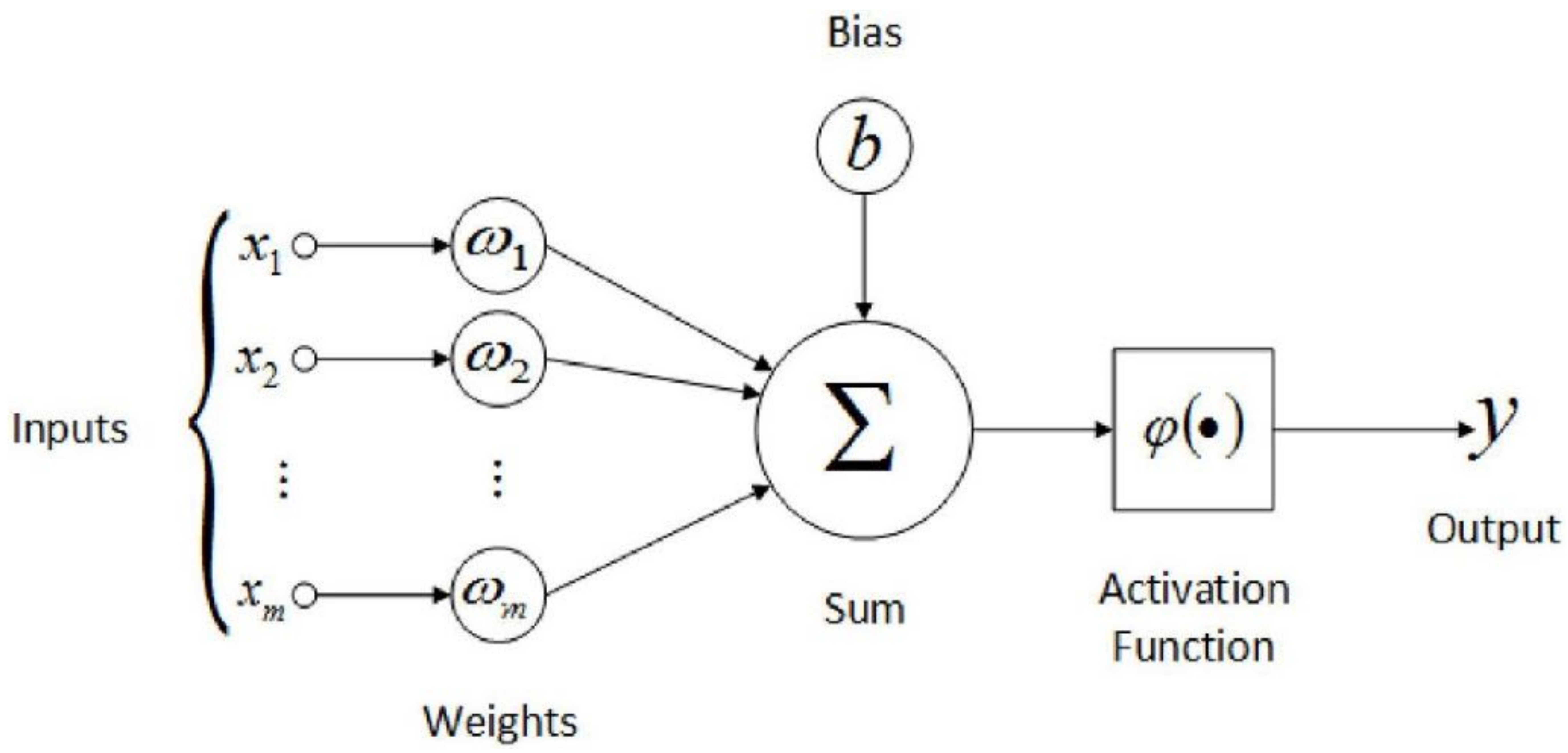
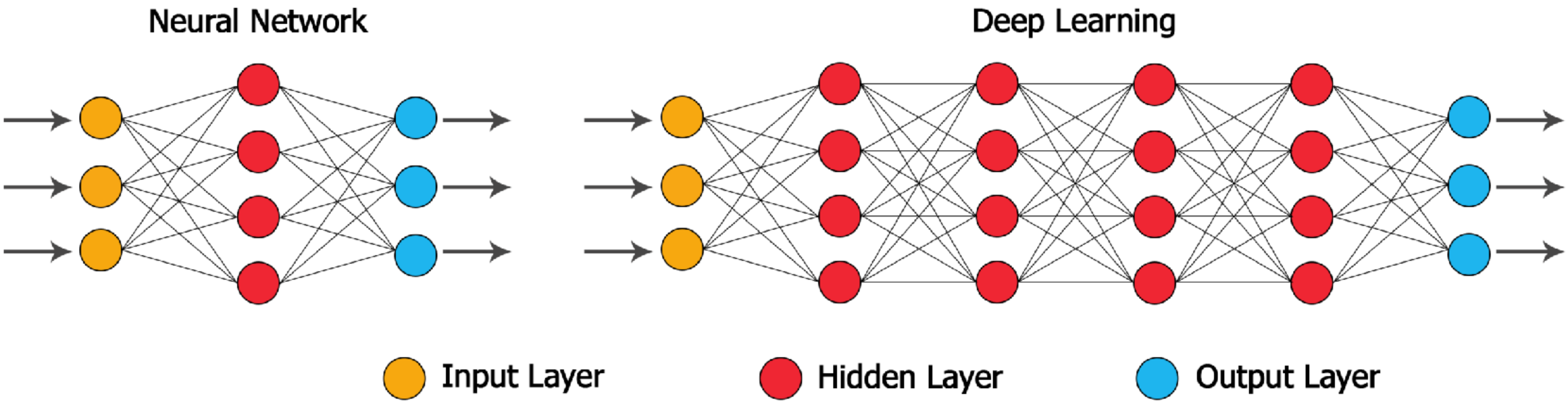
AI 影像辨識之應用
以精準醫療為例

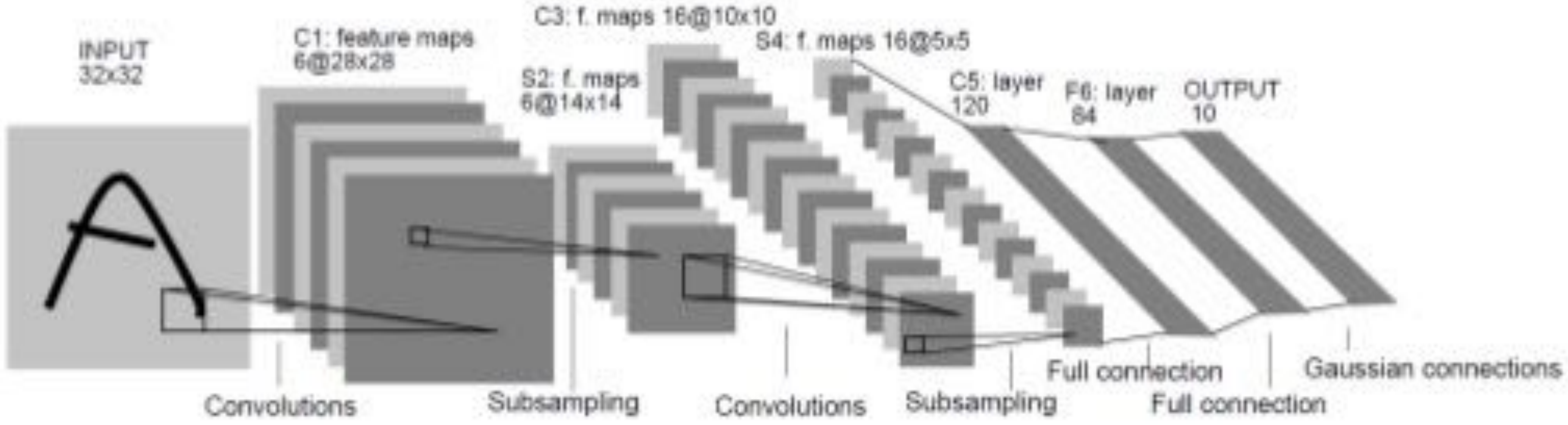
台北長庚 外傷急症外科 廖健宏醫師


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

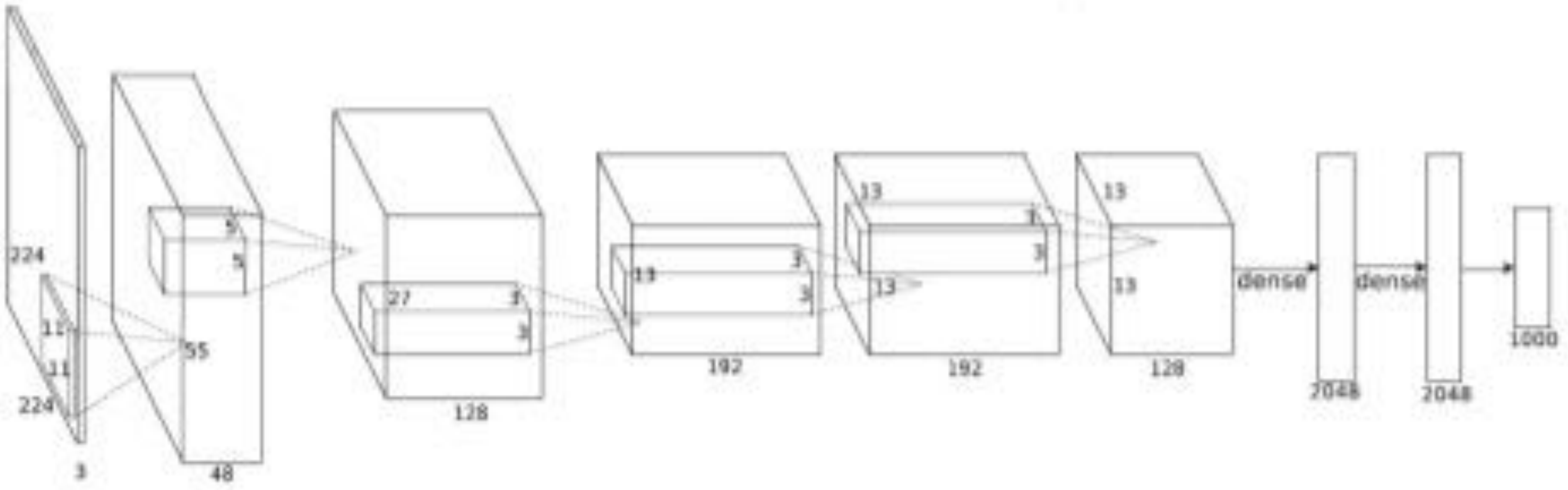

Bias
b
Inputs
x1
x2
xm
ω1
ω2
ωm
Weights
Σ
Sum
φ(•)
Activation
Function
y
Output

神經元


Neural Network
Deep Learning
Input Layer
Hidden Layer
Output Layer

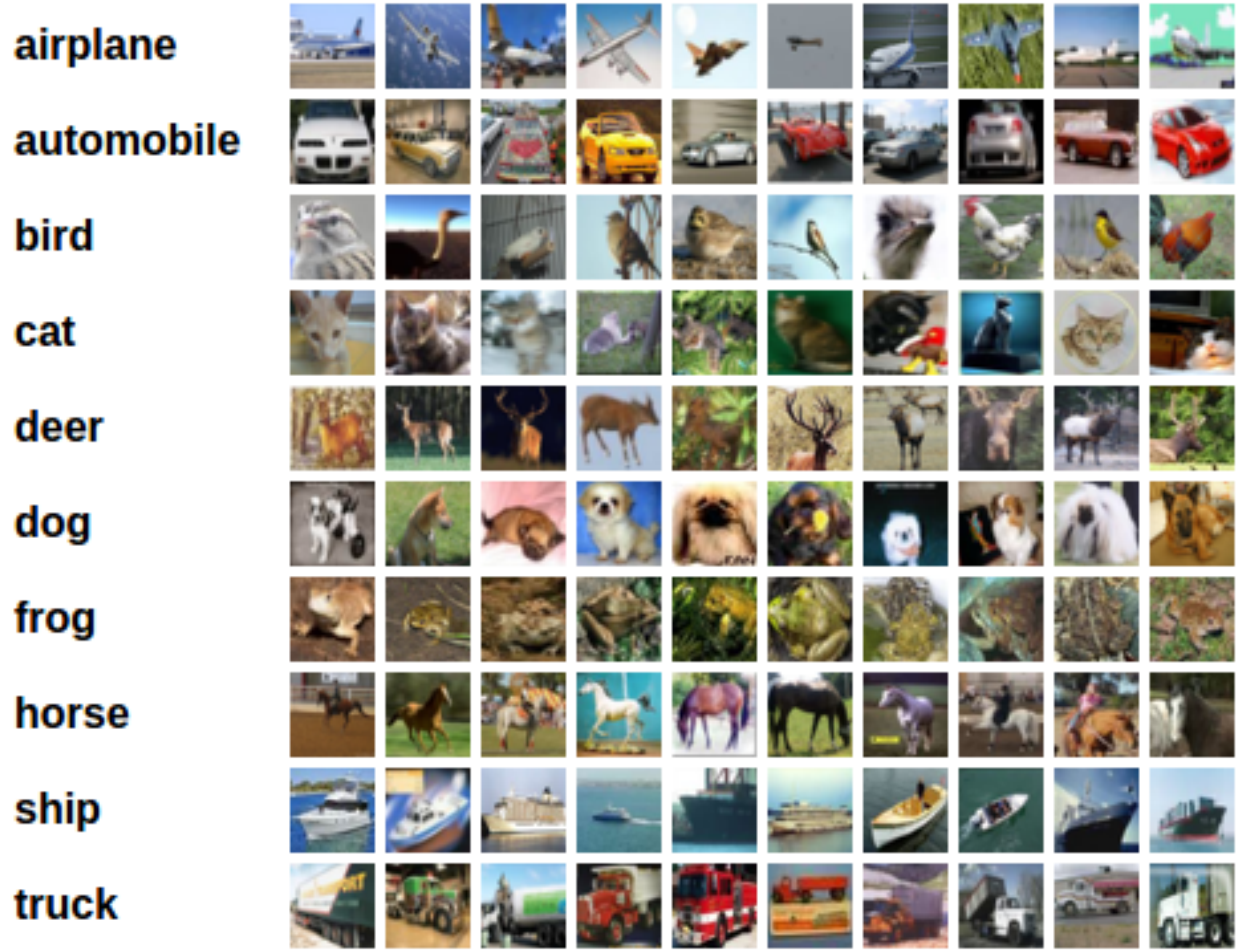


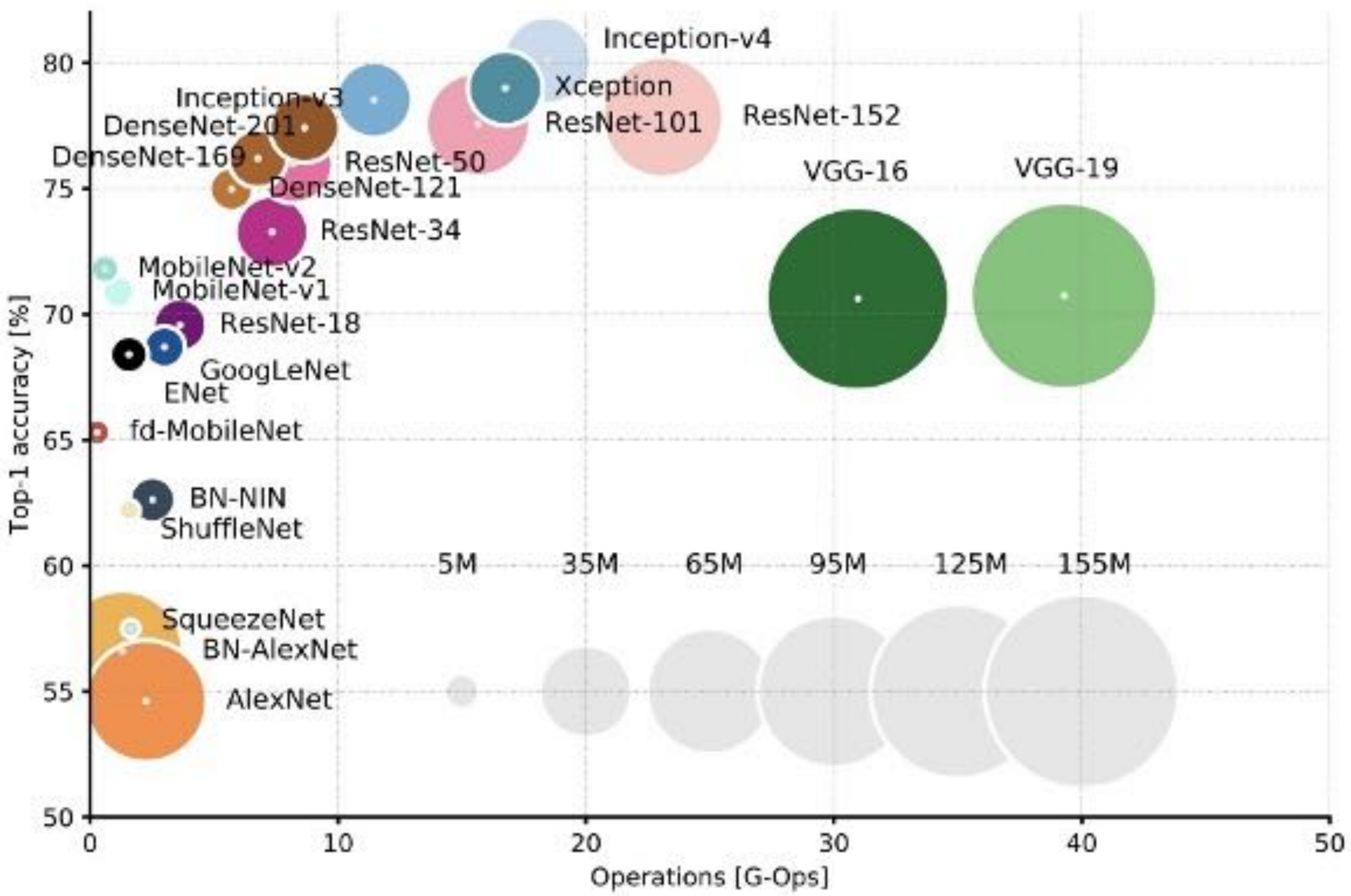
Gradient-Based Learning Applied to Document Recognition, LeCun, Bottou, Bengio and Haffner, Proc. of the IEEE, **1998**



Imagenet Classification with Deep Convolutional Neural Networks, Krizhevsky, Sutskever, and Hinton, NIPS **2012**

影像辨識 現況


airplane
automobile
bird
cat
deer
dog
frog
horse
ship
truck


Inception-v4
Xception
ResNet-101
ResNet-152
Inception-v3
DenseNet-201
DenseNet-169
ResNet-50
DenseNet-121
ResNet-34
VGG-16
VGG-19
MobileNet-v2
MobileNet-v1
ResNet-18
GoogLeNet
ENet
fd-MobileNet
BN-NIN
ShuffleNet
SqueezeNet
BN-AlexNet
AlexNet
5M
35M
65M
95M
125M
155M
Top-1 accuracy [%]
Operations [G-Ops]
80
75
70
65
60
55
50
0
10
20
30
40
50

Object recognition & Classification

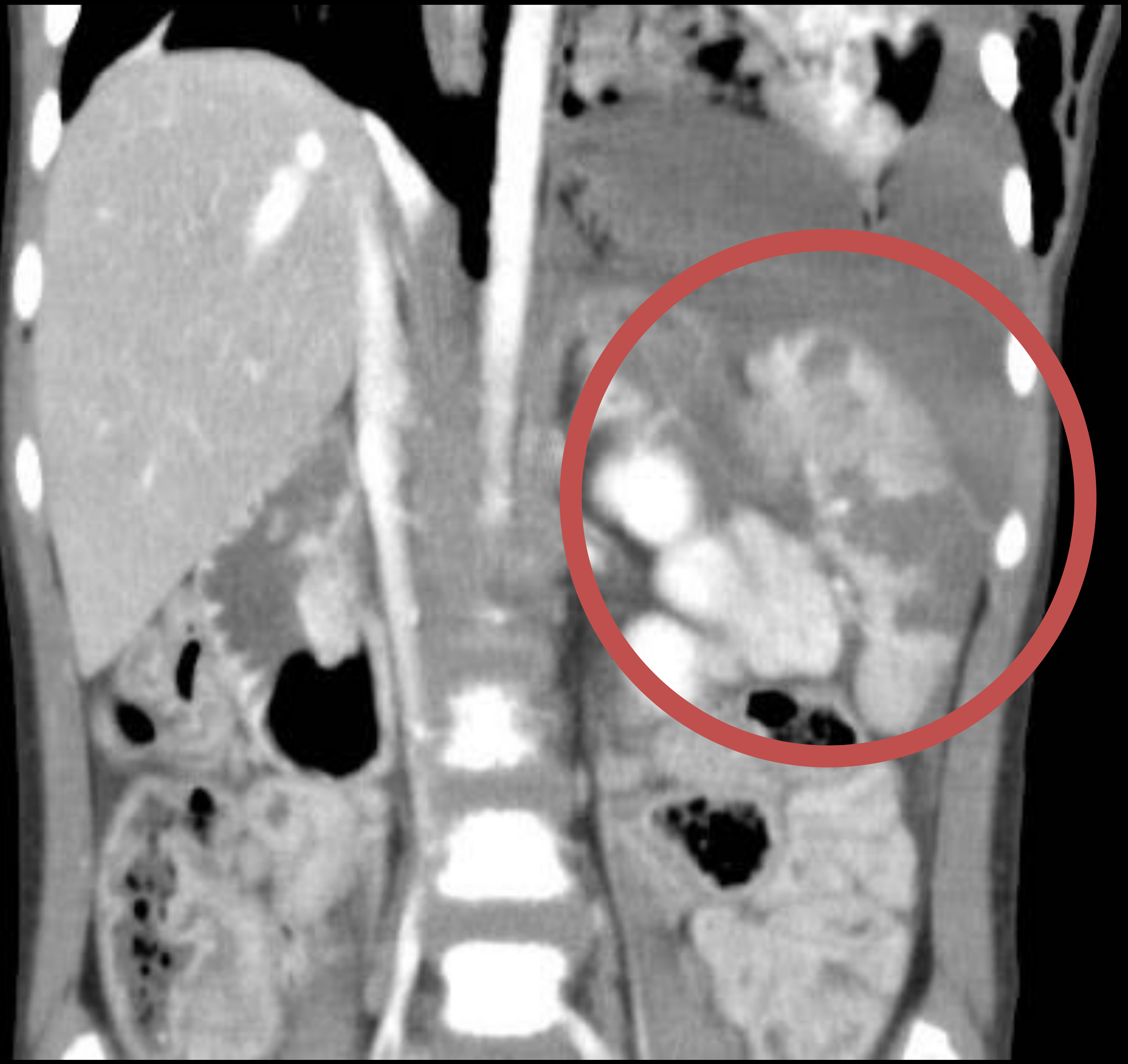
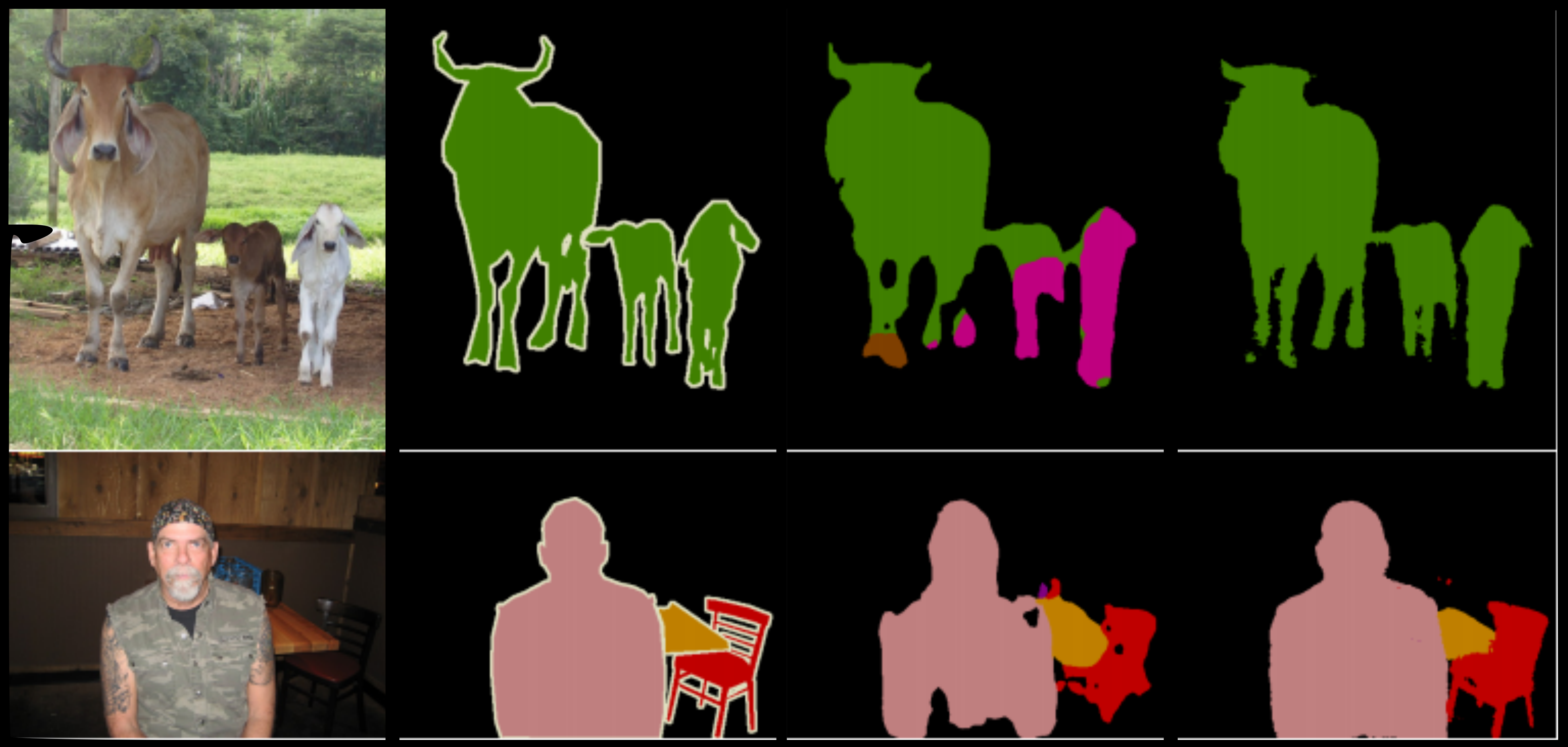
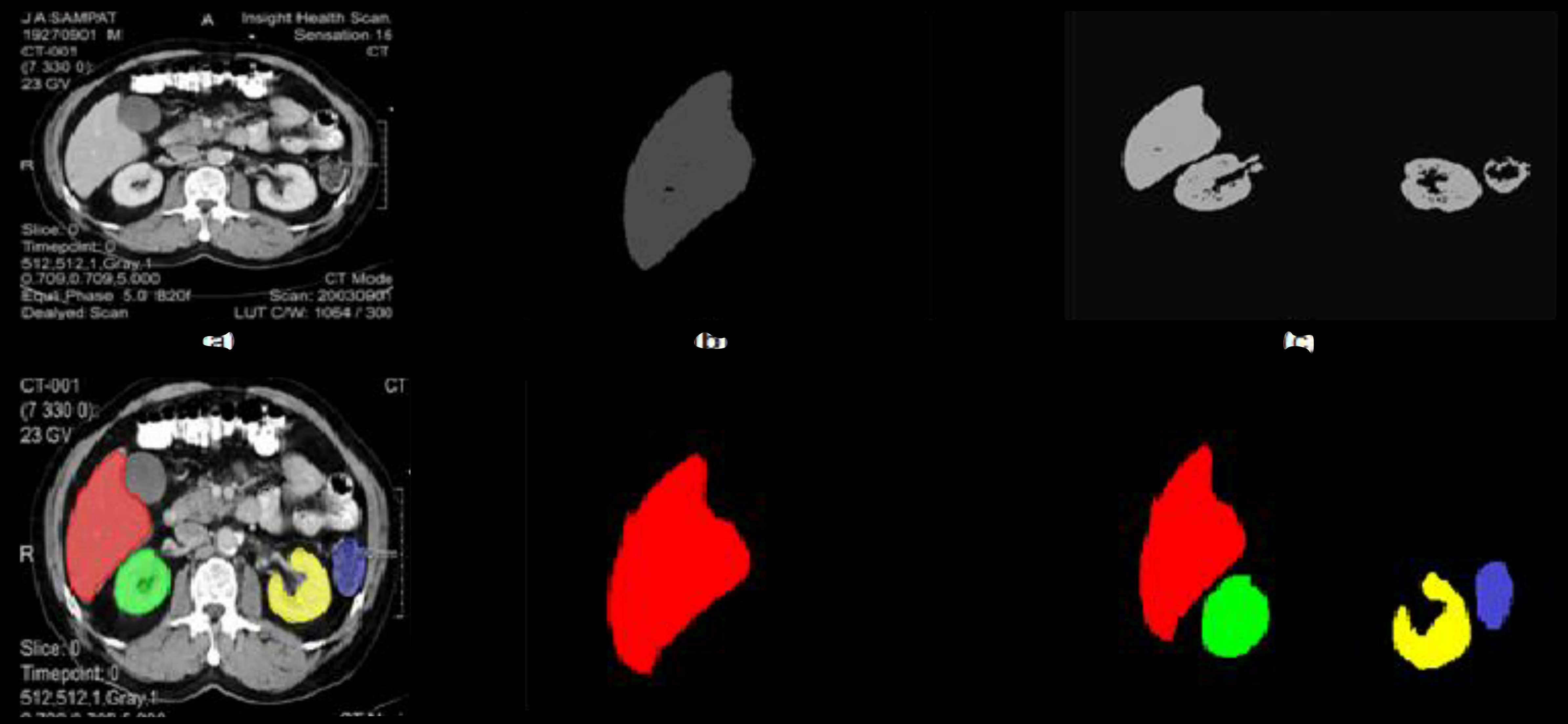
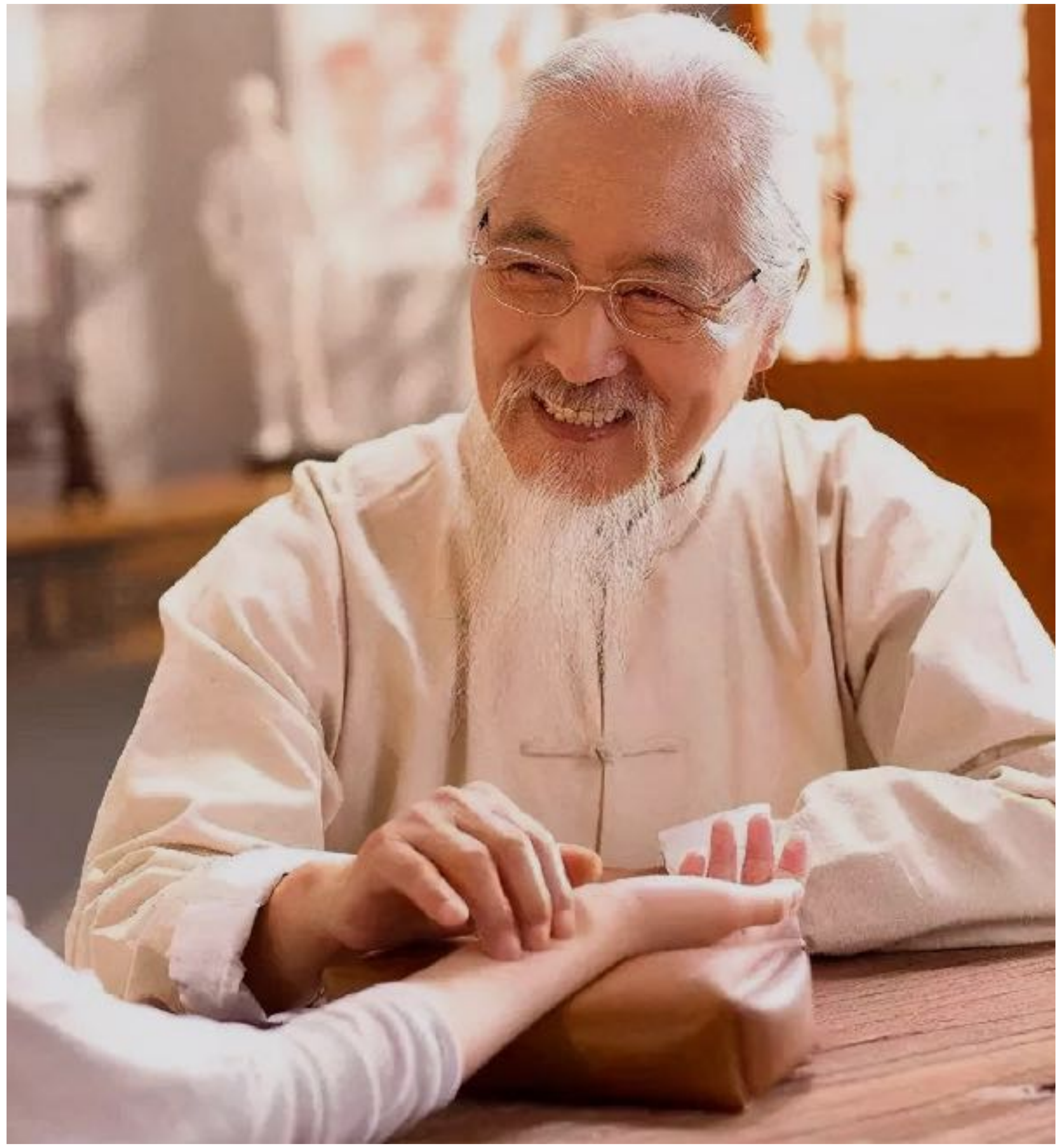


Image segmentation





醫學 高度集中的資料科學

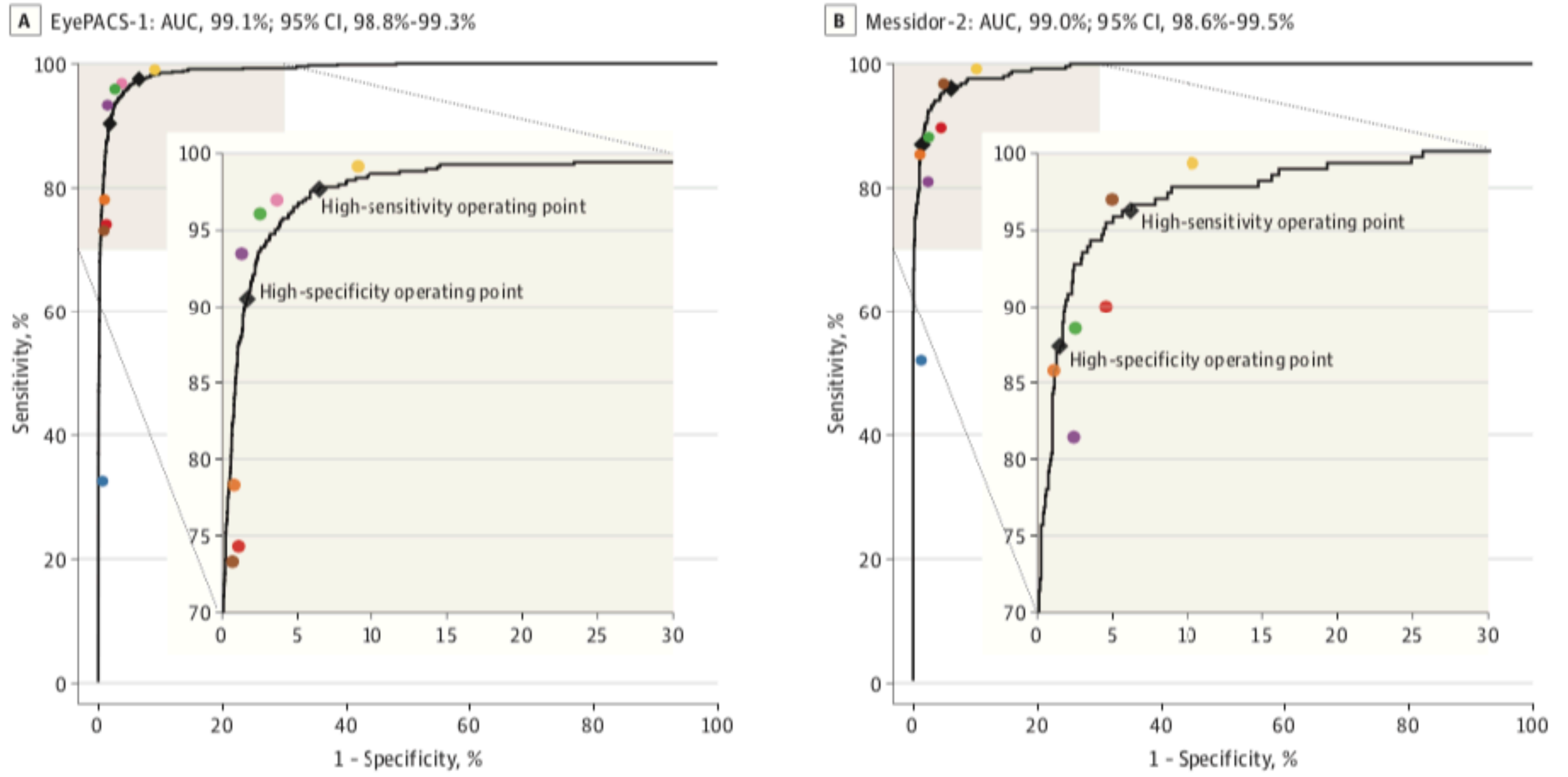


JAMA | Original Investigation | INNOVATIONS IN HEALTH CARE DELIVERY

Development and Validation of a Deep Learning Algorithm for Detection of Diabetic Retinopathy in Retinal Fundus Photographs

Varun Gulshan, PhD; Lily Peng, MD, PhD; Marc Coram, PhD; Martin C. Stumpe, PhD; Derek Wu, BS; Arunachalam Narayanaswamy, PhD; Subhashini Venugopalan, MS; Kasumi Widner, MS; Tom Madams, MEng; Jorge Cuadros, OD, PhD; Ramasamy Kim, OD, DNB; Rajiv Raman, MS, DNB; Philip C. Nelson, BS; Jessica L. Mega, MD, MPH; Dale R. Webster, PhD

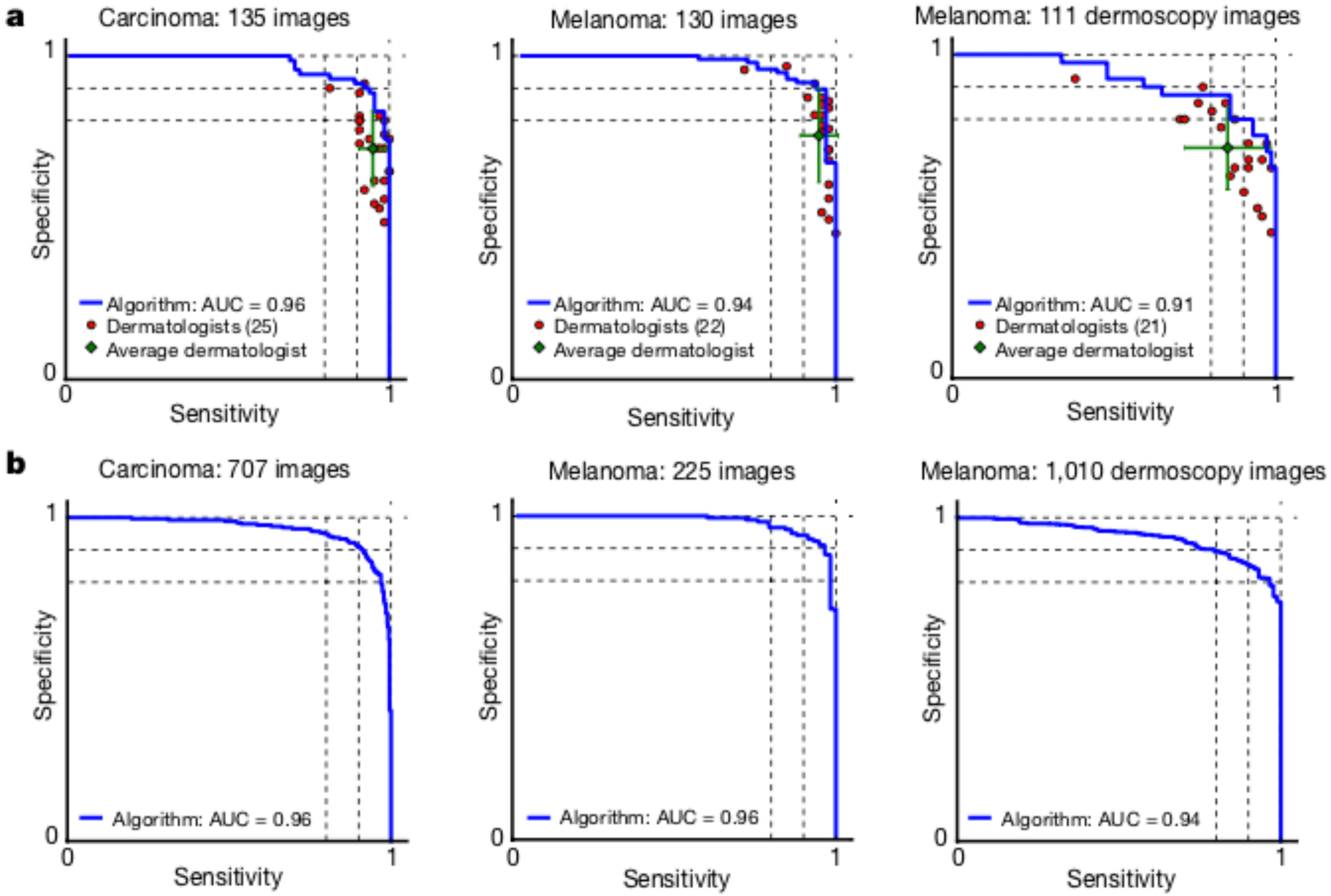
Figure 2. Validation Set Performance for Referable Diabetic Retinopathy



Gulshan V, et al. *JAMA*. 2016;316(22):2402-2410.

Dermatologist-level classification of skin cancer with deep neural networks

Andre Esteva[1*], Brett Kuprel[1*], Roberto A. Novoa[2,3], Justin Ko[2], Susan M. Swetter[2,4], Helen M. Blau[5] & Sebastian Thrun[6]



Esteva A, et al. Nature. 2017;542(7639):115-118.

VIEWPOINT

Deep Learning—A Technology With the Potential to Transform Health Care

Geoffrey Hinton, PhD
Google Brain Team and Department of Computer Science, University of Toronto, Ontario, Canada.

Viewpoint page 1099 and **Editorial** page 1107

Related article page 1192

Widespread application of artificial intelligence in health care has been anticipated for half a century. For most of that time, the dominant approach to artificial intelligence was inspired by logic: researchers assumed that the essence of intelligence was manipulating symbolic expressions, using rules of inference. This approach produced expert systems and graphical models that attempted to automate the reasoning processes of experts. In the last decade, however, a radically different approach to artificial intelligence, called deep learning, has produced major breakthroughs and is now used on billions of digital devices for complex tasks such as speech recognition, image interpretation, and language translation. The purpose of this Viewpoint is to give health care professionals an intuitive understanding of the technology underlying deep learning. In an accompanying Viewpoint, Naylor[1] outlines some of the factors propelling adoption of this technology in medicine and health care.

retrain a convolutional neural network that had previously been trained to recognize everyday objects in cluttered images. The skin lesion images used for retraining varied widely in quality, and no further information was provided to the convolutional neural network other than the image pixels and the lesion label. The network and groups of 21 to 25 board-certified dermatologists then reviewed subsets of the unlabeled test images and decided whether the correct clinical course was a biopsy for possible malignancy or reassurance of the patient. Sensitivity for the majority of the dermatologists was lower than that of the convolutional neural network when matched for specificity, and their specificity was lower than that of the convolutional neural network when matched for sensitivity for identifying images with melanoma, as well as for images of basal and squamous cell carcinoma.

G. Hinton. JAMA. 2018;320(11):1101-1102. doi:10.1001/jama.2018.11100.

The limitation of computer vision in medicine

- No large dataset available (Annotation, imbalance)
- Black box mechanism, accountability
- No general rule for each problem

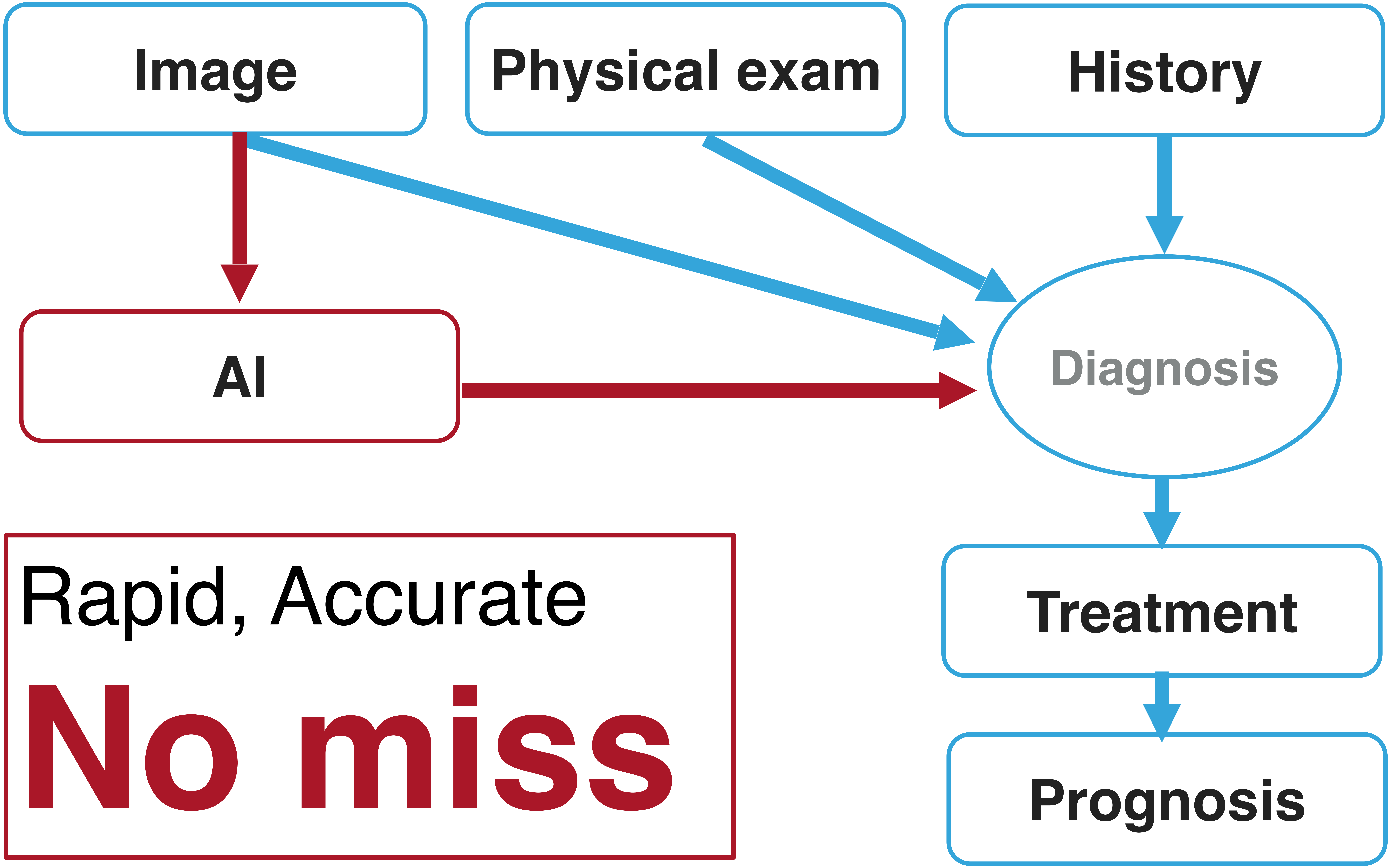
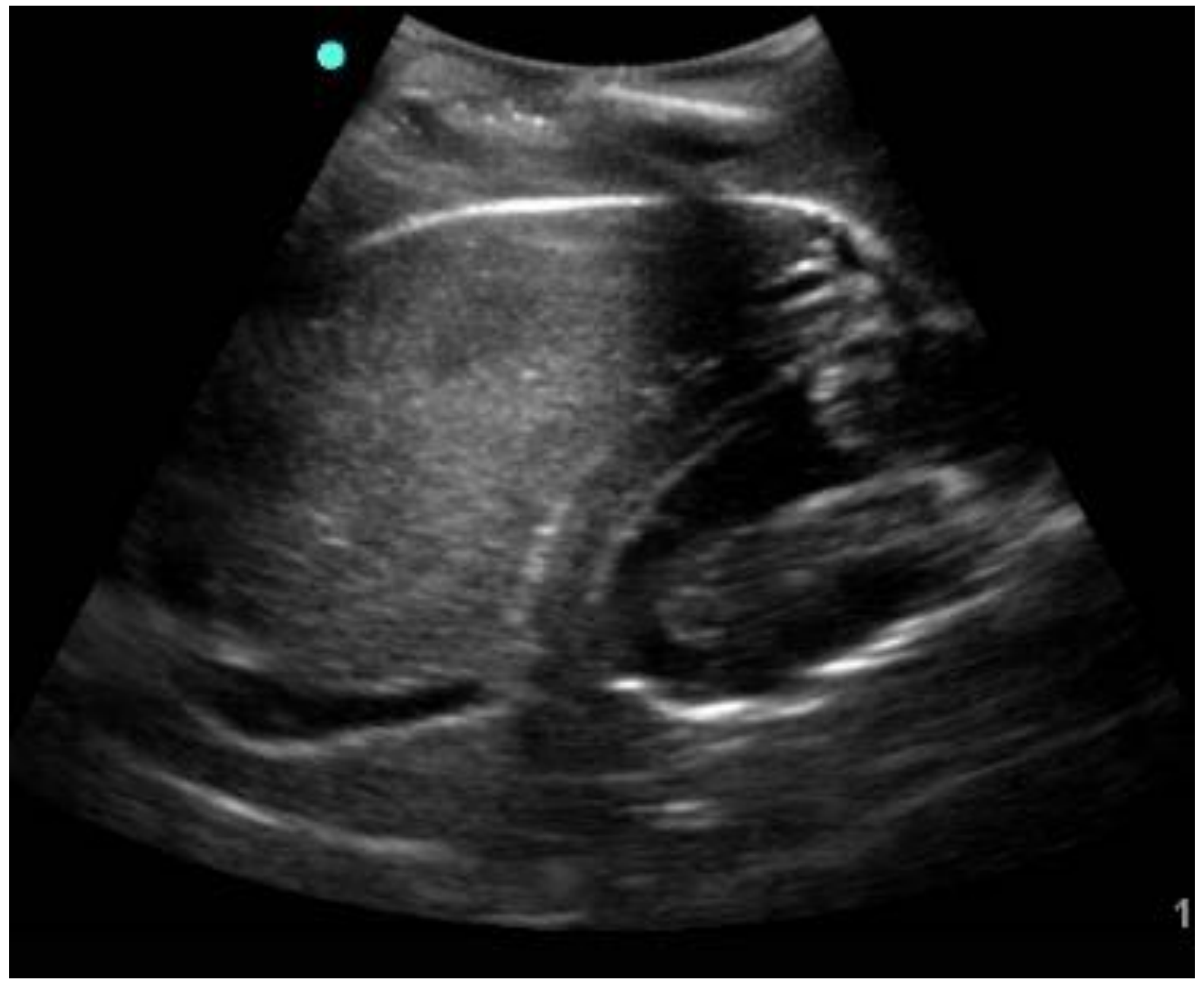


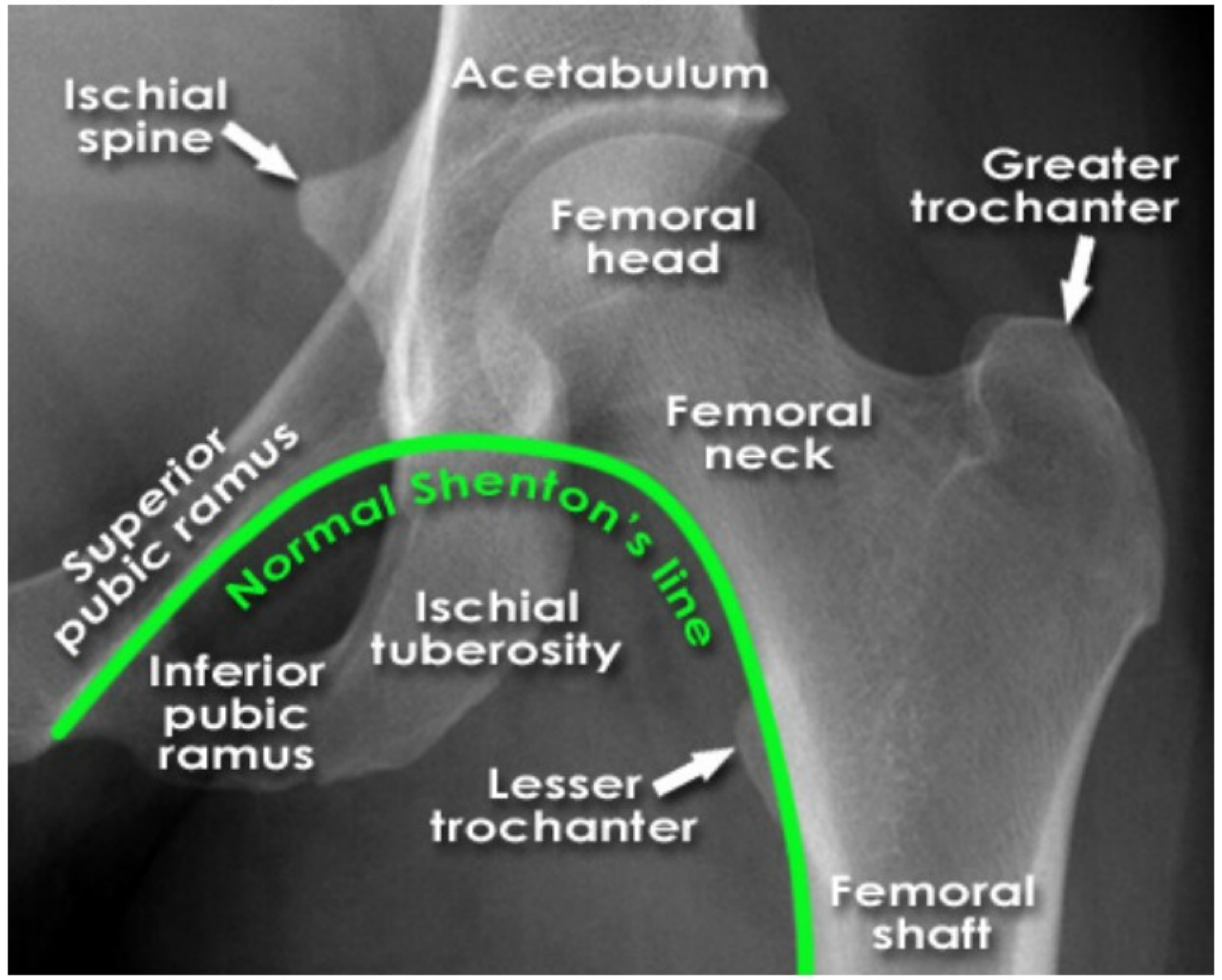
Image
Physical exam
History
AI
Diagnosis
Treatment
Prognosis
Rapid, Accurate
No miss




SUP

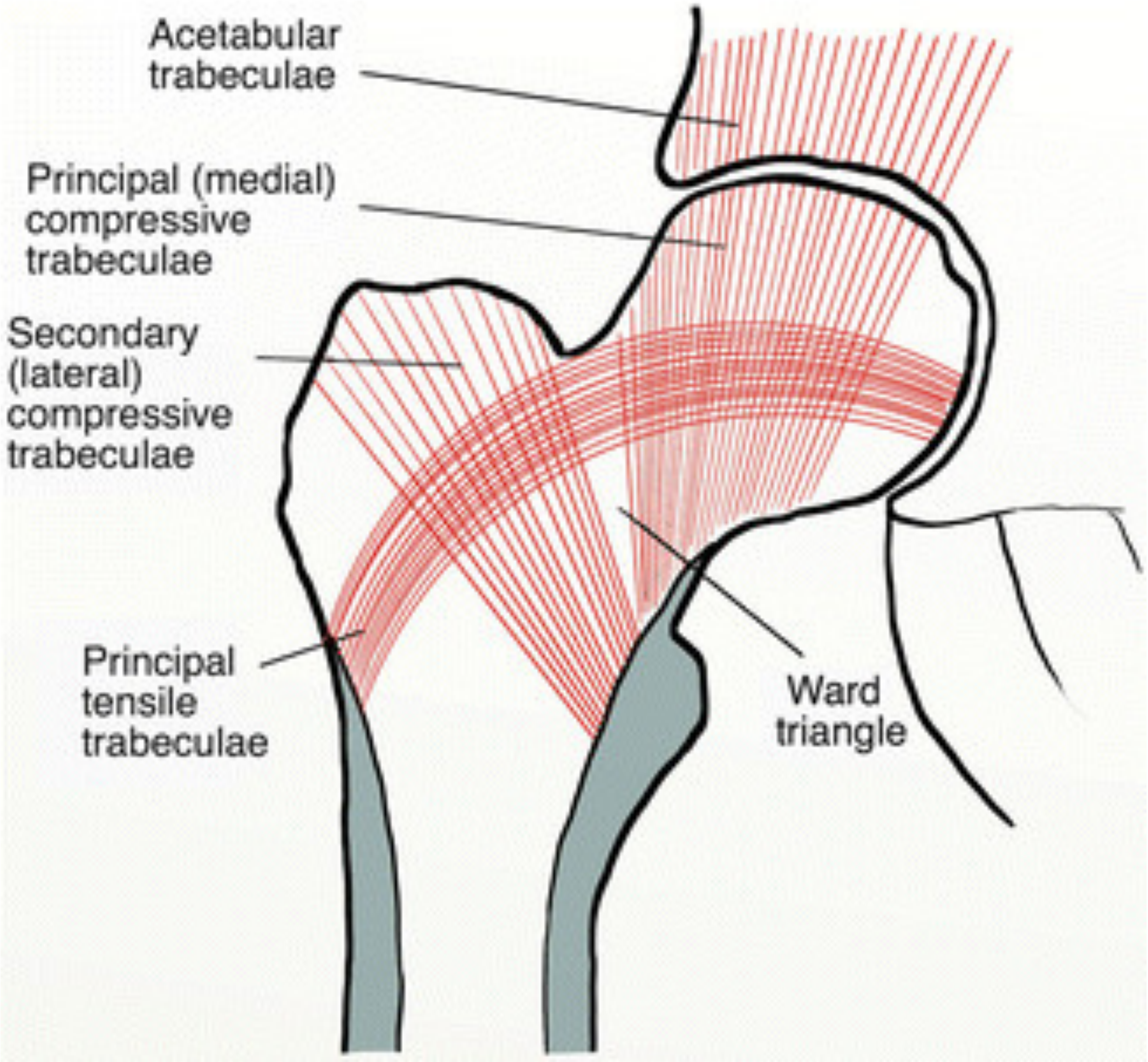
Plain Pelvic film (PXR)
is the essential of
trauma survey

ATLS 10th edition



Hip X-ray anatomy - Normal AP

- Shenton's line is formed by the medial edge of the femoral neck and the inferior edge of the superior pubic ramus
- Loss of contour of Shenton's line is a sign of a fractured neck of femur
- **IMPORTANT NOTE**: Fractures of the femoral neck do not always cause loss of Shenton's line



MARKET EVALUATION

> 65 y/o, annual case of hip fracture : **957.3** /100000 woman

414.4 /100000 man

30% of people with a hip fracture will die in the following year

Kirby et al. Radiographic Detection of Hip and Pelvic Fractures in the Emergency Department. AJR, 2010.

Cabarrus et al. MRI and CT of insufficiency fractures of the pelvis and the proximal femur. AJR, 2008.

Brauer et al. Incidence and Mortality of Hip Fractures in the United States. JAMA 2009.

MARKET EVALUATION

10-14% of people with a hip fracture **miss-diagnosed**

Miss-diagnosed hip fracture **Doubled the risk of dying** before the end of the first postop year

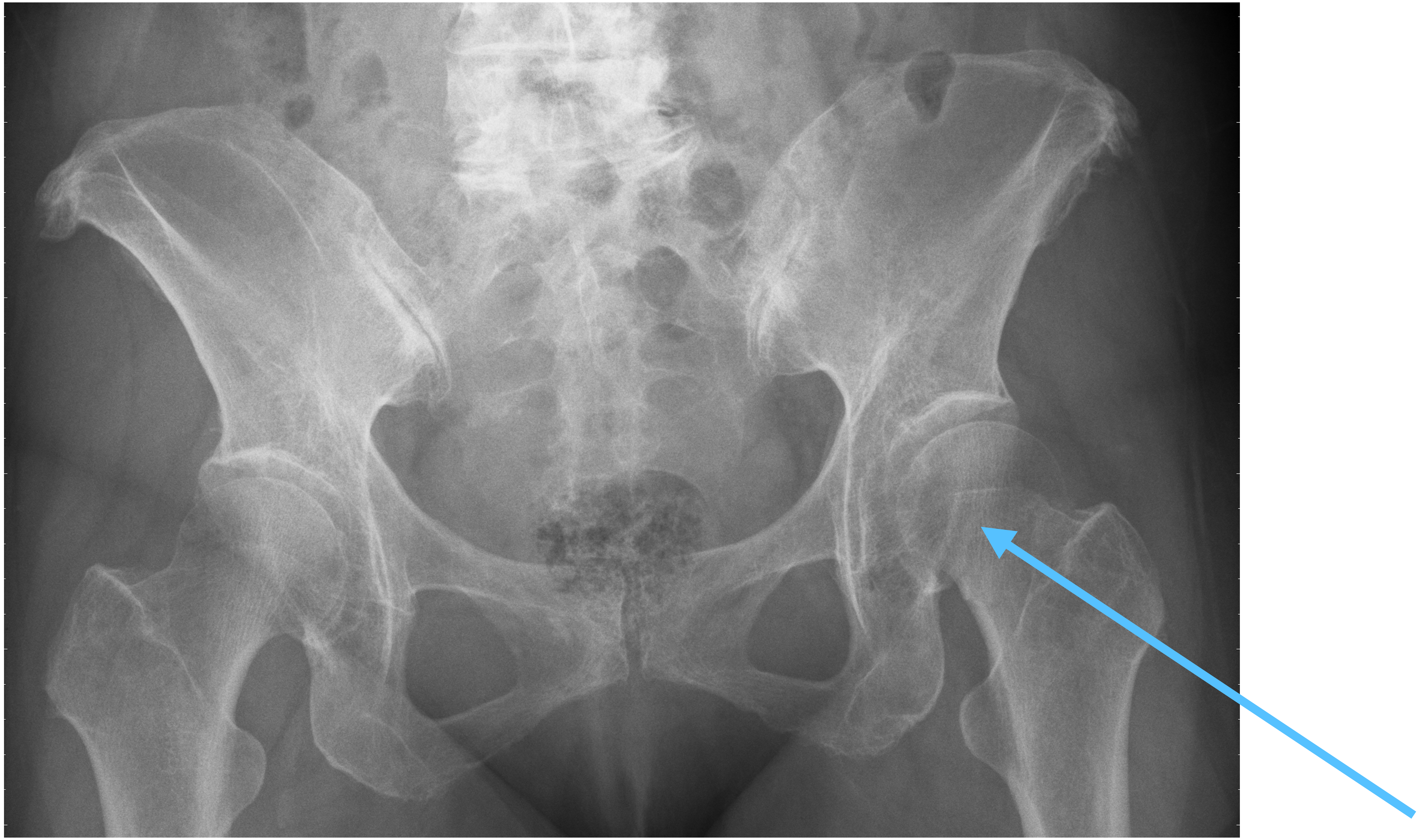
Kirby et al. Radiographic Detection of Hip and Pelvic Fractures in the Emergency Department. AJR, 2010.

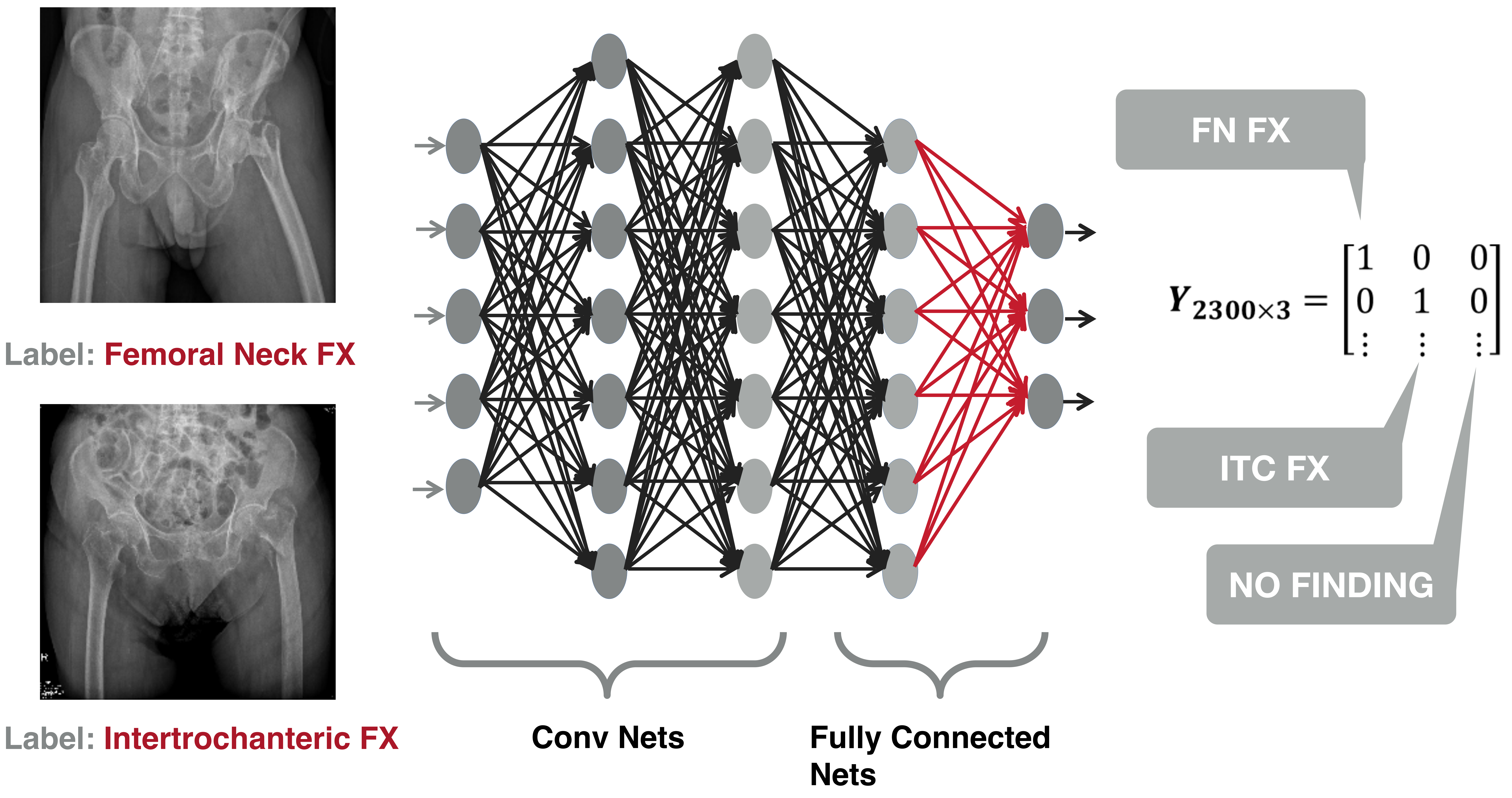
Cabarrus et al. MRI and CT of insufficiency fractures of the pelvis and the proximal femur. AJR, 2008.

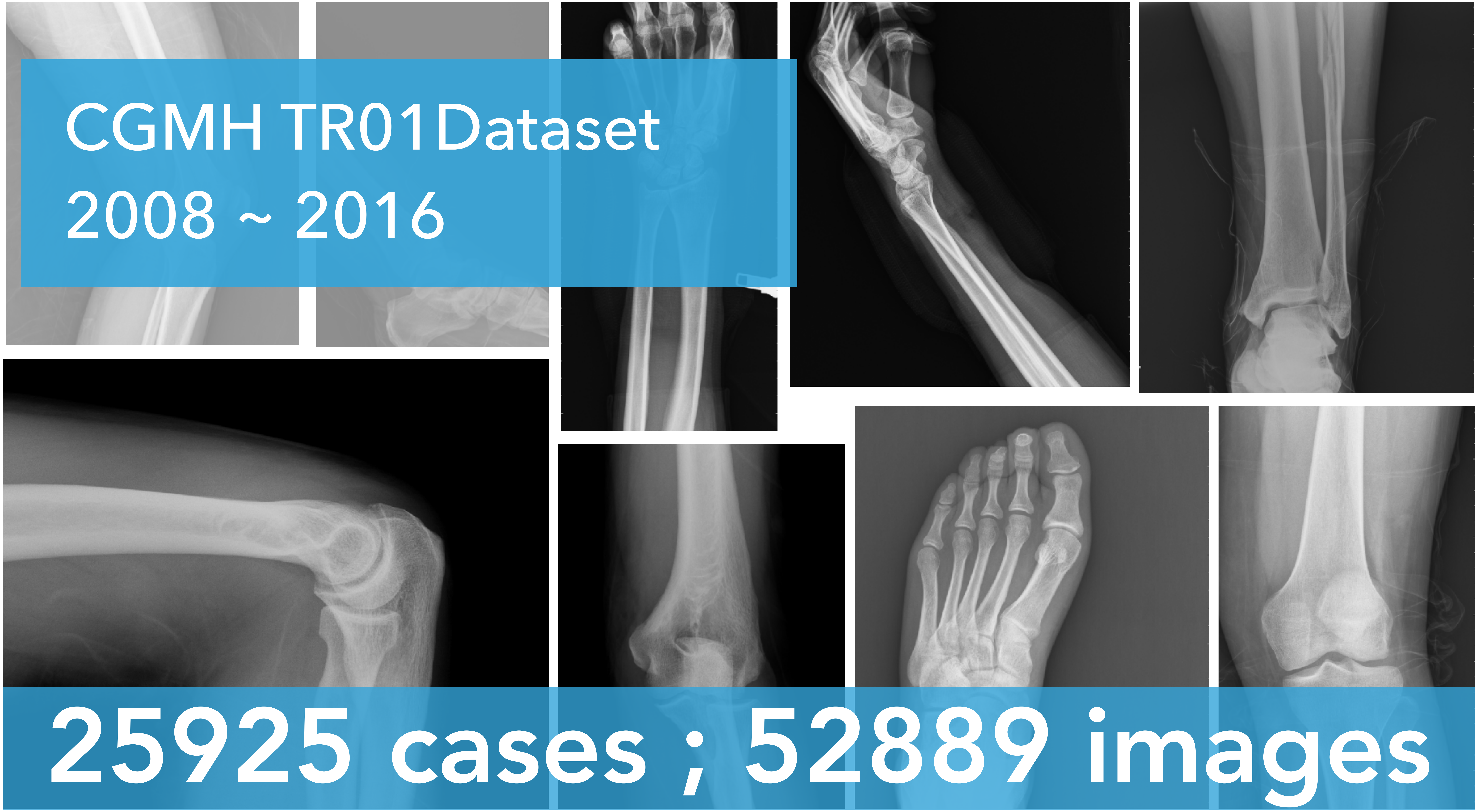
Brauer et al. Incidence and Mortality of Hip Fractures in the United States. JAMA 2009.

Displaced fracture

Non-displaced fracture

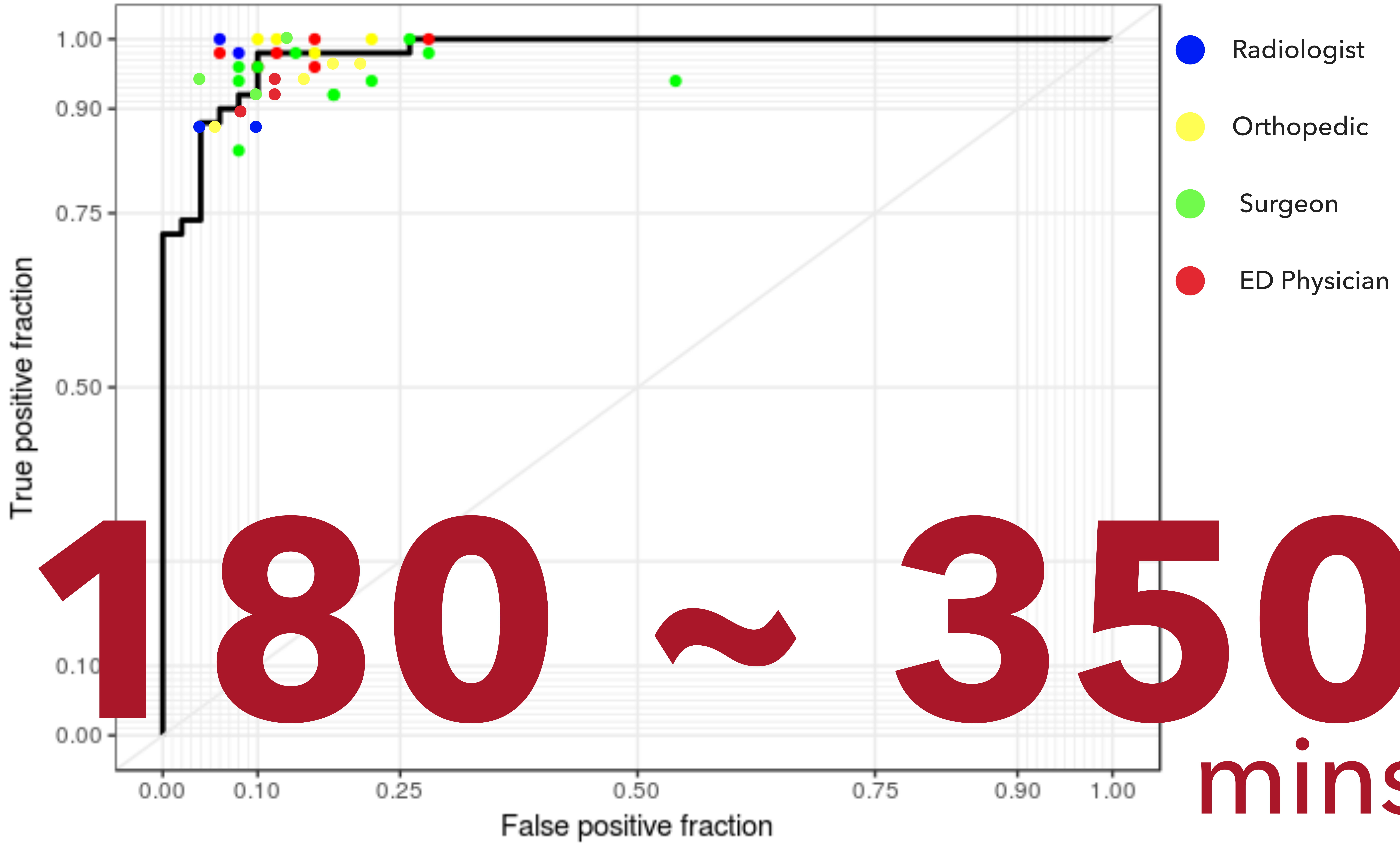

Fracture Site


Label: Femoral Neck FX
Label: Intertrochanteric FX
Conv Nets
Fully Connected Nets
FN FX
ITC FX
NO FINDING
$Y_{2300\times3} = \begin{bmatrix} 1 & 0 & 0 \\ 0 & 1 & 0 \\ \vdots & \vdots & \vdots \end{bmatrix}$


CGMH TR01Dataset
2008 ~ 2016
25925 cases ; 52889 images

PERFORMANCE OF THE SYSTEM

Class	Scratch	ImageNet Pretrained	CGMHTr01 Pretrained	PHYCISIANs
Training set	0.81	0.94	0.96	
Validation set	0.81	0.89	0.91	
Testing set	0.79	0.91	**0.96**	0.70 - 0.96

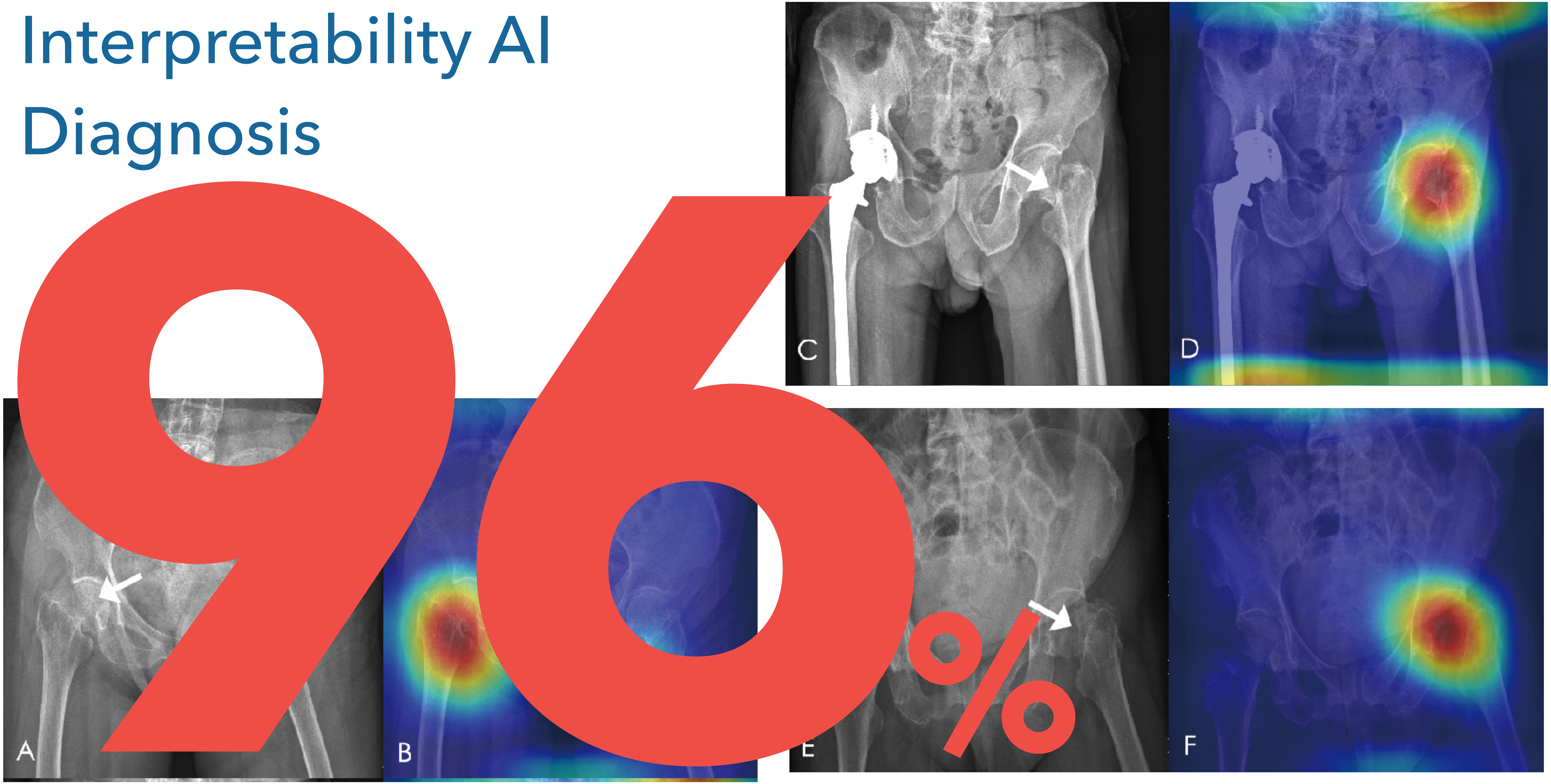

1.00
0.90
0.75
0.50
0.10
0.00
True positive fraction
0.00
0.10
0.25
0.50
0.75
0.90
1.00
False positive fraction
Radiologist
Orthopedic
Surgeon
ED Physician

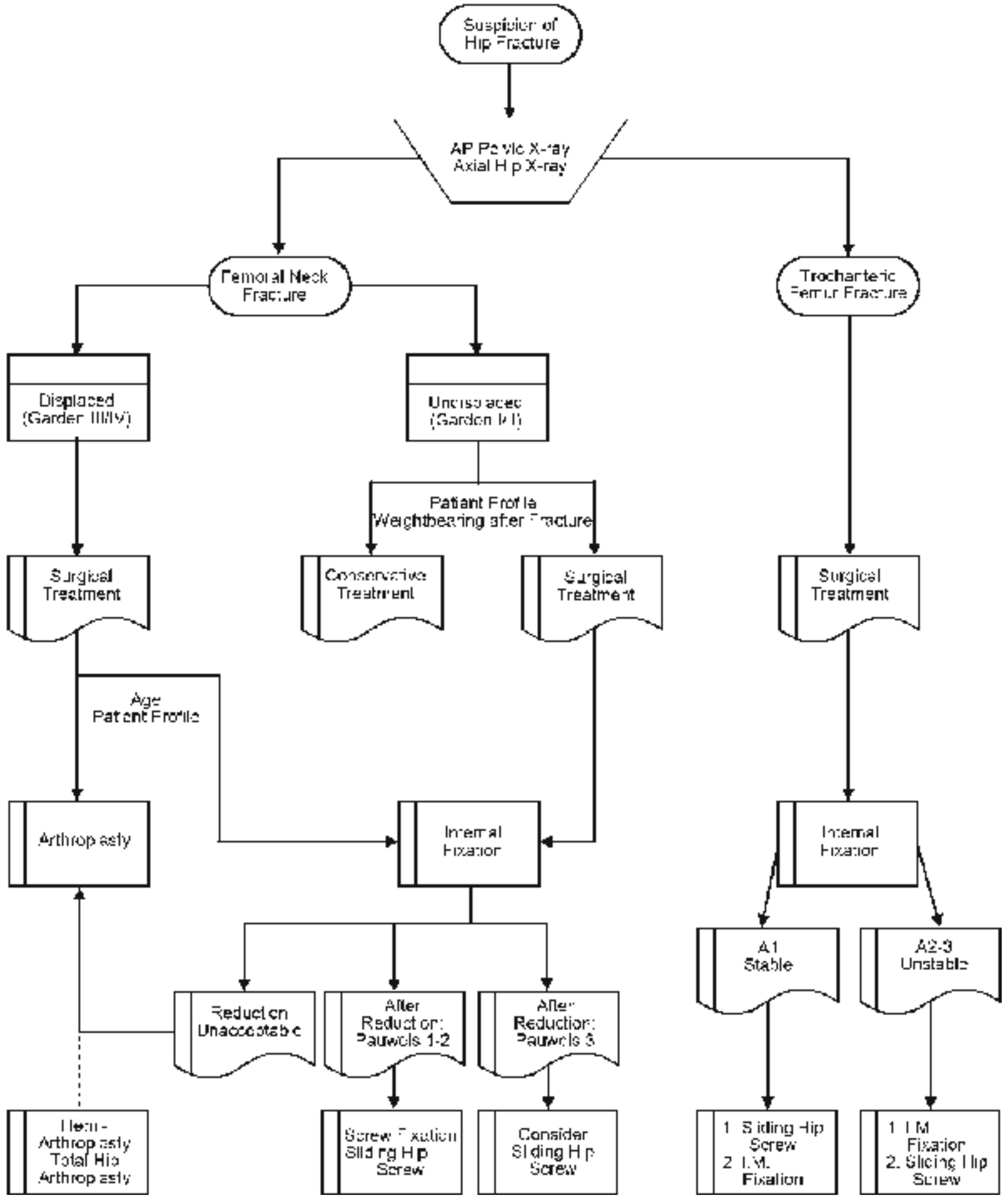
180 ~ 350

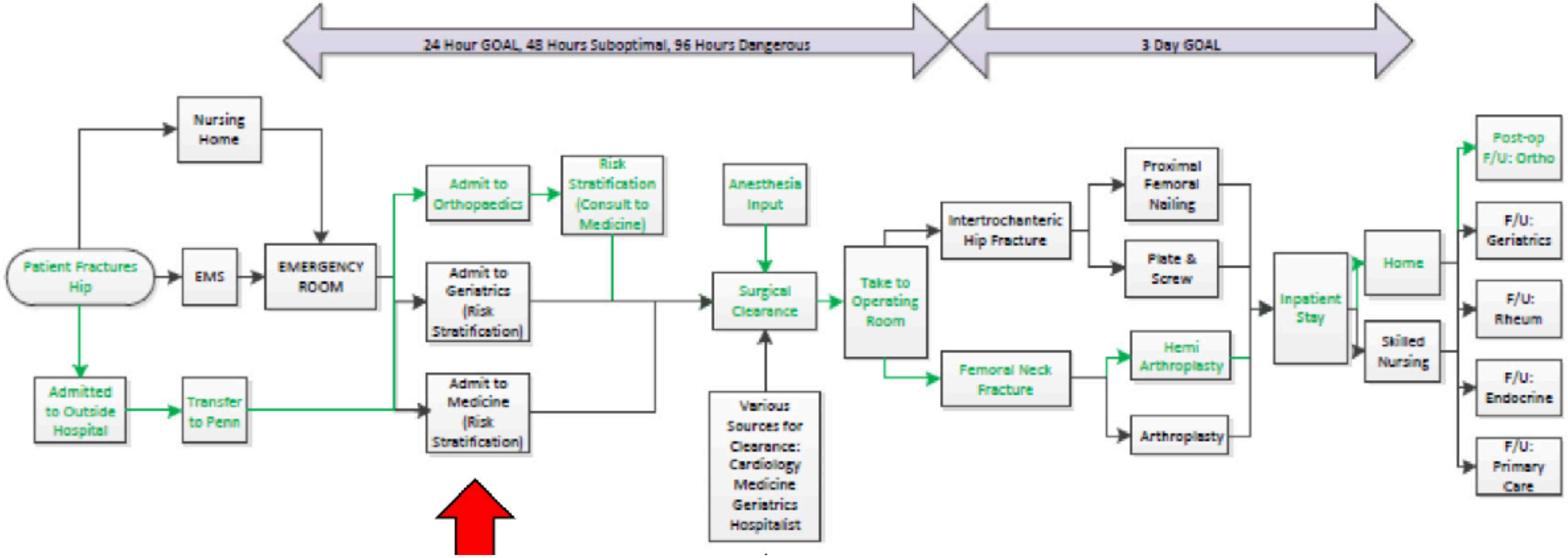
mins

Interpretability AI Diagnosis

96%




Suspicion of Hip Fracture
AP Pelvic X-ray
Axial Hip X-ray
Femoral Neck Fracture
Trochanteric Femur Fracture
Displaced (Garden III/IV)
Undisplaced (Garden I-II)
Patient Profile
Weightbearing after Fracture
Surgical Treatment
Conservative Treatment
Surgical Treatment
Surgical Treatment
Age
Patient Profile
Arthroplasty
Internal Fixation
Internal Fixation
A1 Stable
A2-3 Unstable
Reduction Unacceptable
After Reduction: Pauwels 1-2
After Reduction: Pauwels 3
Hemi-Arthroplasty
Total Hip Arthroplasty
Screw Fixation
Sliding Hip Screw
Consider Sliding Hip Screw
1. Sliding Hip Screw
2. I.M. Fixation
1. I.M. Fixation
2. Sliding Hip Screw


24 Hour GOAL, 48 Hours Suboptimal, 96 Hours Dangerous
3 Day GOAL
Nursing Home
Patient Fractures Hip
EMS
EMERGENCY ROOM
Admitted to Outside Hospital
Transfer to Penn
Admit to Orthopaedics
Risk Stratification (Consult to Medicine)
Admit to Geriatrics (Risk Stratification)
Admit to Medicine (Risk Stratification)
Anesthesia Input
Surgical Clearance
Various Sources for Clearance: Cardiology Medicine Geriatrics Hospitalist
Take to Operating Room
Intertrochanteric Hip Fracture
Femoral Neck Fracture
Proximal Femoral Nailing
Plate & Screw
Hemi Arthroplasty
Arthroplasty
Inpatient Stay
Home
Skilled Nursing
Post-op F/U: Ortho
F/U: Geriatrics
F/U: Rheum
F/U: Endocrine
F/U: Primary Care