Automatic Measurement of Femoral Neck-Shaft Angle Using Keypoint Detection Technique

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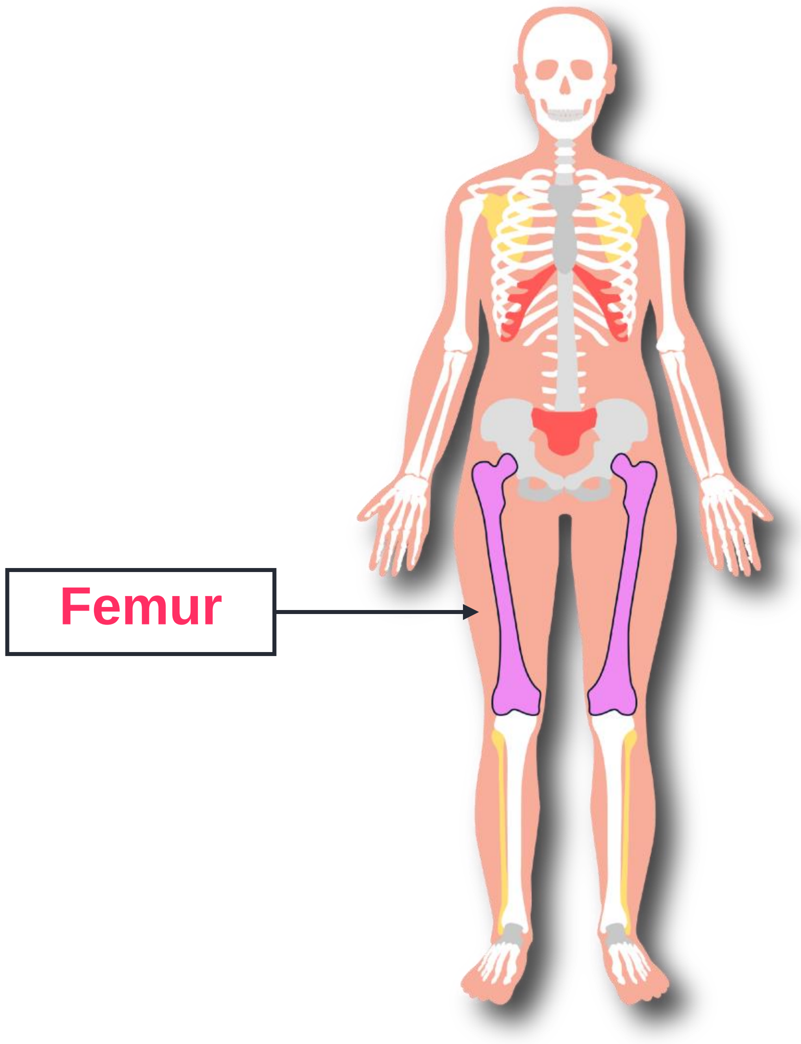
Outlines

1. Introduction
2. Objectives & Scopes of work
3. Theories
4. Literature Review
5. Research methods
6. Results & Discussion
7. Limitations and Future work

Introduction

What is the Femur?

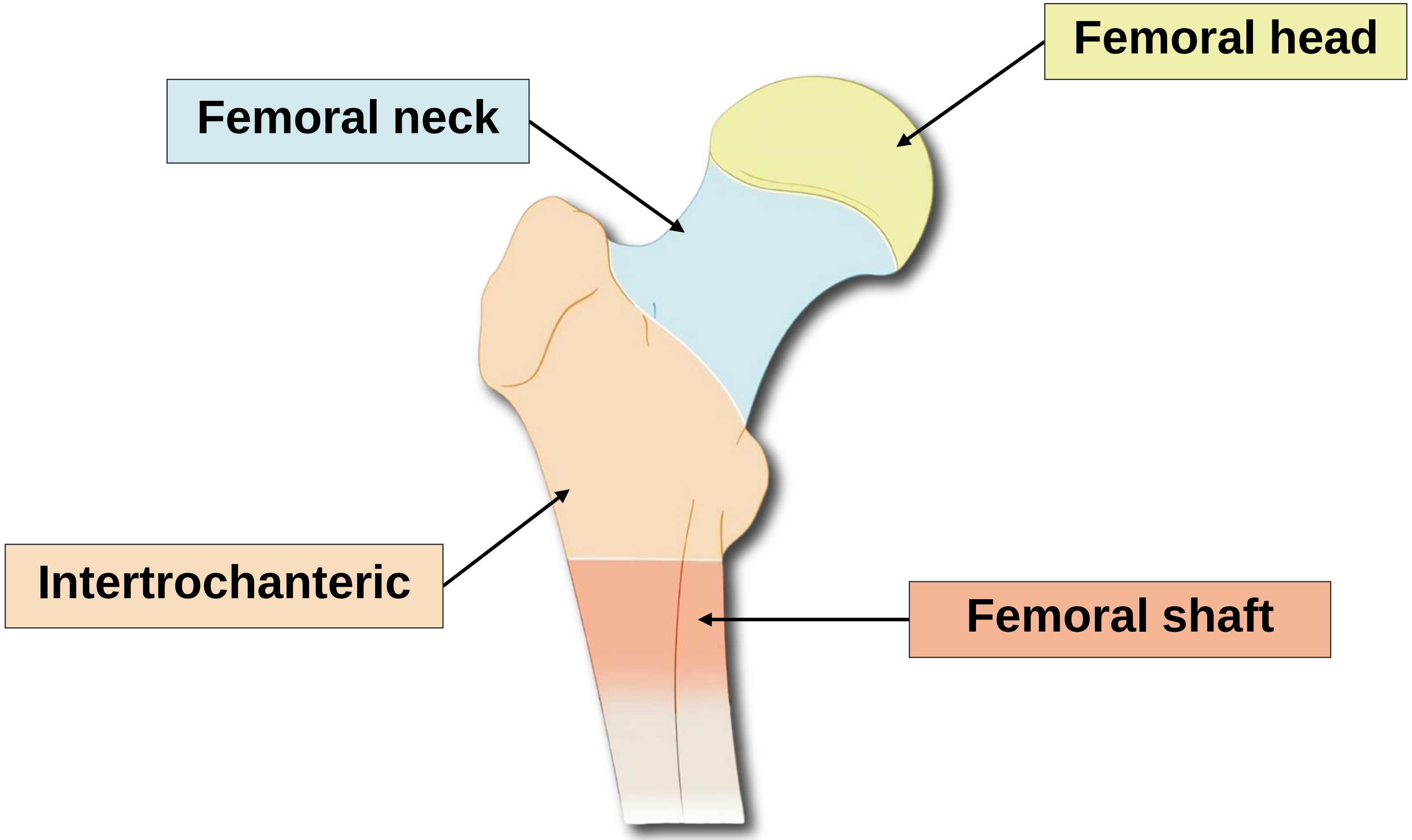
Definition



- The term **“Femoral”** refers to anything related to **the femur (thigh bone)**.
- The **longest** and **strongest bone**.
- Essential for **standing** and **moving.**
- **Supports body weight** when **walking, running,** and **high-impact activities [1].**

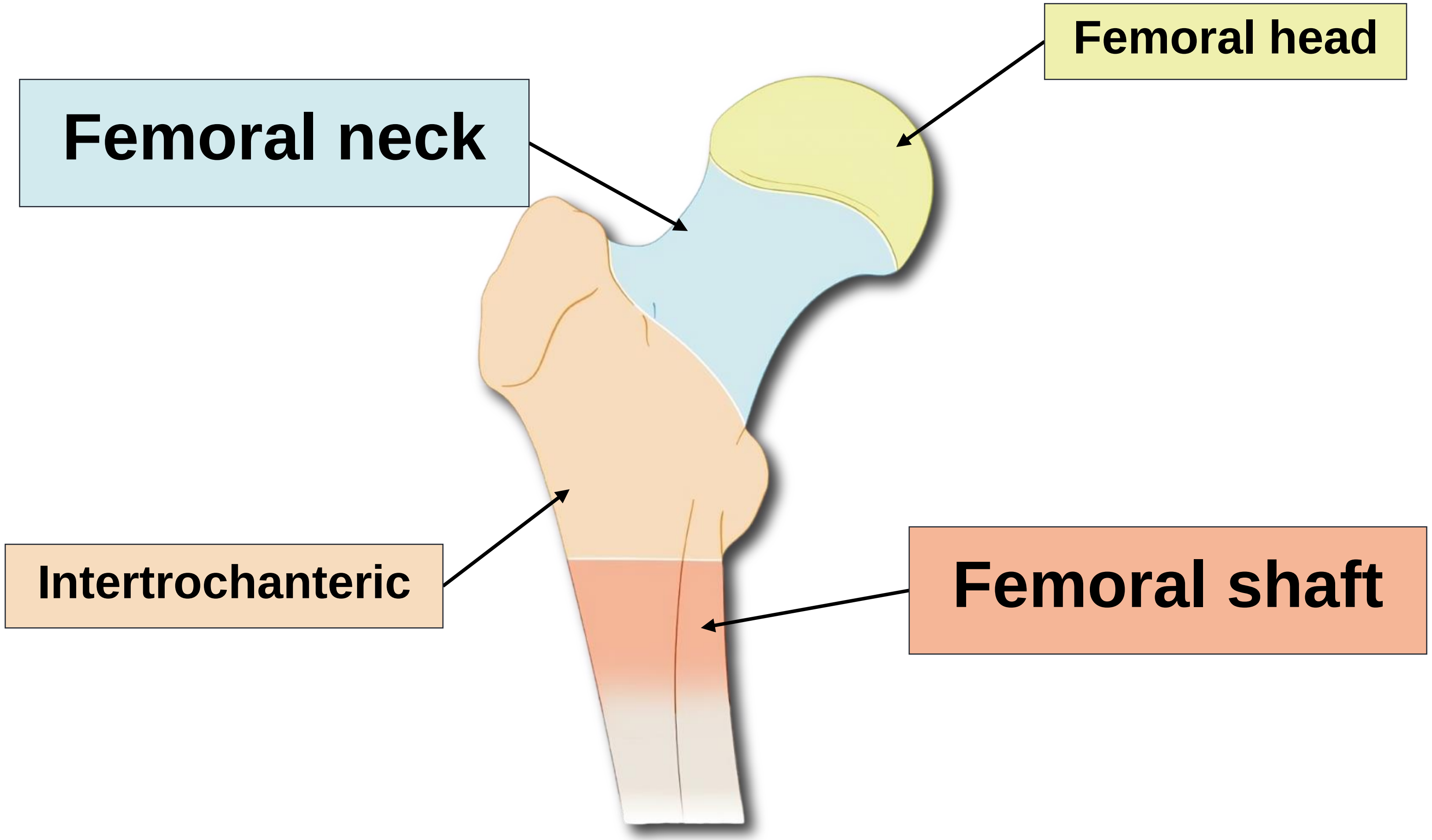
Anatomical Regions of the Femur

The regions of the femur



Regions Relevant to Neck-Shaft Angle Evaluation

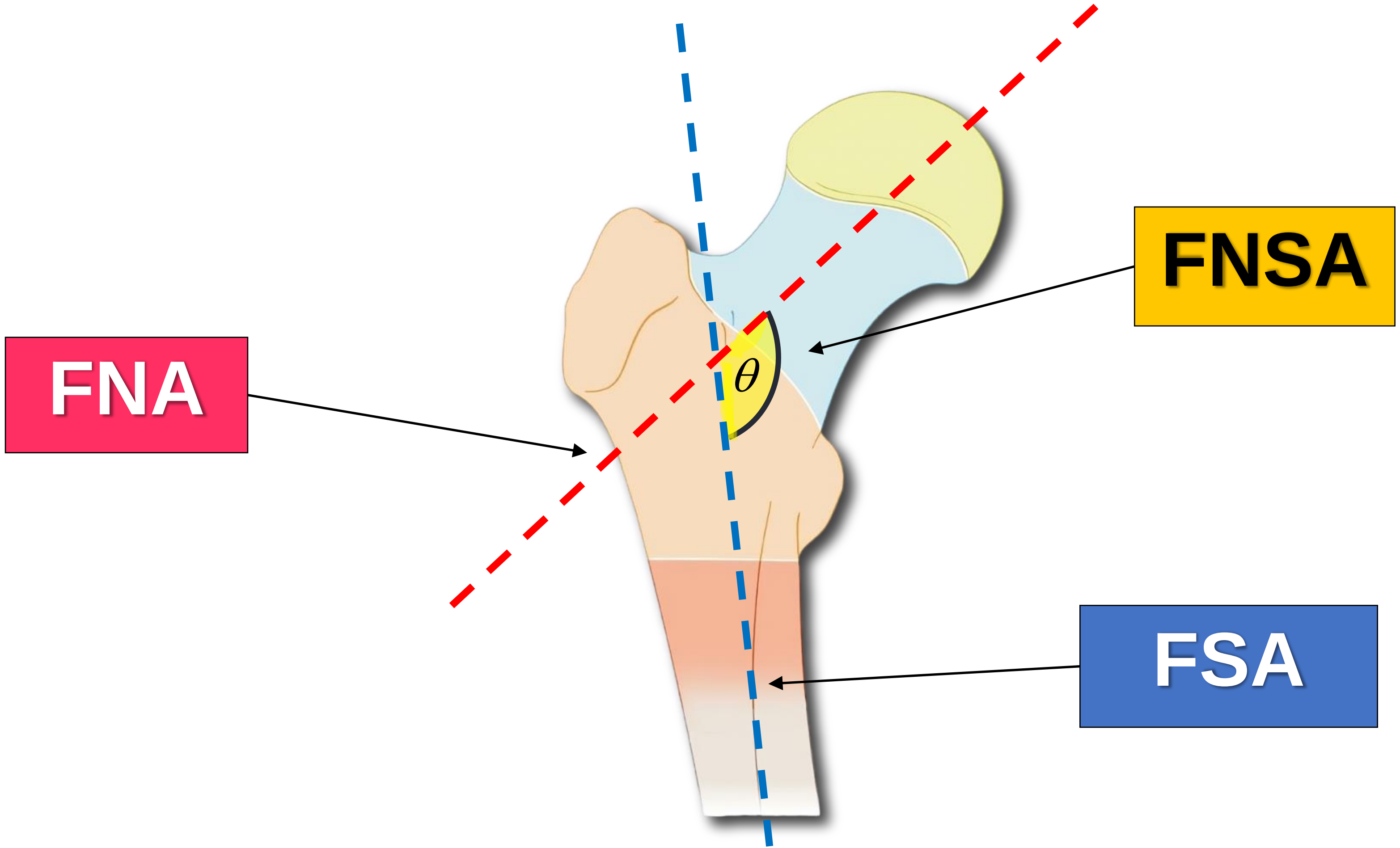
This study focuses on **two anatomical regions**:



Femoral Neck-Shaft Angle (FNSA)

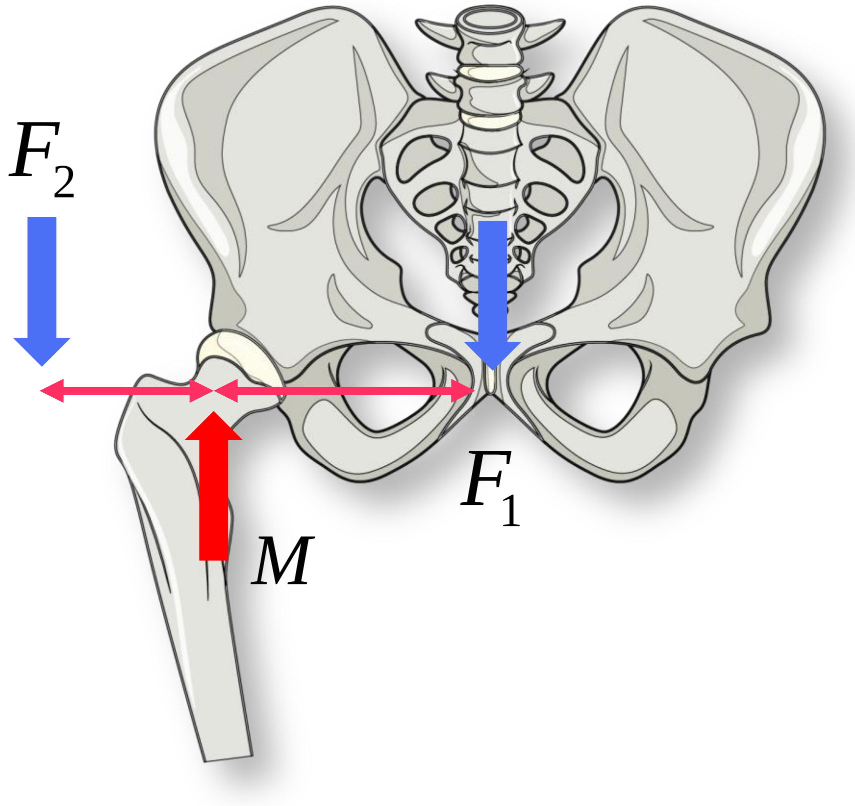
The femoral neck-shaft angle (FNSA) is the intersection between

the femoral neck axis (FNA) and ***the femoral shaft axis (FSA)*** [2].



Femoral Neck-Shaft Angle (FNSA) (cont.)

The femoral neck-shaft angle (FNSA) is a critical anatomic measurement index to **"evaluate the biomechanics of the hip joint"** [3].



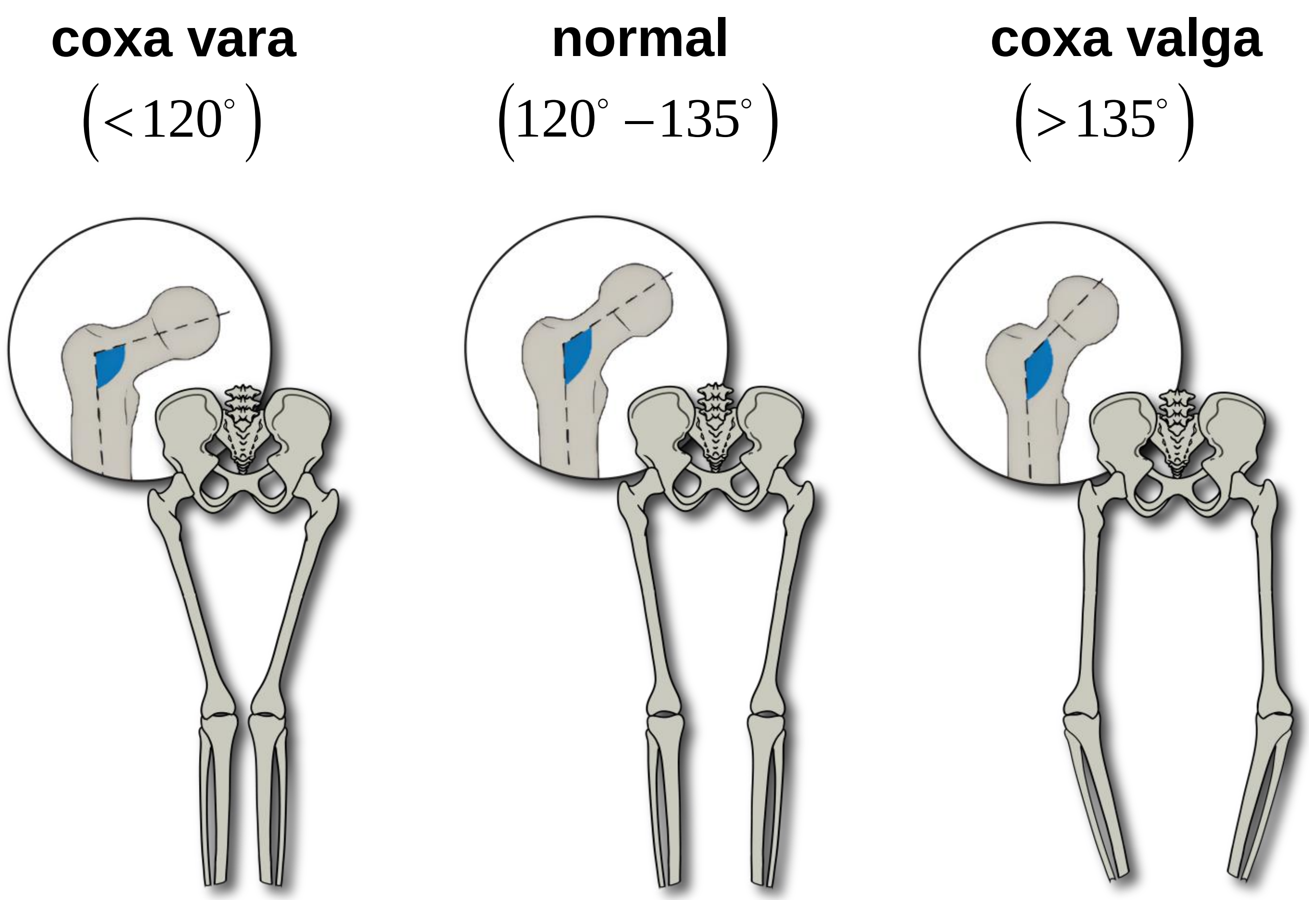
M = joint reaction force

F_1 = body weight

F_2 = muscle pull

Femoral Neck-Shaft Angle (FNSA) (cont.)

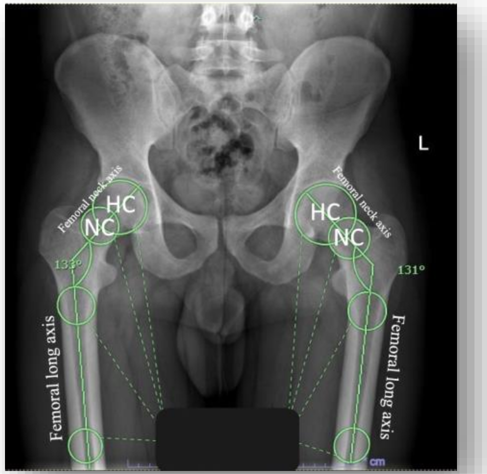
Impacts of coxa valga and coxa vara

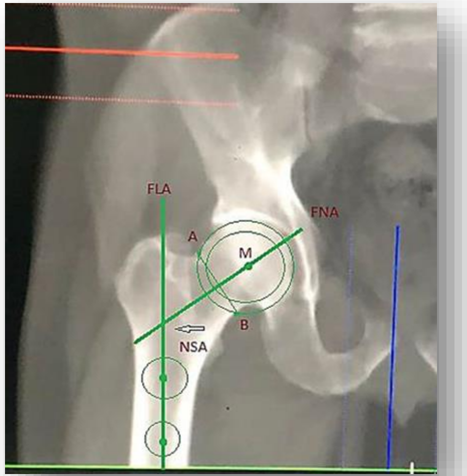


- Osteoarthritis
- Hip dysplasia
- Abnormal movement
- Risk of fracture
- Disability

Lack of Standardized Protocol for FNSA Measurement

Fact





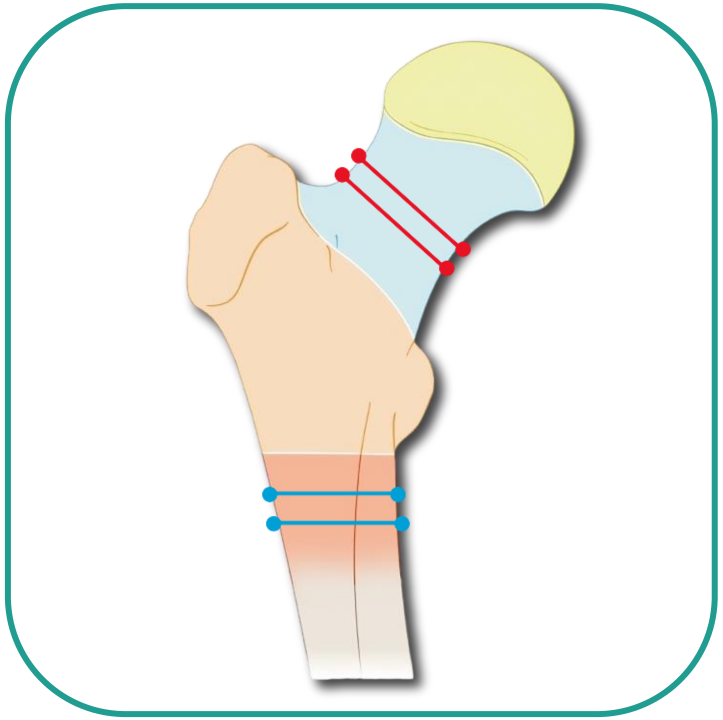
No standardized protocol for measuring the FNSA [4-6].

However, **a critical step** is to define the **FNA** and **FSA**

for calculating the FNSA.

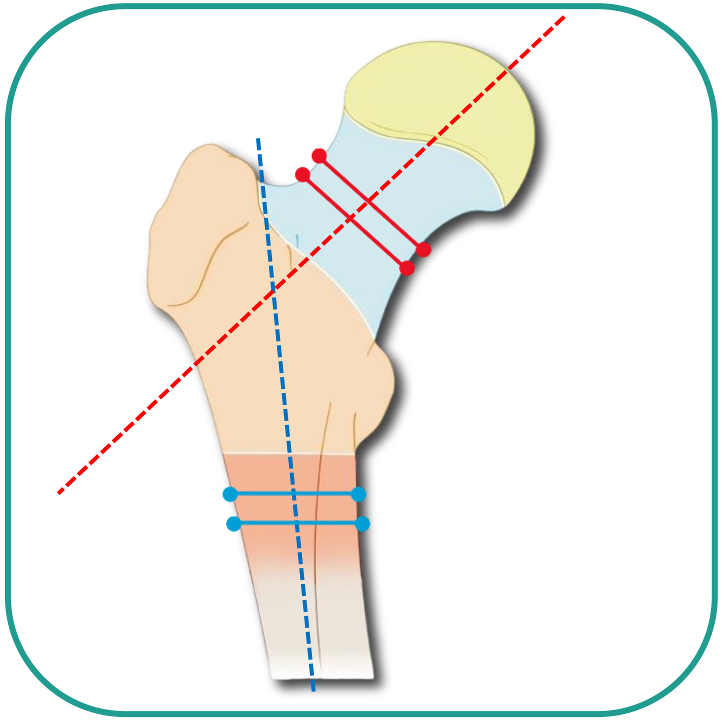
Manual Estimation of FNSA in Clinical Practice

Step 1:



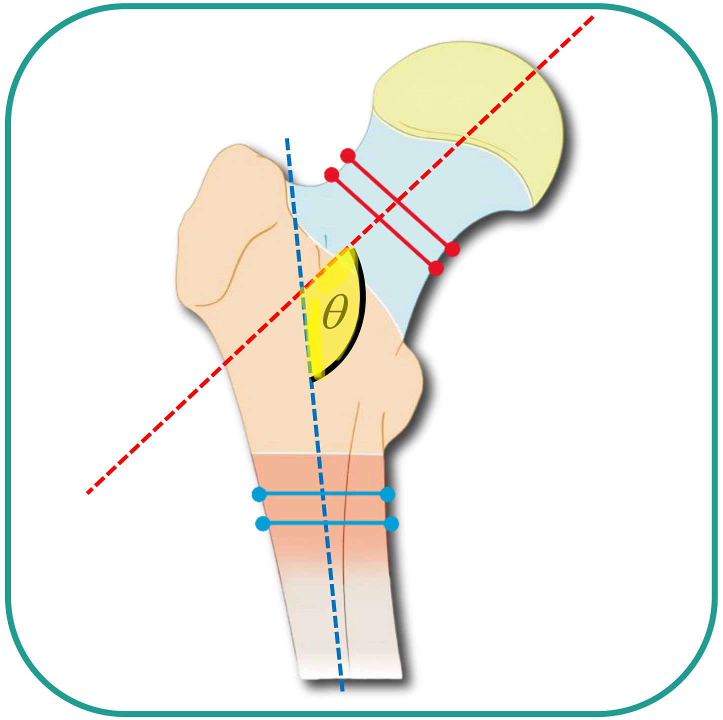
Identify anatomical landmarks.

Step 2:



Draw midlines through the center of the femoral neck and the femoral shaft.

Step 3:



Use a protractor or angle measuring tool.

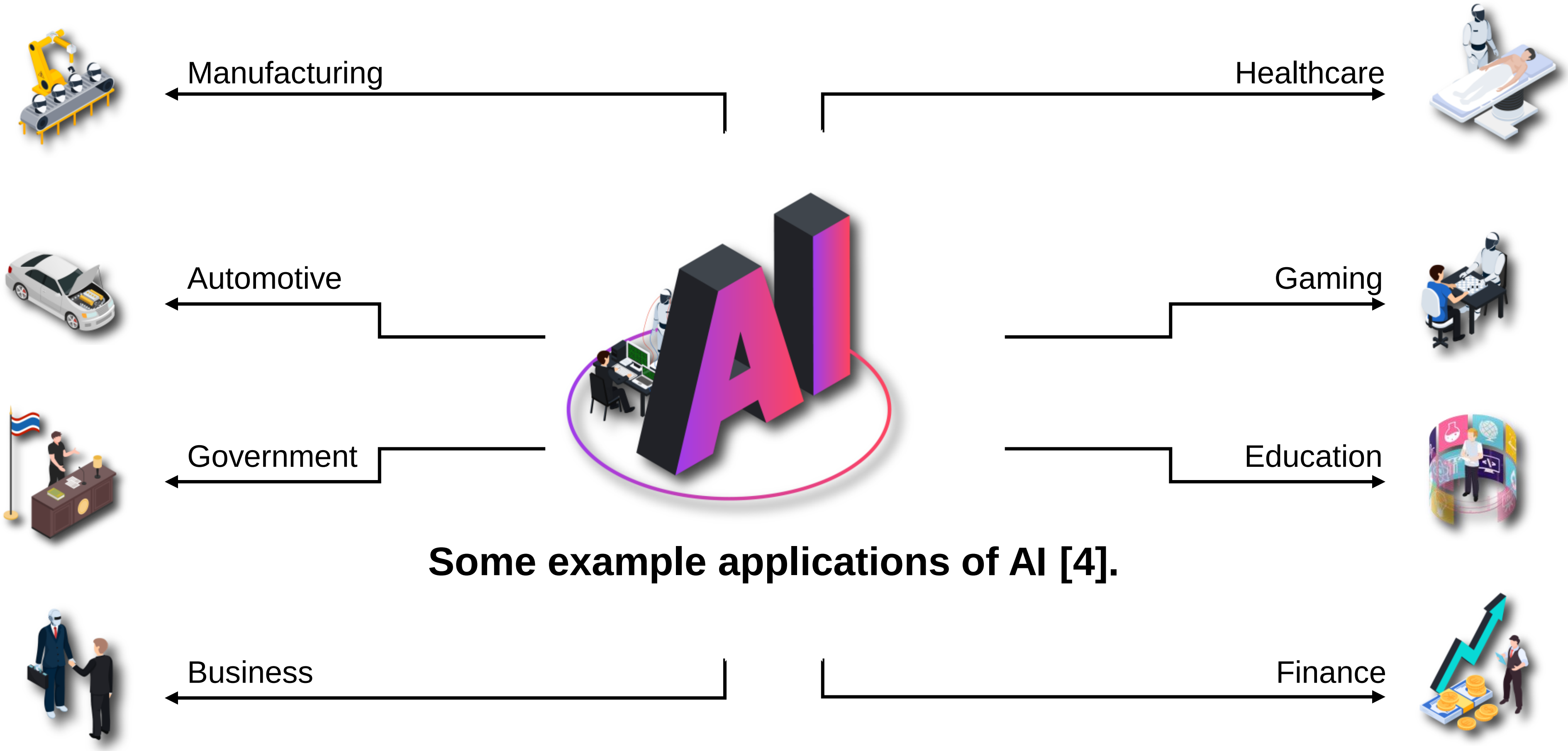
Problems with traditional FNSA measurement

Manual FNSA measurement issues [5][6].

- Variable results
- Time-consuming

What is AI?

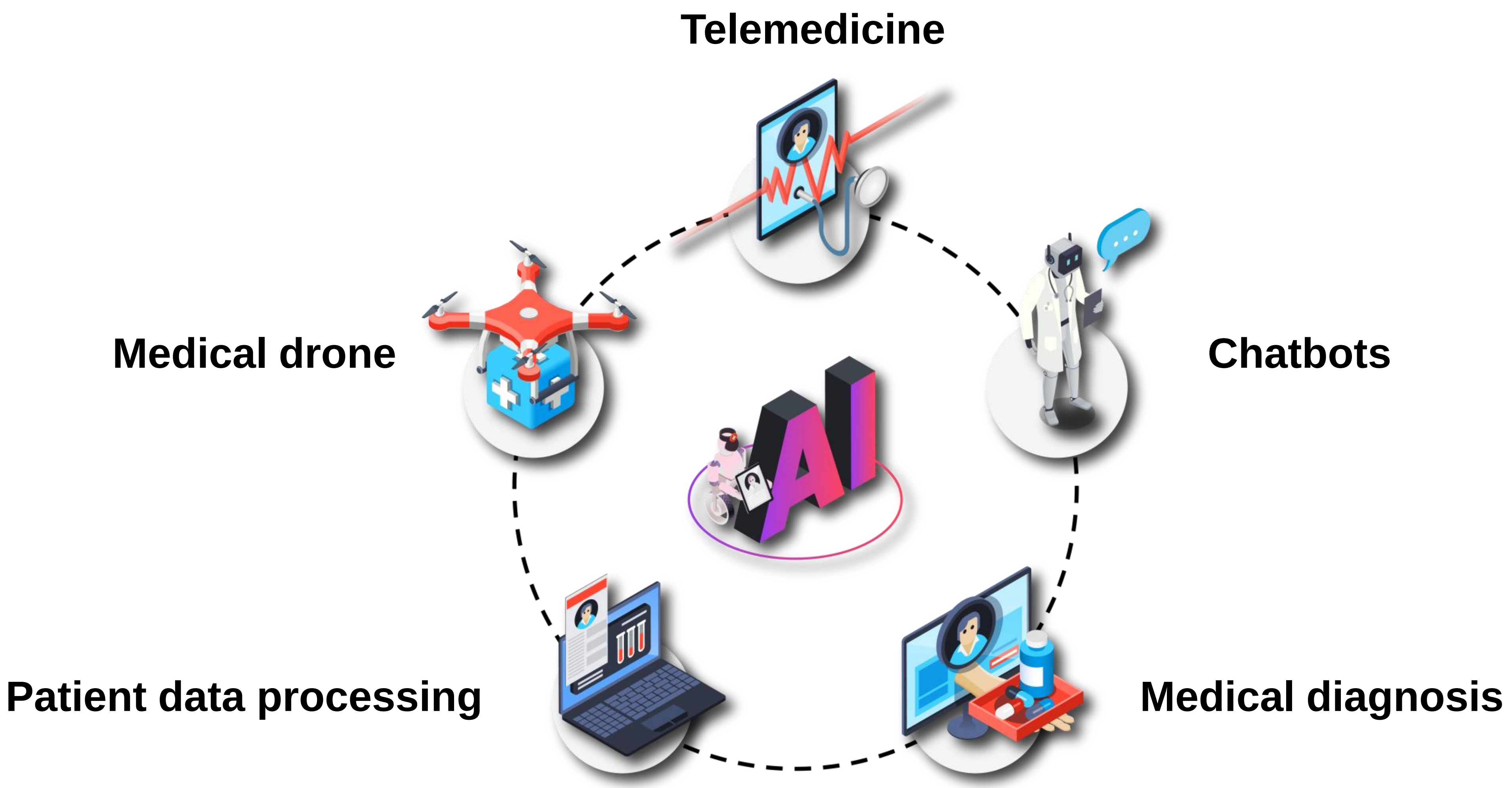
- Artificial Intelligence (AI)
- Understand and learn akin to human intelligence [7].



Some example applications of AI [4].

AI Applications in Healthcare

AI use case in healthcare [8].



AI Models in Medical Image Processing

Applications of AI models in medical image processing:

- **Object Detection**

  Detecting brain tumors in MRI scans [9].

- **Segmentation**

  Identifying and outlining cancerous tissue in CT scans [10].

- **Keypoint Detection**

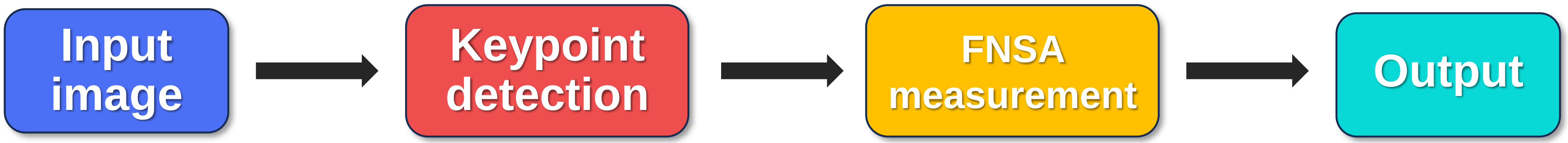
  Estimating the Cobb angle in scoliosis diagnosis [11].

Motivation

Year	Keypoint detection
2022	Automatic prosthetic-parameter estimation from anteroposterior pelvic radiographs after total hip arthroplasty using deep learning-based keypoint detection [12].
2023	Domain randomization and CNN-based keypoint-regressing pose initialization for relative navigation with uncooperative finite-symmetric spacecraft targets using monocular camera images [13].
2023	Applying a Deep-Learning-Based Keypoint Detection in Analyzing Surface Nanostructures [14].
2023	Key-Point Detection Algorithm of Deep Learning Can Predict Lower Limb Alignment with Simple Knee Radiographs [15].
2024	Surgical Tool Detection and Pose Estimation using YOLOv8-pose Model: A Study on Clipper Tool [16].
2024	Improved YOLOv8-Pose Algorithm for Albacore Tuna (Thunnus alalunga) Fork Length Extraction and Weight Estimation [17].
2024	Estimation of Artificial Reef Pose Based on Deep Learning [18].
2024	Aircraft engine danger areas incursion detection using keypoint detection and IoT [19].
2024	Monitoring Cattle Ruminating Behavior Based on an Improved Keypoint Detection Model [20].

“Keypoint detection is an effective technique for identifying significant features in images.”

Automated FNSA Measurement Using Keypoint Detection

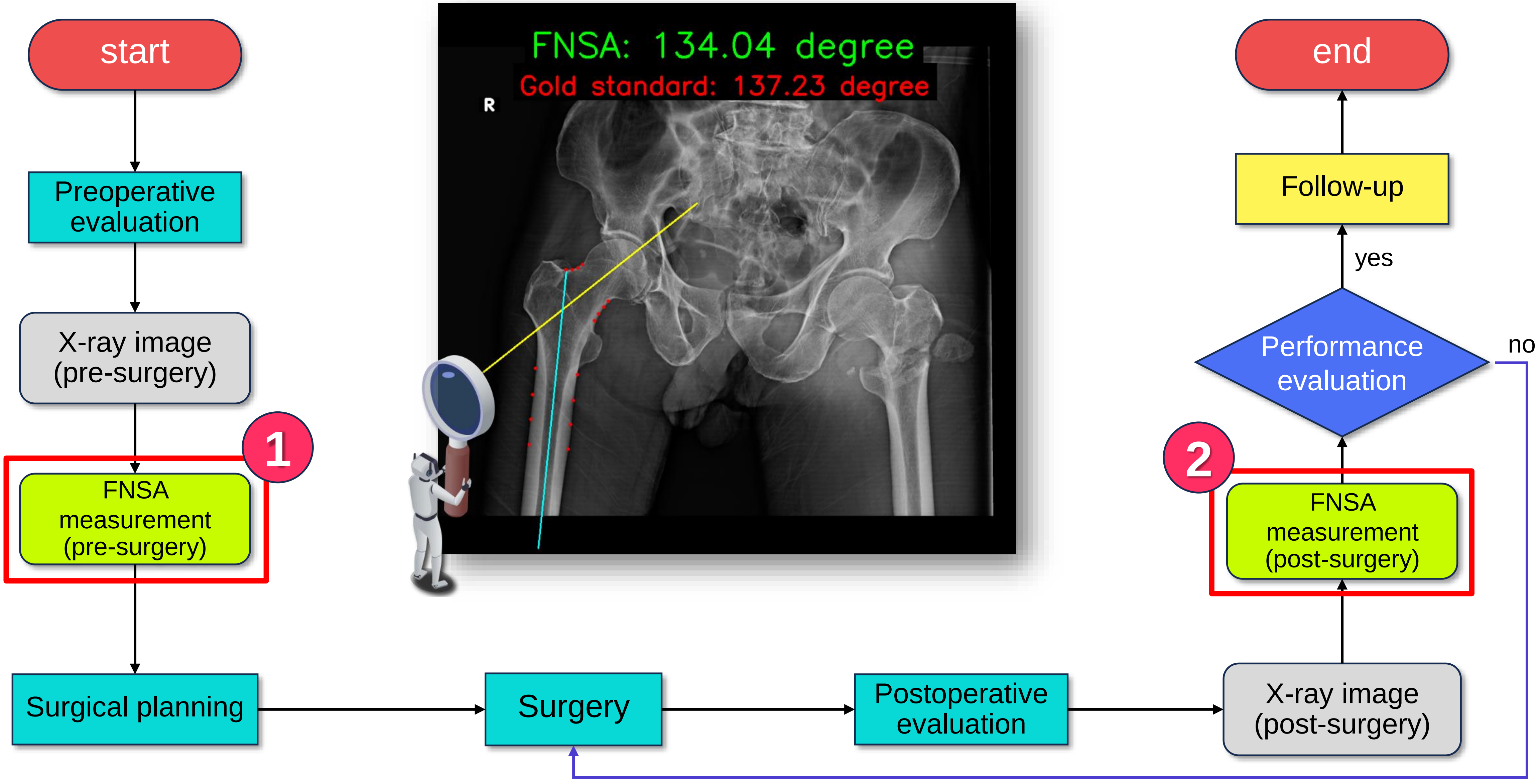


The proposed method consists of three main stages:

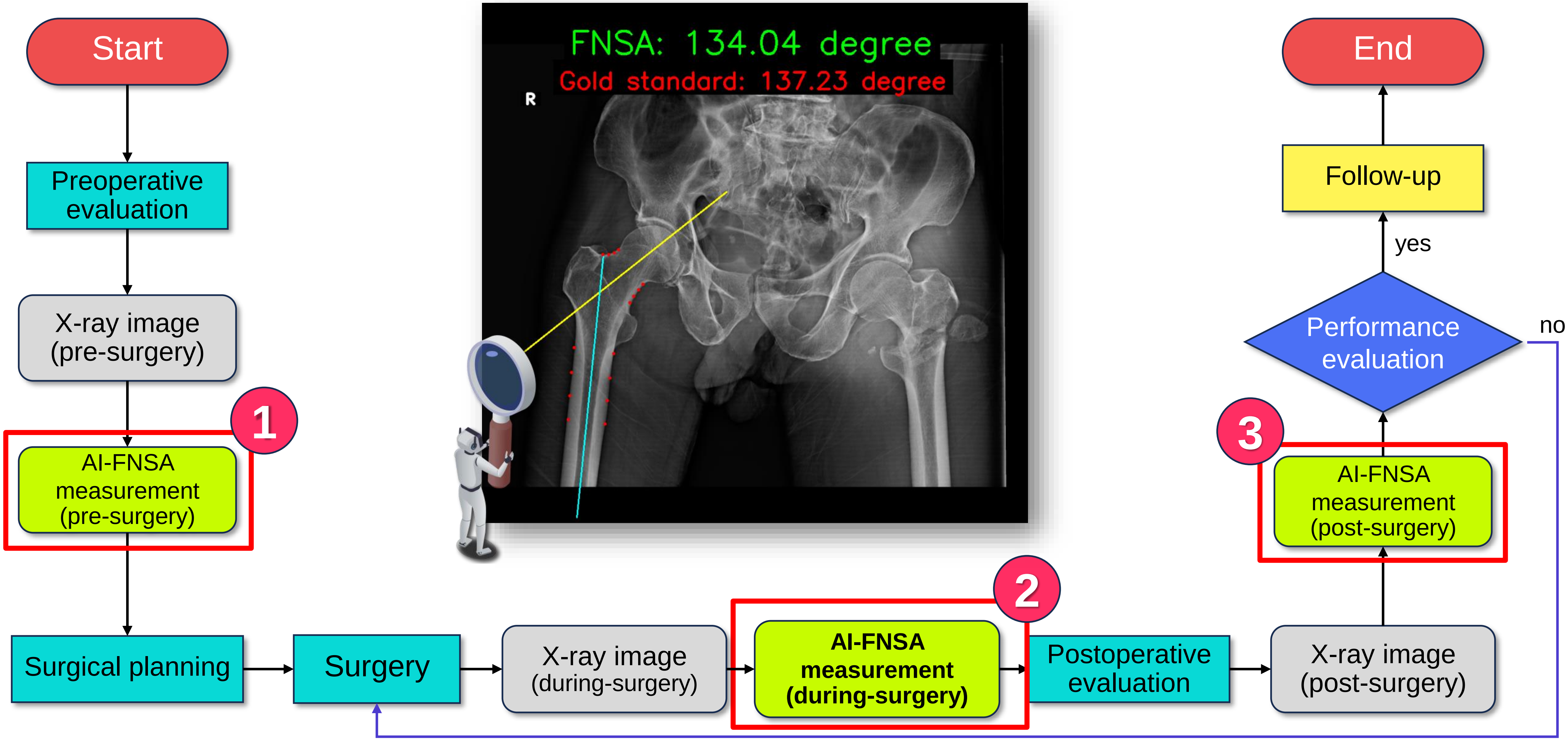
image input, keypoint detection, and **FNSA computation.**

This workflow supports **automatic estimation** of the FNSA.

Overall Traditional Surgery Method



Proposed AI-Based Workflow for FNSA Measurement.



Objectives and Scopes of Work

Objectives

1. To automate the measurement of FNSA using **keypoint detection.**

2. To evaluate the model efficiency and accuracy, aiming for **an average absolute deviation ≤ 5°** compared to **physician measurement.**

Scopes of Work

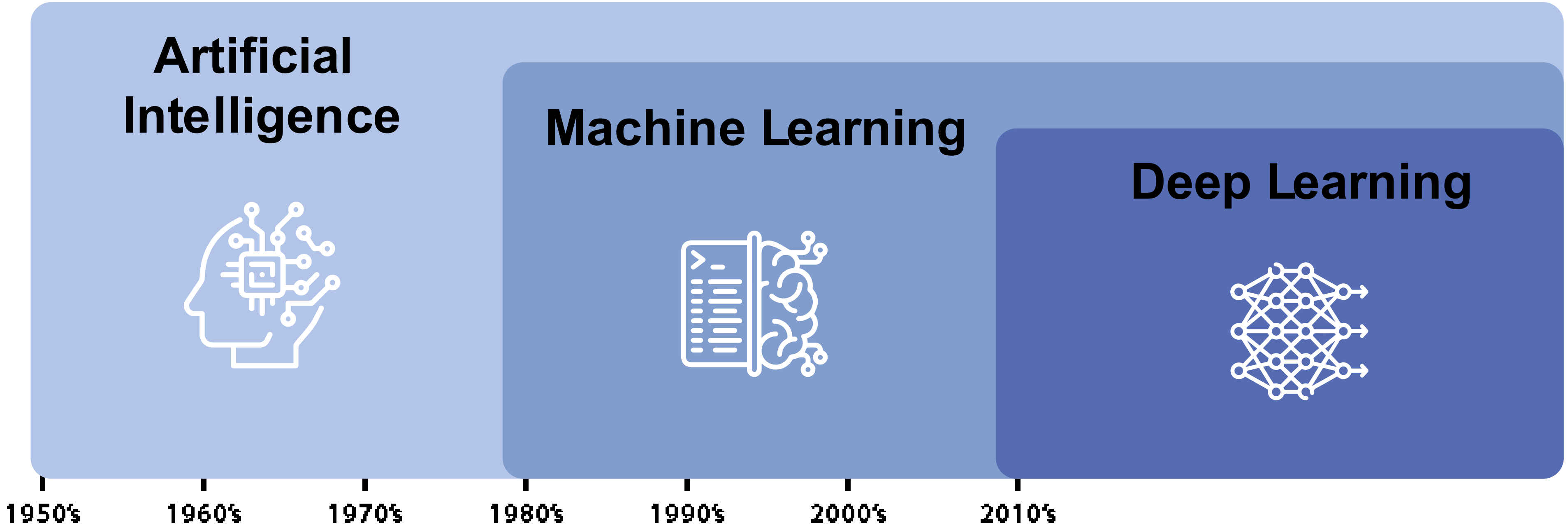
1. Develop a femoral keypoint detection model using **YOLOv8n-pose.**

2. Train and evaluate the model on **500 AP-view** femoral radiographs from Srinagarind Hospital, Khon Kaen University.

Theories

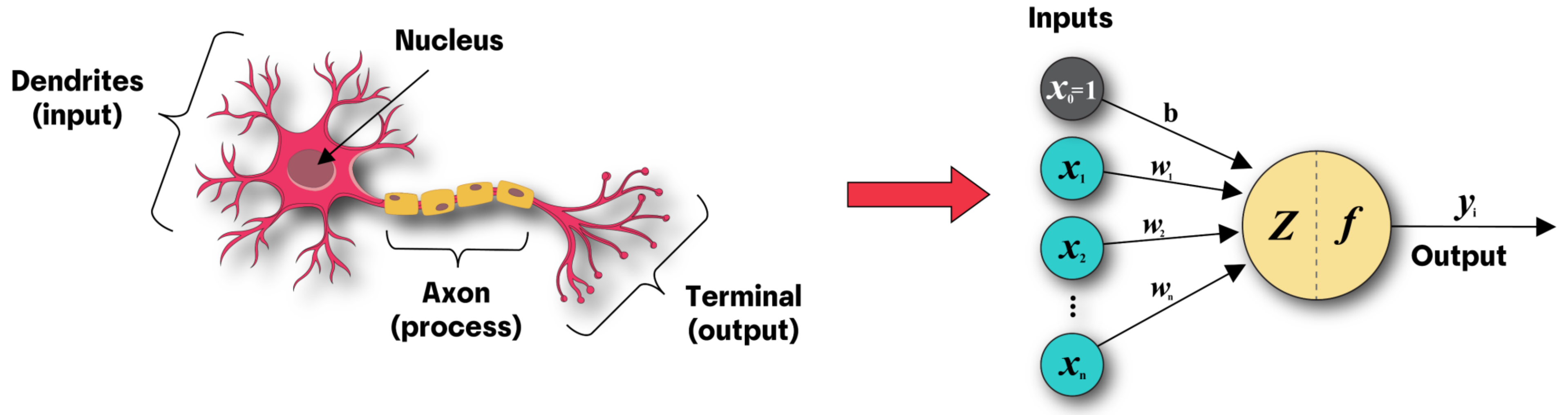
Artificial Intelligence

Artificial Intelligence(AI) is the **simulation of human intelligence** process by machines [21].



Artificial neural

Artificial neuron is a mathematical model inspired by **biological neurons.** It processes **weighted inputs** to produce an output.



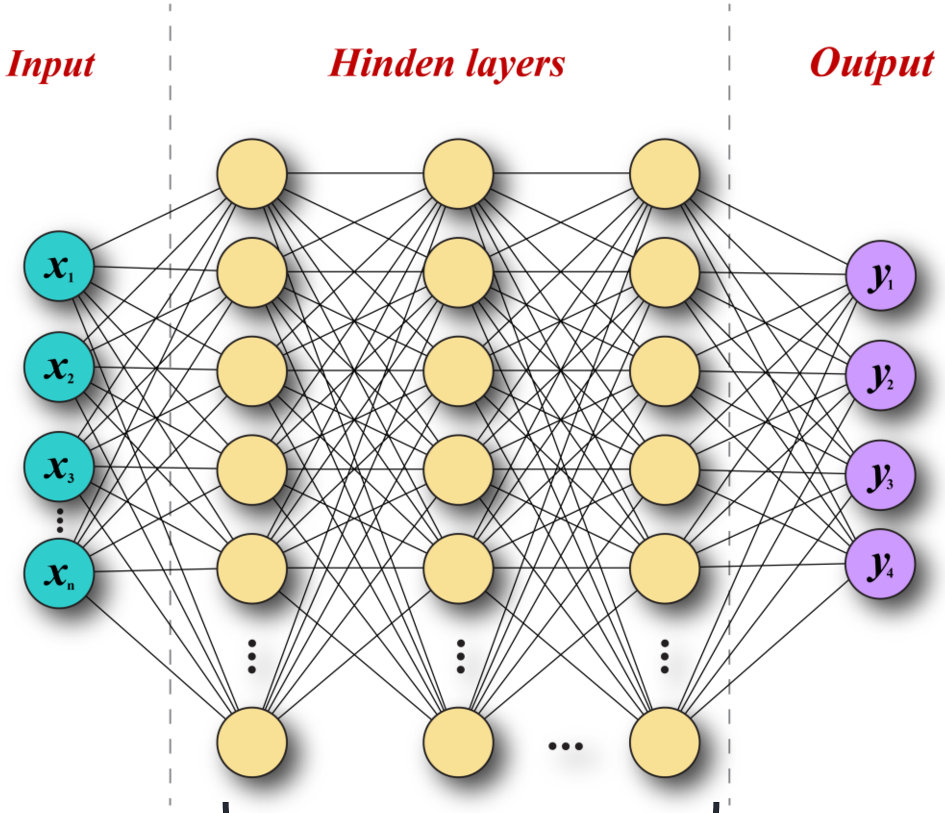
single neuron

artificial neuron

Deep Neural Networks

Deep neural networks use multiple layers of **artificial neurons** to **simulate complex decision-making in the human brain.** [23].

input

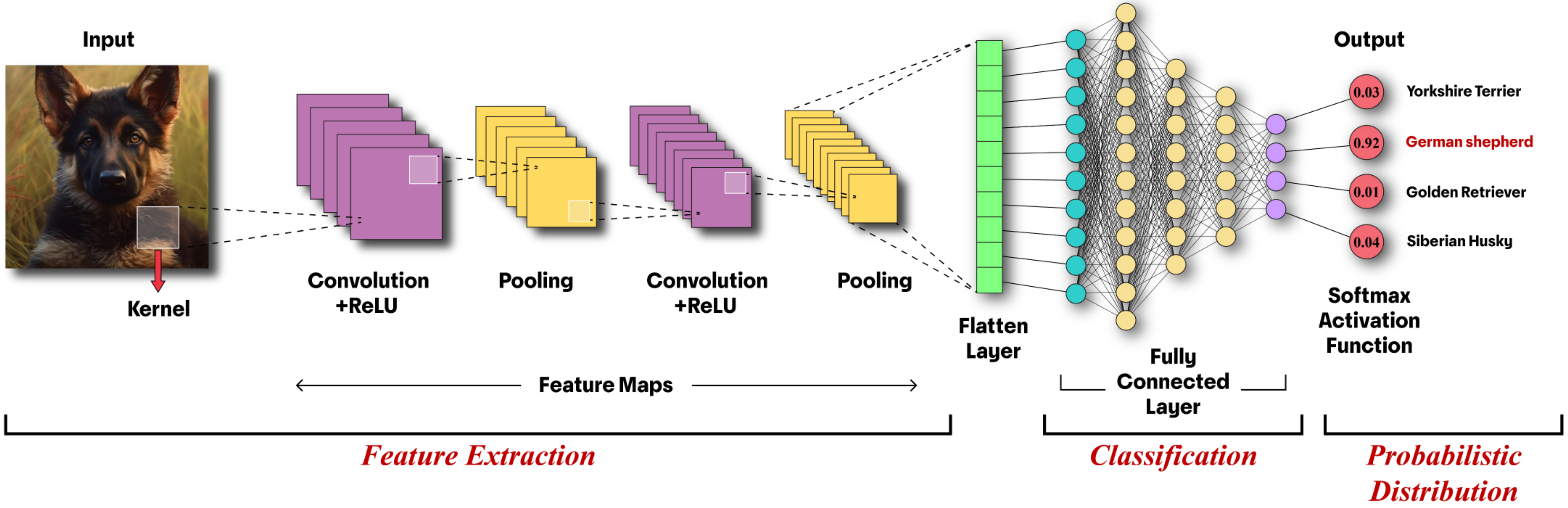


output

deep neural networks

Convolutional Neural Networks

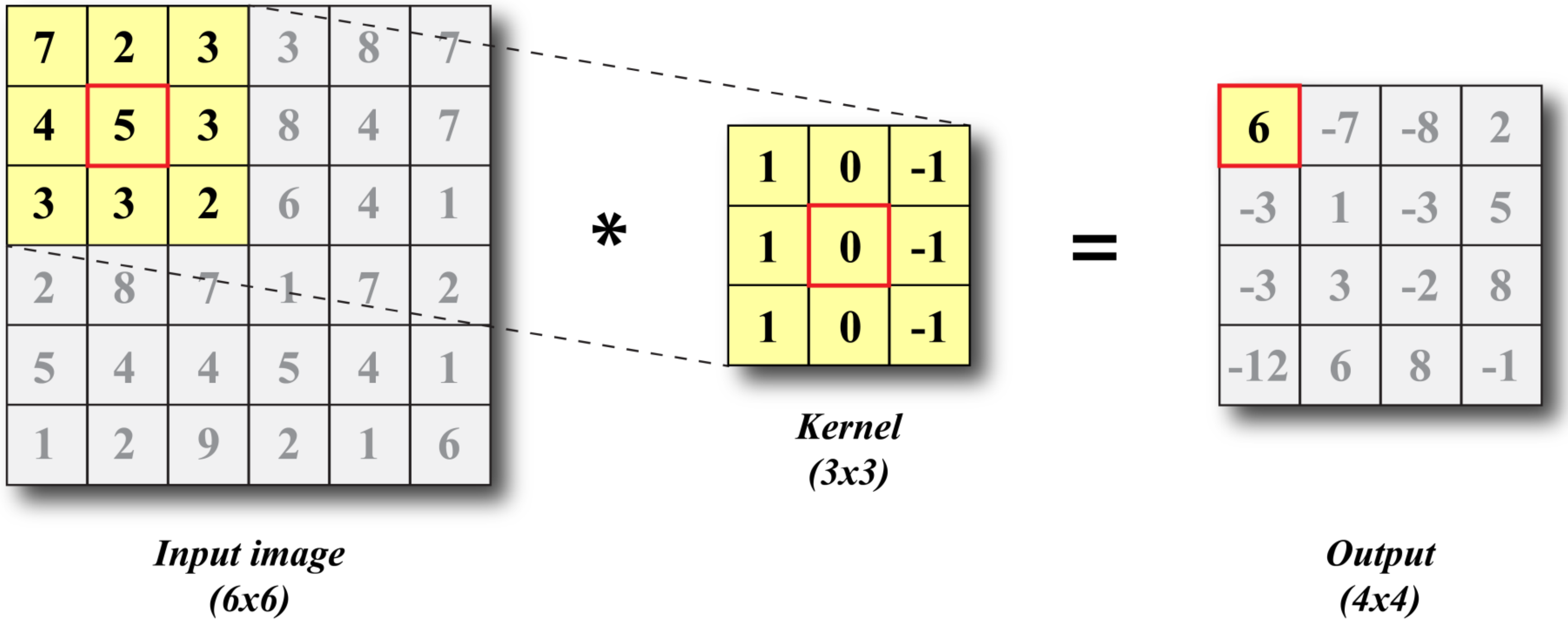
Convolutional neural networks (CNNs) are a specialized type of deep neural networks, **effective for visual data analysis, pattern recognition, and feature extraction** [25].



CNNs architecture

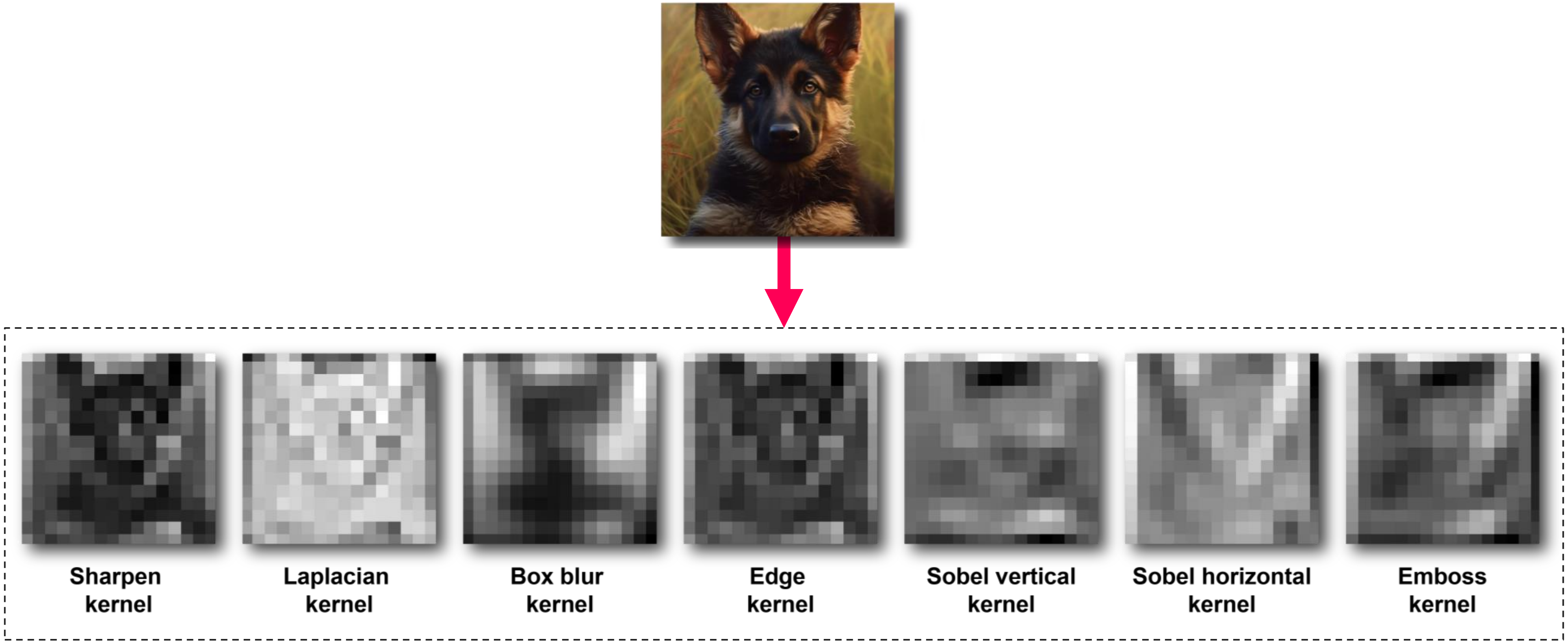
Convolution layer

In CNNs, convolutional layers **extract features** from input images through **the use of kernels**.



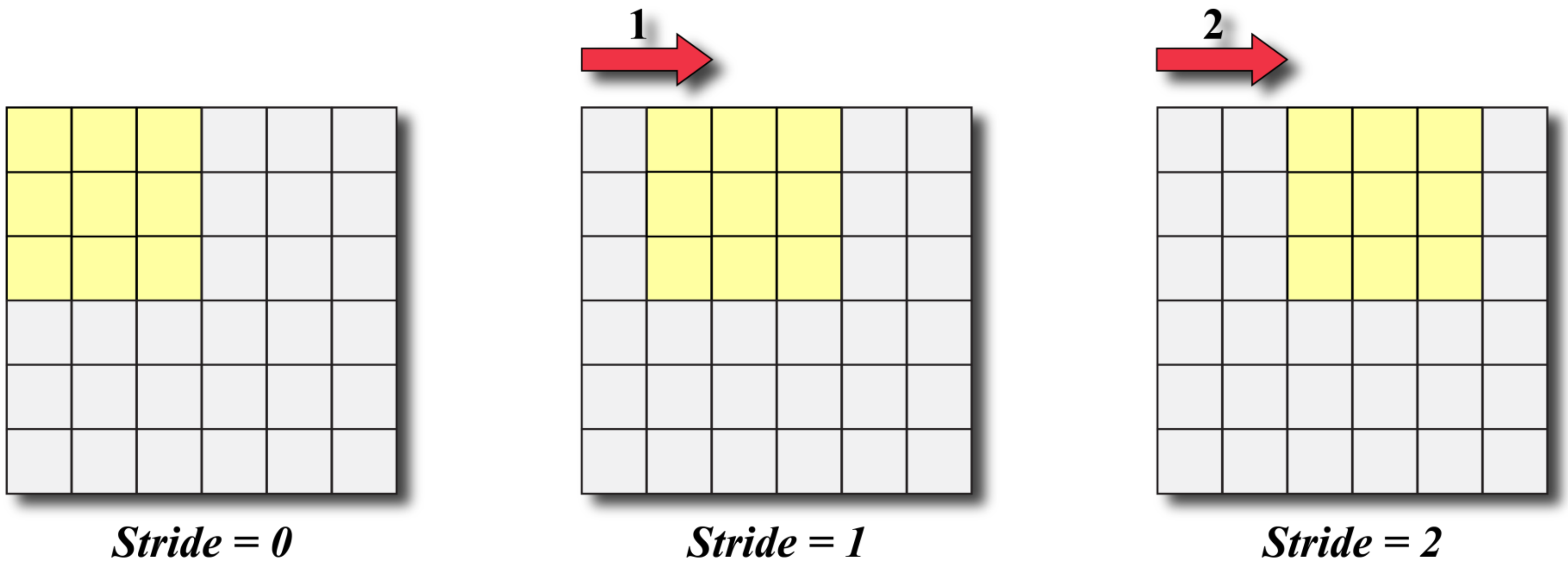
Kernel or Filter

2D convolution uses **a kernel (or filter)** to scan an image and **extract visual features** such as **edges**, **textures**, and **corners**, resulting in a feature map that highlights local patterns.



Stride

Stride is the step size that determines how far the **filter or pooling** window **shifts across the input**, directly affecting the reduction in output dimensions.



Padding

Padding **adds pixels around an image** to preserve spatial dimensions and retain important features before convolution.

6	7	8	2
2	1	3	5
3	3	2	9
4	6	8	1

No padding

0	0	0	0	0	0
0	6	7	8	2	0
0	2	1	3	5	0
0	3	3	2	9	0
0	4	6	8	1	0
0	0	0	0	0	0

Zero padding

6	6	7	8	2	2
6	6	7	8	2	2
2	2	1	3	5	5
3	3	3	2	9	9
4	4	6	8	1	1
4	4	6	8	1	1

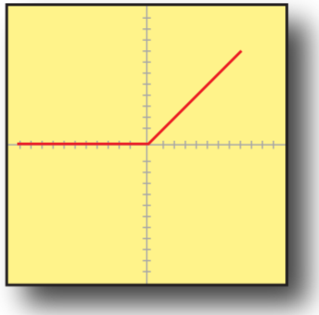
Replication padding

Activation function

Activation function introduces **non-linearity** to a neural network, allowing it to **learn complex patterns** and **enhance decision-making.**

6	-7	-8	2
-3	1	-3	5
-3	3	-2	8
-12	6	8	-1

Features maps



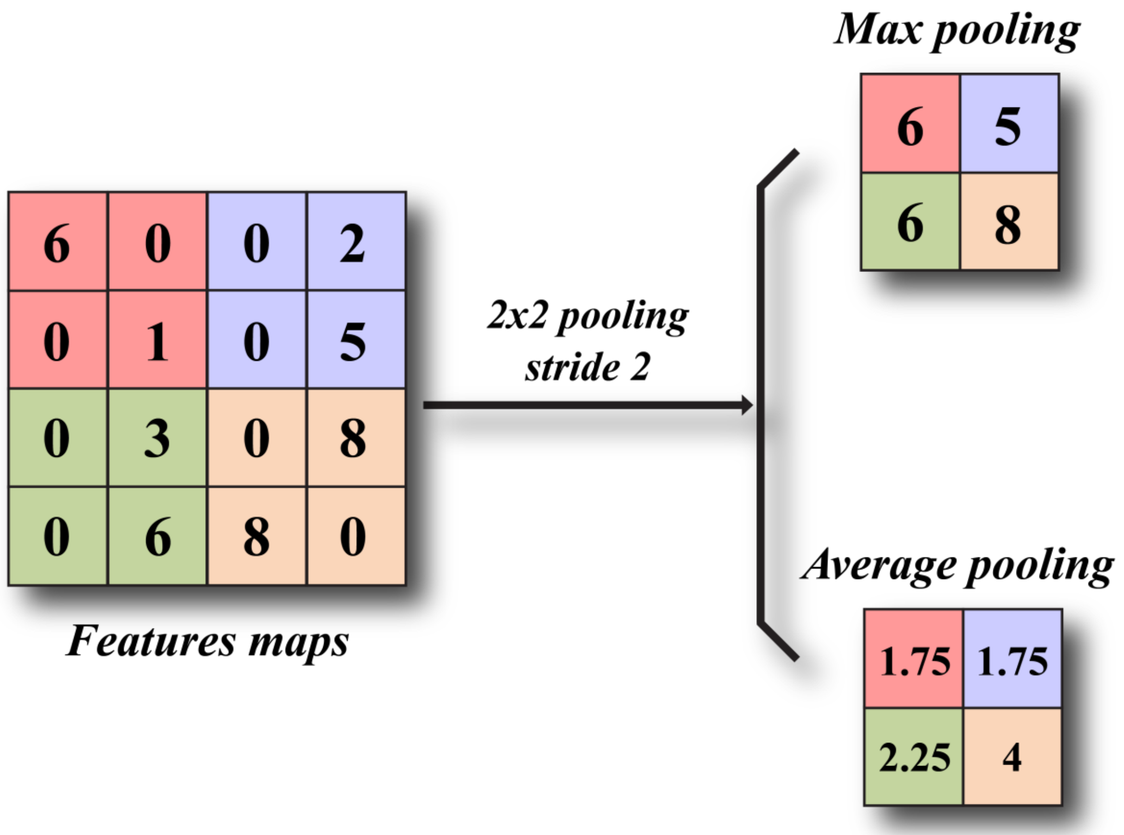
Activation funtion (e.g., Relu)

6	0	0	2
0	1	0	5
0	3	0	8
0	6	8	0

Output

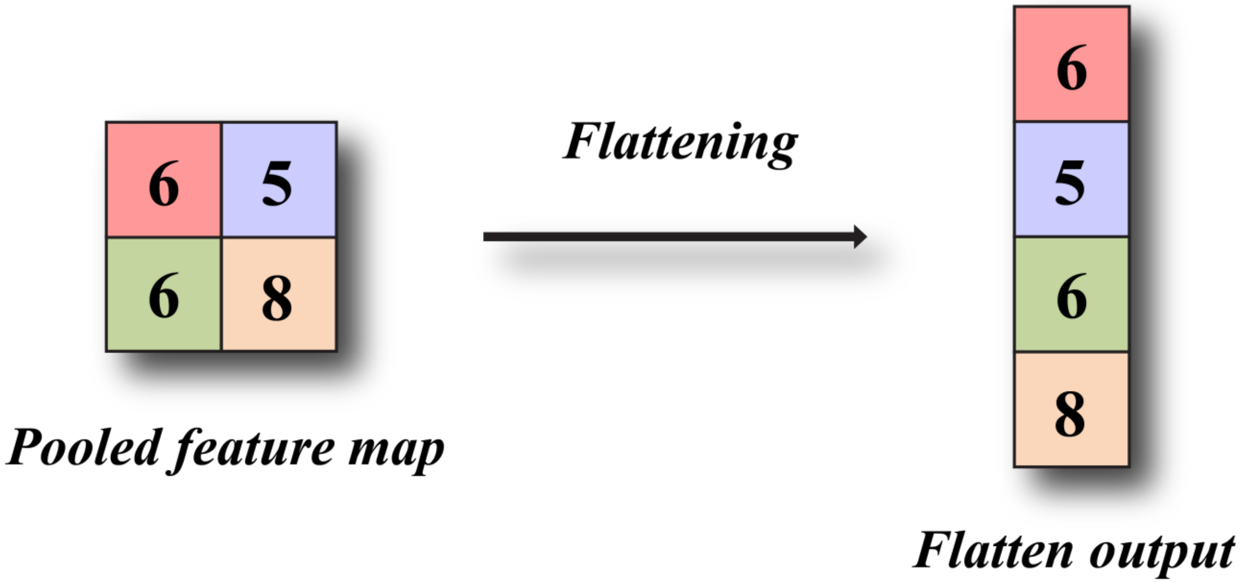
Pooling layer

Pooling layer reduces the **spatial dimensions** of the **feature map** while preserving **key features**.



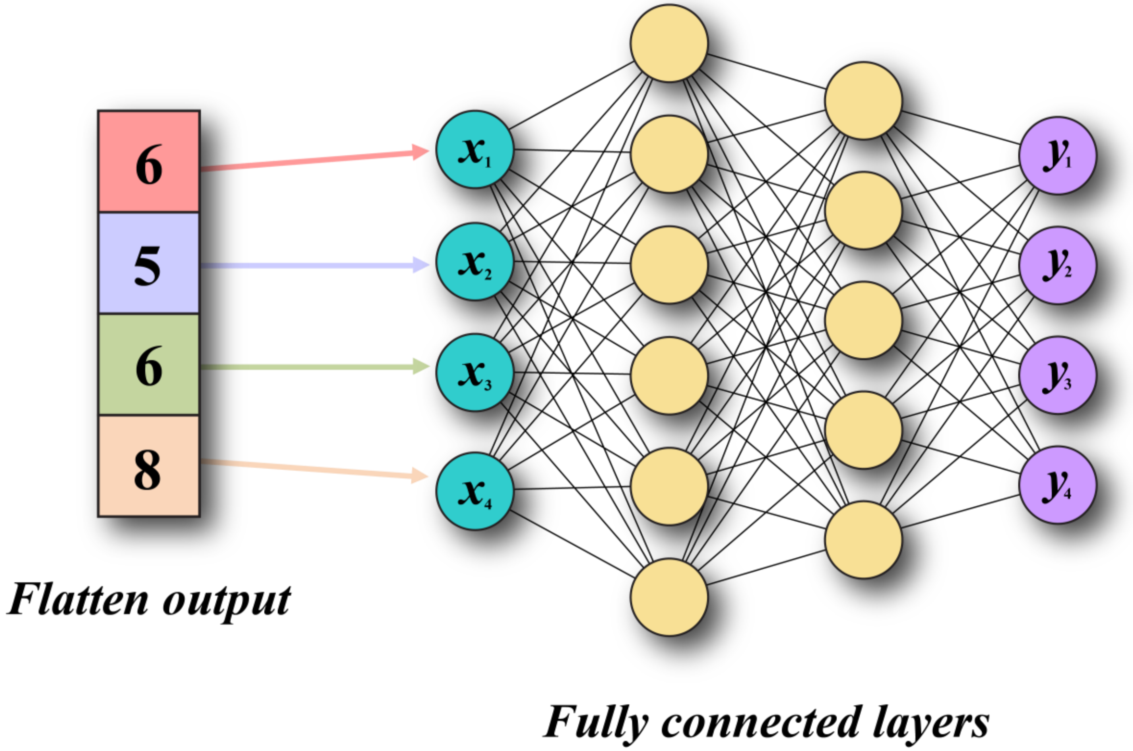
Flatten layers

Flatten is a process that **converts multi-dimensional data** into **a 1D vector.**



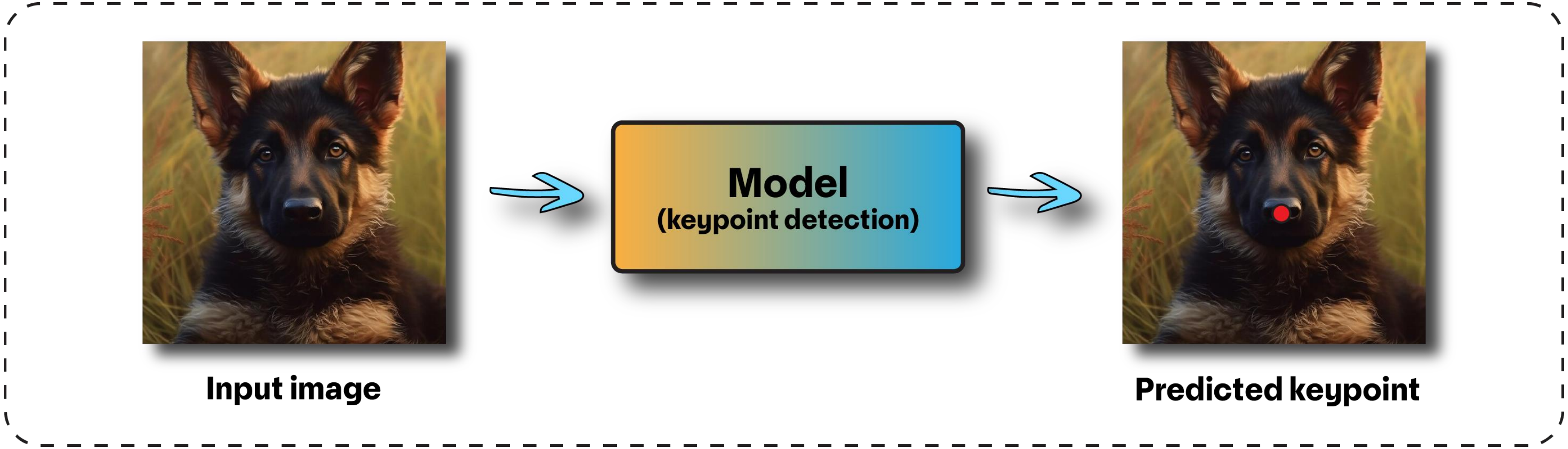
Fully Connected Layers

Fully connected layers connect all neurons between layers, enabling the model to **make final decisions** based on **the extracted features**.



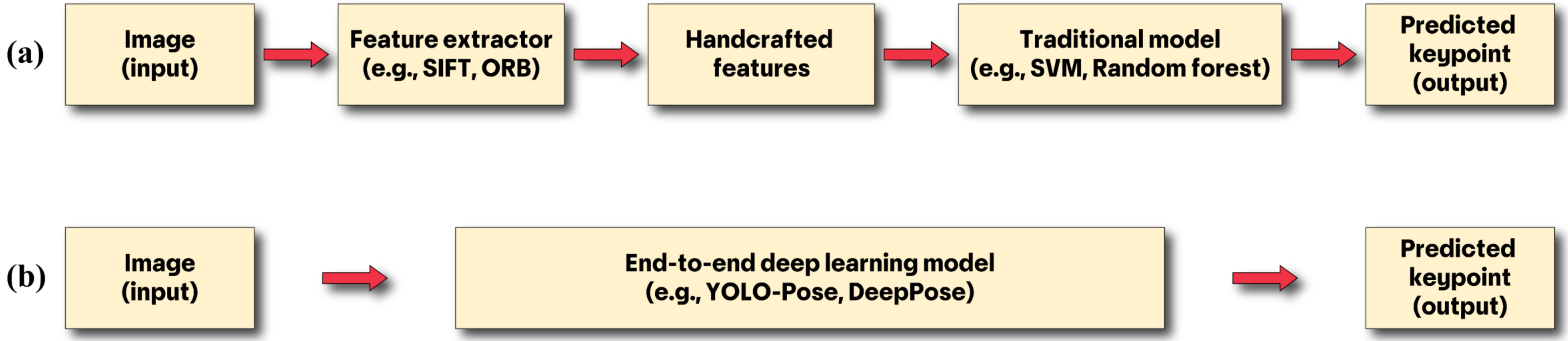
Keypoint Detection

Keypoint detection is a computer vision task that aims to **locate specific landmarks** of an object within an image [26].



Keypoint Detection (cont.)

Keypoint detection methods can be categorized into **2 main groups**, including **(a) traditional** and **(b) deep learning-based** methods [26].



Keypoint Detection (cont.)

Traditional keypoint detection [27]:

- The Scale-Invariant Feature Transform (SIFT).
- Oriented FAST and Rotated BRIEF (ORB).
- Features from Accelerated Segment Test (FAST).

SIFT ORB FAST

"Traditional keypoint detection techniques identify keypoints by analyzing image regions with high contrast or distinctive texture patterns."

Keypoint Detection (cont.)

Keypoint detection based on deep learning tends to outperform traditional methods because it can **automatically extract complex features** from images [27].

"Deep learning-based methods identify keypoints by learning complex patterns and enable robust detection under diverse conditions."

Keypoint Detection (cont.)

Keypoint localization using deep learning follows two main strategies:

heatmap regression and **direct regression.**

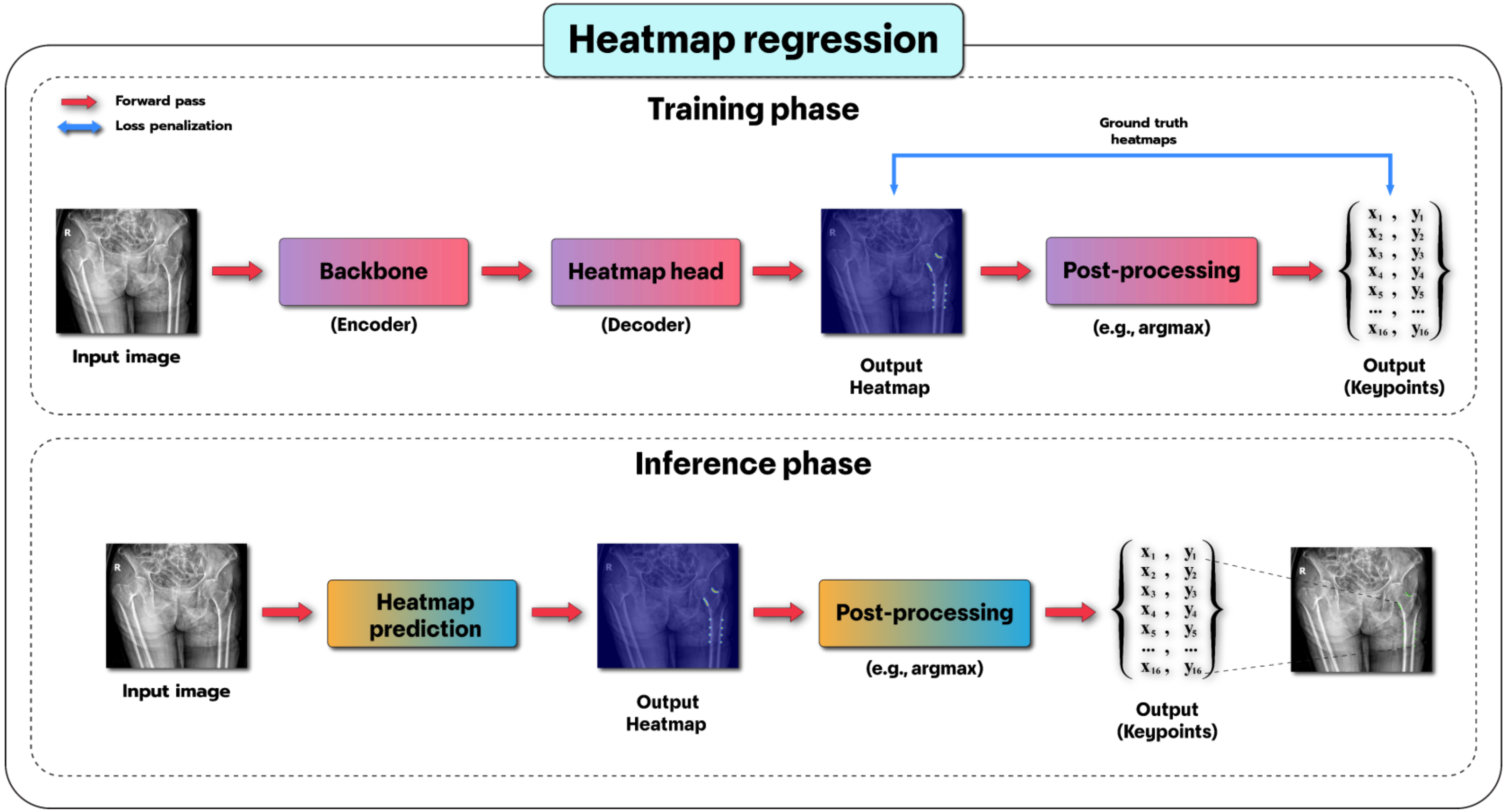
Model	Strategy
YOLO-Pose	direct regression
MediaPipe	direct regression
DeepLabCut	direct regression
OpenPose	heatmap prediction
HRNet	heatmap prediction
Hourglass Networks	heatmap prediction

*Strategies are categorized based on how models estimate keypoint coordinates.

Keypoint Detection (cont.)

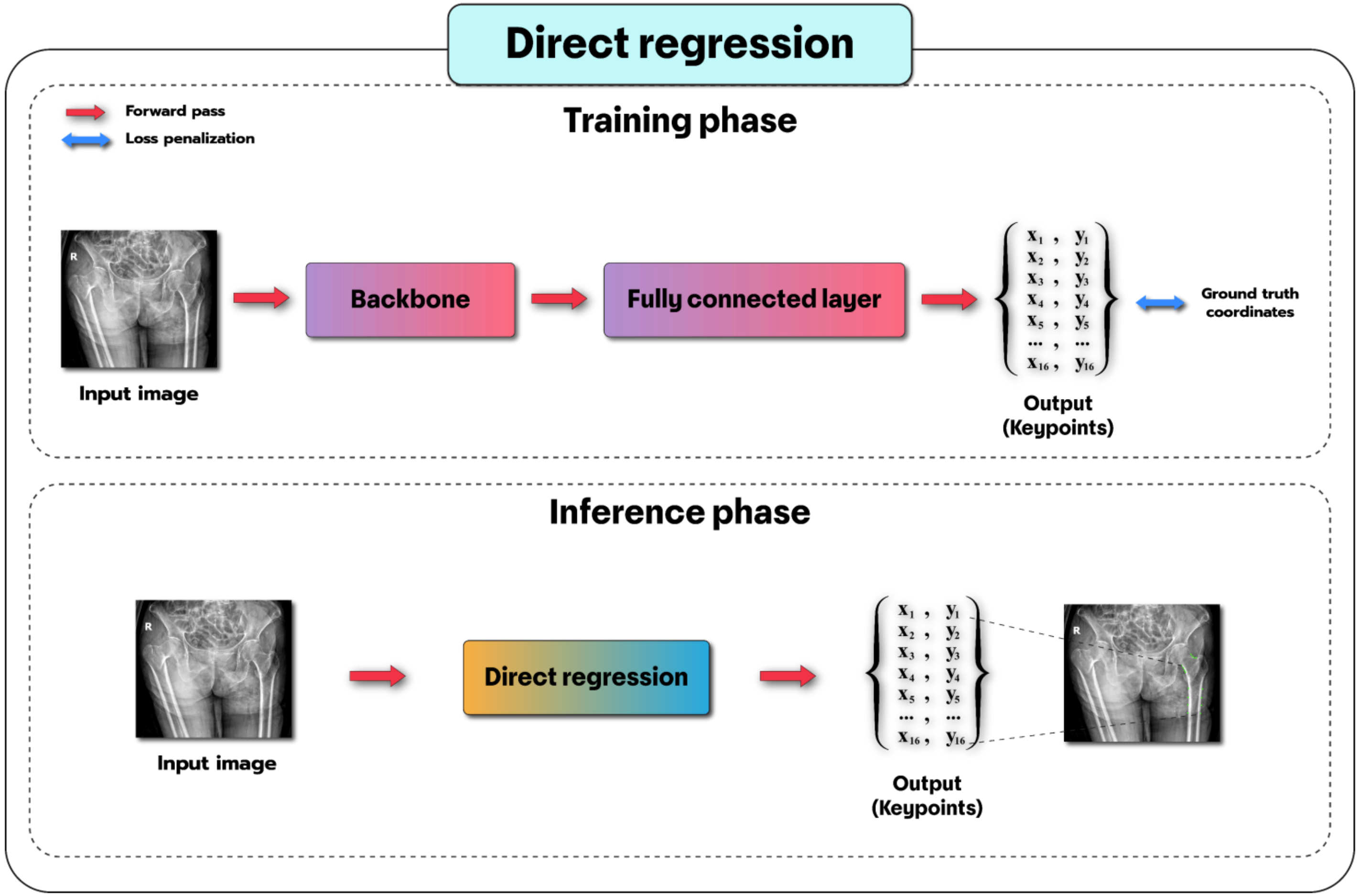
Heatmap regression **generates a probability map for each keypoint**,

indicating the most likely locations within the image [27].



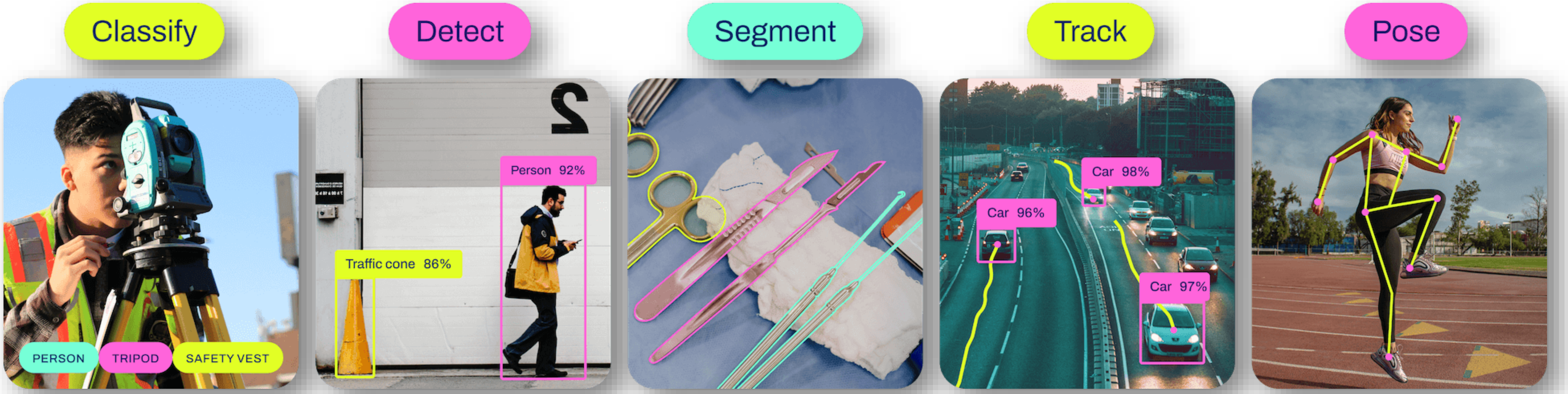
Keypoint Detection (cont.)

Direct regression predicts keypoint coordinates **directly from images** using CNNs, with **the output as (x, y) values** [27].



What is YOLO?

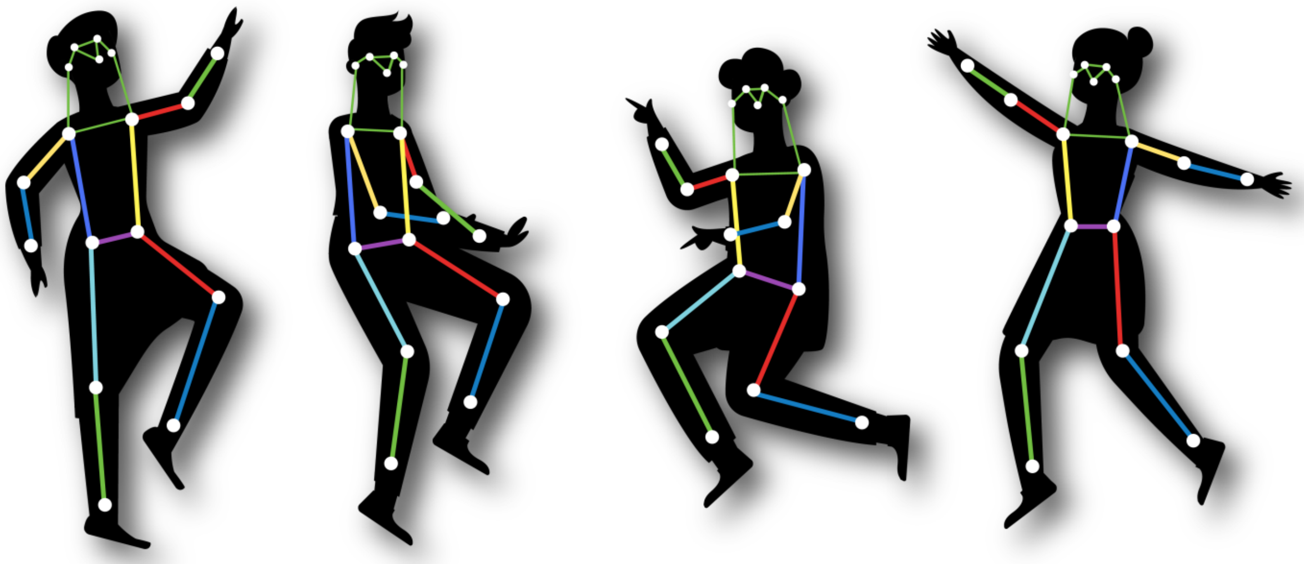
- YOLO (You Only Look Once).
- **Real-time object detection system.**
- **High accuracy and speed.**
- **Single-shot**



https://docs.ultralytics.com/tasks/

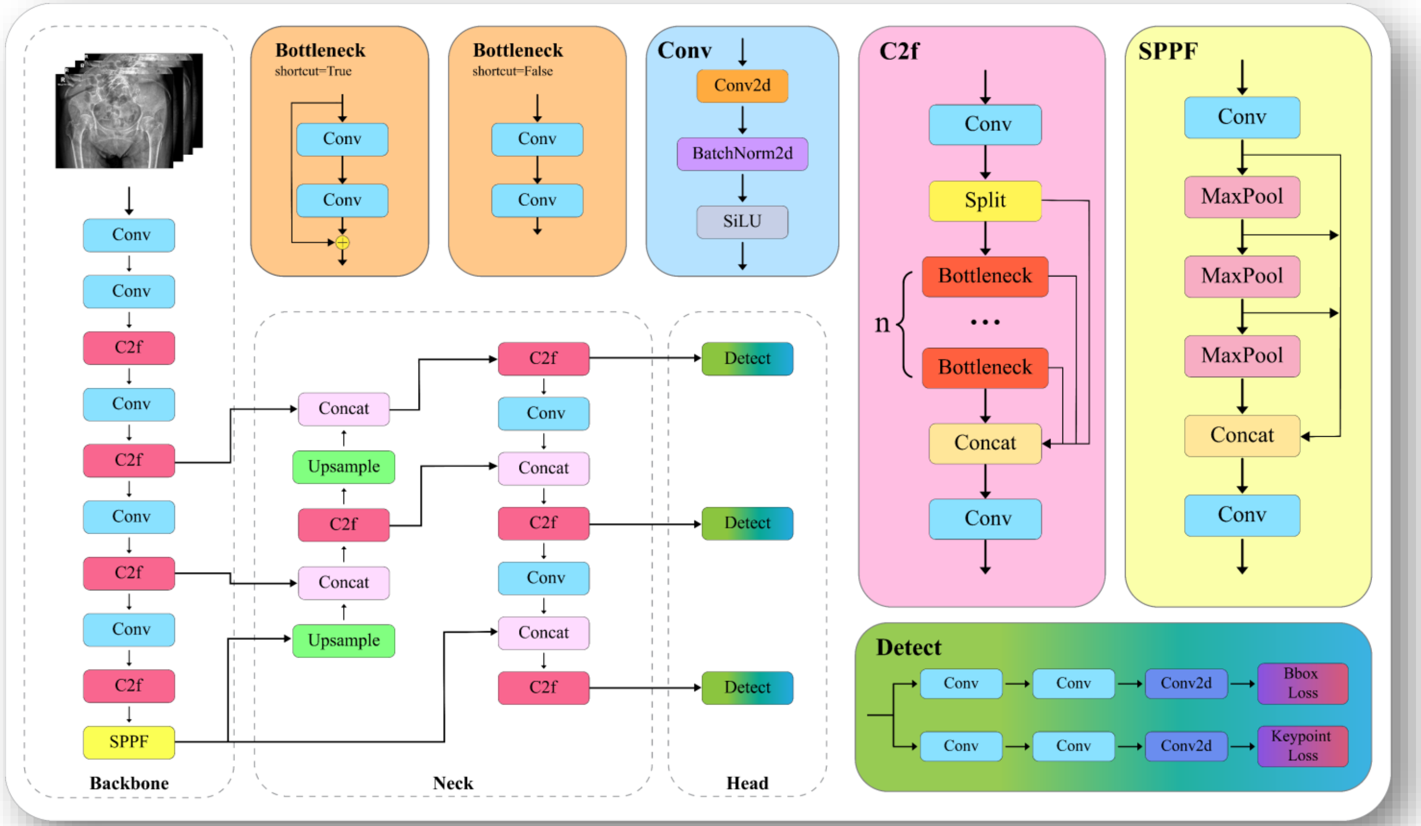
YOLO-Pose

YOLO-Pose is trained for pose estimation**,** which uses **keypoints** to represent human posture. The model can also be **retrained for detecting task-specific keypoints** in different applications [26].



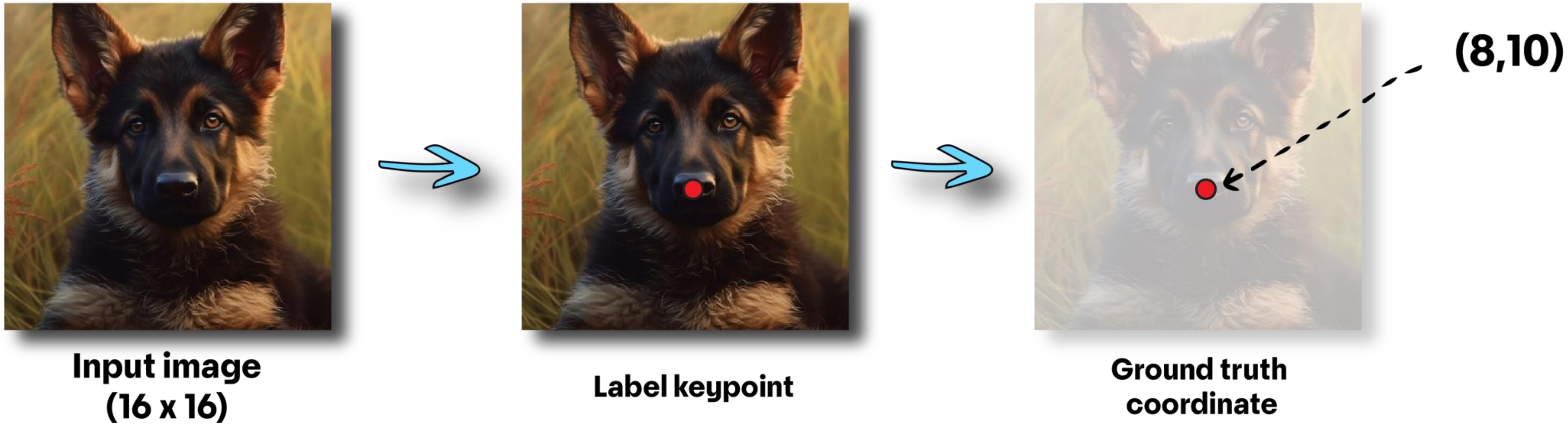
YOLO-Pose Architecture

YOLO-Pose architecture includes a Backbone for feature extraction, a Neck for multi-scale fusion, and a Head for final predictions.



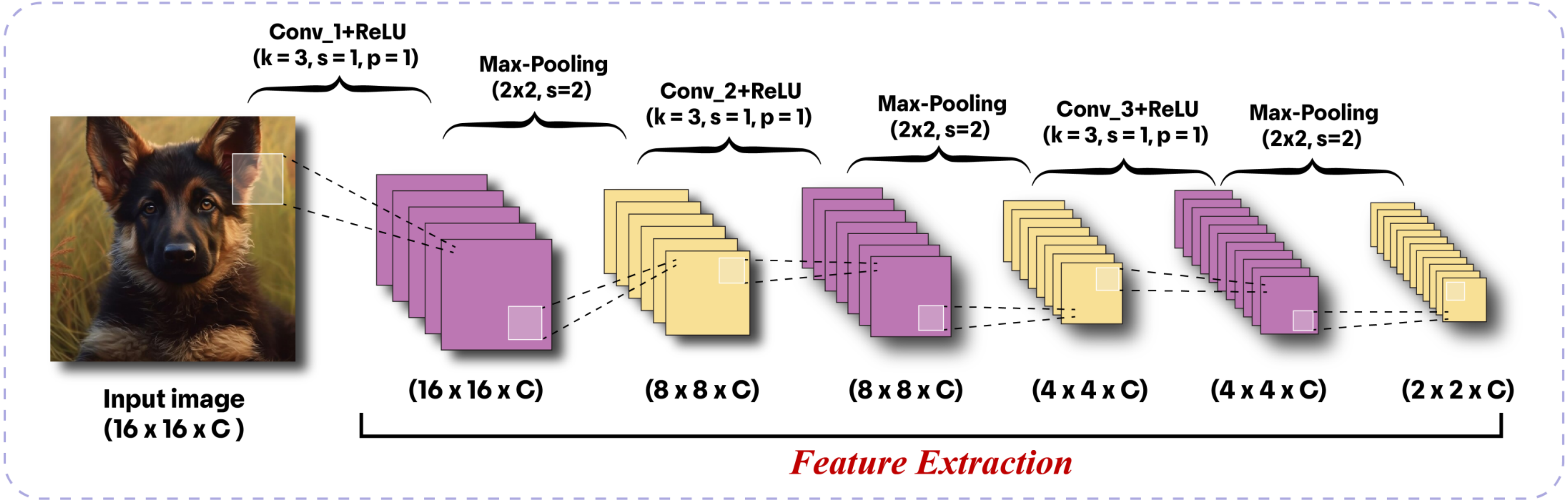
How does the model know the point of interest?

Keypoint detection is a supervised learning task where **the model learns from labeled coordinates.** These **keypoint labels** serve as **ground truth**, guiding the model to associate **spatial features** with the correct positions.



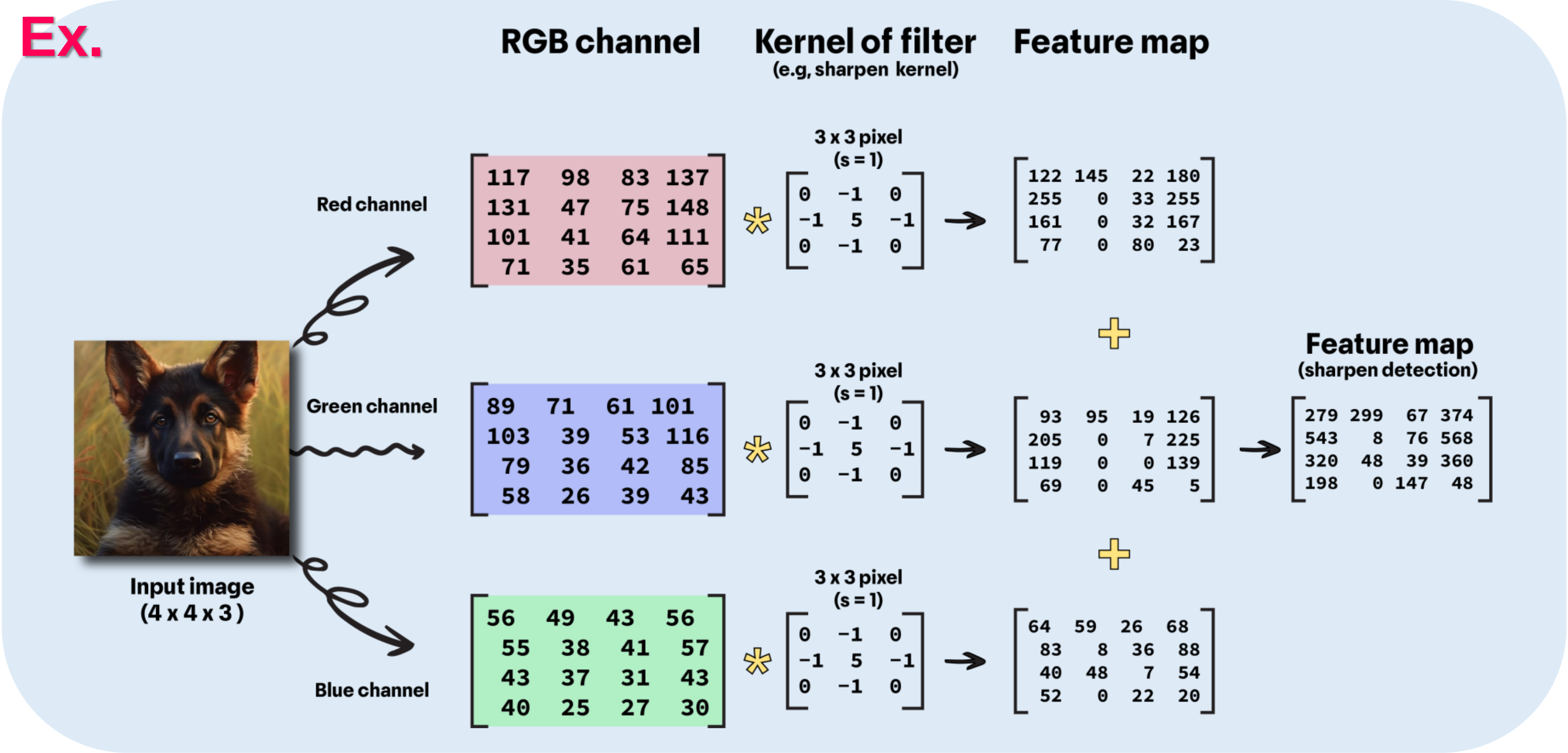
How does the model learn spatial features?

The model uses CNNs to **extract spatial features**. These **extracted features** are utilized to **predict keypoint coordinates.**



How does the model learn spatial features?

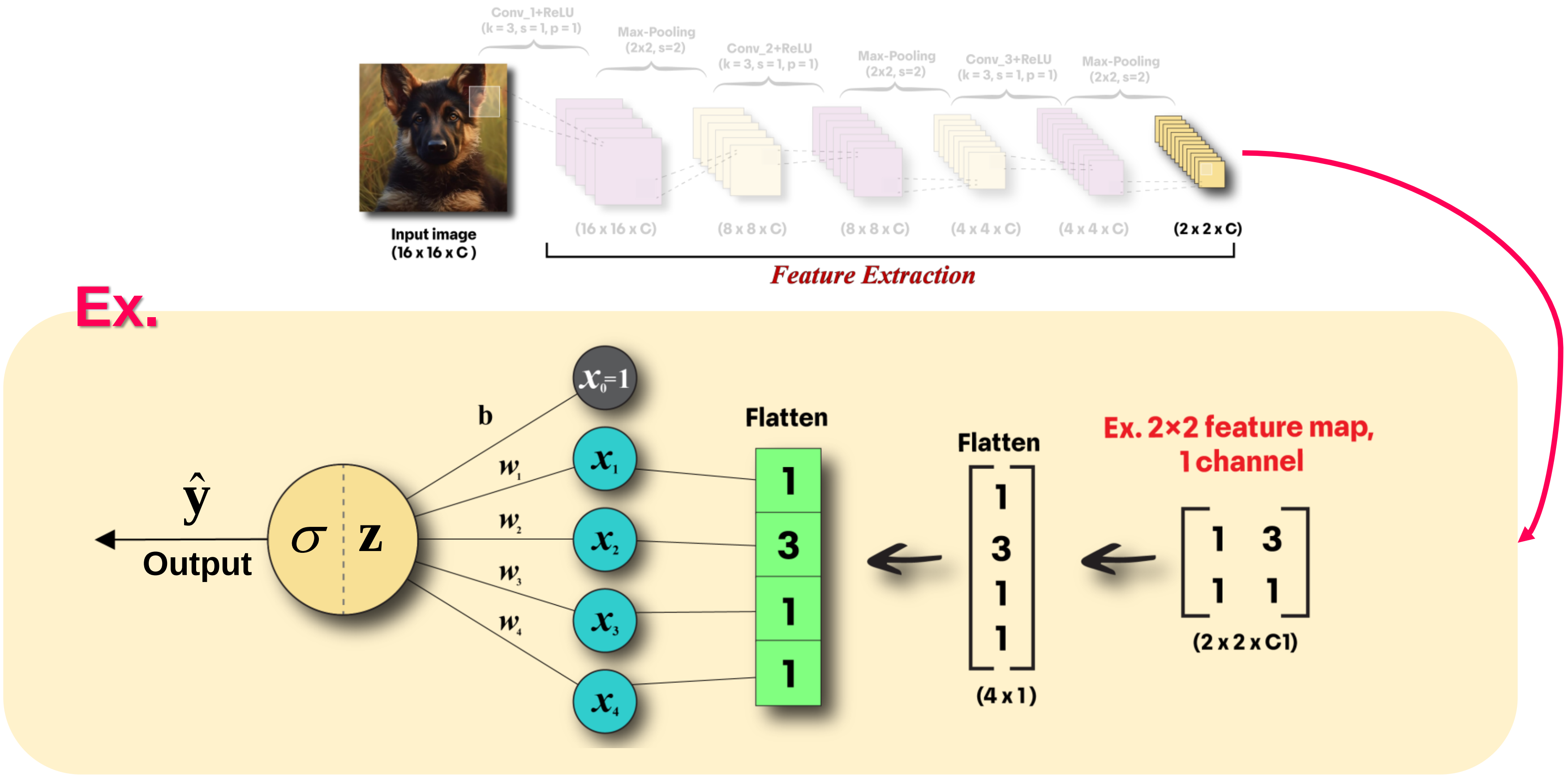
CNNs extract **spatial patterns** using **kernels,** producing feature maps that highlight **significant features.**



How does the model predict keypoints?

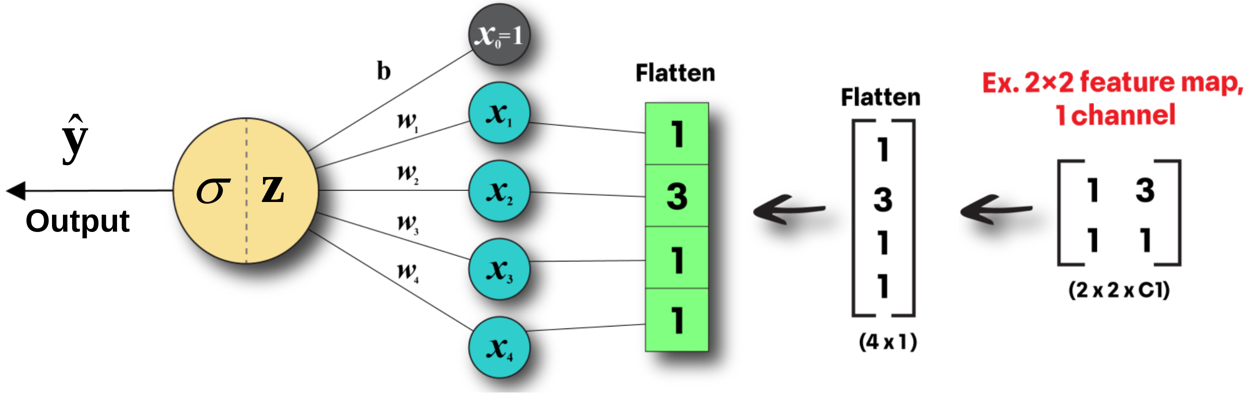
This example simulates keypoint prediction using **a simplified 2×2 feature map** from the final layer.

Ex.



How does the model predict keypoints?

Flattened features are passed through **weights** and **biases** to estimate the keypoint position.

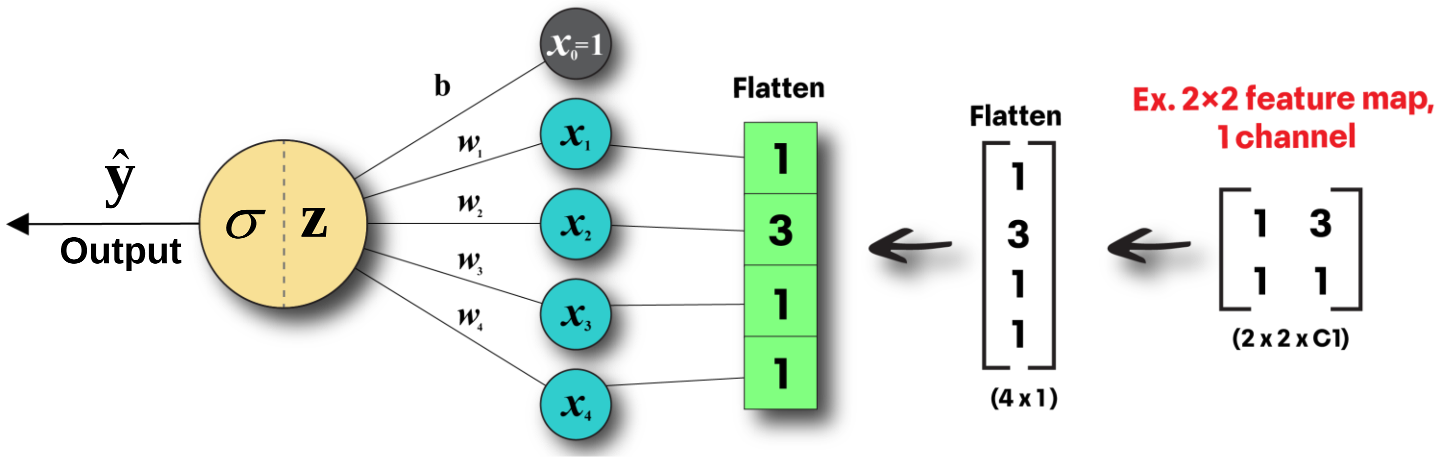


$$\mathbf{x} = \begin{bmatrix} 1 \\ 3 \\ 1 \\ 1 \end{bmatrix}, \quad W = \begin{bmatrix} w_{x1} & w_{x2} & w_{x3} & w_{x4} \\ w_{y1} & w_{y2} & w_{y3} & w_{y4} \end{bmatrix}, \quad b = \begin{bmatrix} b_x \\ b_y \end{bmatrix}$$

$$\hat{\mathbf{y}} = \sigma(\mathbf{z}), \quad \mathbf{z} = W\mathbf{x} + b$$

How does the model predict keypoints?

Step1: initial weights and bias



Ex.

$$\mathbf{x} = \begin{bmatrix} 1 \\ 3 \\ 1 \\ 1 \end{bmatrix}, \quad W = \begin{bmatrix} 0.2 & 0.1 & 0.5 & -0.1 \\ -0.3 & 0.4 & 0.2 & 0.3 \end{bmatrix}, \quad b = \begin{bmatrix} 0.1 \\ 0.2 \end{bmatrix}$$

$$\hat{\mathbf{y}} = \sigma(\mathbf{z}), \quad \mathbf{z} = W\mathbf{x} + b$$

How does the model predict keypoints?

Step2: multiply weights and add bias

$$\hat{\mathbf{y}} = \sigma(\mathbf{z}) = W\mathbf{x} + b = \begin{bmatrix} 0.2 & 0.1 & 0.5 & -0.1 \\ -0.3 & 0.4 & 0.2 & 0.3 \end{bmatrix} \begin{bmatrix} 1 \\ 3 \\ 1 \\ 1 \end{bmatrix} + \begin{bmatrix} 0.1 \\ 0.2 \end{bmatrix}$$

Ex.

$$\mathbf{z} = W\mathbf{x} + b = \begin{bmatrix} (0.2)(1) + (0.1)(3) + (0.5)(1) + (-0.1)(1) \\ (-0.3)(1) + (0.4)(3) + (0.2)(1) + (0.3)(1) \end{bmatrix} + \begin{bmatrix} 0.1 \\ 0.2 \end{bmatrix}$$

$$= \begin{bmatrix} 0.2 + 0.3 + 0.5 - 0.1 \\ -0.3 + 1.2 + 0.2 + 0.3 \end{bmatrix} + \begin{bmatrix} 0.1 \\ 0.2 \end{bmatrix}$$

$$= \begin{bmatrix} 0.9 \\ 1.4 \end{bmatrix} + \begin{bmatrix} 0.1 \\ 0.2 \end{bmatrix}$$

$$= \begin{bmatrix} 1.0 \\ 1.6 \end{bmatrix}$$

How does the model predict keypoints?

Step3: pass through sigmoid

$$\hat{\mathbf{y}} = \sigma(\mathbf{z}) = \sigma\begin{bmatrix}1.0\\1.6\end{bmatrix} \Rightarrow \begin{bmatrix}\sigma(1.0)\\\sigma(1.6)\end{bmatrix} = \begin{bmatrix}0.7311\\0.8320\end{bmatrix}$$

Ex.

$$\sigma(1.0) = \frac{1}{1+e^{-1.0}} = \frac{1}{1+0.3679} = \frac{1}{1.3679} \approx 0.7311$$

$$\sigma(1.6) = \frac{1}{1+e^{-1.6}} = \frac{1}{1+0.2019} = \frac{1}{1.2019} \approx 0.8320$$

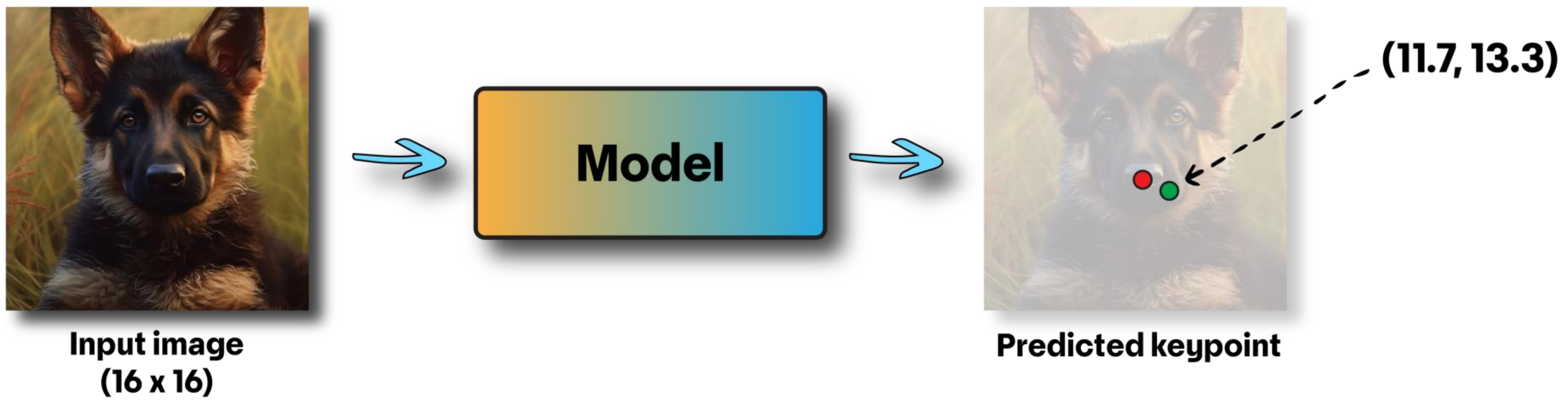
How does the model predict keypoints?

Step4: convert to pixel position

Ex.

$$\hat{\mathbf{x}}_{pixel} = 0.7311 \times 16 = 11.70$$

$$\hat{\mathbf{y}}_{pixel} = 0.8320 \times 16 = 13.31$$



Literatures Reviews

Automatic Measurement using AI

2020

A fully automatic approach for femoral neck-shaft angle evaluation from radiographs [28].

2021

Automatic femoral neck-shaft angle measurement based on CT scan data [29].

2022

An AI-based system for automated quantitative analysis and radiology reporting of leg length radiographs [30].

2023

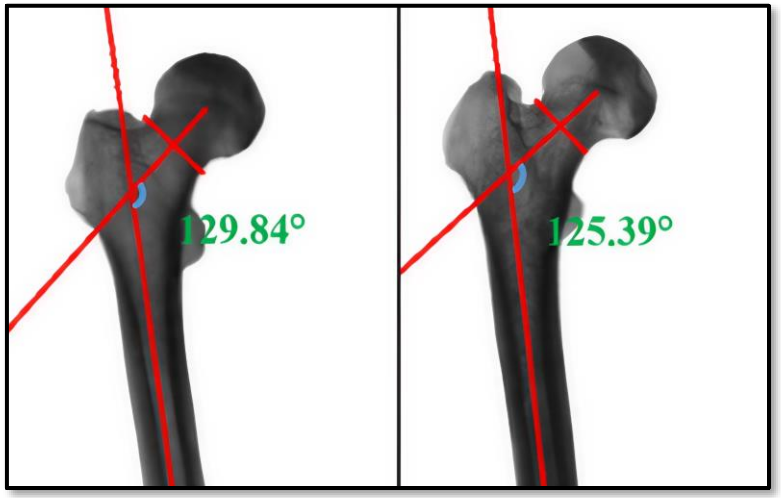
A deep learning keypoint detection algorithm for predicting lower limb alignment from plain knee radiographs [31].

2025

Automated measurement of proximal femoral morphology using point cloud semantic segmentation [32].

Core Paper

An approach for fully automatic femoral neck-shaft angle evaluation on radiographs [28].



Develop an automated system to measurement FNSA from hip radiographs for improved accuracy and speed.

Methodology

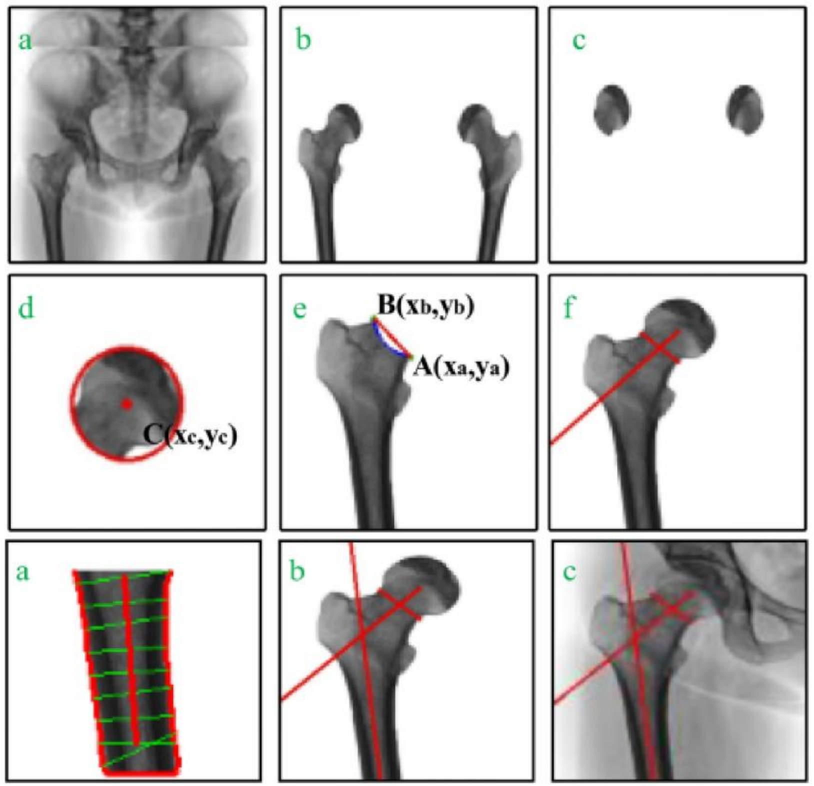
An approach for fully automatic femoral neck-shaft angle evaluation on radiographs [28].

segmentation:

- Used **DCGAN** to segment femur and femoral head.

FNSA calculation:

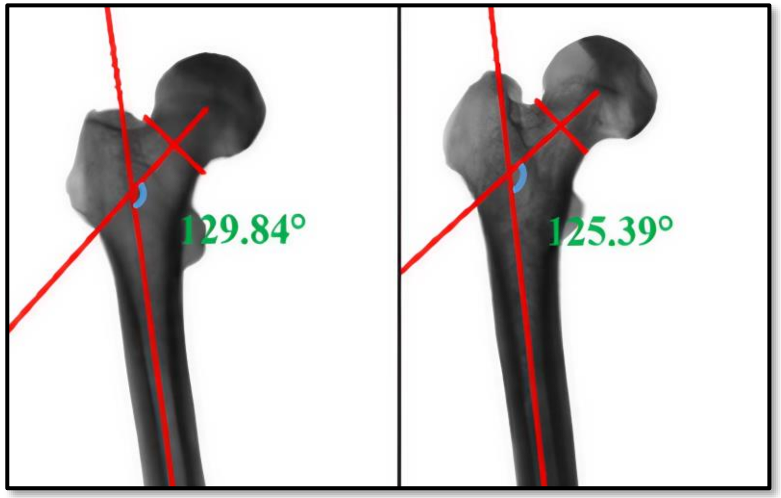
- Applied **minimum enclosing circle** for femoral neck axis (FNA).
- Used **edge detection** for femoral shaft axis (FSA).
- Calculated NSA from the angle between FNA and FSA.



Results

An approach for fully automatic femoral neck-shaft angle evaluation on radiographs [28].

- **Average accuracy** is **97.24%**
- **Average deviation** is **2.58°**
- **Pearson correlation coefficient** is **0.904**



“ Less accuracy with image deviations or the bone structure is incomplete ”

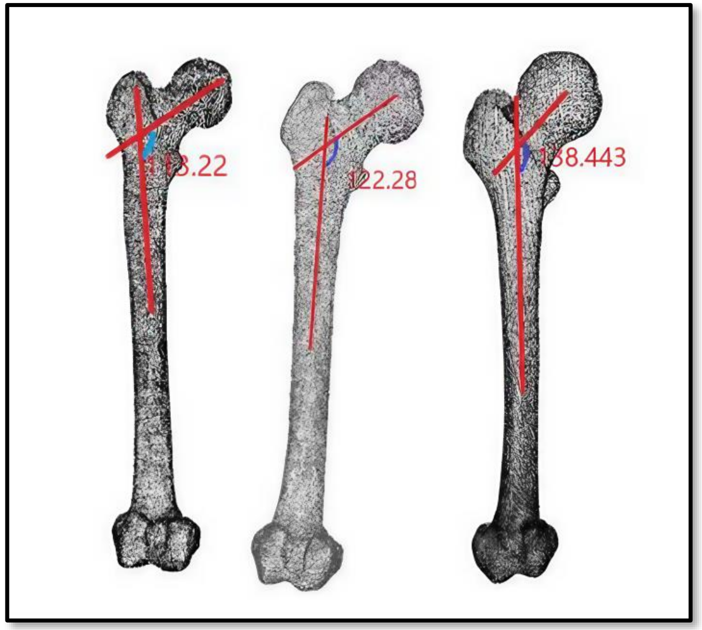
Limitations

An approach for fully automatic femoral neck-shaft angle evaluation on radiographs [28].

- Data from Xi’an Honghui Hospital with **80 radiographs.**
- Small sample size limited to **60 femoral** for **testing**
- **Poor image quality** affects **accuracy.**

Medical Measurement Automated using AI

Automatic measurement of femoral neck-shaft angle based on CT scan data [29].



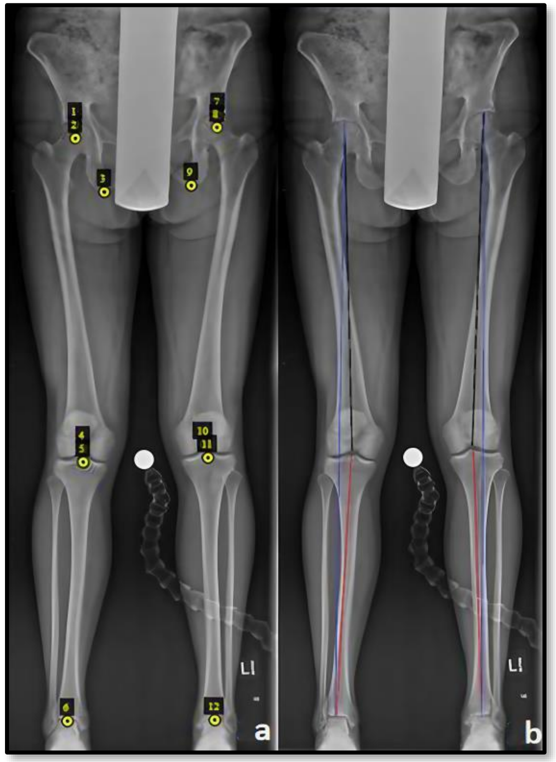
- Automatic FNSA measurement **using CT scans.**
- **PointNet++** used for bone **segmentation**.
- **Average accuracy is 98.04%.**
- **Average error is 2.35°.**
- **Manual measurements** have **higher error rates.**

“ CT scans are expensive and high radiation exposure ”

AI Medical Measurement (cont.)

Artificial Intelligence system for automatic quantitative analysis and radiology reporting of leg length radiographs [30].

Parameters	Absolute mean error	Standard deviation
leg length	0.22%	8.93 pixels
femur length	0.64%	7.89 pixels
tibia length	0.47%	8.61 pixels
mech angle	0.42°	0.54°
pelvic tilt	0.67°	1.74°



- Length measurement **less than 1%**
- Average deviation of **less than 1°**

“ Keypoint detection is used to accurately identify critical anatomical landmark on radiographs ”

AI Medical Measurement (cont.)

Keypoint detection algorithm of deep learning can predict lower limb alignment with simple knee radiographs [31].

validation set	mean absolute error	ICC
AL and DL	0.064 ± 0.007	0.89 ± 0.09
test set	mean absolute error	ICC
AL and DL	0.051 ± 0.007	0.88 ± 0.08

- Mean absolute error (MAE) **is 0.051**
- Intraclass correlation coefficient (ICC) **is 0.88**

“ Keypoint detection for predicting lower limb alignment on knee radiographs ”

Research Gap

Previous work on

FNSA measurement focuses on

using **SEGMENTATION** and **EDGE DETECTION**.

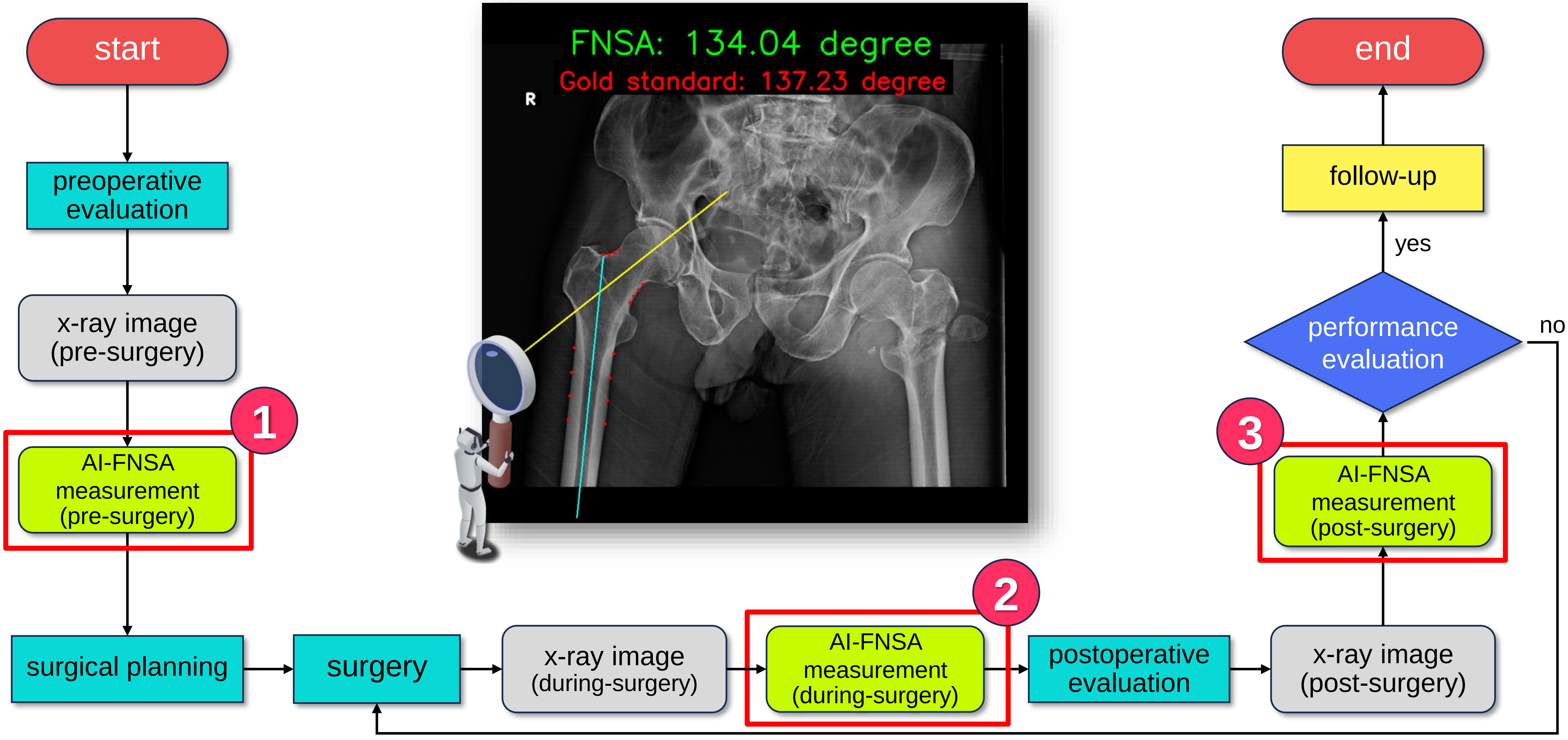
However,

"Keypoint detection" has **high potential**

to be alternative approach.

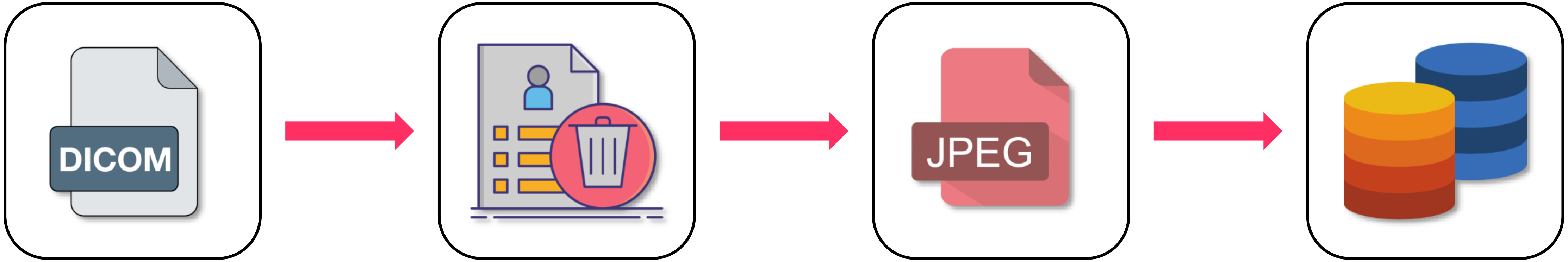
Research Methods

Remind that..


start
preoperative evaluation
x-ray image (pre-surgery)
1
AI-FNSA measurement (pre-surgery)
surgical planning
surgery
x-ray image (during-surgery)
2
AI-FNSA measurement (during-surgery)
postoperative evaluation
x-ray image (post-surgery)
3
AI-FNSA measurement (post-surgery)
performance evaluation
no
yes
follow-up
end
FNSA: 134.04 degree
Gold standard: 137.23 degree
R

Data Collection & Preparation

500 femoral (AP) radiographs from Srinagarind Hospital, Khon Kaen University



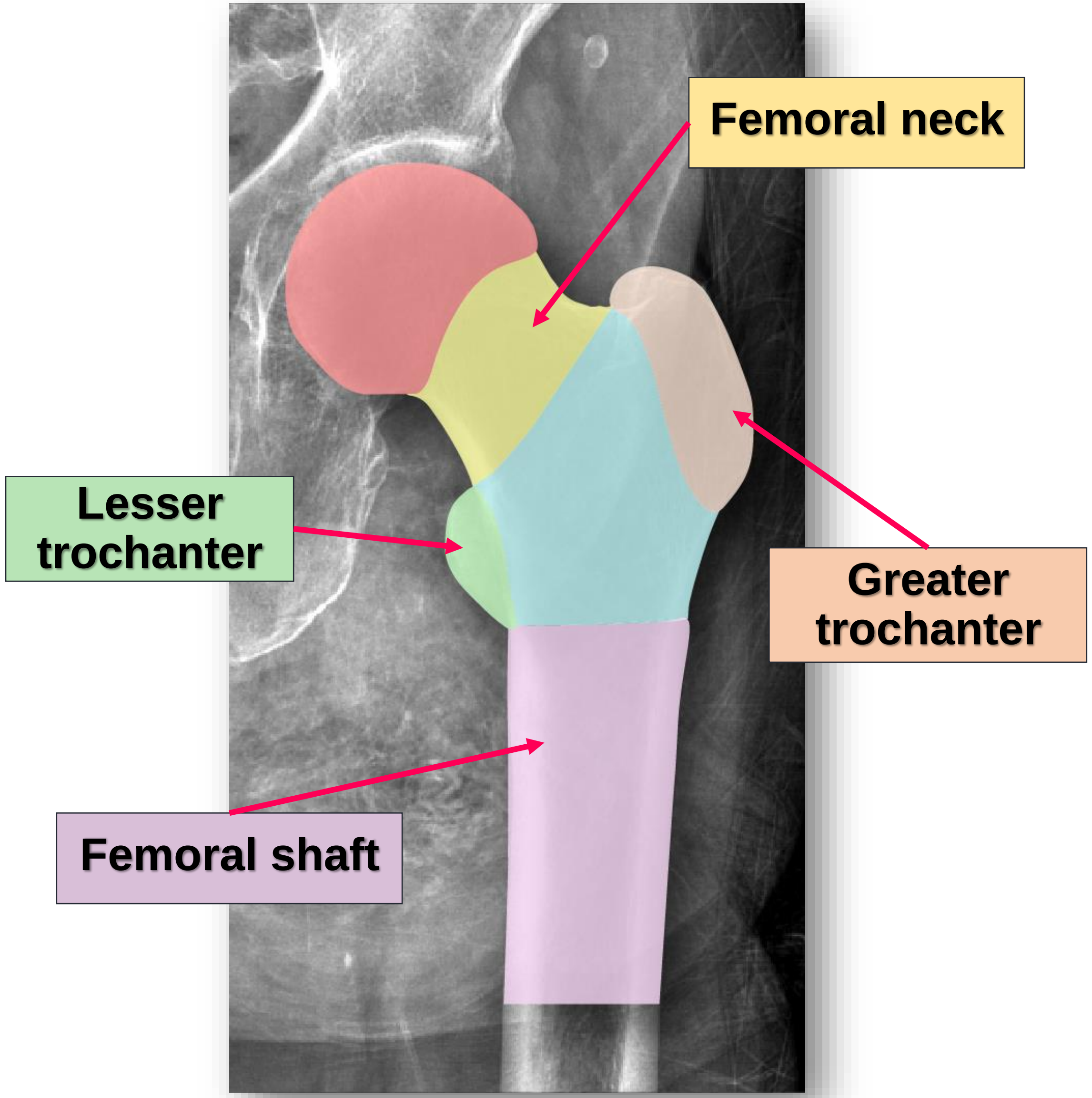
Raw data **De-identification** **Convert to jpeg file** **Dataset**

Note that!!!

Image selection:

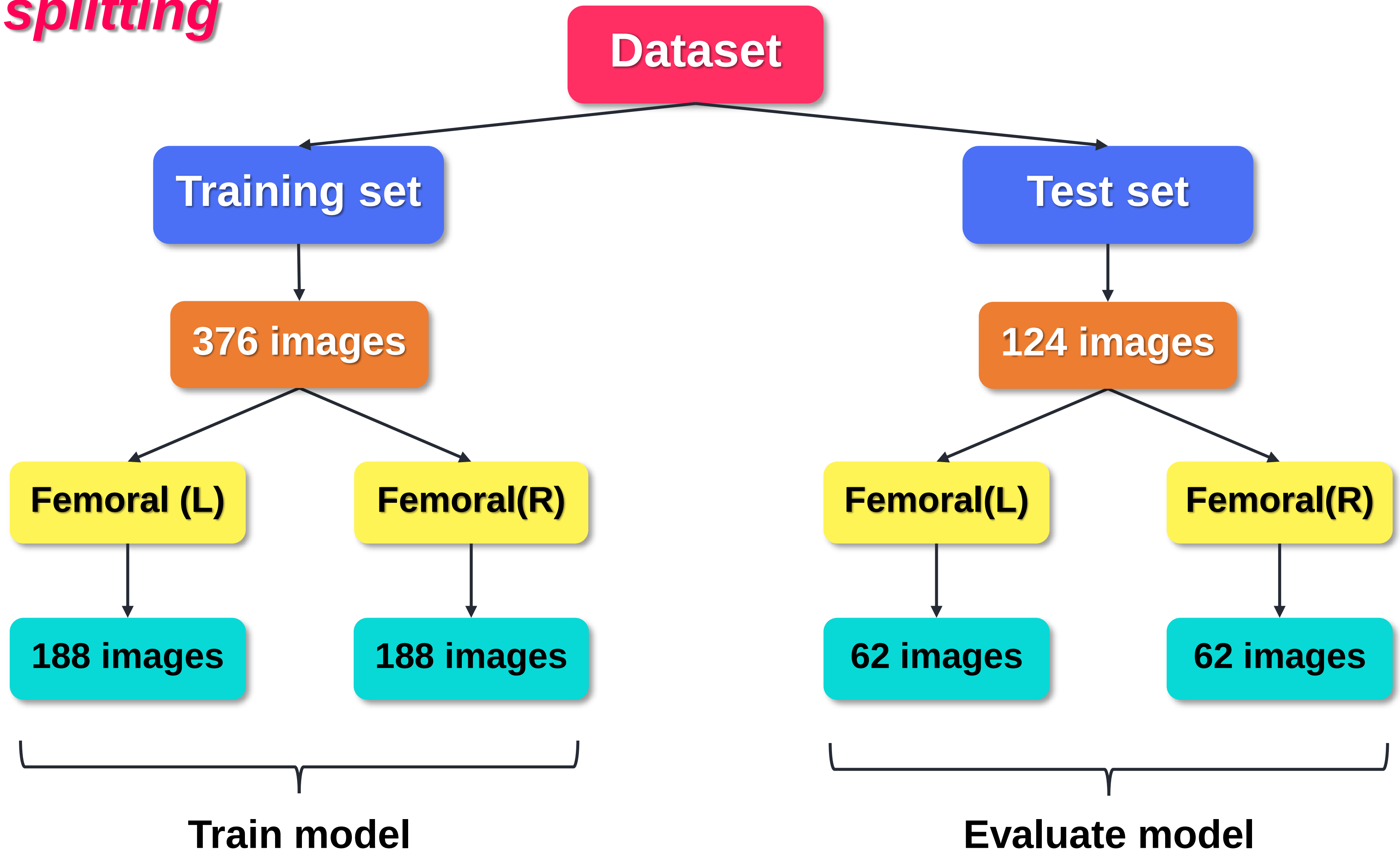
1. Clearly show **the femoral neck** and **shaft.**

2. Prominently display **the lesser** and **greater trochanters.**



Data Collection & Preparation (cont.)

Data splitting



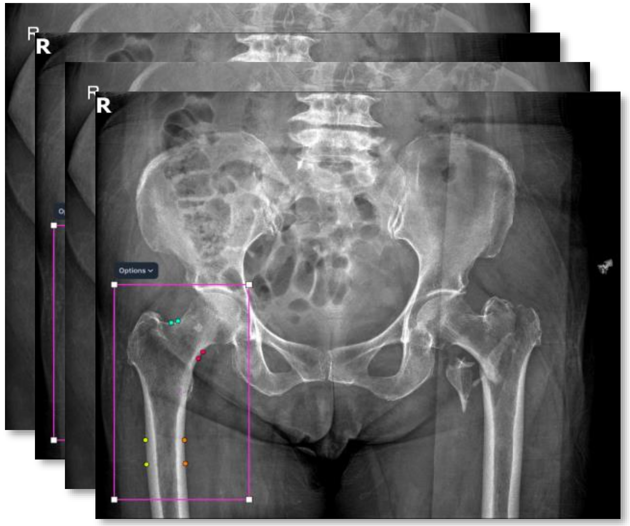
Data Collection & Preparation (cont.)

Data annotation

unlabeled data

roboflow

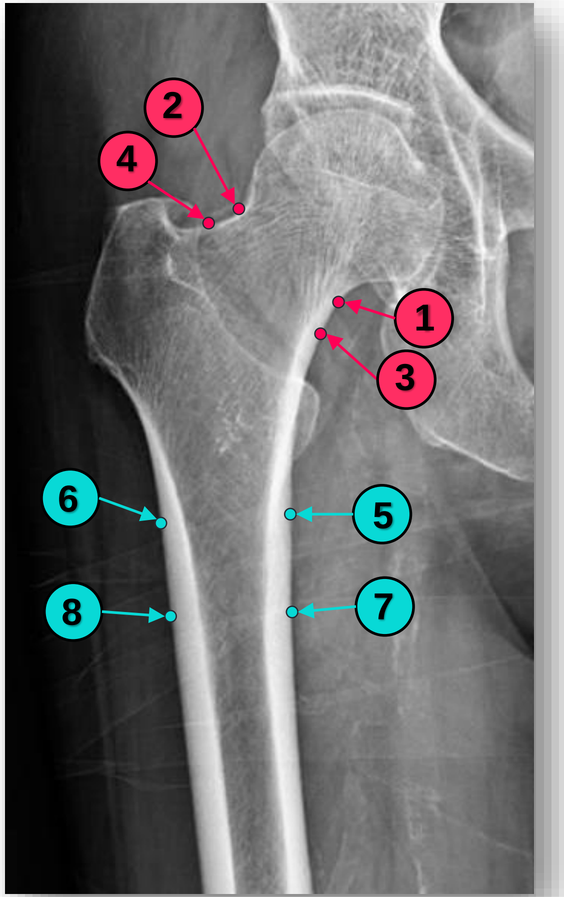
data labeling platforms



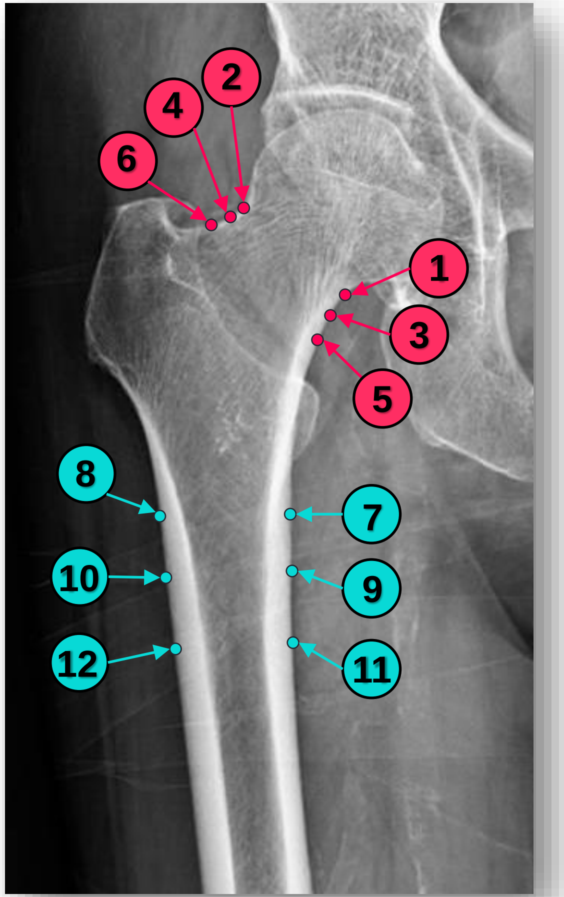
annotate Keypoints

Data Collection & Preparation (cont.)

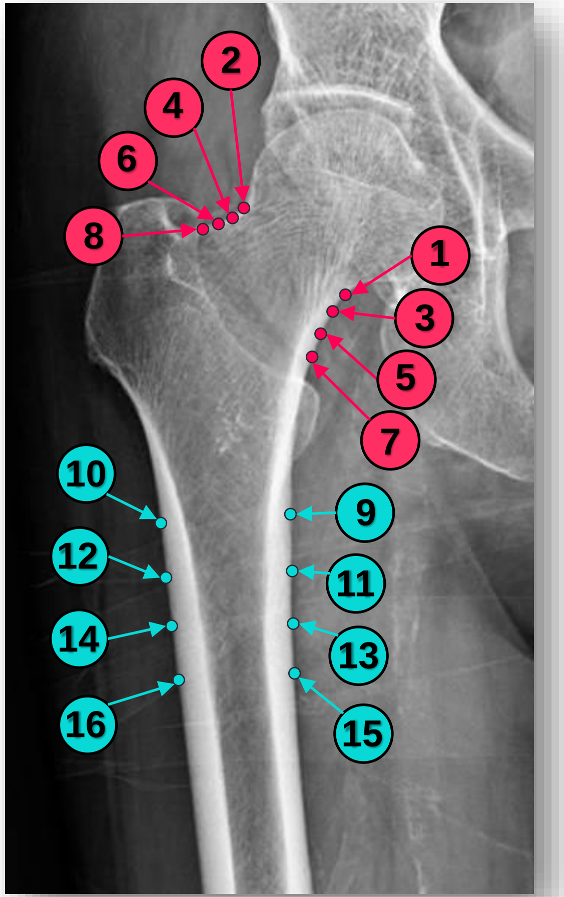
Data annotation 3 models



8-point model



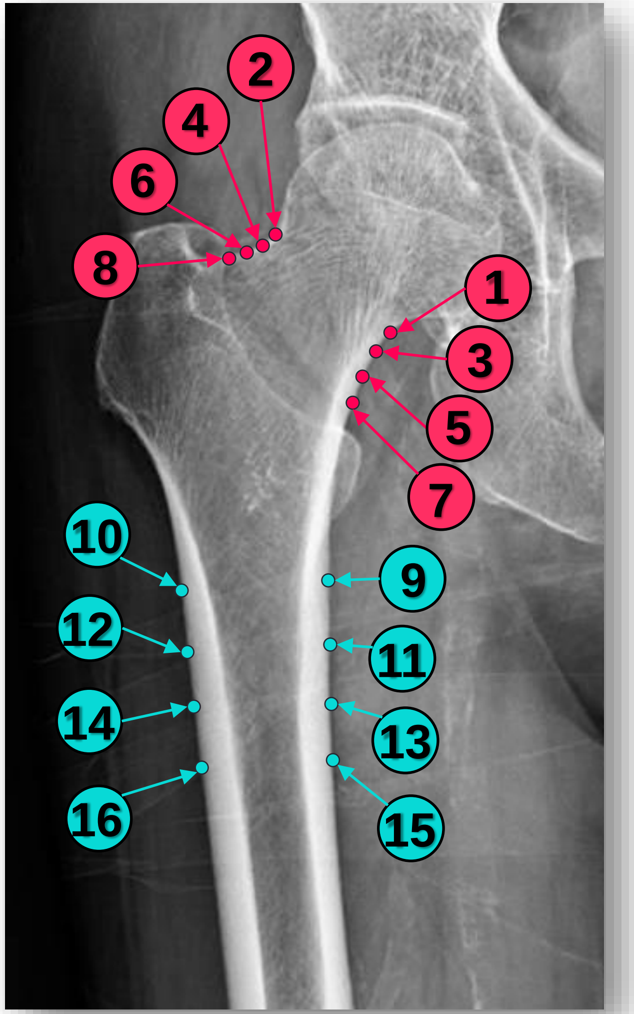
12-point model



16-point model

Data Collection & Preparation (cont.)

Export data



Annotate keypoints

Export

Image file & text file

Data Collection & Preparation (cont.)

The dataset label format for model training.

JPG

image file

unlabeled data

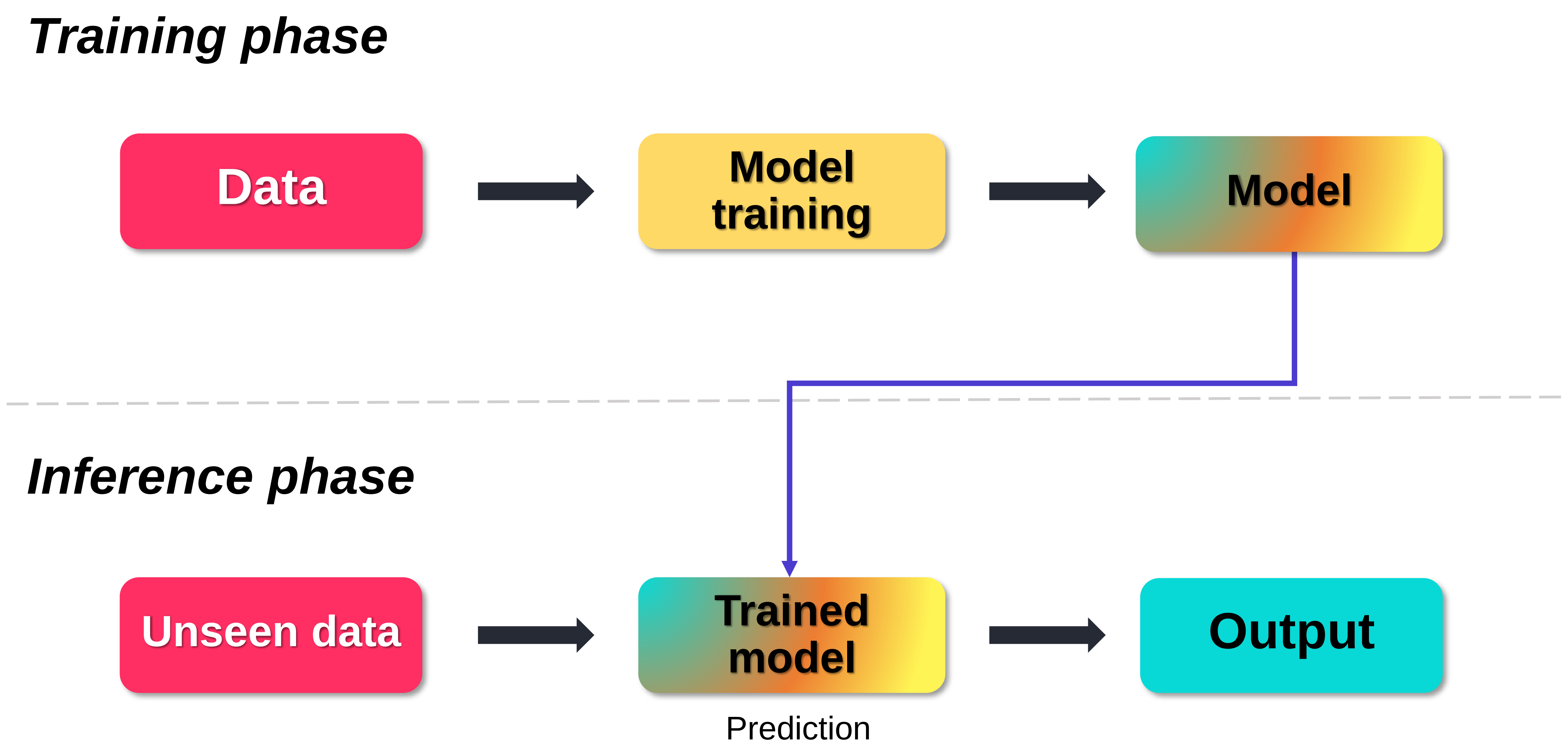
640 x 640 pixels

TXT

text file

$$(class_{index})(x_{center})(y_{center})(width)(height)$$
$$(px_1)(py_1)(p_1 visibility)$$
$$(px_2)(py_2)(p_2 visibility)$$
$$\vdots$$
$$(px_n)(py_n)(p_n visibility)$$

AI Model


Training phase
Data
Model training
Model
Inference phase
Unseen data
Trained model
Output
Prediction

Training Phase

JPG

Image file

640 x 640 pixels

Input image

Model training

YOLOv8n-Pose

TXT

Text file

$(class_{index})$

$(x_{center})(y_{center})$

$(width)(height)$

$(p_{x1})(p_{x1})(p_1 visibility)$

$(p_{x2})(p_{x2})(p_2 visibility)$

$(p_{x3})(p_{x3})(p_3 visibility)$

$(p_{x4})(p_{x4})(p_4 visibility)$

$(p_{x5})(p_{x5})(p_5 visibility)$

$(p_{x6})(p_{x6})(p_6 visibility)$

$\vdots$

$(p_{xn})(p_{xn})(p_n visibility)$

Target output

Inference phase

Input image

Unseen data

Trained model

Predict using model

Output

$(class_{index})$

$(x_{top-left})(y_{bottom-right})$

$(width)(height)$

$(p_{x1})(p_{x1})(p_1 confidence)$

$(p_{x2})(p_{x2})(p_2 confidence)$

$(p_{x3})(p_{x3})(p_3 confidence)$

$(p_{x4})(p_{x4})(p_4 confidence)$

$(p_{x5})(p_{x5})(p_5 confidence)$

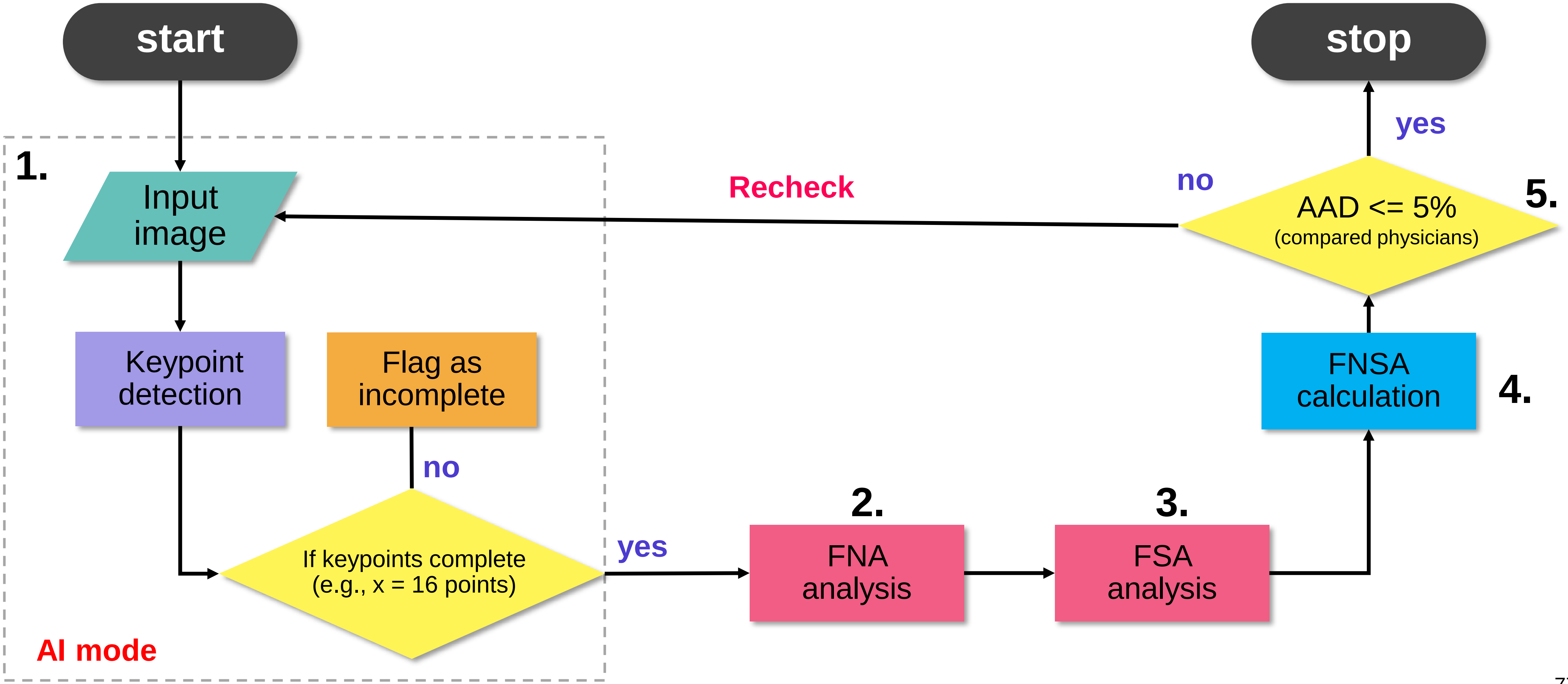
$(p_{x6})(p_{x6})(p_6 confidence)$

$\vdots$

$(p_{xn})(p_{xn})(p_n confidence)$

Model Evaluation Workflow

Flow chart



STEP01 : Keypoint Detection

Predict keypoint

The model processes the image and **predicted keypoints** as **coordinate values** for each point.

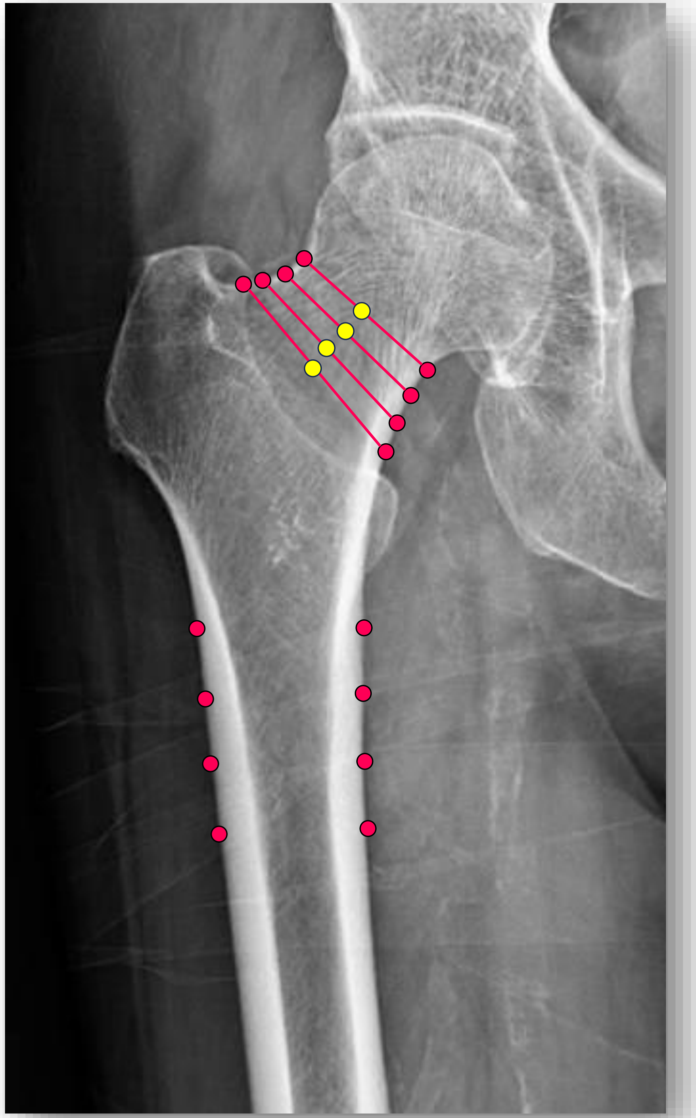
Input image

Trained model

Prediction

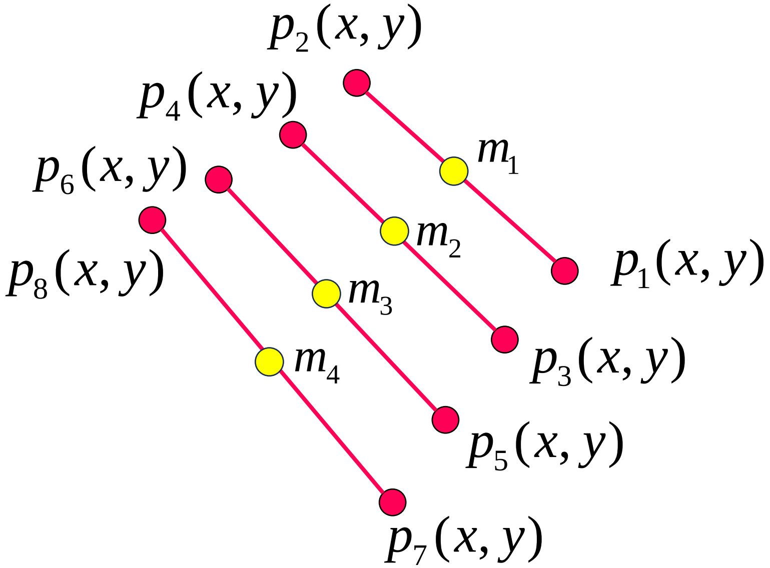
Keypoint prediction result

STEP02: FNA Analysis



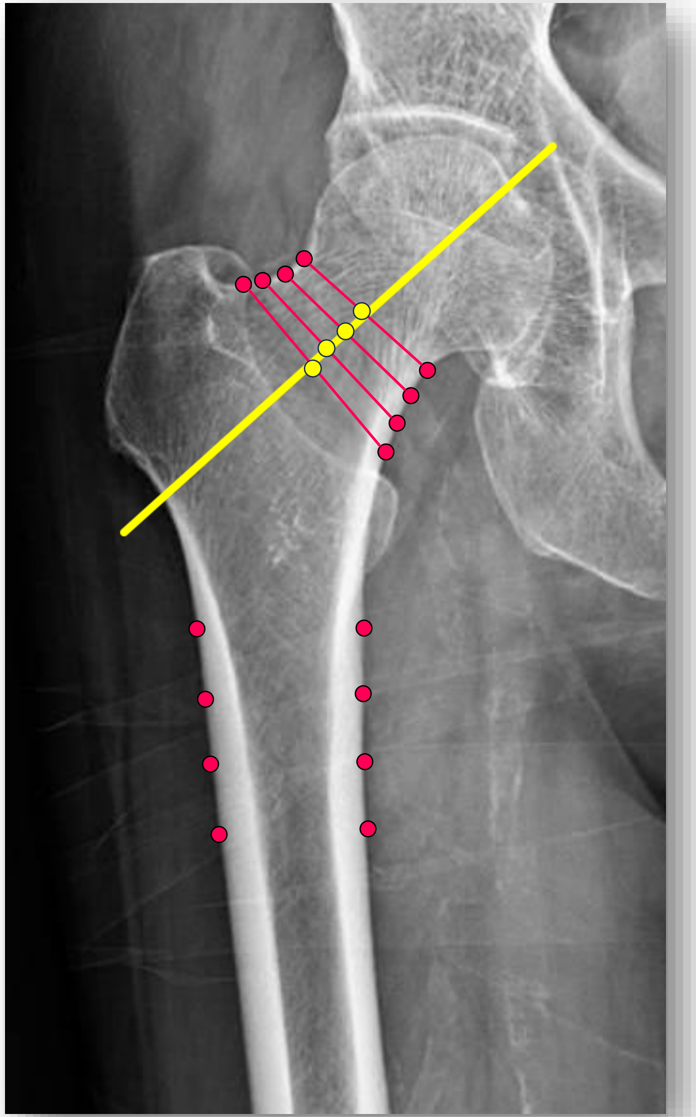
FNA analysis

Calculate midpoints :



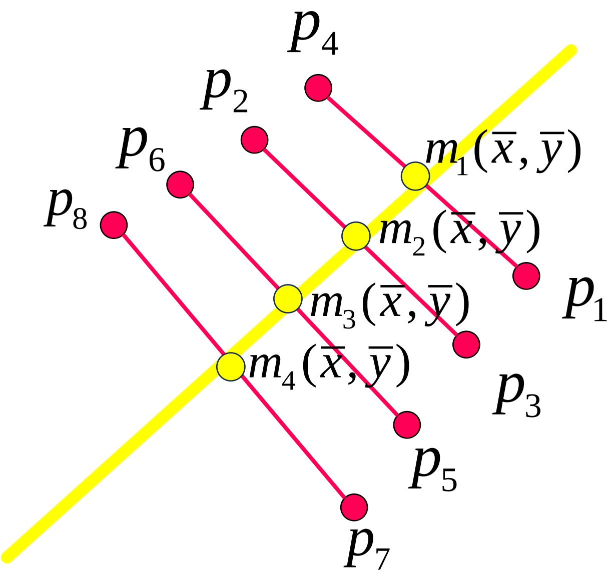
$$m = \left(\frac{x_1 + x_2}{2}, \frac{y_1 + y_2}{2} \right)$$

STEP02: FNA Analysis (cont.)



FNA analysis

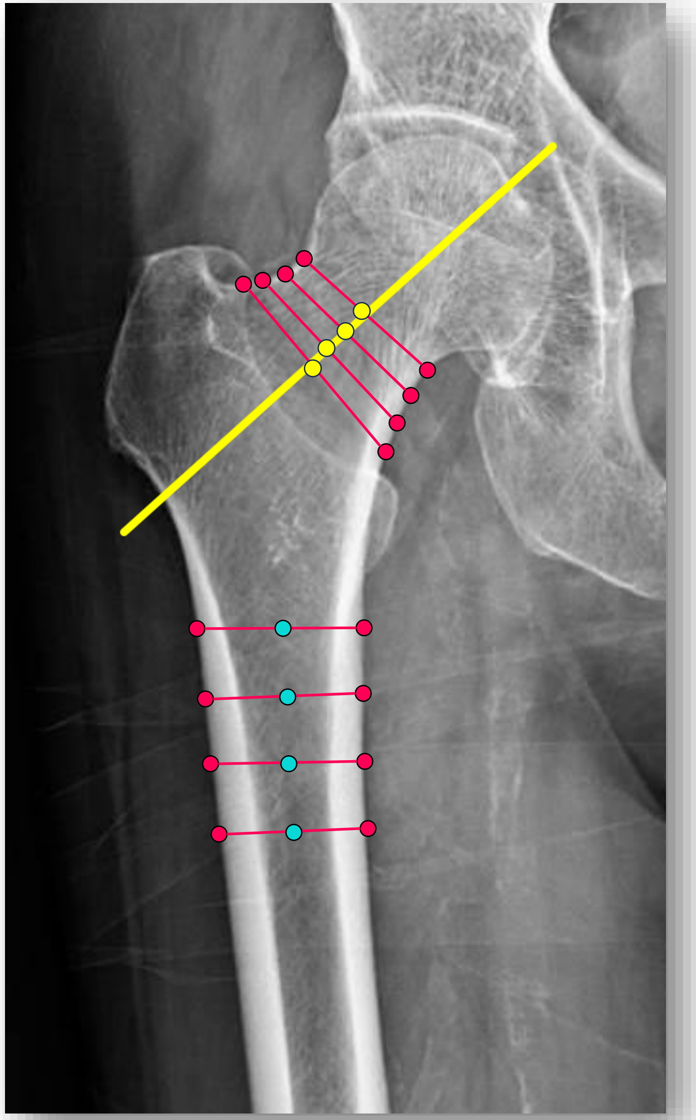
Calculation of FNA :



draw a line using **linear regression**

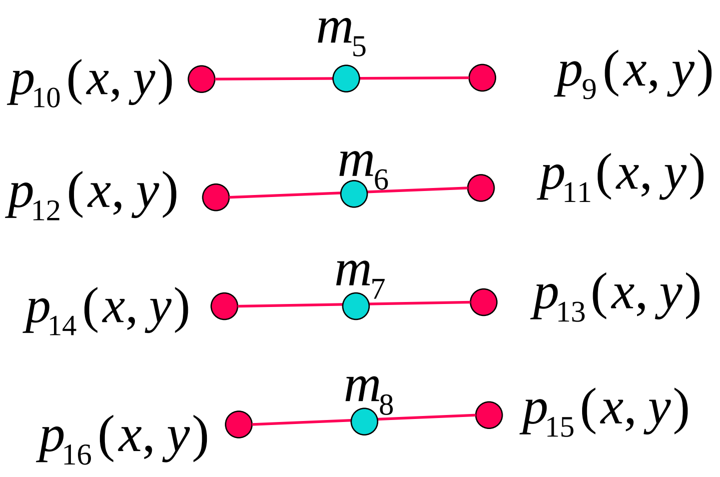
$$y = mx + c$$

STEP03: FSA Analysis



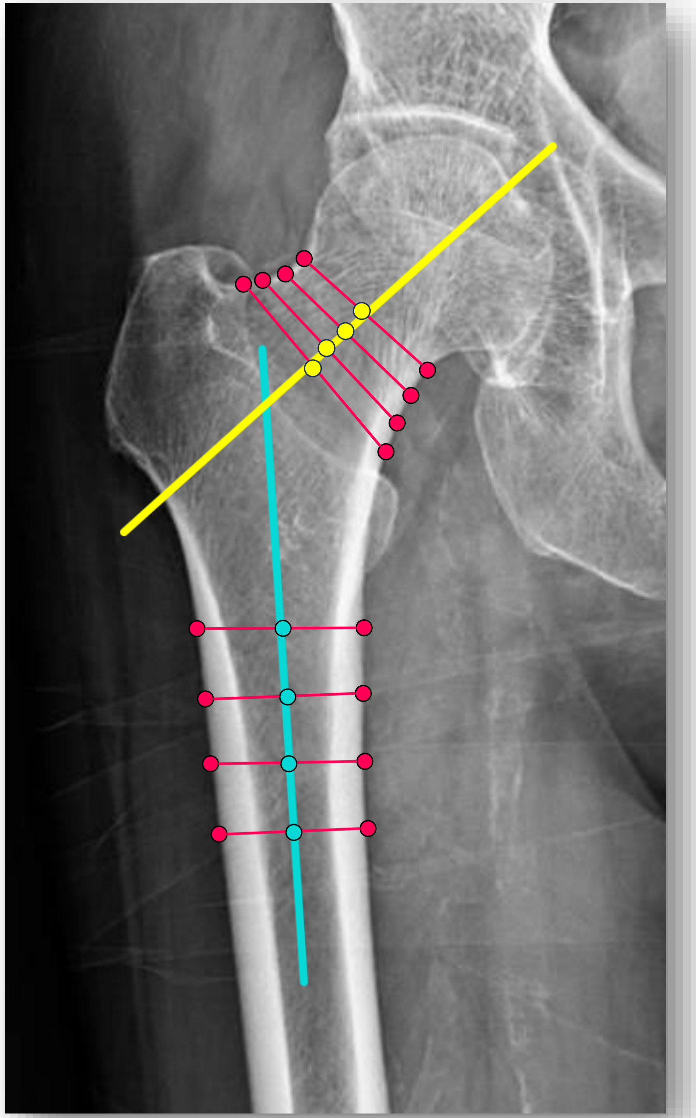
FSA analysis

Calculate midpoints :



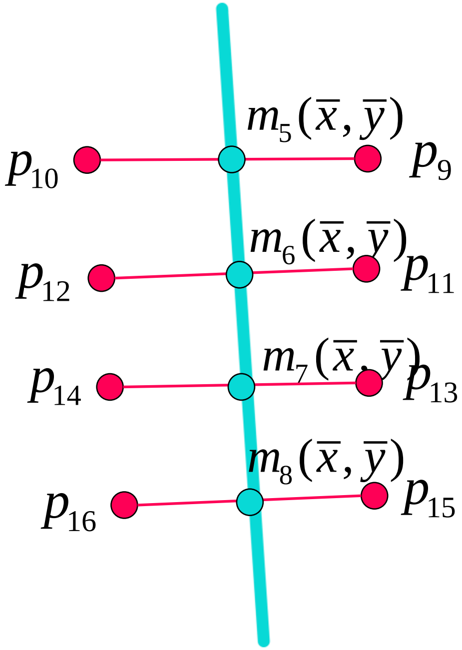
$$m = \left(\frac{x_1 + x_2}{2}, \frac{y_1 + y_2}{2} \right)$$

STEP03: FSA Analysis (cont.)



FSA analysis

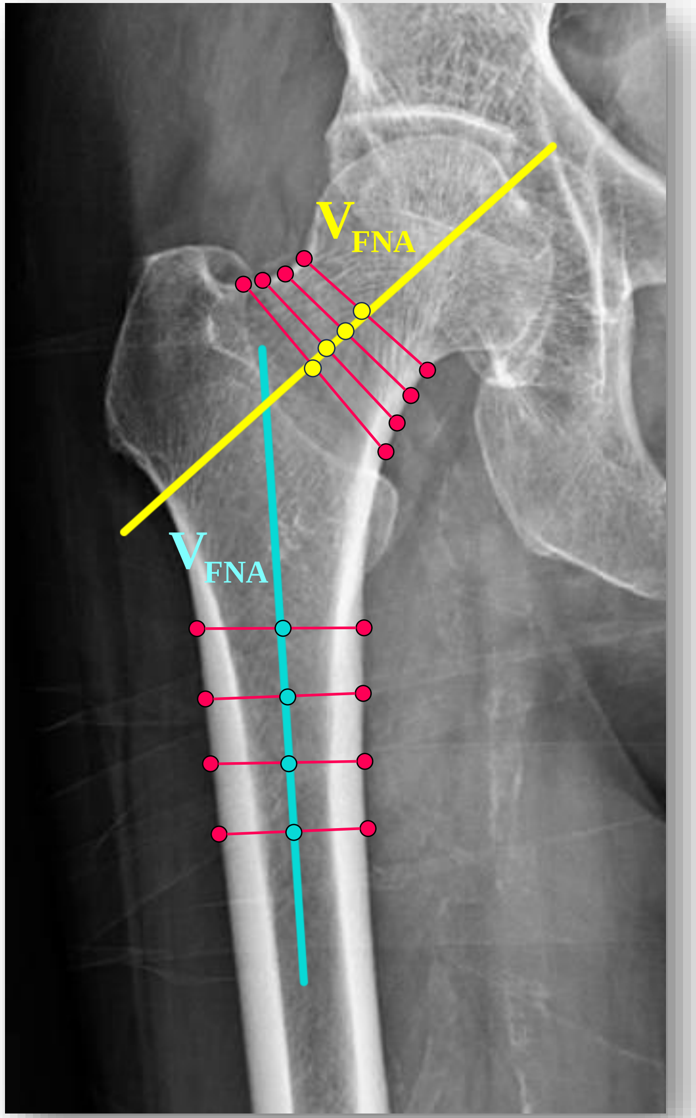
Calculate of FSA :



draw a line using **linear regression**

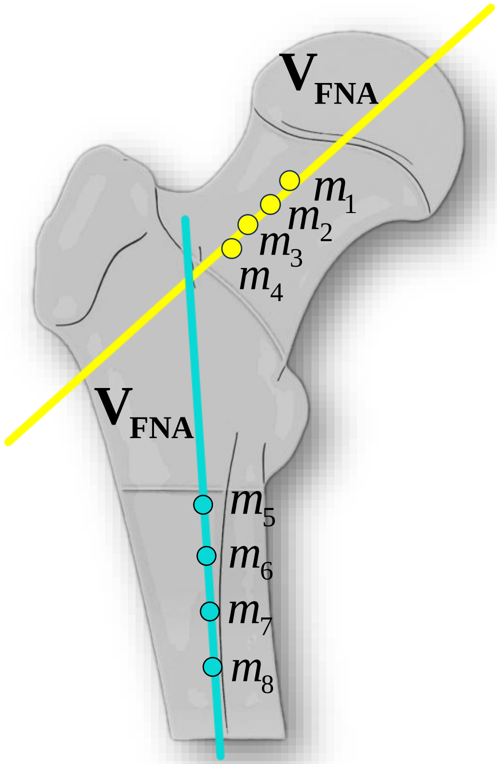
$$y = mx + c$$

STEP04: Calculation of FNSA



The vector of FNA and FSA

Convert to vectors :



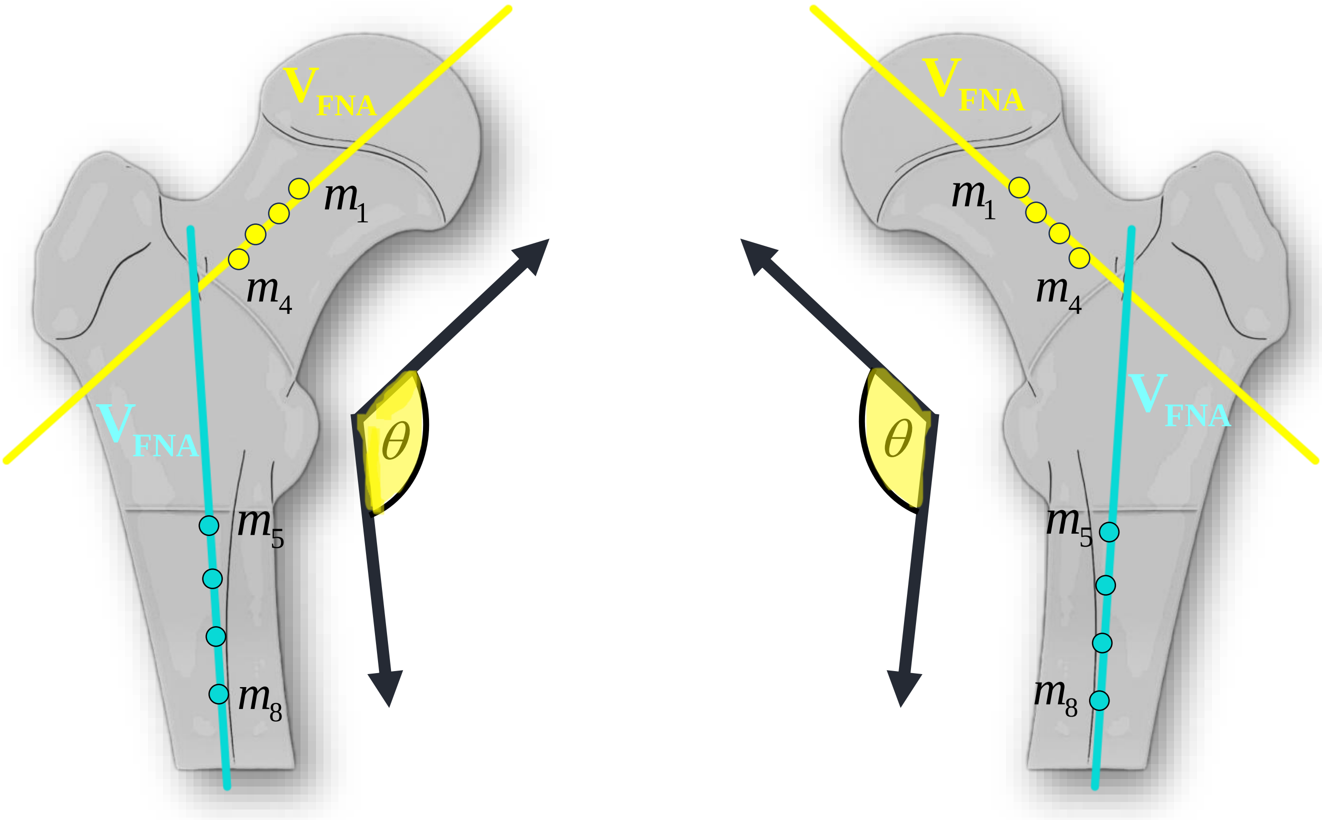
$$\mathbf{v}_{\mathbf{FNA}} = (x_{FNA_1} - x_{FNA_2}, y_{FNA_1} - y_{FNA_2})$$

$$\mathbf{v}_{\mathbf{FSA}} = (x_{FSA_1} - x_{FSA_2}, y_{FSA_1} - y_{FSA_2})$$

Note that!!!

Consistent direction:

Left side

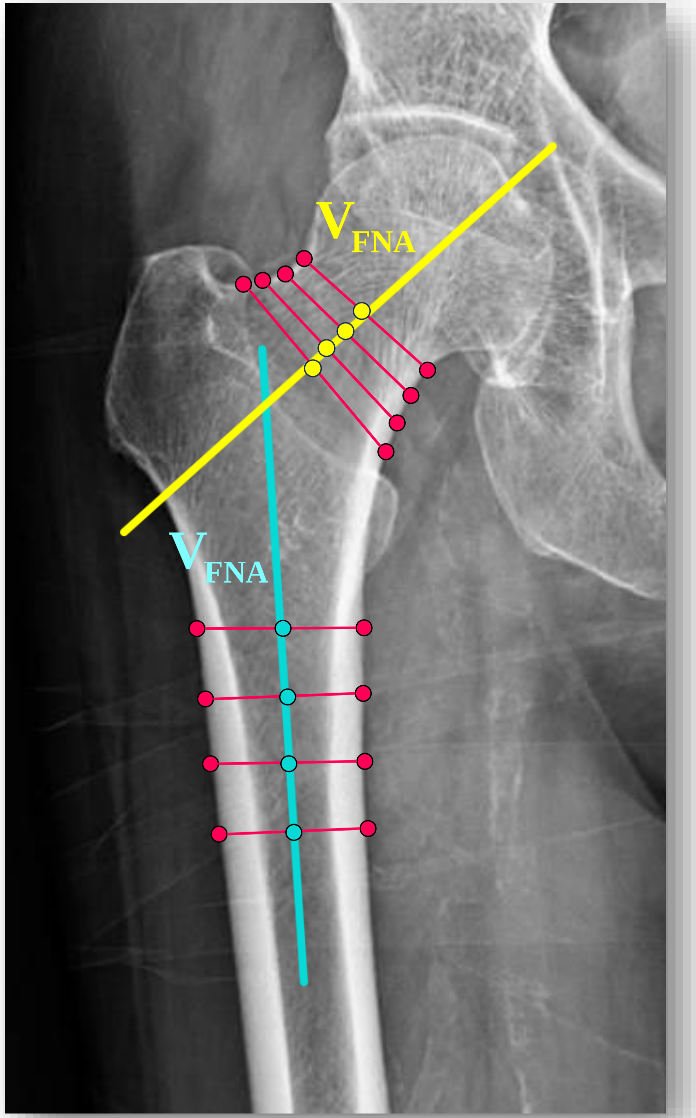


Right side

$$\mathbf{V}_{\mathbf{FNA}} = (\underbrace{x_{FNA_1} - x_{FSA_2}}_{m_4}, \underbrace{y_{FNA_1} - y_{FSA_2}}_{m_1})$$

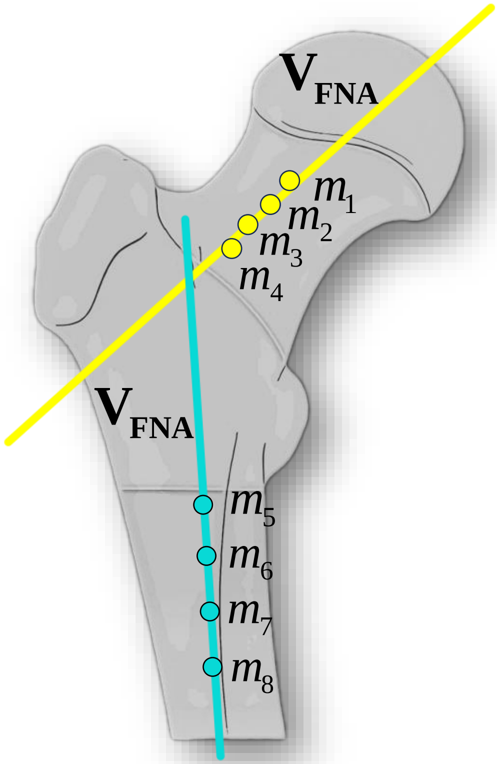
$$\mathbf{V}_{\mathbf{FSA}} = (\underbrace{x_{FSA_1} - x_{FSA_2}}_{m_5}, \underbrace{y_{FSA_1} - y_{FSA_2}}_{m_8})$$

STEP04: Calculation of FNSA (cont.)



The vector of FNA and FSA

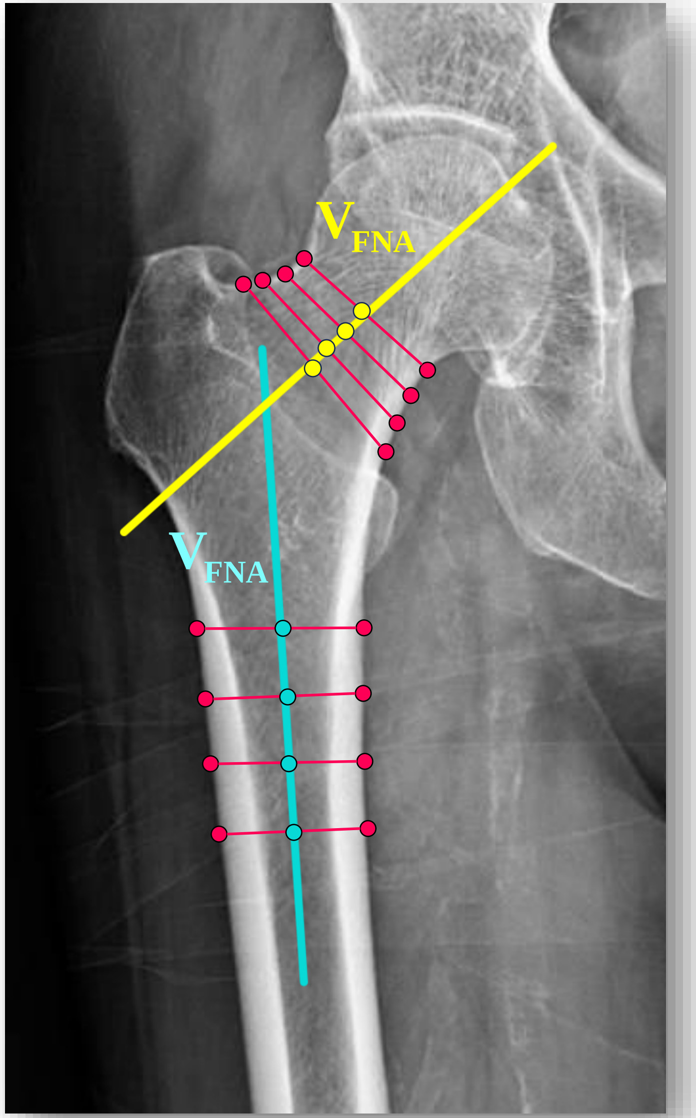
Calculate dot product:



the **dot product** between the FNA and FSA vectors.

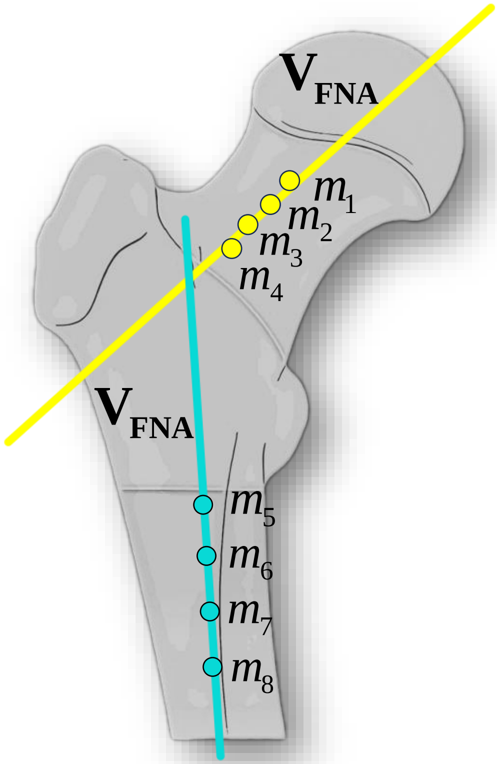
$$\mathbf{V}_{\mathbf{FNA}} \cdot \mathbf{V}_{\mathbf{FSA}} = (x_{FNA} x_{FSA}, y_{FNA} y_{FSA})$$

STEP04: Calculation of FNSA (cont.)



The vector of FNA and FSA

Length of vector :

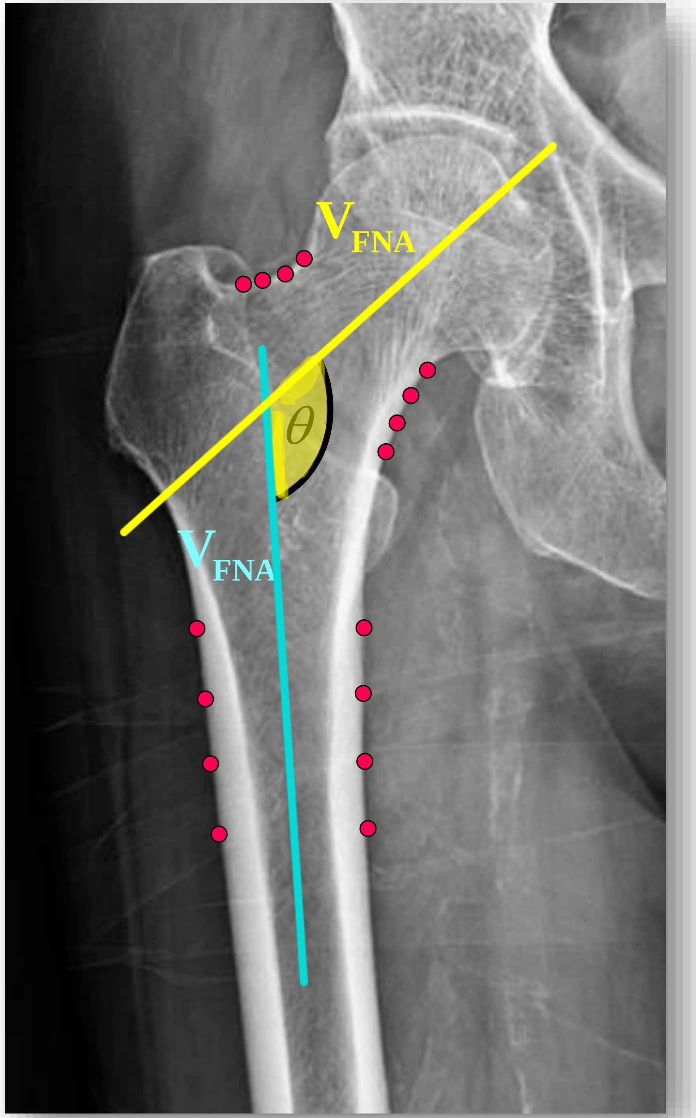


$$\left\|\vec{\mathbf{v}}_{\mathbf{FNA}}\right\| = \sqrt{(x_{FNA_1} - x_{FNA_2})^2 + (y_{FNA_1} - y_{FNA_2})^2}$$

$$\left\|\vec{\mathbf{v}}_{\mathbf{FSA}}\right\| = \sqrt{(x_{FSA_1} - x_{FSA_2})^2 + (y_{FSA_1} - y_{FSA_2})^2}$$

the length of FNA and FSA.

STEP04: Calculation of FNSA (cont.)



The angle of FNSA in radians.

The cosine of the angle:

$$\cos(\theta) = \frac{\vec{\mathbf{V}}_{\mathbf{FNA}} \cdot \vec{\mathbf{V}}_{\mathbf{FSA}}}{\left\|\vec{\mathbf{V}}_{\mathbf{FNA}}\right\| \left\|\vec{\mathbf{V}}_{\mathbf{FSA}}\right\|}$$

Determine the angle using arccos function:

$$\theta = \cos^{-1}\left(\frac{\vec{\mathbf{V}}_{\mathbf{FNA}} \cdot \vec{\mathbf{V}}_{\mathbf{FSA}}}{\left\|\vec{\mathbf{V}}_{\mathbf{FNA}}\right\| \left\|\vec{\mathbf{V}}_{\mathbf{FSA}}\right\|}\right)$$

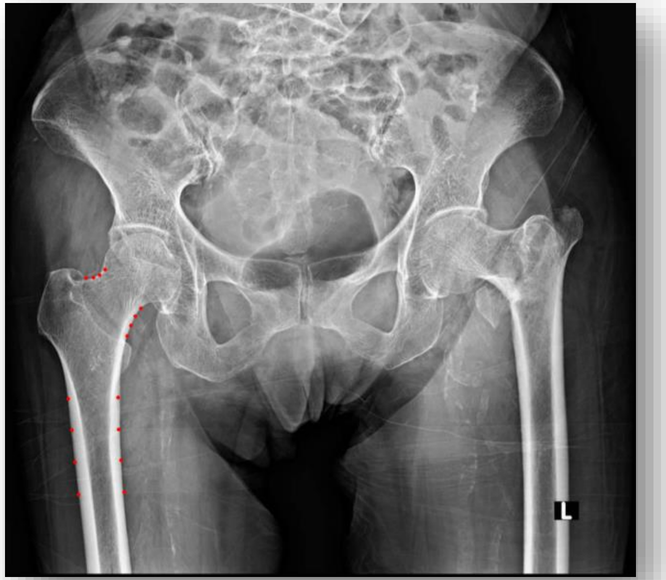
The result will be the **angle** in **radians.**

Automatic Measurement of FNSA

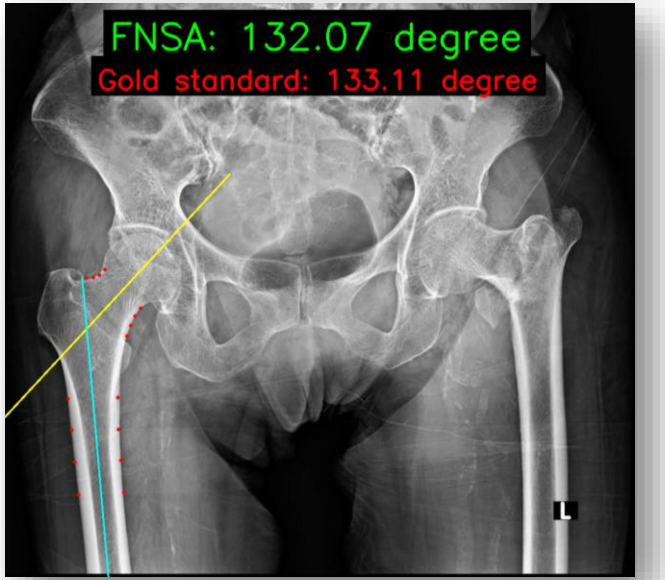
Femoral-neck shaft angle calculate

automatic calculate FNSA from detected keypoints

Input image



Keypoints detection



The result of FNSA

The Criteria for Assessment

Average Absolute Deviation (AAD):

This indicates how close the model predictions are to the actual values.

$$Average\ \ Absolute\ \ Deviation = \frac{\sum_{i=1}^{N} \left| NSA_{m_i} - NSA_{a_i} \right|}{N}$$

Average Accuracy:

The overall accuracy of the model is compared to manual measurements.

$$Average\ \ Accuracy = \frac{\sum_{i=1}^{N} \left(1 - \frac{\left| NSA_{m_i} - NSA_{a_i} \right|}{NSA_{m_i}} \right) \times 100\%}{N}$$

The Criteria for Assessment (cont.)

Object Keypoint Similarity (OKS)

This measure the similarity between the predicted keypoints and the actual keypoints for an object.

$$OKS = \frac{\sum_i \left[\exp\left(-\frac{d_i^2}{2 s_i \sigma_i^2} \right) \cdot \delta\left(\upsilon_i > 0 \right) \right]}{\sum_i \left[\delta\left(\upsilon_i > 0 \right) \right]}$$

- This metric ranges between 0 and 1.
- The closer the predicted keypoint to the actual, the closer will **OKS approach 1.**

Results & Discussion

Results and Discussions

Performance evaluation of FNSA measurement models.

Model	Average Accuracy	AAD	OKS
8-point	95.17%	6.3010°	0.4983
12-point	96.25%	4.8433°	0.7836
16-point	**97.49%**	**3.6909°**	**0.9873**

"Among all configurations,
the 16-point model achieves
the best overall performance
across all metrics."

Results and Discussions (cont.)

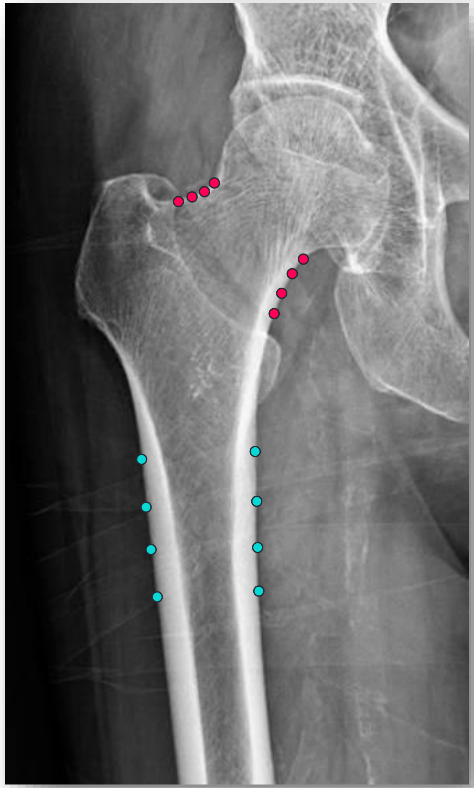
Why Not Keep Increasing Keypoints?

Model	Total annotation workload (500 images)
16-point	8,000 points
20-point	10,000 points
24-point	12,000 points

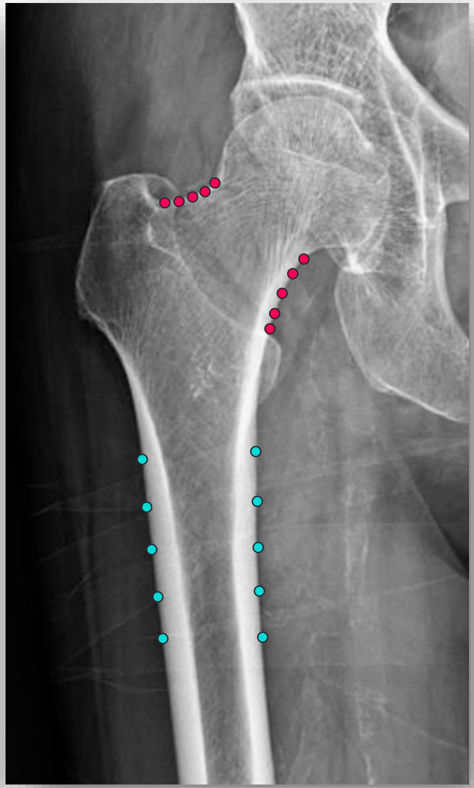
"The 16-point configuration achieves a practical trade-off between accuracy, model efficiency, and annotation workload."

Results and Discussions (cont.)

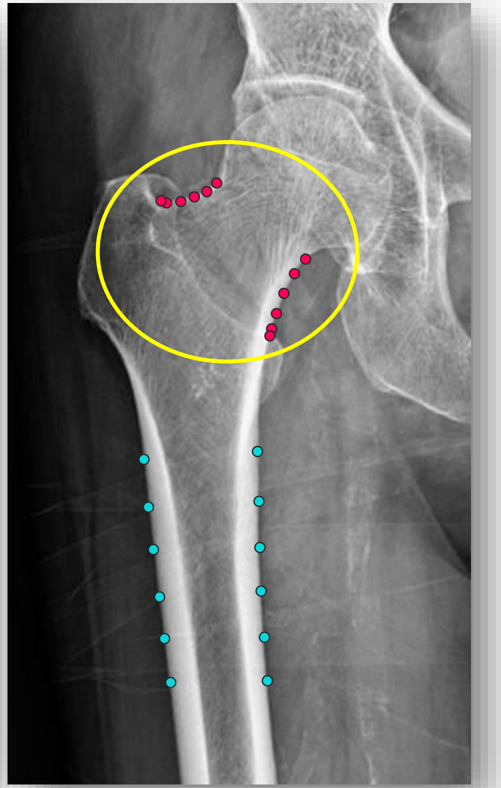
Why Not Keep Increasing Keypoints?



16-point model



20-point model



24-point model

"Adding more keypoints in anatomically ambiguous regions increases the risk of annotation noise, potentially reducing model reliability."

Results and Discussions (cont.)

OKS Evaluation of Model vs Physician-Annotated Keypoints

Model	Left	Right	Overall OKS
8-point	0.5010	0.4958	0.4983
12-point	0.5227	0.7817	0.7836
16-point	**0.9867**	**0.9880**	**0.9873**

"The 16-point model consistently outperformed others in OKS on both sides, indicating more accurate FNSA estimation aligned with physician annotations."

Results and Discussions (cont.)

Comparison of AI-based FNSA measurement methods.

Method	Images	Maximum	Minimum	Mean	SD
Manual measurement	124	145.34	114.67	131.60	6.02
Proposed approach	124	139.40	124.55	131.51	**3.34**
Wei, Qiang et al. [28]	60	137.41	117.67	129.51	5.59
Yang, Jia Yu et al. [29]	78	138.4	112.9	126.4	5.08

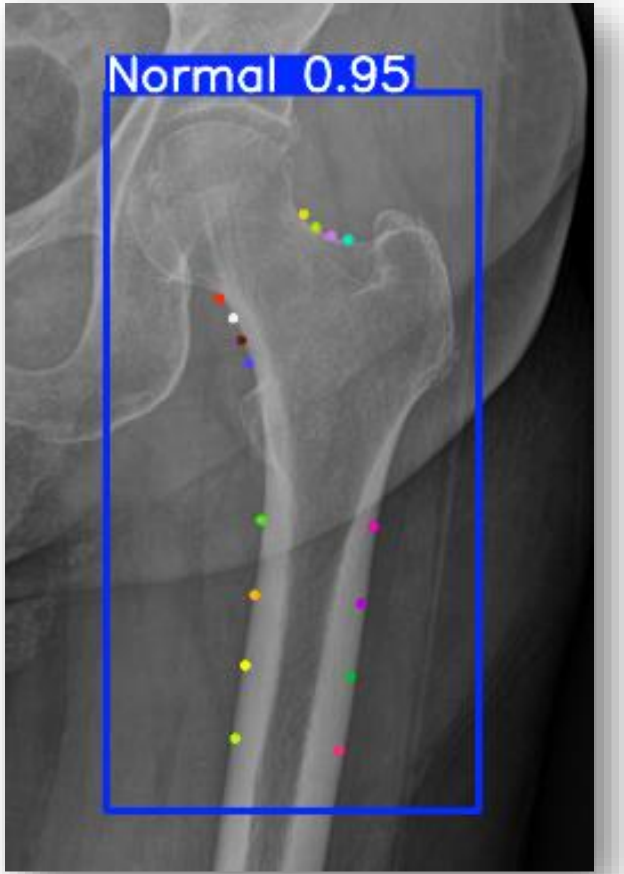
"The proposed method shows the lowest SD (3.34), reflecting more consistent and reliable FNSA measurements than other methods."

Results and Discussions (cont.)

Keypoints prediction

8-point model

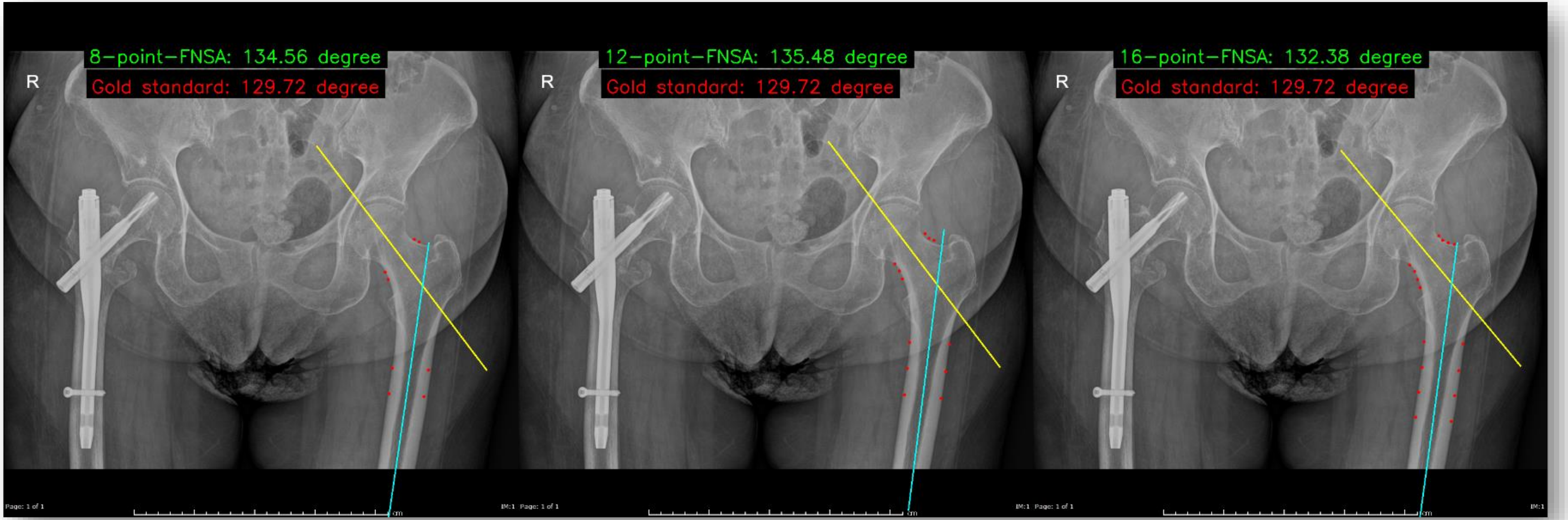
12-point model



16-point model

Results and Discussions (cont.)

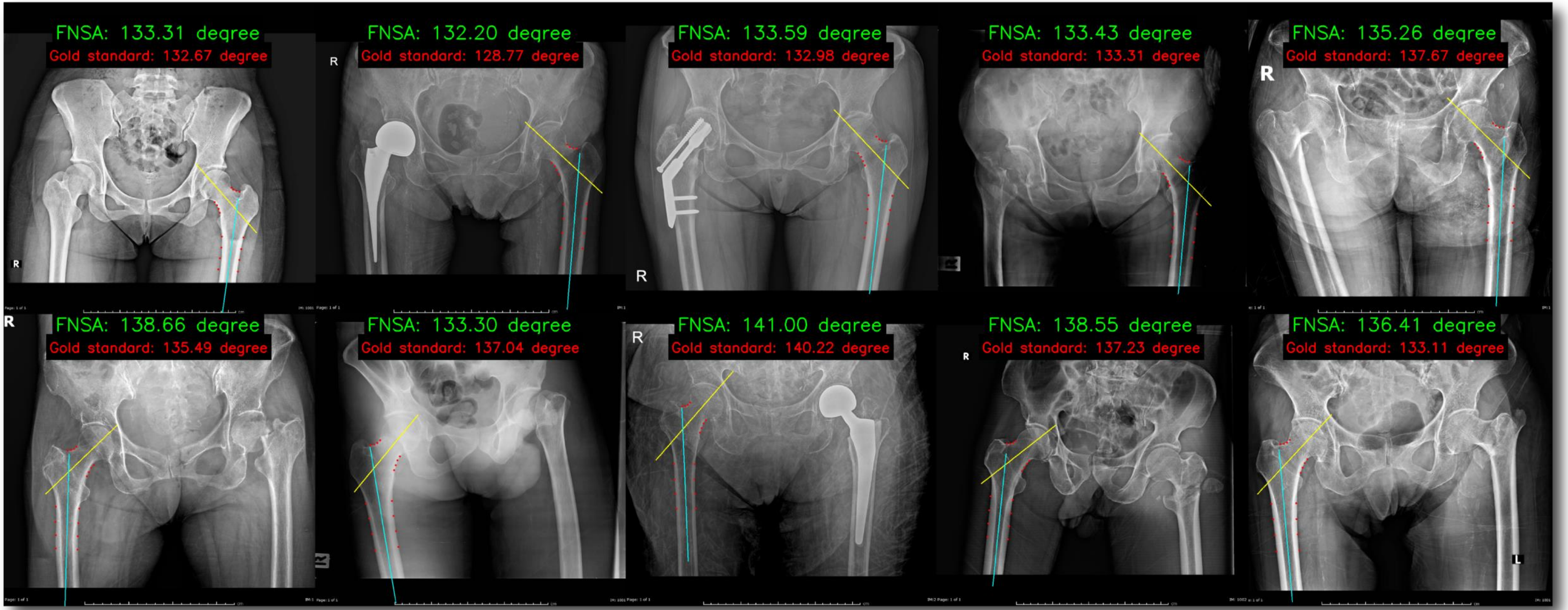
FNSA measurement



8-point model **12-point model** **16-point model**

Results and Discussions (cont.)

Visualization results of the 16-point model in various input sources.



Limitations and Future works

Limitations

- **Small dataset** limits generalization
- **Manual annotations** may introduce **bias**
- Reduced performance on **low-quality images**

Future Works

- **Collect** more **diverse** and **representative data**
- **Improve annotation consistency**
- **Tune hyperparameters** for better optimization
- **Enhance robustness** to image quality through preprocessing techniques

References

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THANK YOU

Automatic Measurement of Femoral Neck-Shaft Angle Using Keypoint Detection Technique

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Backup

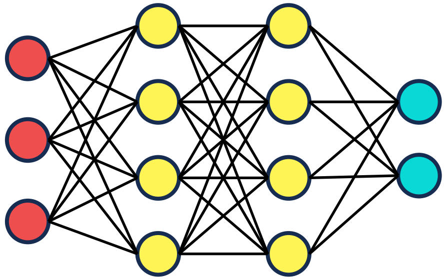
TEST

Example of Automatic measurement of FNSA

Test set

femoral left

➡



model

➡

FNSA?

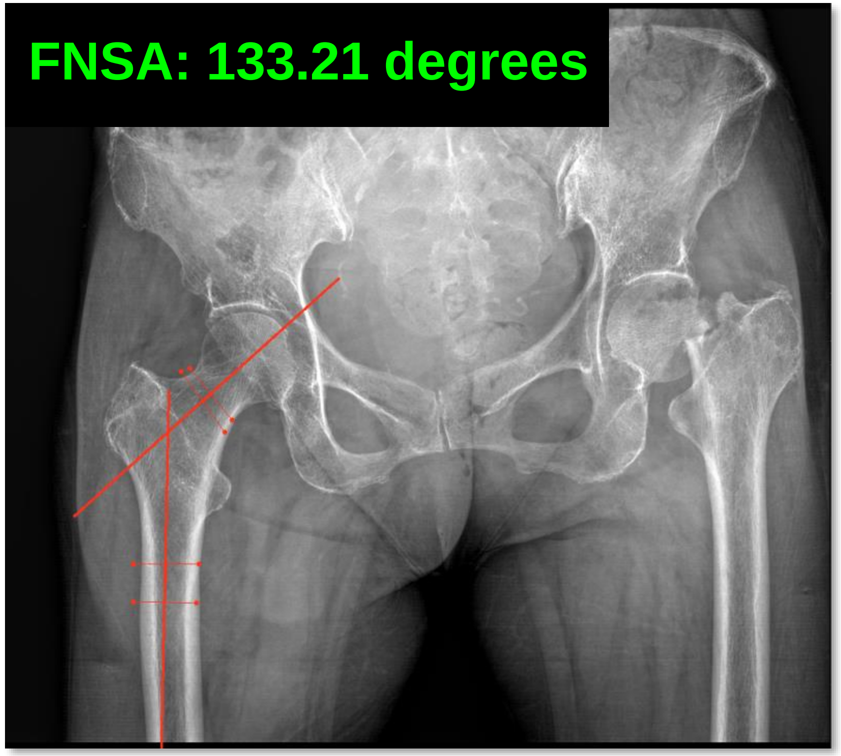
Example of Automatic measurement of FNSA

Test model

```python
import cv2 # type: ignore
import numpy as np # type: ignore
import ast
from sklearn.linear_model import LinearRegression # type: ignore
from ultralytics import YOLO # type: ignore

i = 1
s = "L"

# Load the YOLO model
model = YOLO(r"D:\Neck-Shaft-Angle\best-2point-less-data.pt")

# Predict with the model
image_path = rf"D:\Neck-Shaft-Angle\Testset-Normal-{s}-62img\Testset-Normal-{s}-{i}.jpg"
image = cv2.imread(image_path)
results = model(image_path)

def load_keypoints_from_file(filepath):
    with open(filepath, 'r') as file:
        data = file.read().strip()
        keypoints = ast.literal_eval(data)
    return keypoints

# Read average manual NSA from file
GSD_manual_file = rf"D:\Neck-Shaft-Angle\NSA_Gold_Standard-{s}.txt"
with open(GSD_manual_file, 'r') as file:
    GSD_manual_data = file.read()

GSD_manual = eval(GSD_manual_data)

# Load ground truth keypoints
manual_keypoint = rf"D:\Neck-Shaft-Angle\test-markpoint\M-testset-normal(L)-1.txt"
gt_keypoints = load_keypoints_from_file(manual_keypoint)

# Variables for Cal OKS
ground_truth_keypoints = np.array(gt_keypoints)
```

Automatic measurement of FNSA

The results of test set (124 images)



- Average absolute deviation = **3.40 degree**
- Average accuracy = **94.94%**
- Average OKS = **0.8763**

CNN

Spatial Information

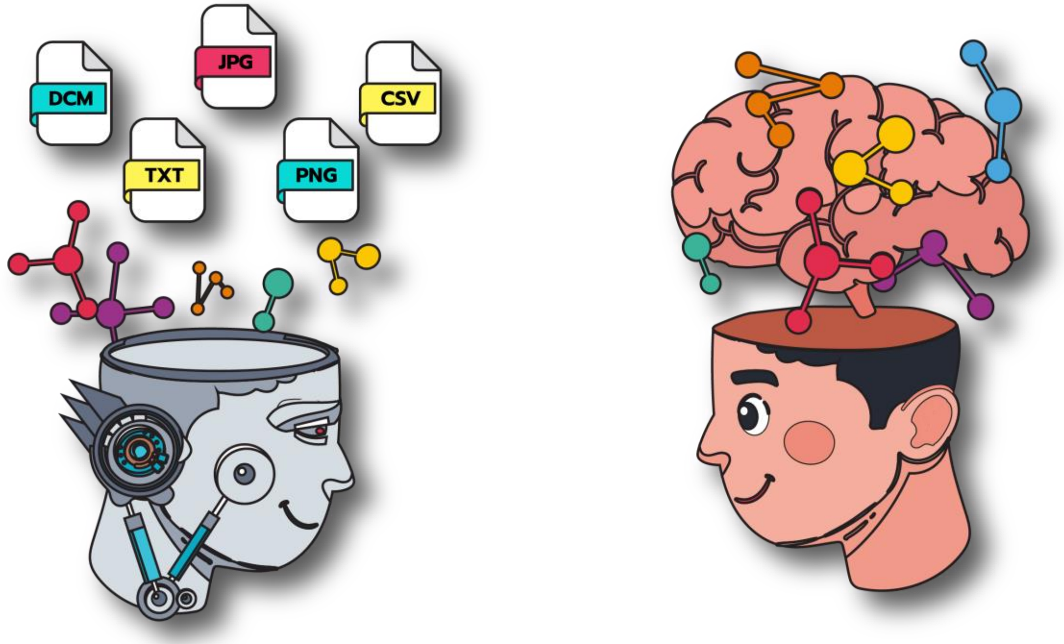
ยังไม่เสร็จ

Spatial information captures the **positional relationships** in data, allowing CNNs to **recognize patterns** and **understand context.**

ML & DL

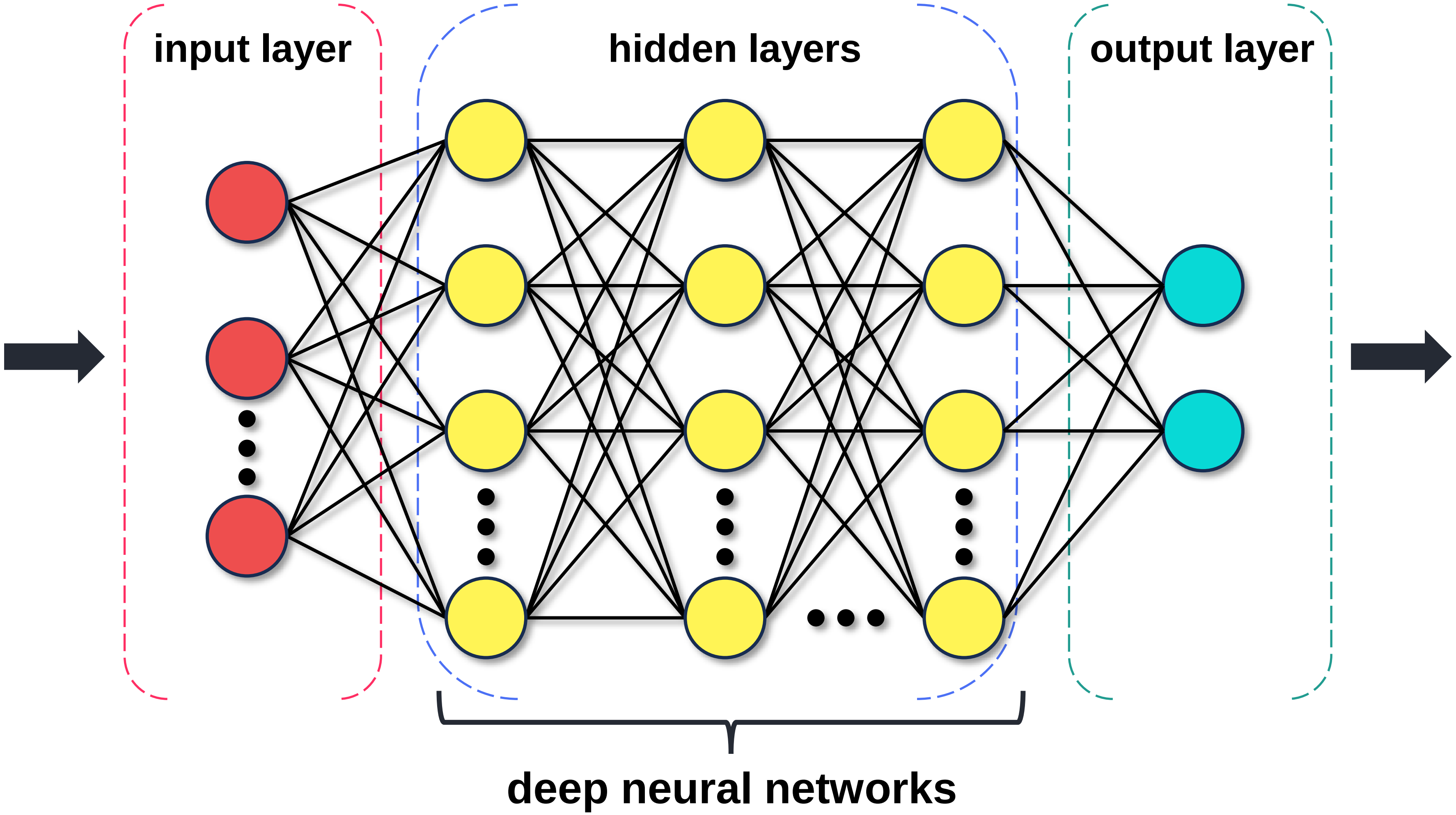
Machine learning

Machine learning is a method for developing computers to **learn, predict,** and **make decisions** based on the provided data [22].



Artificial Neural Networks

Simulate the structure of the **human brain [24]**.

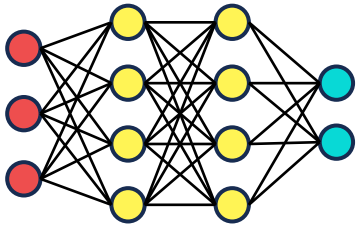


Watermelon or Orange?

Traditional Machine Learning

input image

feature extraction



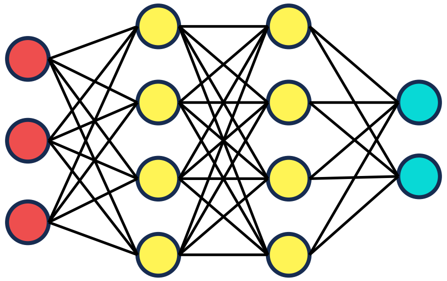
classification

output

watermelon

Deep Learning

input image



feature extraction + classification

output

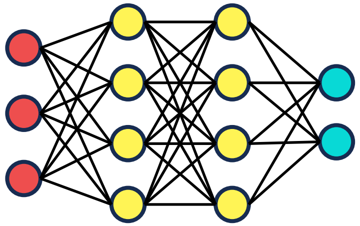
watermelon

Watermelon or Orange?

Traditional machine learning

input image

feature extraction

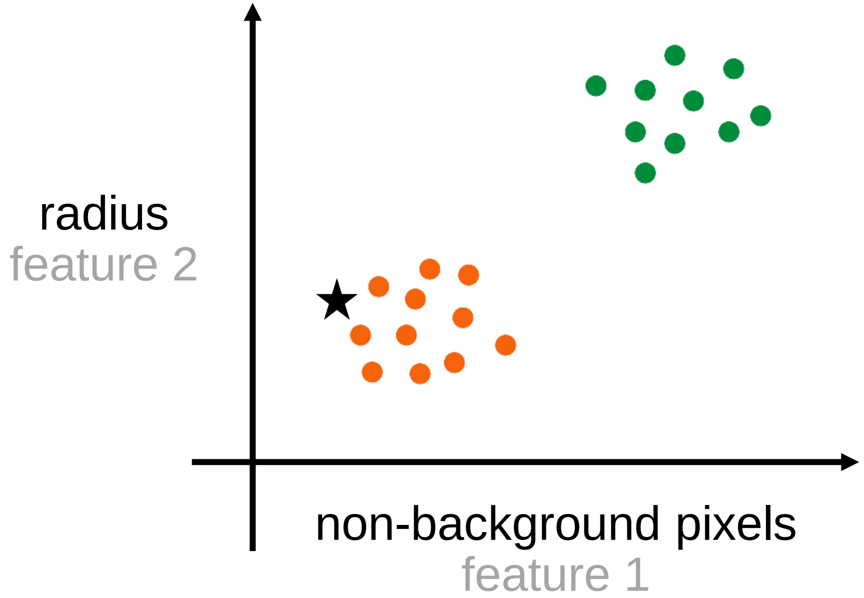


classification

output

watermelon

Phase: training

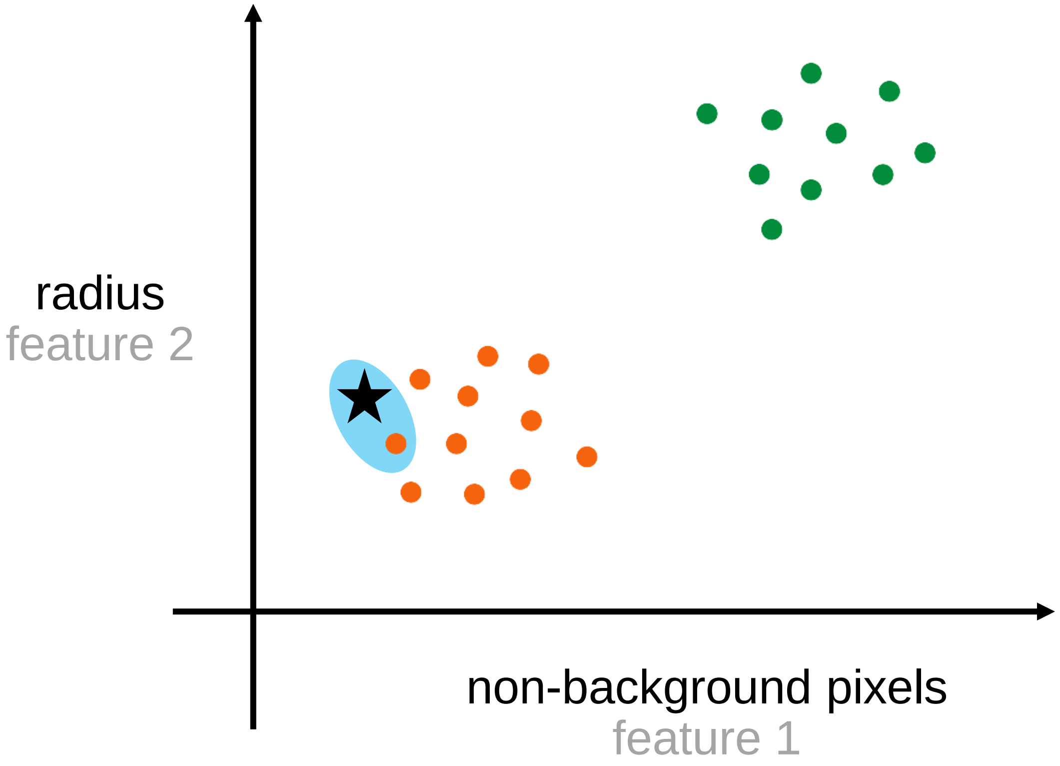


current sample

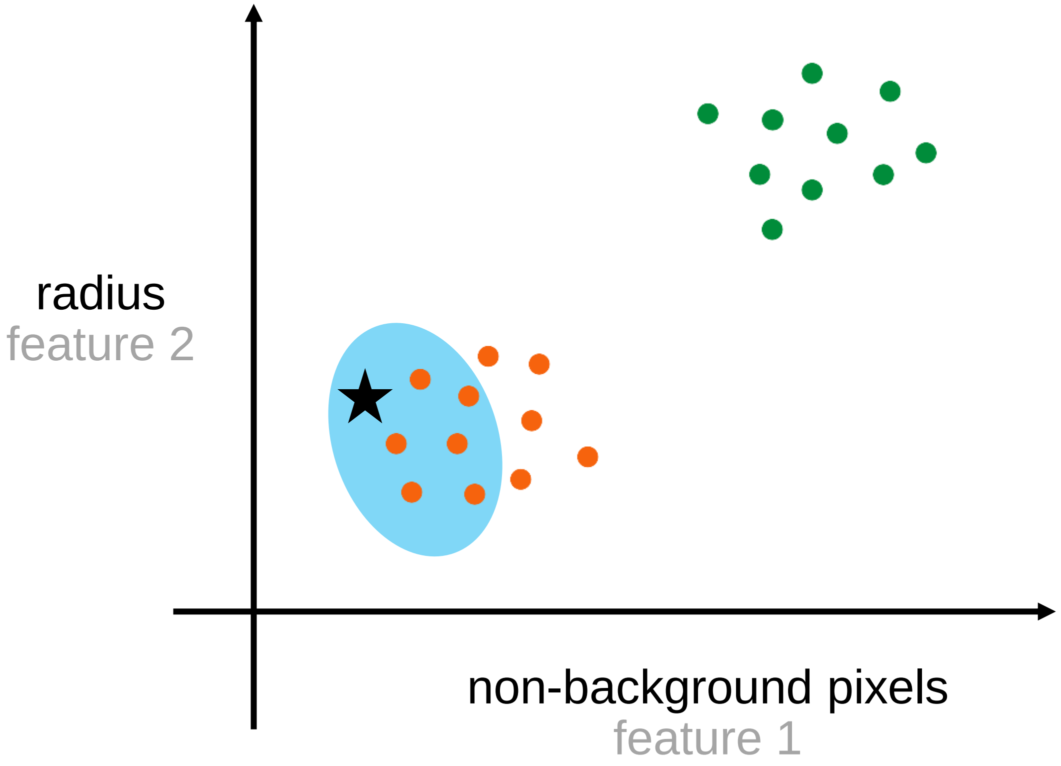
orange

Classical Method of Machine Learning

Nearest Neighbor

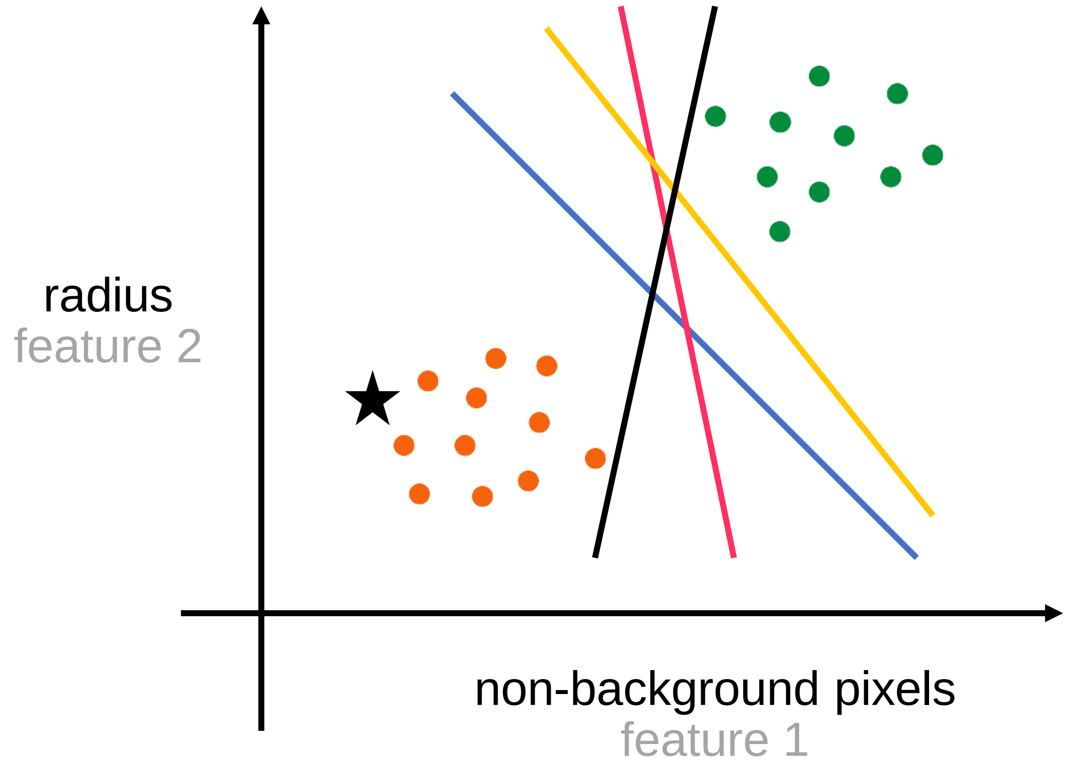


k-Nearest Neighbor (kNN)

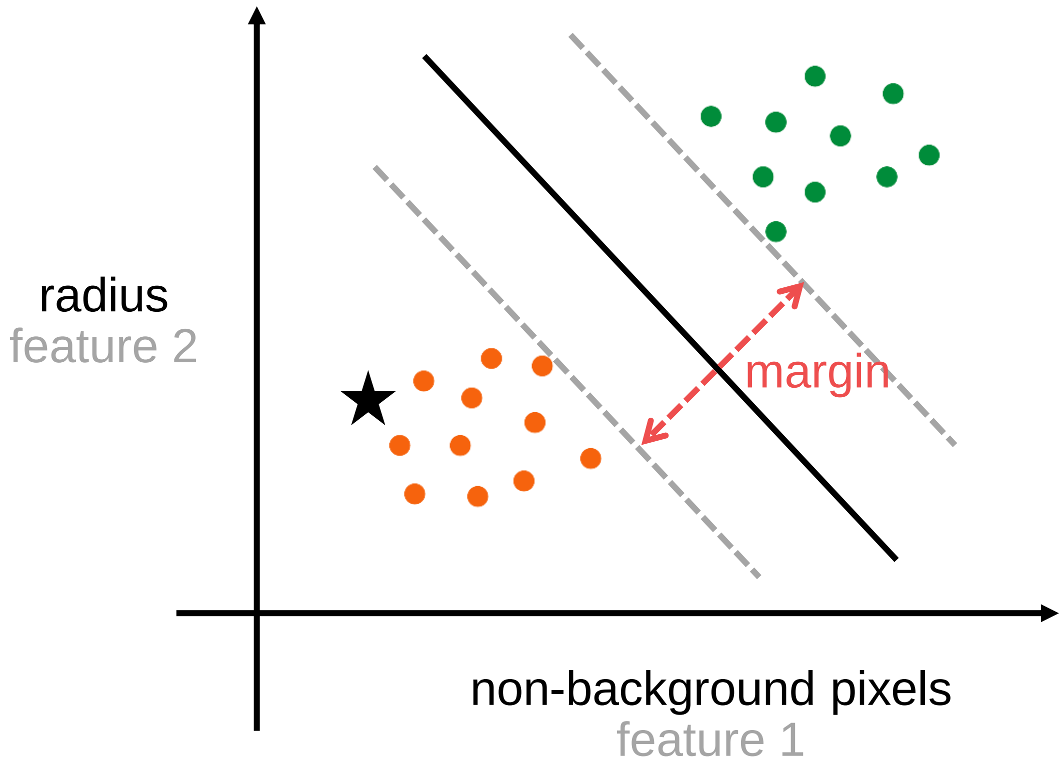


Classical Method of Machine Learning

Linear Classifier



Support Vector Machine (SVM)



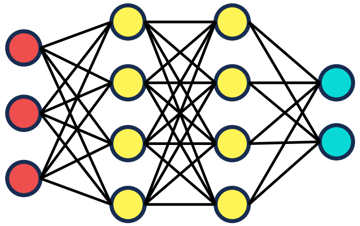
Watermelon or Orange?

Traditional machine learning

input image

feature extraction

classification

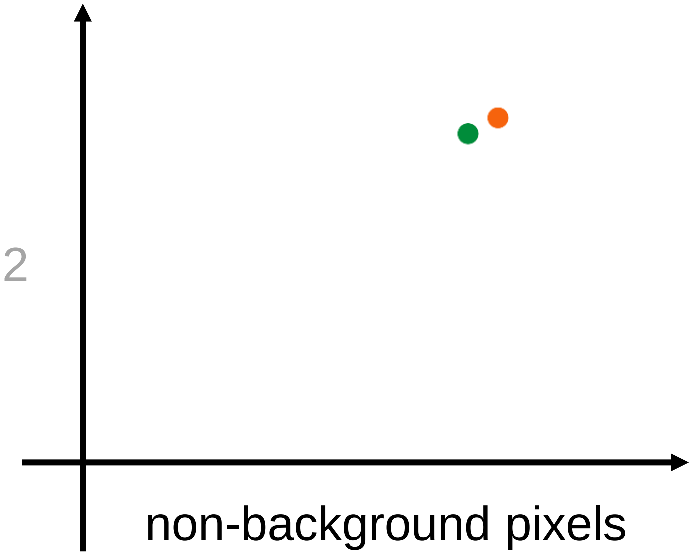


output

watermelon

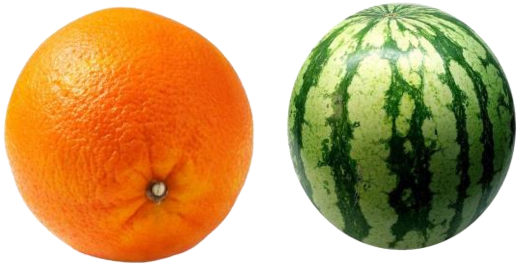
Phase: testset

radius
feature 2



non-background pixels
feature 1

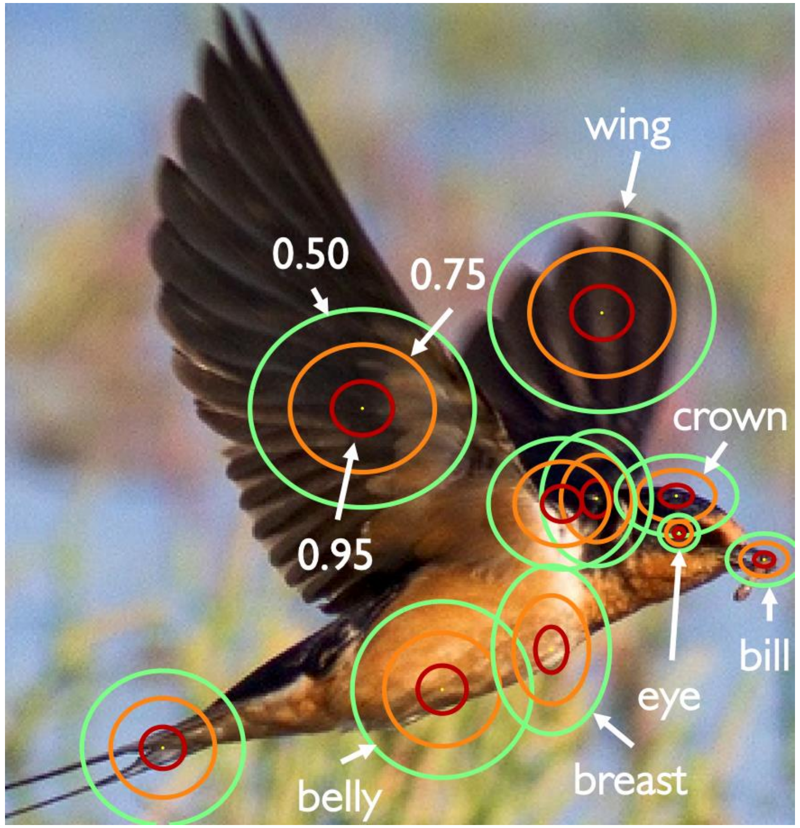
current sample



OKS

Object Keypoint Similarity (OKS)

OKS is used to measure the similarity between the predicted keypoints and the actual keypoints for an object.



https://weinman.cs.grinnell.edu/research/vlkp.shtml

- This metric ranges between 0 and 1.
- The closer the predicted keypoint to the actual, the closer will **OKS approach 1.**

Object Keypoint Similarity (OKS) (cont.)

$$OKS = \frac{\sum_i \left[\exp\left(-\frac{d_i^2}{2 s_i \sigma_i^2} \right) \bullet \delta\left(\upsilon_i > 0 \right) \right]}{\sum_i \left[\delta\left(\upsilon_i > 0 \right) \right]}$$

d_i is the euclidian distance between actual keypoint and predicted keypoint.

s_i is scale the area of the bounding box.

σ_i is the standard deviation between actual keypoint and predicted keypoint.

υ_i is the visibility of the i keypoint.

Object Keypoint Similarity (OKS) (cont.)

$$d = 10 \ , \quad s = 20$$

$$\sigma = [\,0.01,\ 0.1,\ 0.5,\ 0.8,\ 1\,]$$

$$OKS = \exp\left(-\frac{d_i^2}{2 s_i \sigma_i^2}\right) = \exp\left(-\frac{10^2}{2\cdot(20\cdot 0.01)^2}\right) = \exp\left(-\frac{100}{2\cdot(0.04)}\right) = \exp\left(-\frac{100}{0.08}\right) = \exp(-12.5) \approx 0$$

$$OKS = \exp\left(-\frac{d_i^2}{2 s_i \sigma_i^2}\right) = \exp\left(-\frac{10^2}{2\cdot(20\cdot 0.1)^2}\right) = \exp\left(-\frac{100}{2\cdot 4}\right) = \exp\left(-\frac{100}{8}\right) = \exp(-12.5) \approx 0.000003726$$

$$OKS = \exp\left(-\frac{d_i^2}{2 s_i \sigma_i^2}\right) = \exp\left(-\frac{10^2}{2\cdot(20\cdot 0.5)^2}\right) = \exp\left(-\frac{100}{2\cdot 100}\right) = \exp\left(-\frac{100}{200}\right) = \exp(-0.5) \approx 0.6065$$

$$OKS = \exp\left(-\frac{d_i^2}{2 s_i \sigma_i^2}\right) = \exp\left(-\frac{10^2}{2\cdot(20\cdot 0.8)^2}\right) = \exp\left(-\frac{100}{2\cdot 256}\right) = \exp\left(-\frac{100}{512}\right) = \exp(-0.1953) \approx 0.8225$$

$$OKS = \exp\left(-\frac{d_i^2}{2 s_i \sigma_i^2}\right) = \exp\left(-\frac{10^2}{2\cdot(20\cdot 1)^2}\right) = \exp\left(-\frac{100}{2\cdot 400}\right) = \exp\left(-\frac{100}{800}\right) = \exp(-0.125) \approx 0.8825$$