

YOLO object detection model

Journal Club : October 4, 2024

Commentator

Ekapob Sangariyanich, MD.



Outline

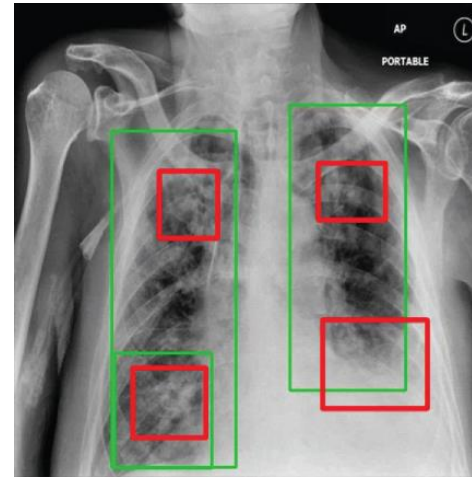
- Object detection model
- Object detection metrics
- Example use of YOLO in medical images

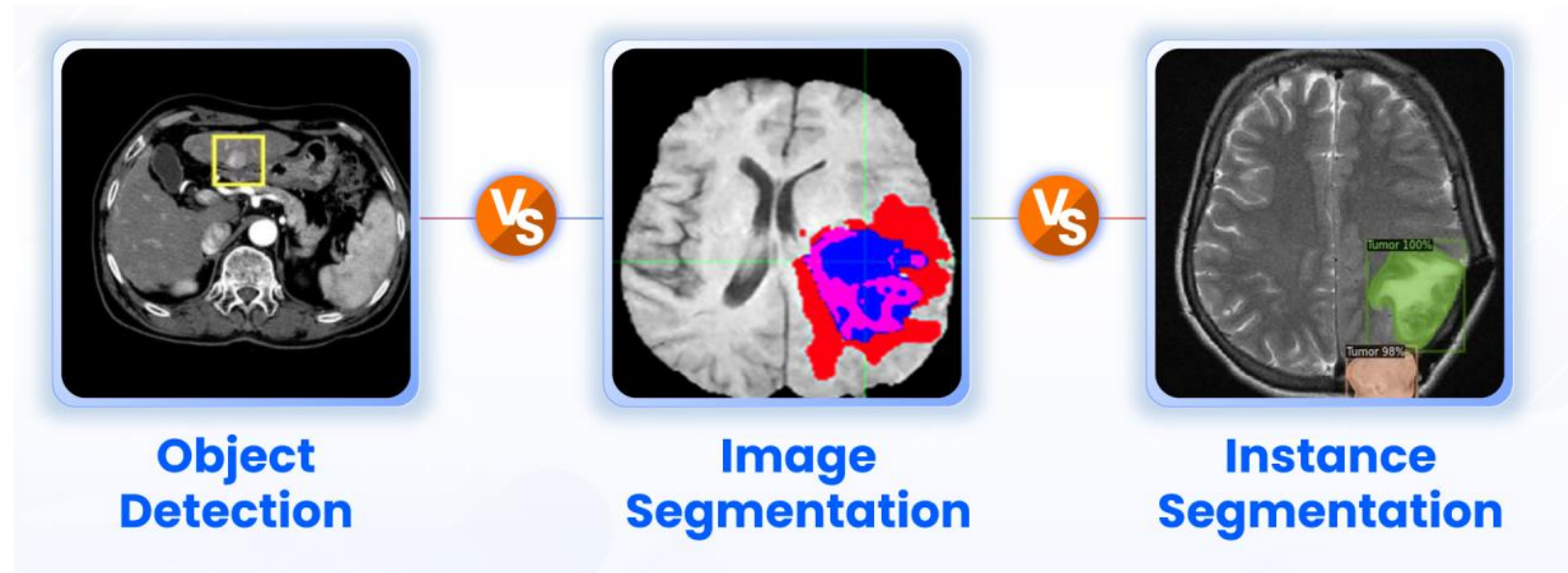


Object detection VS Image classification

Advantage of object detection

- Localization
- Detail orientation
- Contextual understanding
- Dynamic monitoring

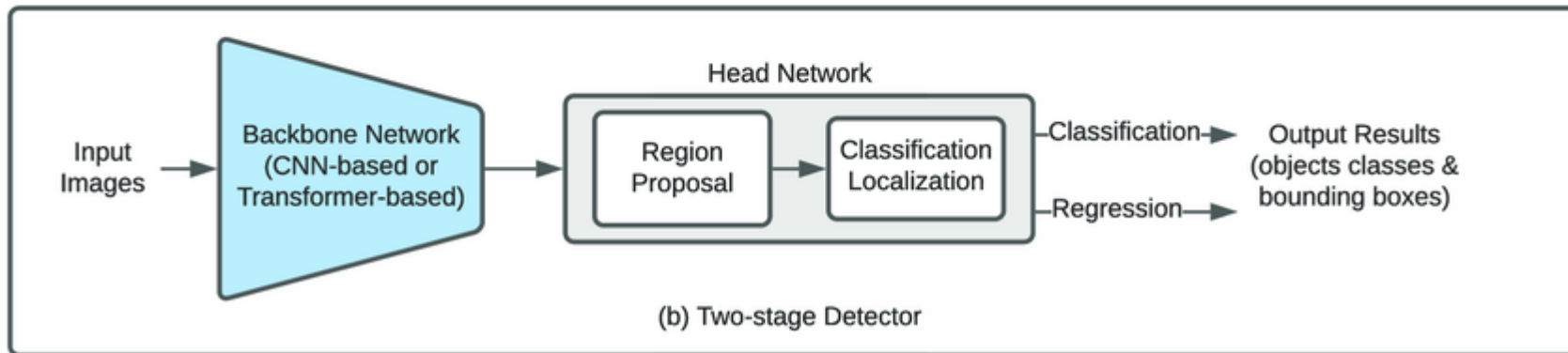
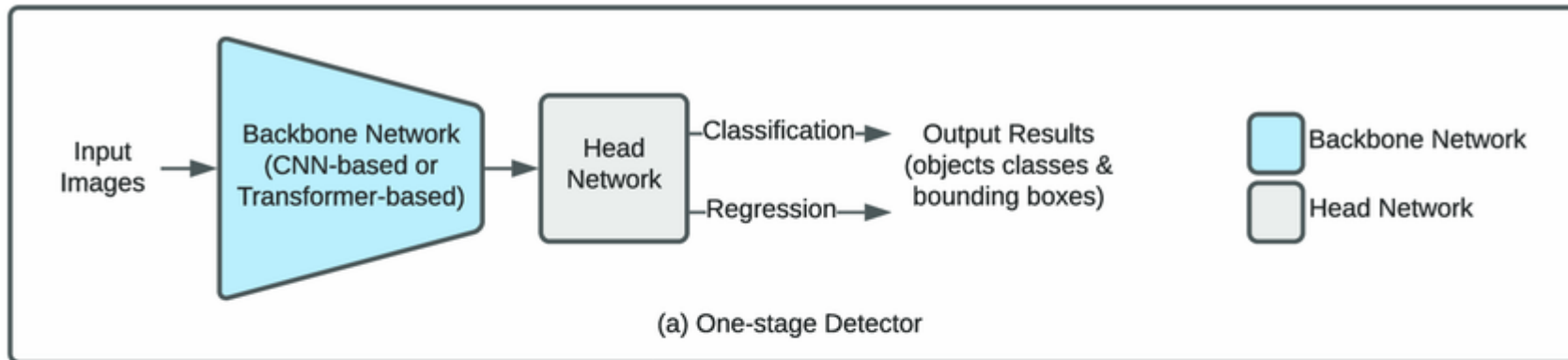




Advantage	Speed	Comprehensive understanding	Detail and precision
Application	Identify fracture in ER	Brain MRI scan	lung CT scans for detecting lung nodules



Object detection model



1. Single stage e.g.

- YOLO (You Only Look Once)
- SSD (Single Shot Multibox Detector)
- RetinaNet

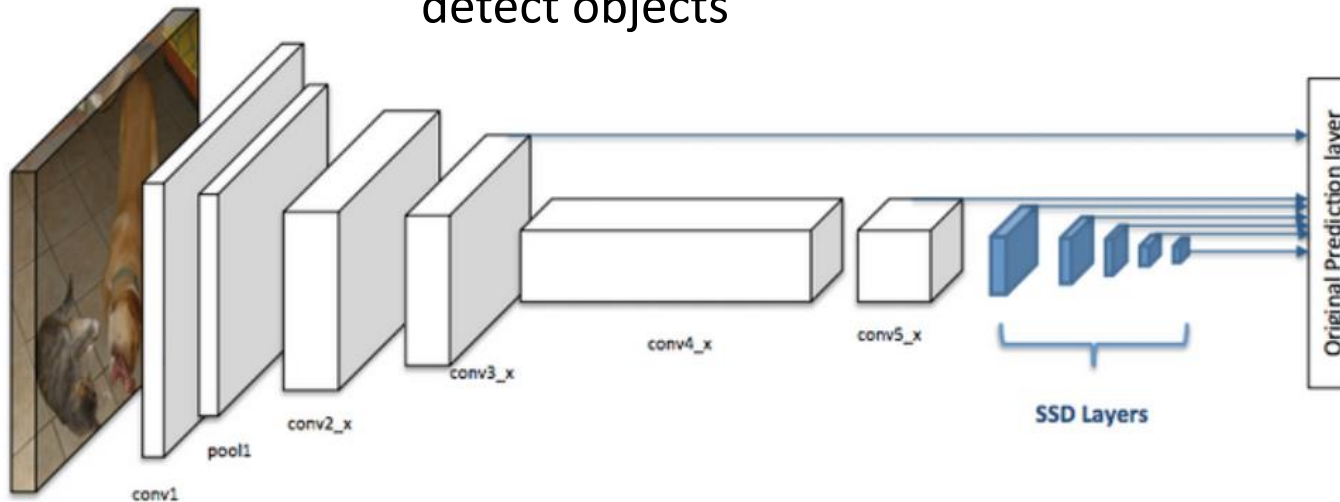
2. Two stage e.g.

- RCNN (Region-based Convolution Neural Network)
- Fast RCNN , Faster RCNN
- SPP (Spatial Pyramid Pooling networks)



SSD (2016)

- Backbone : Conv. network for feature extraction
- SSD head : Apply multi-scale feature map for detect objects



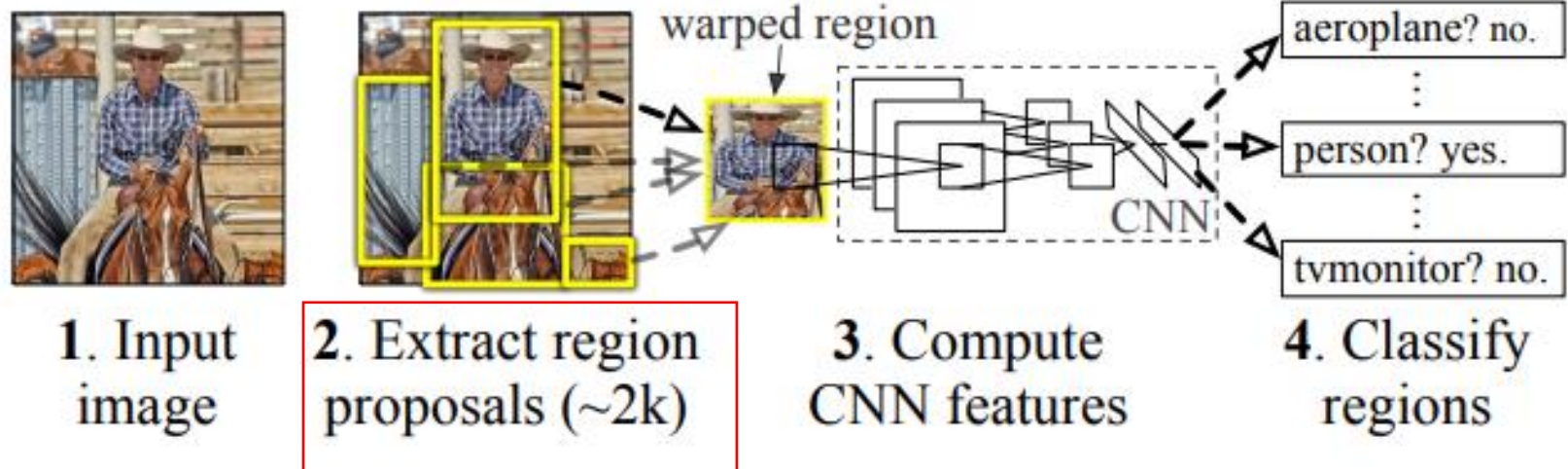
- Fast but slightly slower than YOLO
- SSD usually performs badly for small objects comparing with other detection methods.
- Good accuracy than YOLO

Figure 3. Architecture of a convolutional neural network with a SSD detector [2]



R-CNN (2013)

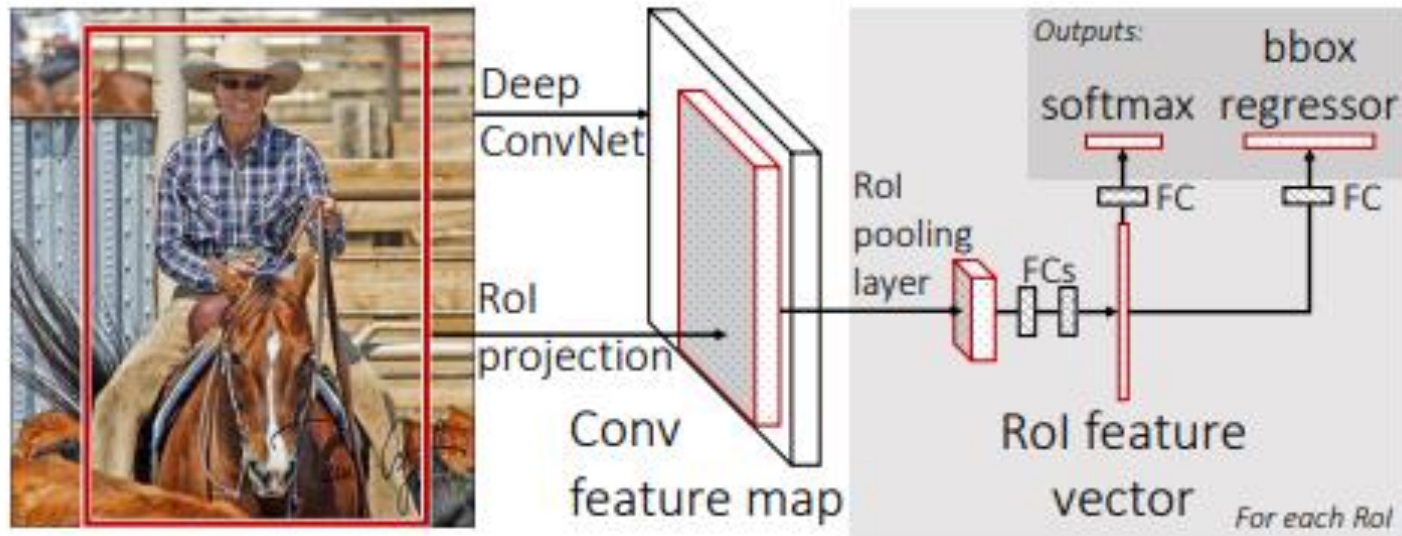
R-CNN: *Regions with CNN features*



Selective search



Fast R-CNN (2015)

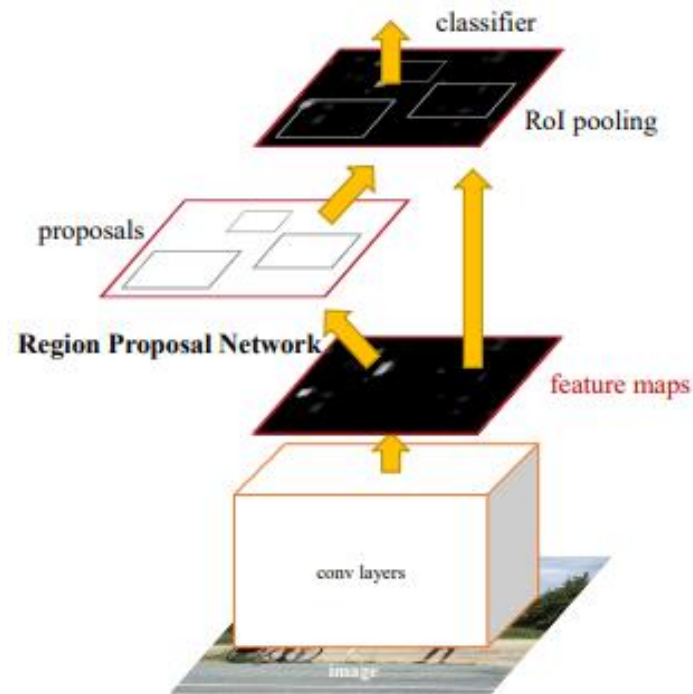


-Girshick, Ross B.. "Fast R-CNN." (2015).

-Ren, Shaoqing, et al. "Faster R-CNN: Towards real-time object detection with region proposal networks." *IEEE transactions on pattern analysis and machine intelligence* 39.6 (2016): 1137-1149.



Faster R-CNN (2015)



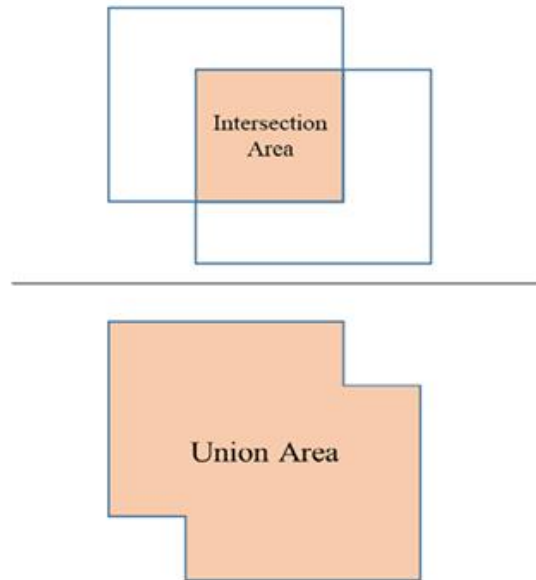
- **Region proposal network**
predicting whether there is an object or not and also predicting the bounding box of those objects.
- **ROI pooling layer**
reshape RPN region to fixed size for classification and bounding box regression



Object detection performance metrics

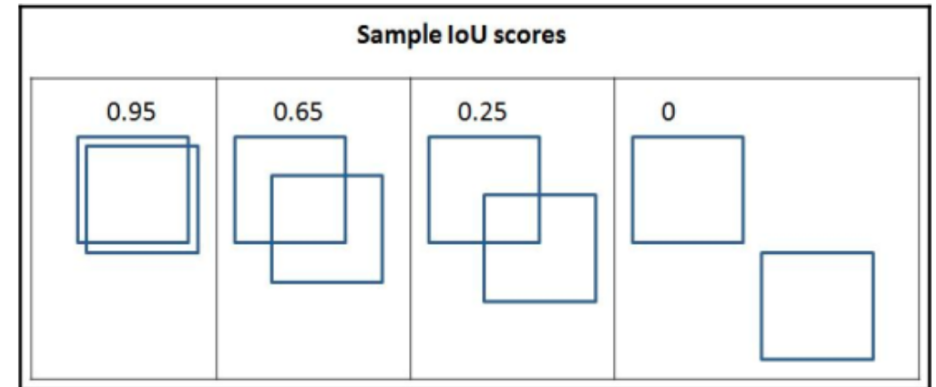
- Intersection over Union (IoU)

$$IoU = \frac{\text{overlapping area}}{\text{union area}} =$$



- > 0.5 Acceptable
- > 0.7 Good
- > 0.95 Excellent

- Class prediction :
Positive if $IoU \geq IoU \text{ threshold}$
Negative if $IoU < IoU \text{ threshold}$





Department of Clinical Epidemiology and Biostatistics

True Positive



IoU = 0.922

False Positive

- Incorrect localization
- Incorrect classification



IoU = 0.258

False Negative



IoU = 0.00

IoU Threshold = 0.5

True Positives [TP]

Object detections with
 $\text{IoU} \geq \text{IoU threshold}$

False Positives [FP]

Object detections with
 $\text{IoU} < \text{IoU threshold}$

False Negatives [FN]

No objects detected

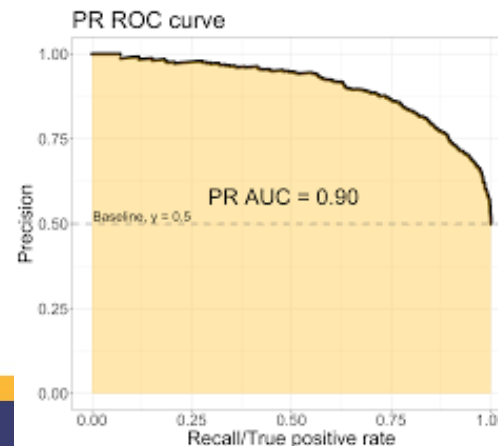


Object detection performance metrics

- Accuracy, Precision, F1-score, Recall, Specificity
- Average Precision (AP)

= AUC for precision-recall curve (AUPRC)

- PR Curve is plot between precision and recall with varying IOU threshold



◦ Precision (P) = $TP / (TP + FP)$

◦ Recall (R) = $TP / (TP + FN)$



- Mean average precision(mAP)

-The mAP is calculated by finding Average Precision(AP) for each class and then average over a number of classes.

$$mAP = \frac{1}{n} \sum_{k=1}^{k=n} AP_k$$

AP_k = the AP of class k

n = the number of classes

- mAP50 calculates AP at an IoU of 0.5 .

- mAP50-95 averages AP calculated at IoU thresholds from 0.5 to 0.95 with a step size of 0.05 .



- Detection speed (FPS)

$$\text{FPS} = \frac{\text{Number of frames processed}}{\text{Total time taken (seconds)}}$$

- real-time detector → at least 30 frames per second (FPS)
- smooth performance → at least 60 frames per second (FPS)



Example use of YOLO in medical images

STBi-YOLO: A Real-Time Object Detection Method for Lung Nodule Recognition

KEHONG LIU ^{ID}

College of Computer Science and Technology, Xi'an University of Science and Technology, Xi'an, Shaanxi 710054, China

K. Liu, "STBi-YOLO: A Real-Time Object Detection Method for Lung Nodule Recognition," in *IEEE Access*, vol. 10, pp. 75385-75394, 2022, doi: 10.1109/ACCESS.2022.3192034

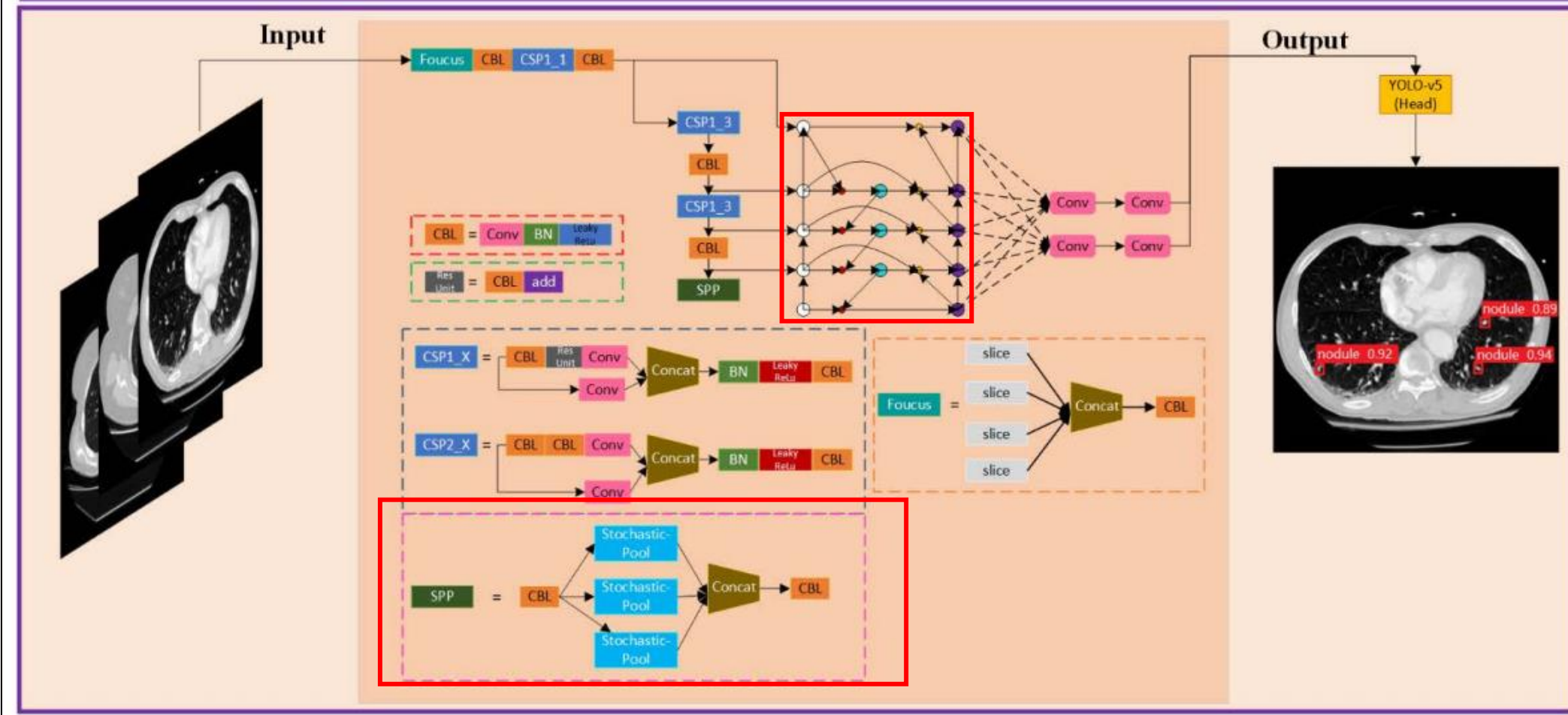


Introduction

- Lung nodules, which can indicate early-stage lung cancer, typically appear as small, round shadows on CT scans, measuring up to 3 cm in diameter.
- Tiny size nodules are similar to blood vessels.
- This complicates accurate diagnosis, making the screening process inefficient and increasing the risk of misdiagnosis.
- When applying the YOLO-v5 algorithm to lung CT images, it performs with poor detection accuracy and low processing speed.



Lung nodule detection based on STBi-YOLO





Experimental settings

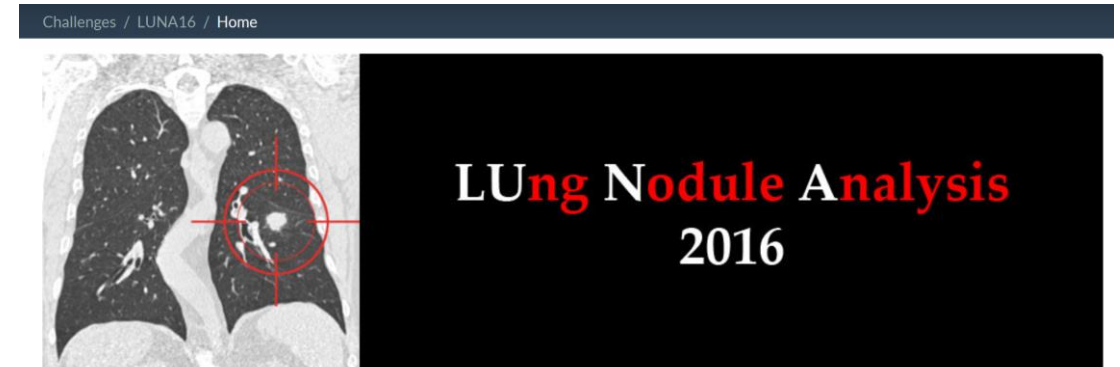
- Tensorflow deep learning network
- GPU:NVIDIA Tesla K80; accelerated using CUDA v11.0 and CuDNN v8.0
- The programming language of this model is Python.
- Train proposed model (STBI-YOLO), YOLO-v3, YOLO -v4, and YOLO-v5 with the same parameter settings.
- Model parameter settings

Parameters	Values
weight decay	0.0005
batch size	4
learning rate	0.01
epoch	300



Experimental dataset

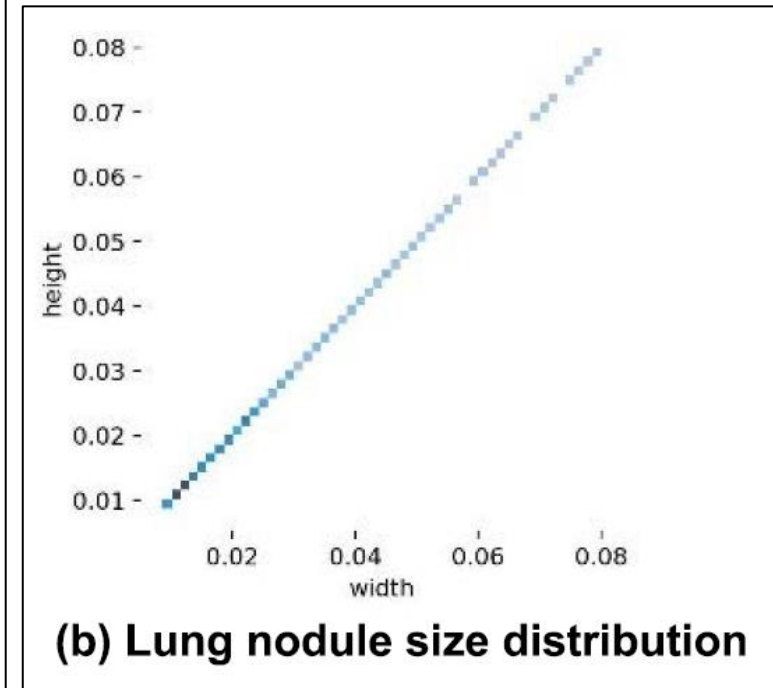
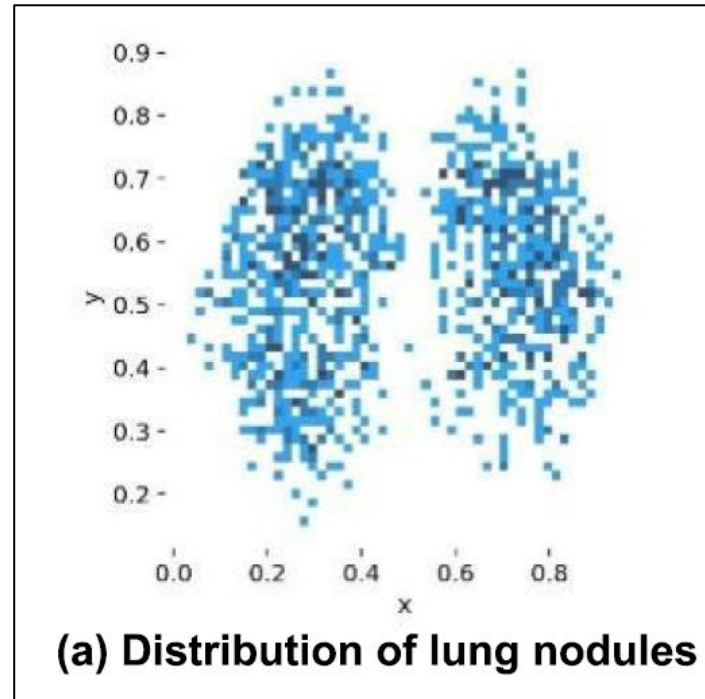
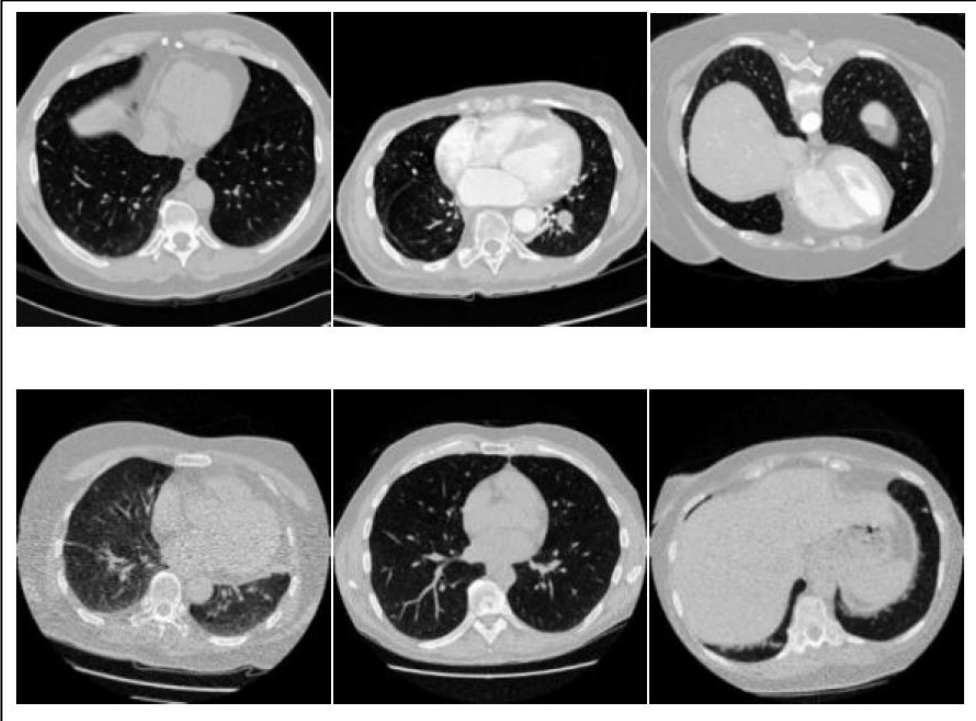
- LUNA16 (high quality lung nodule CT image dataset launched in 2016)
- This dataset contains a total of 888 3D lung CT image, 1,186 lung nodules and 36,378 annotated information by four professional radiologists.
- The dataset consists of four main parts:
 - 1) the original CT images
 - 2) the annotation files of lung nodule locations
 - 3) the original CT lung regional segmentation files
 - 4) the diagnosis result files
- Train-test-validation = 70% : 15% : 15%



<https://luna16.grand-challenge.org/>



Department of Clinical Epidemiology and Biostatistics



Dataset analysis

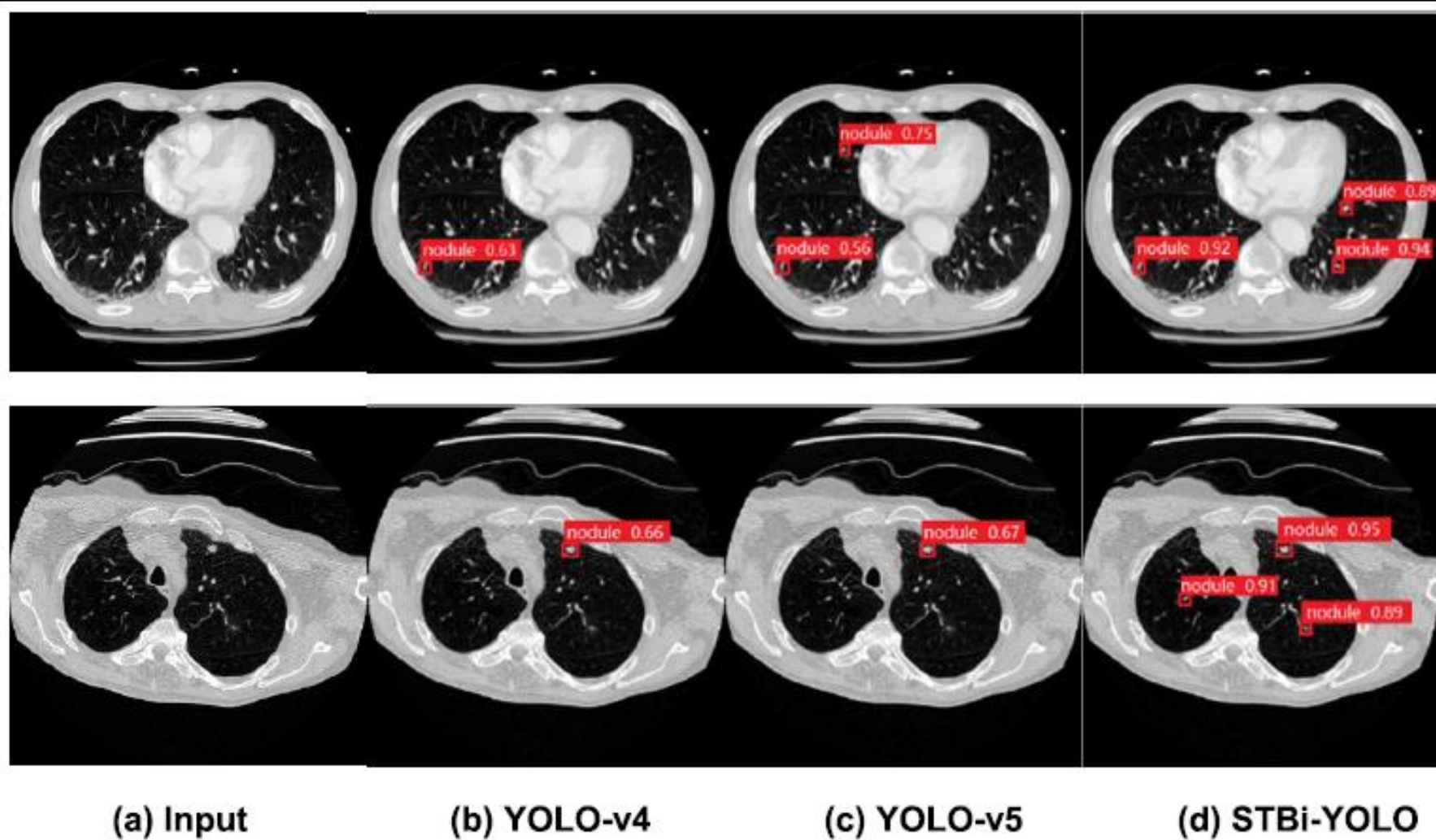


FIGURE 10. Experimental results.



Experimental results

Model	Weights/MB	mAP/%	Recall/%	Detection speed/FPS
Faster R-CNN	159	91.9	92.5	191
Mask R-CNN	121	73.65	78.3	54
SSD	100.2	75.2	77.0	98
YOLO-v3	235	81.3	82.9	59
YOLO-v4	246	88.4	90.0	41
YOLO-v5s	41.9	90.8	91.1	25
STBi-YOLO	43.6	95.9	96.7	27



Thank you for your attention