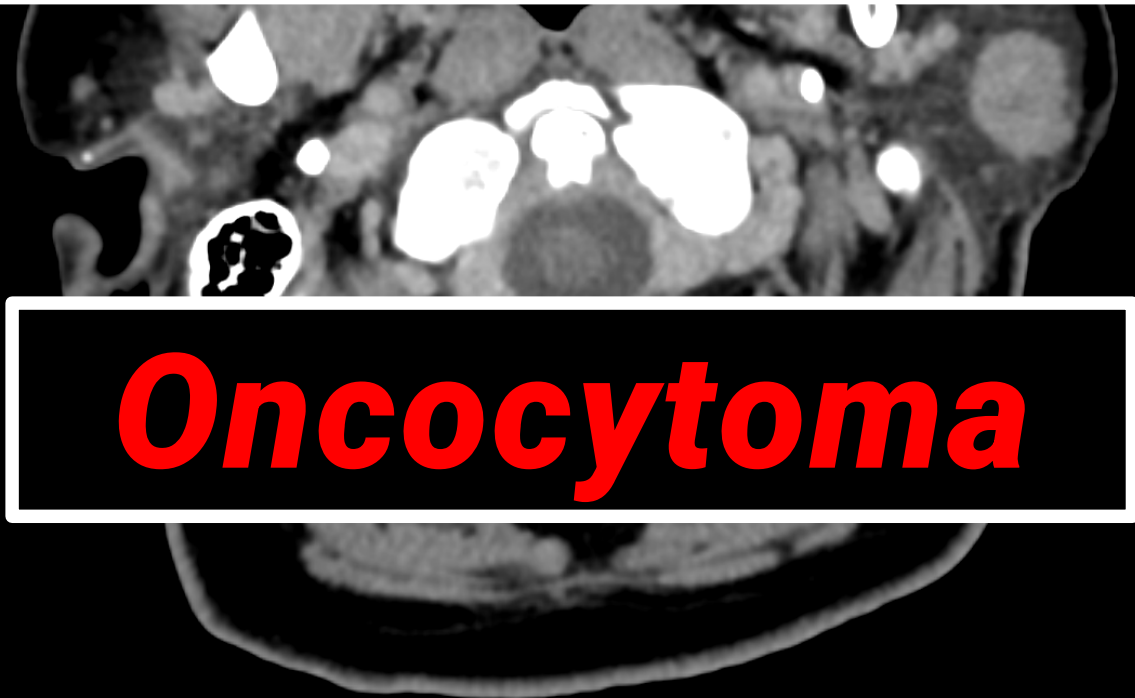
~~Adenoid Cystic~~

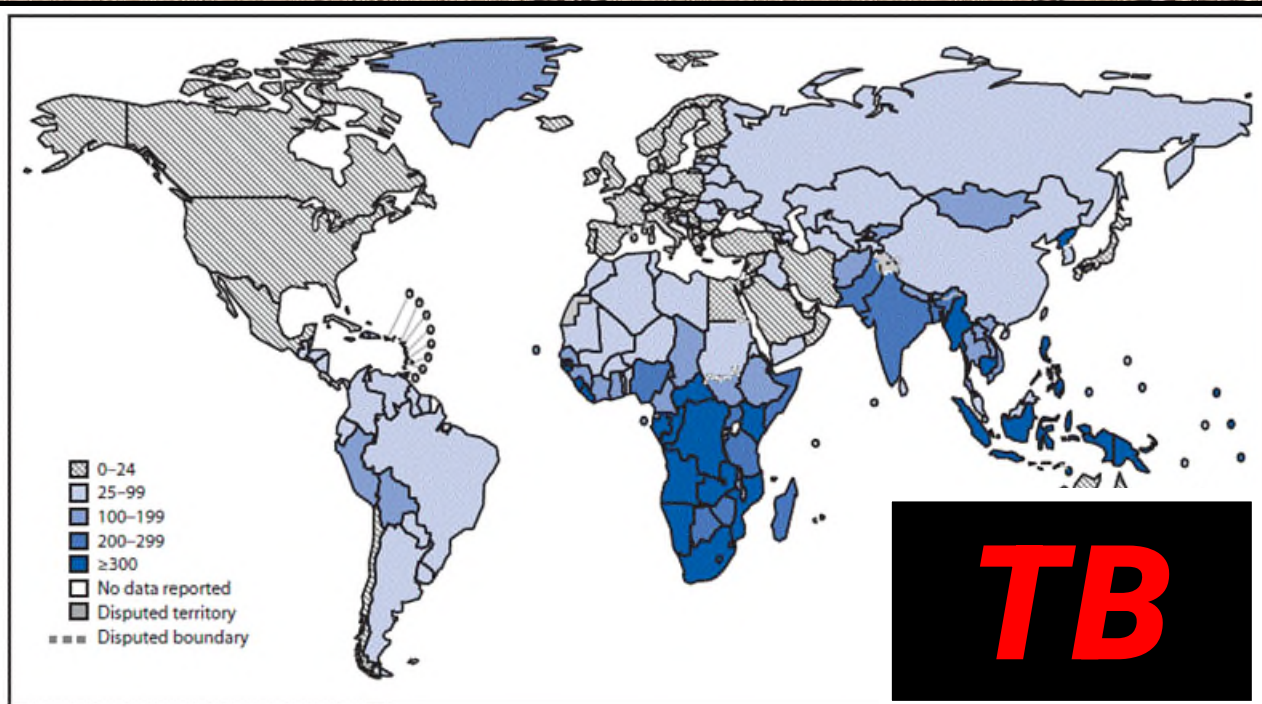
~~Mucoep~~

~~Met LN~~

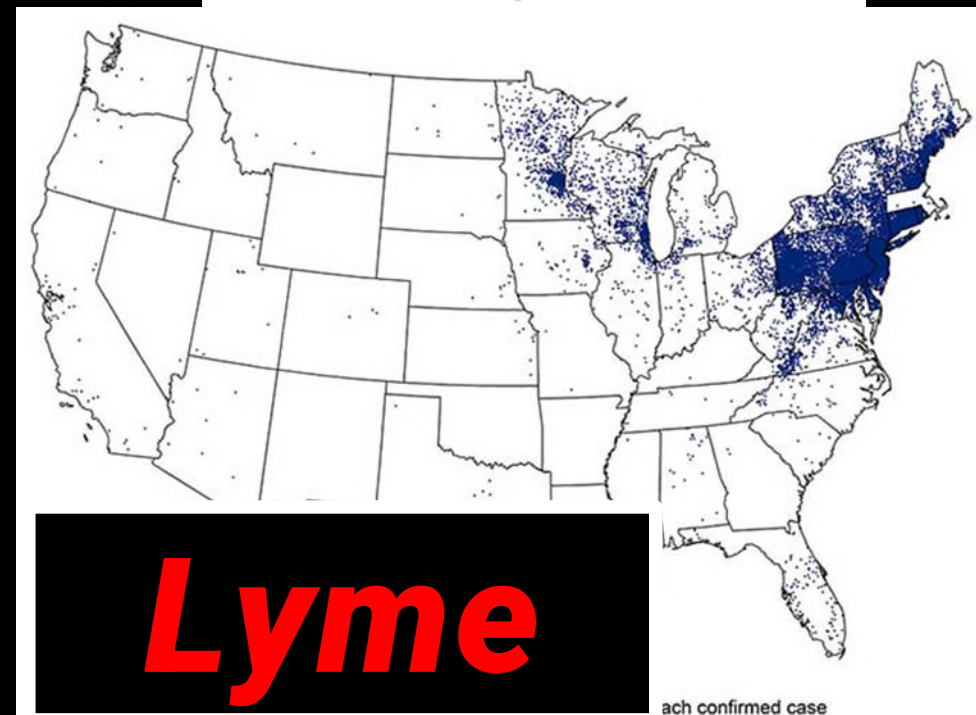
***Rare diseases
underrepresented
in data sets***

Oncocytoma





TB



Lyme

each confirmed case

Regulatory Approval

- **Safety**
- **Technical performance**
- **Environment: controlled**

Clinical Adoption

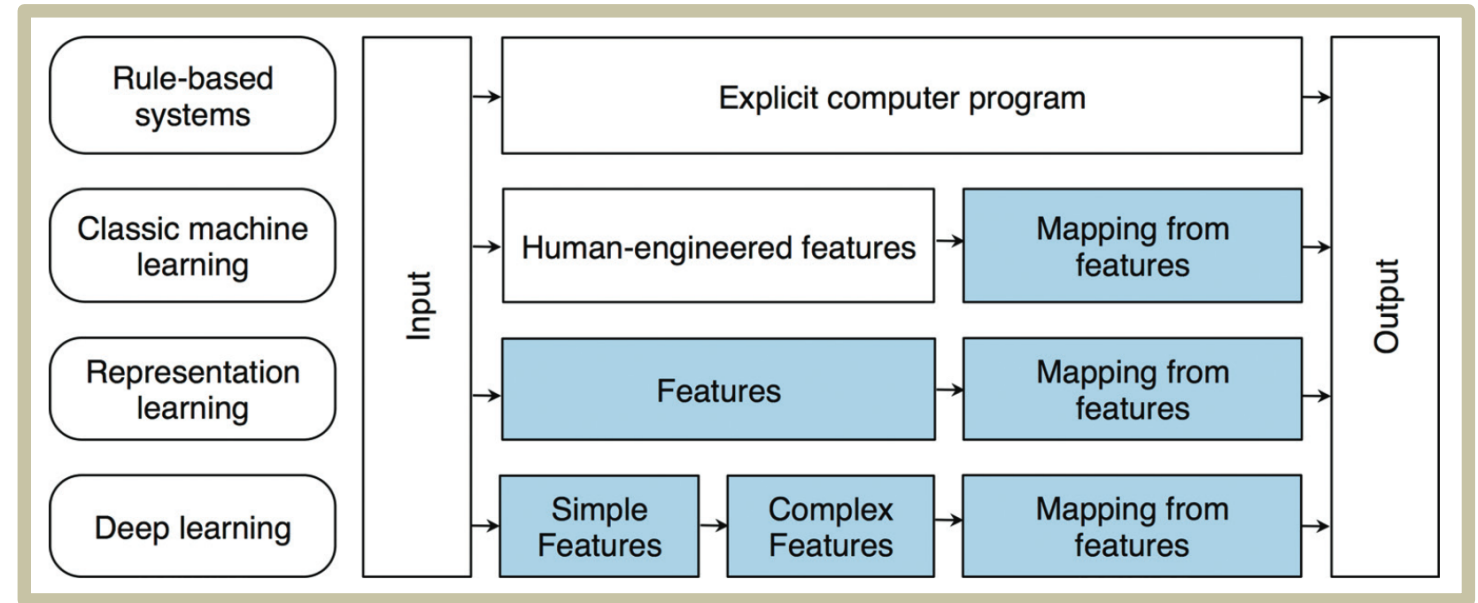
- **Integration**
- **User friendliness**
- **Solving clinical problem**
- **Environment: unpredictable**

Other Limitations

Transparency

Data Security

Liability



Other Limitations

Transparency

Data Security

Liability



Other Limitations

The NEW ENGLAND JOURNAL of MEDICINE

Transparency

Data Security

Liability

HEALTH LAW, ETHICS, AND HUMAN RIGHTS

Understanding Liability Risk from Using Health Care Artificial Intelligence Tools

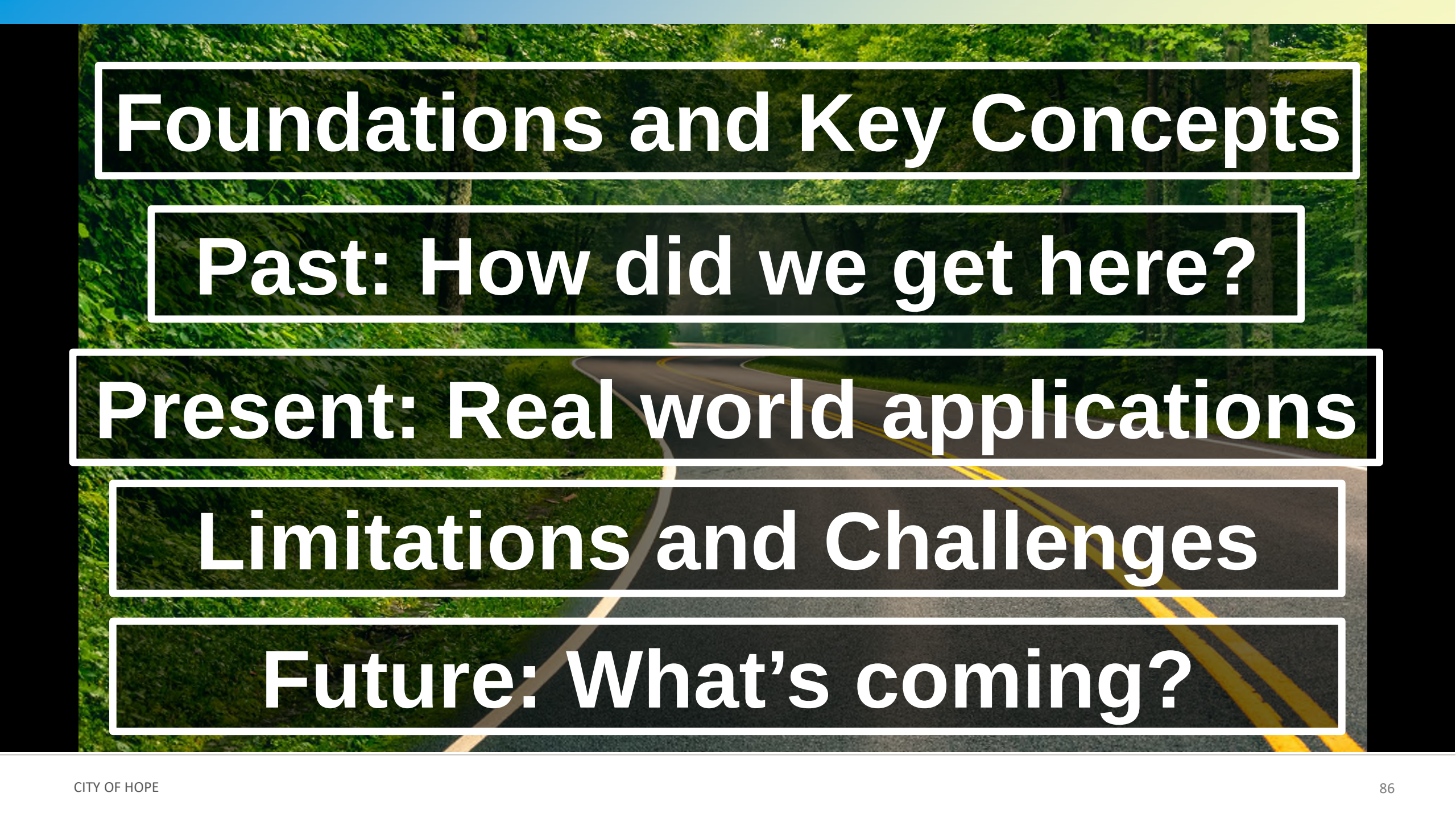
Michelle M. Mello, J.D., Ph.D., and Neel Guha, M.S.

Optimism about the explosive potential of artificial intelligence (AI) to transform medicine is tempered by worry about what it may mean for the clinicians being “augmented.” One question is especially problematic because it may chill adoption: when AI contributes to patient injury, who will be held responsible?

injury claims result in written opinions. As this area of law matures, it will confront several challenges.

Ordinarily, when a physician uses or recommends a product and an injury to the patient results, well-established rules help courts allocate liability among the physician, product maker,

N Engl J Med. 2024



Foundations and Key Concepts

Past: How did we get here?

Present: Real world applications

Limitations and Challenges

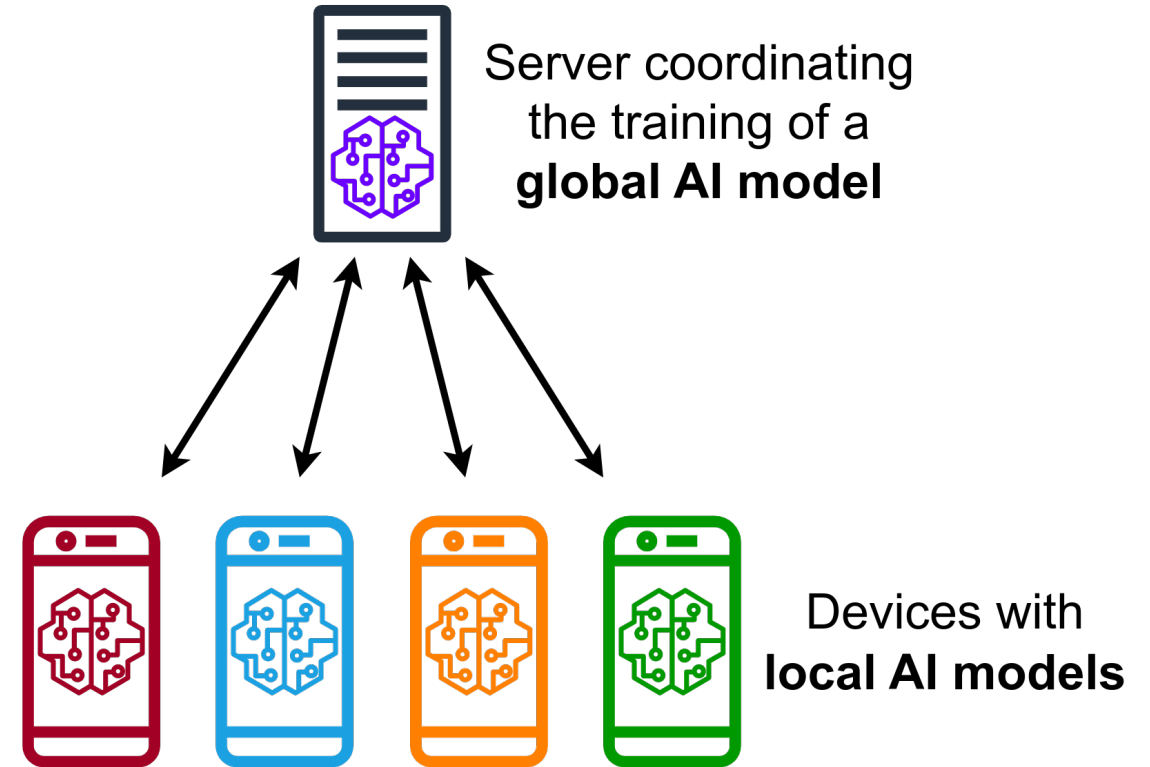
Future: What's coming?

FUTURE DIRECTIONS

Federated Learning

Foundation Models

Human – AI collaboration

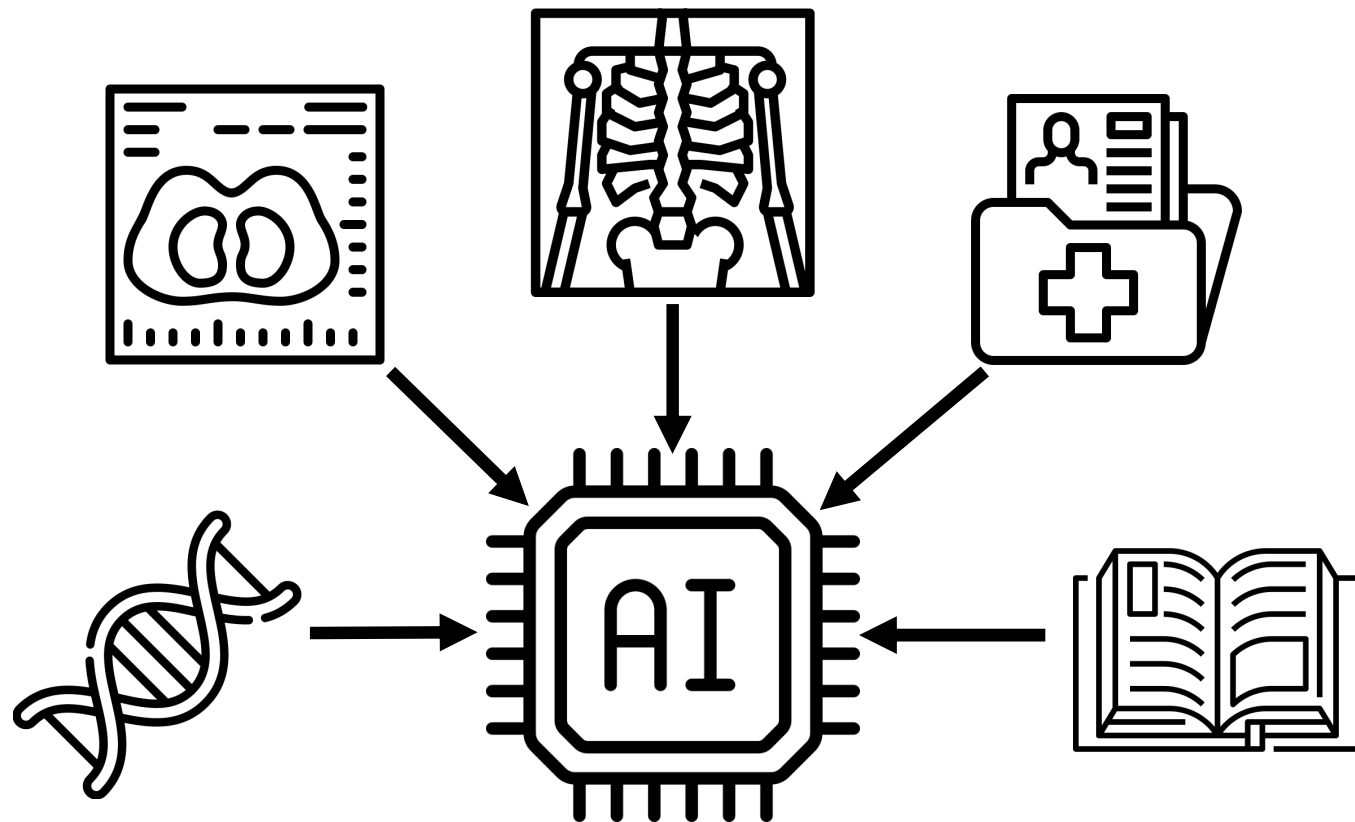


FUTURE DIRECTIONS

Federated Learning

Foundation Models

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FUTURE DIRECTIONS

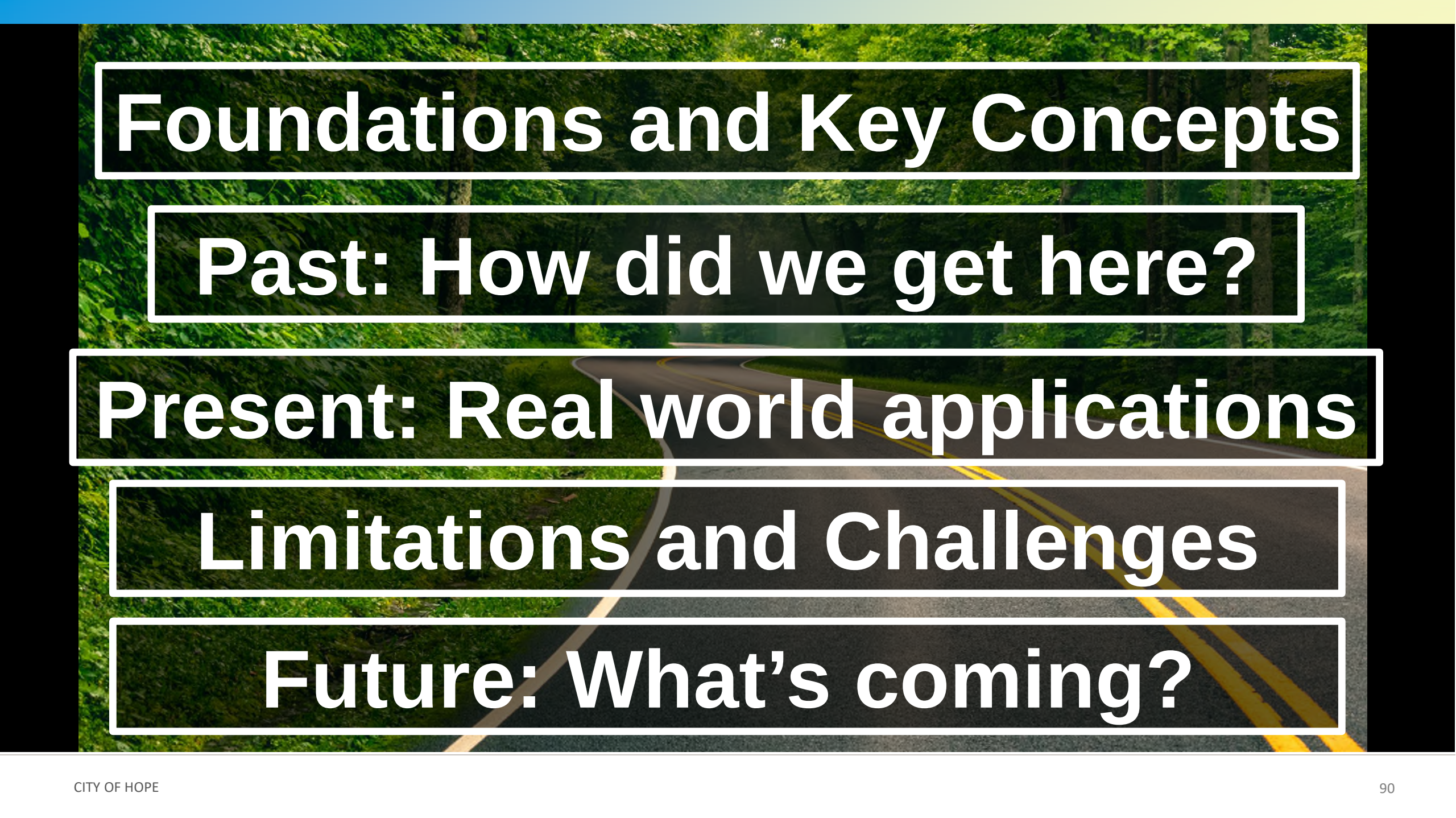
Federated Learning

Foundation Models

Human – AI collaboration



Photo by [Cash Macanaya](#) on [Unsplash](#)



Foundations and Key Concepts

Past: How did we get here?

Present: Real world applications

Limitations and Challenges

Future: What's coming?

FUTURE DIRECTIONS

AI can augment imaging and medicine to improve health outcomes

Must fit into our workflows or we must adapt

Focus on biases prevent unnecessary harm

Rapid development – rapid learning!



Multidisciplinary Approaches to Cancer Symposium

Artificial Intelligence and the Future of Imaging

Luke Ledbetter, MD

Clinical Professor, Department of Radiology

Vice Chair of Education, Department of Radiology

Neuroradiology Section Chief

City of Hope