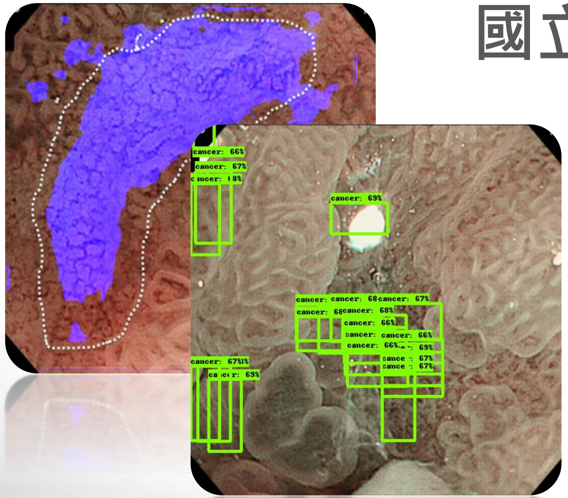
基於輕量型密集連接網路之擴大窄頻影像圖像胃癌區域檢測

Gastric Cancer Region Detection for Magnified Narrow Band Imaging images Based on Lightweight Densely Connected Convolutional Networks

國立屏東科技大學 資訊管理系



報告人：簡志宇
指導教授： 許志仲 助理教授

Outline

- Introduction
- Related Work
- Motivation
- Limitations of the Study
- Method
- Experiment Result
- Conclusion

Introduction

- The demand for endoscopy of gastric cancer is increasing, but not all doctors can determine the condition of a patient's symptoms immediately.
- Computer-aided detection (CADe) can effectively help doctors in areas that require special attention during the detection

※Reducing errors caused by fatigue caused by repeated detections by doctors.

Introduction

- High-performance detection network, conditions must include:
  - The Sensitivity of the lesion area must be high
  - The False-negative must be low
  - The detection time must be short
- It is difficult to achieve these performances only by using the published network for deep learning training.

Introduction

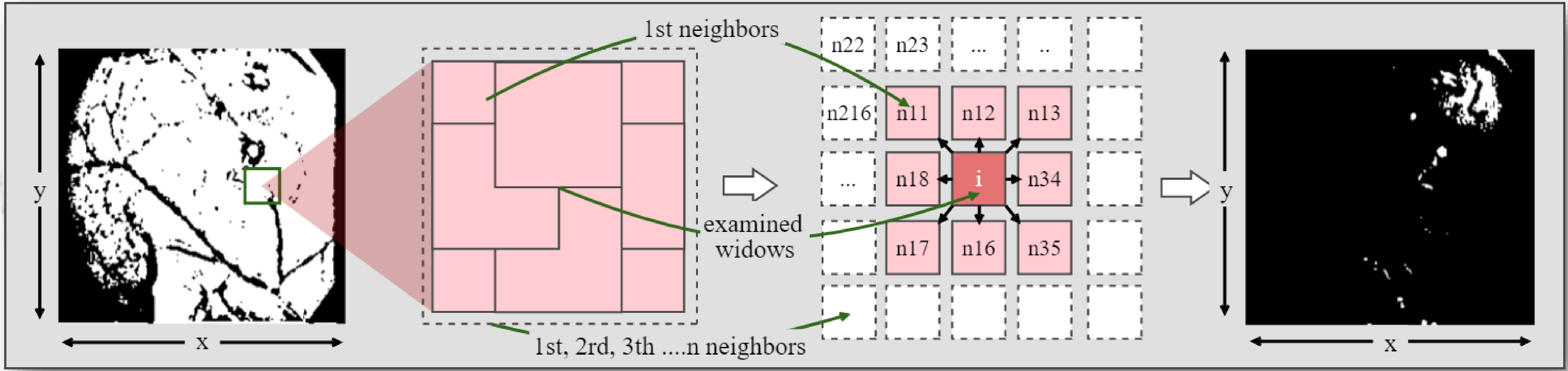
Semantic Segmentation network

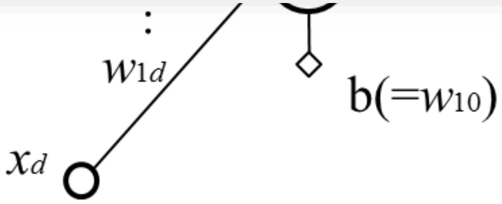
※not fast enough !

Object Detection network	+	Semantic Segmentation network	=	Combined Two Network

※ more faster?
※ same performance or inefficient?

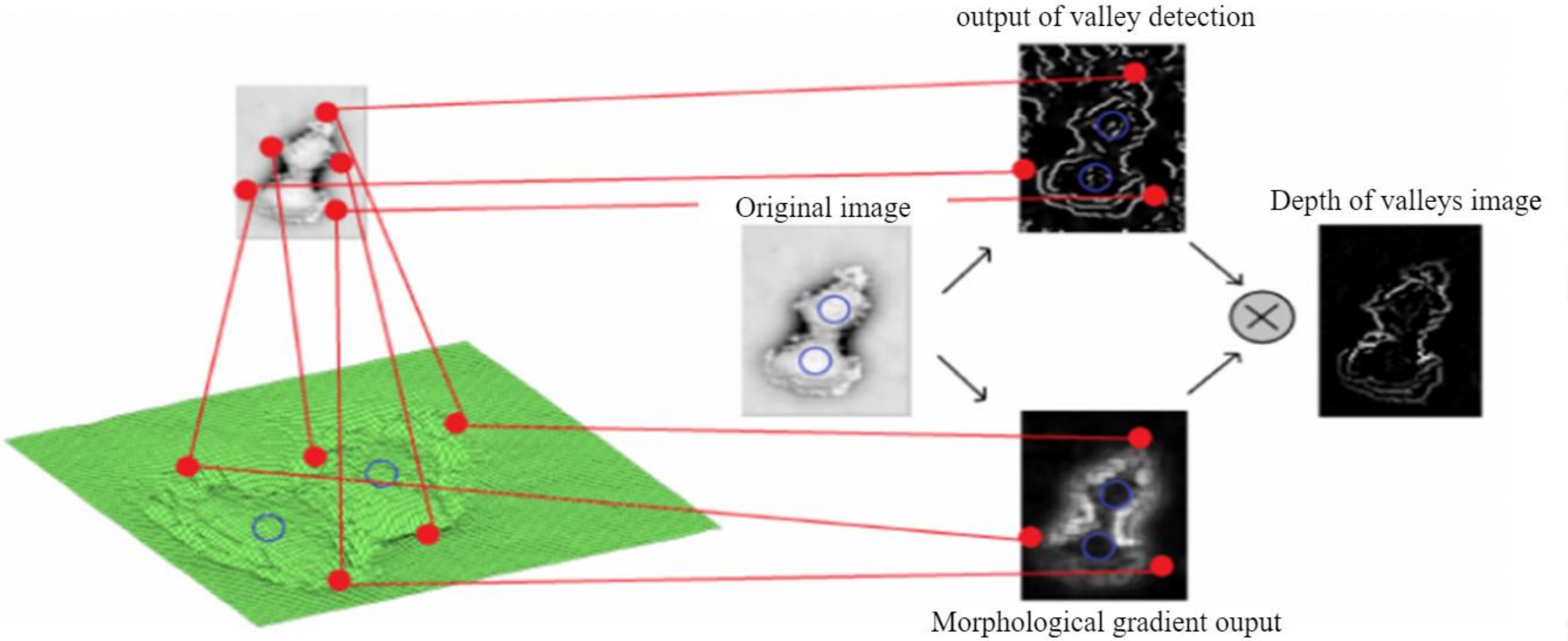
Related Work – Related technologies I





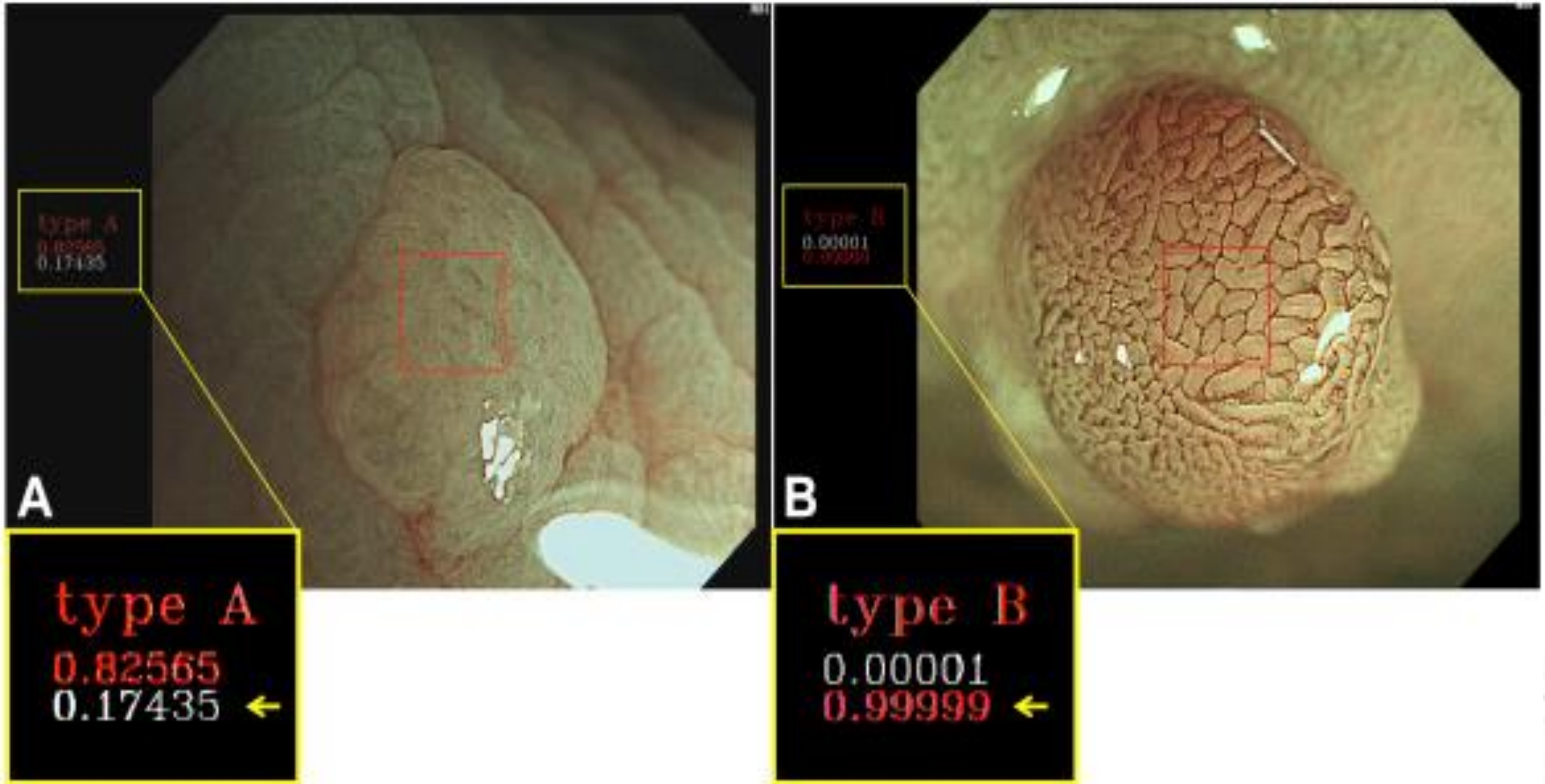
Maroulis, Dimitrios E., et al., "CoLD: a versatile detection system for colorectal lesions in endoscopy video-frames," Computer Methods and Programs in Biomedicine , Vol. 70, No.2, pp.151-166, 2003.

Related Work – Related technologies II



Bernal, Jorge, et al., "WM-DOVA maps for accurate polyp highlighting in colonoscopy: Validation vs. saliency maps from physicians," Computerized Medical Imaging and Graphics , Vol. 43, pp. 99-111, 2015

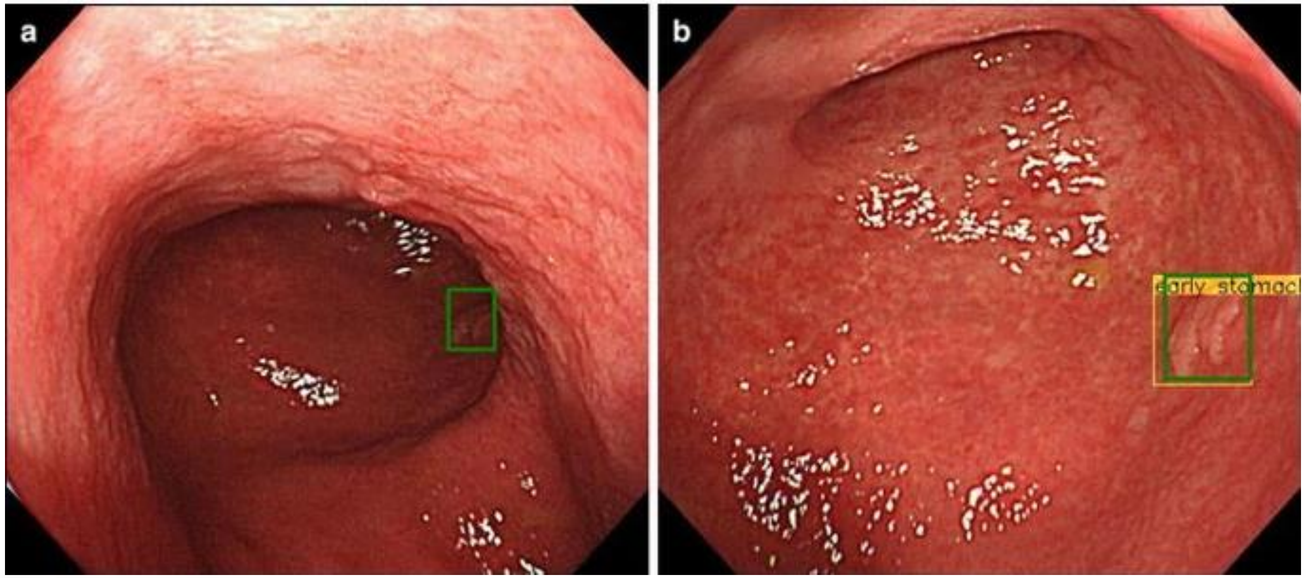
Related Work – Related technologies III



imaging magnifying colonoscopy," Gastrointestinal endoscopy , Vol. 83, No.3, pp. 643-649,2016.

Related Work – Related technologies IV

- Using Deep Learning for detecting gastric cancer
  - Using SSD (Single Shot Multibox Detector) net build detect network



Green box = ground truth

Yellow box = predicted result

Hirasawa, Toshiaki, et al., "Application of artificial intelligence using a convolutional neural network for detecting gastric cancer in endoscopic images." Gastric Cancer , Vol. 21, No. 4 ,pp. 653-660, 2018.

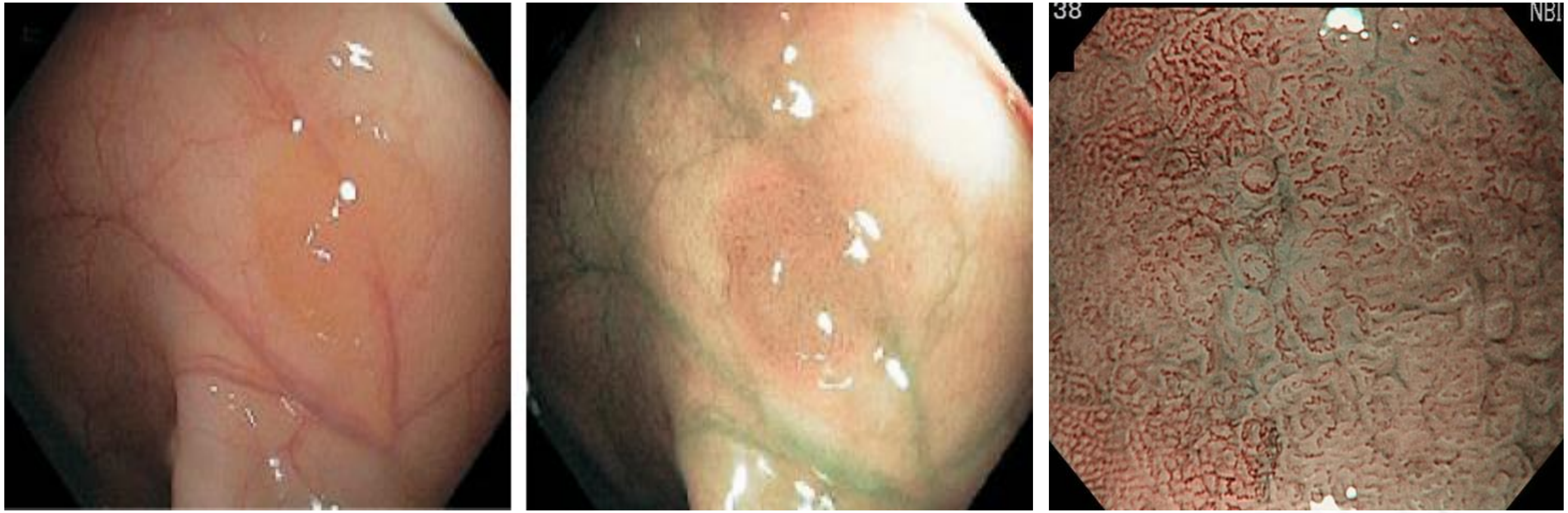
Related Work – Related technologies IV

- Current CAD testing equipment can help doctors quickly find diseased areas.
- Most device are very expensive.
- Difficult to detection early diseased cells.

- It must needs a lot of data to train a good deep learning network.
- Need a doctor to help make a good dataset.

Related Work – M-NBI

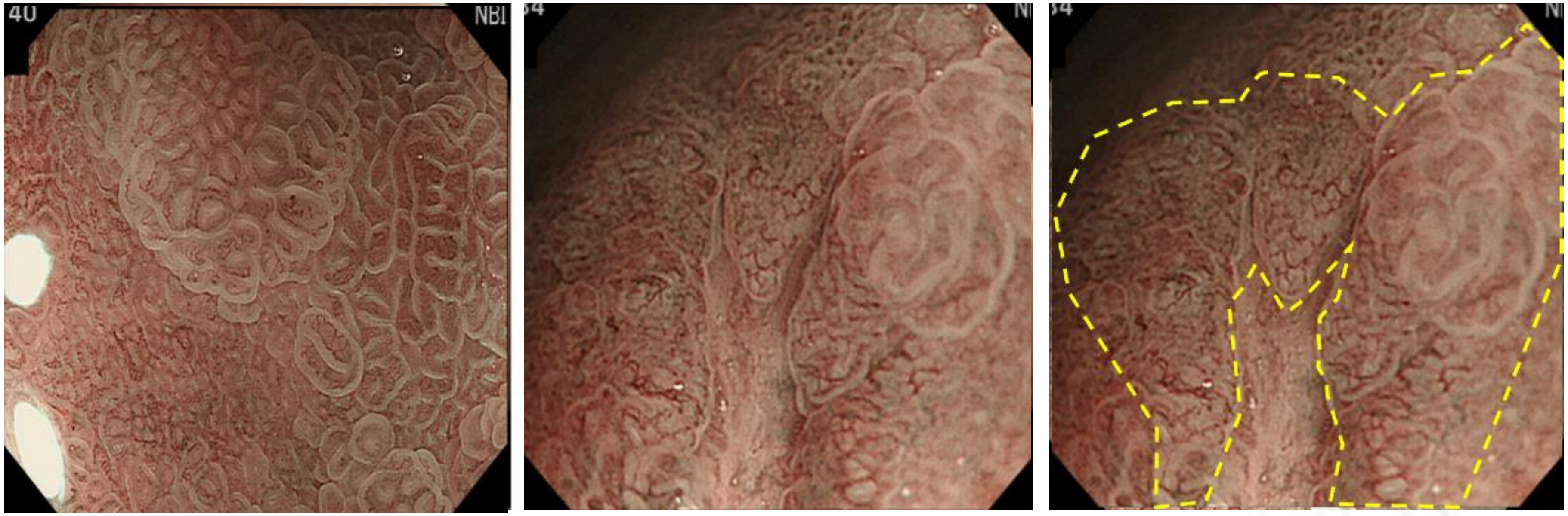
- M-NBI



Endoscopy	NBI	M-NBI

Related Work – M-NBI

- M-NBI



No-cancer	Cancer	Segmentation Map (Ground Truth)

Related Work – Data Augmentation

- Data Augmentation

=4 + 1 =5

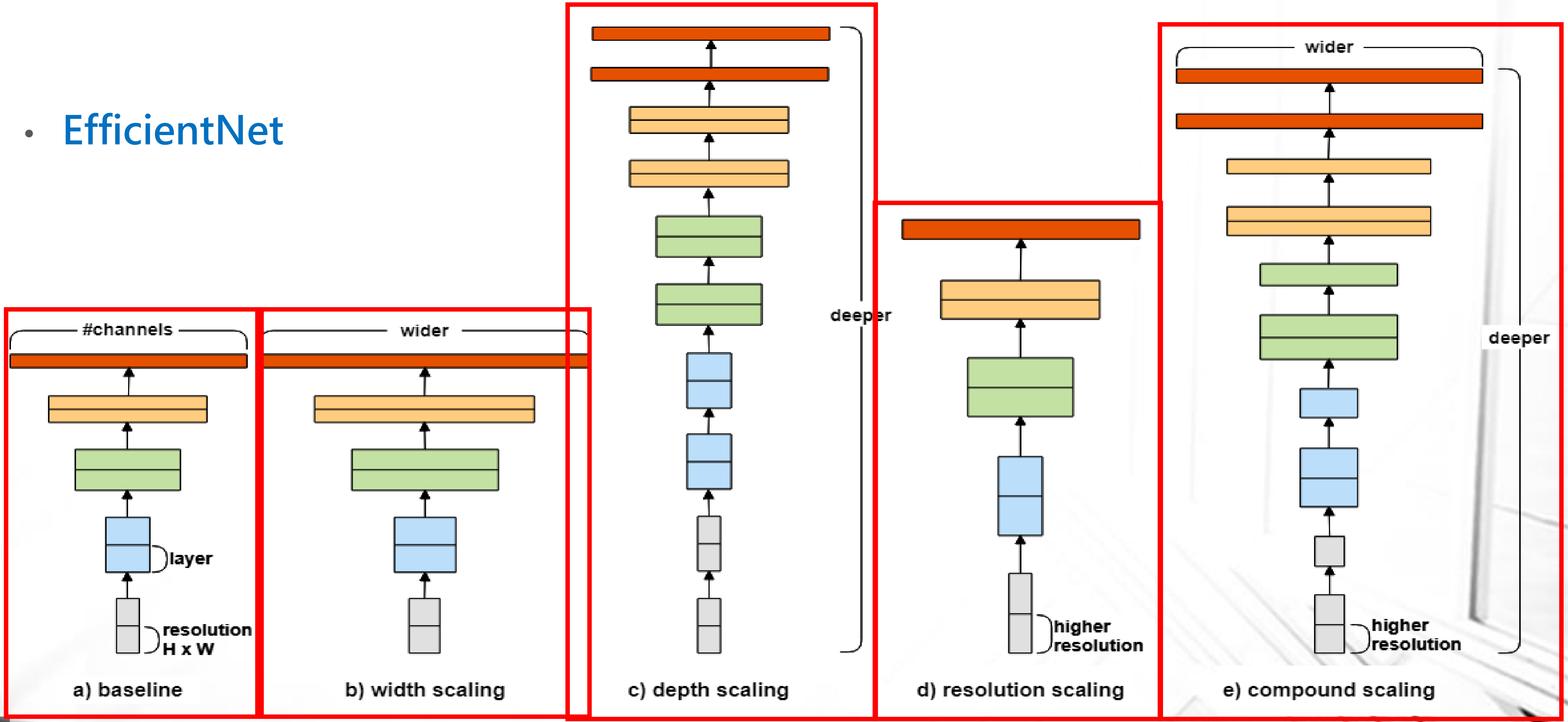
=4 + 1 =5

=4 + 4 + 1 =9

Zhong, Zhun, et al., "Random erasing data augmentation," arXiv preprint arXiv:1708.04896 , 2017.

Related Work – Backbone Network

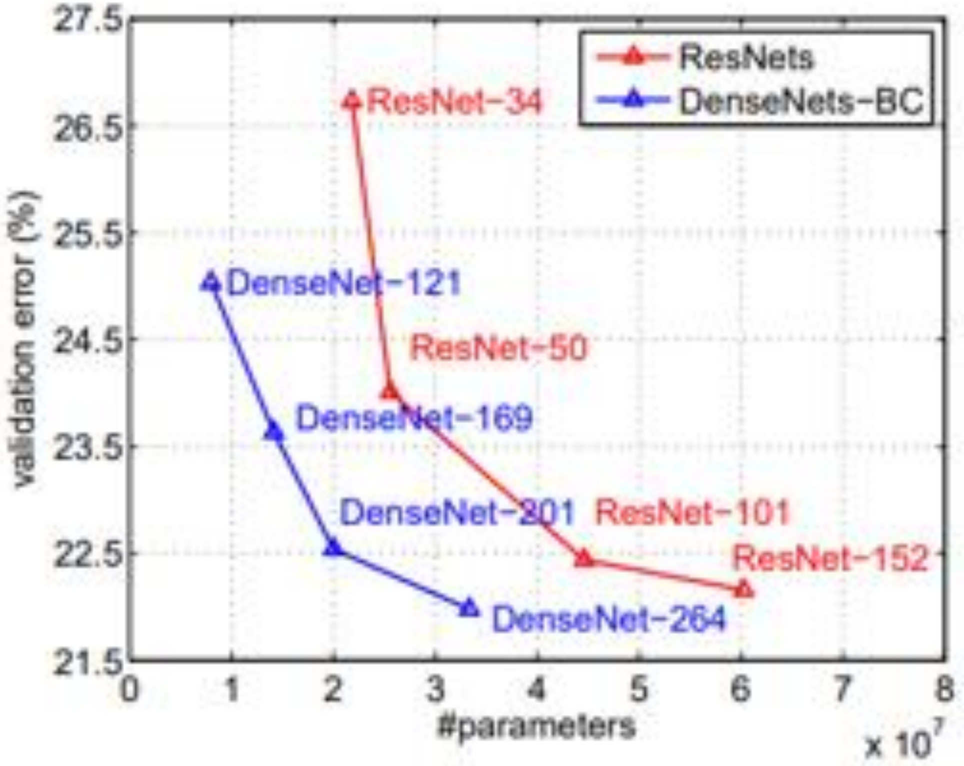
- EfficientNet

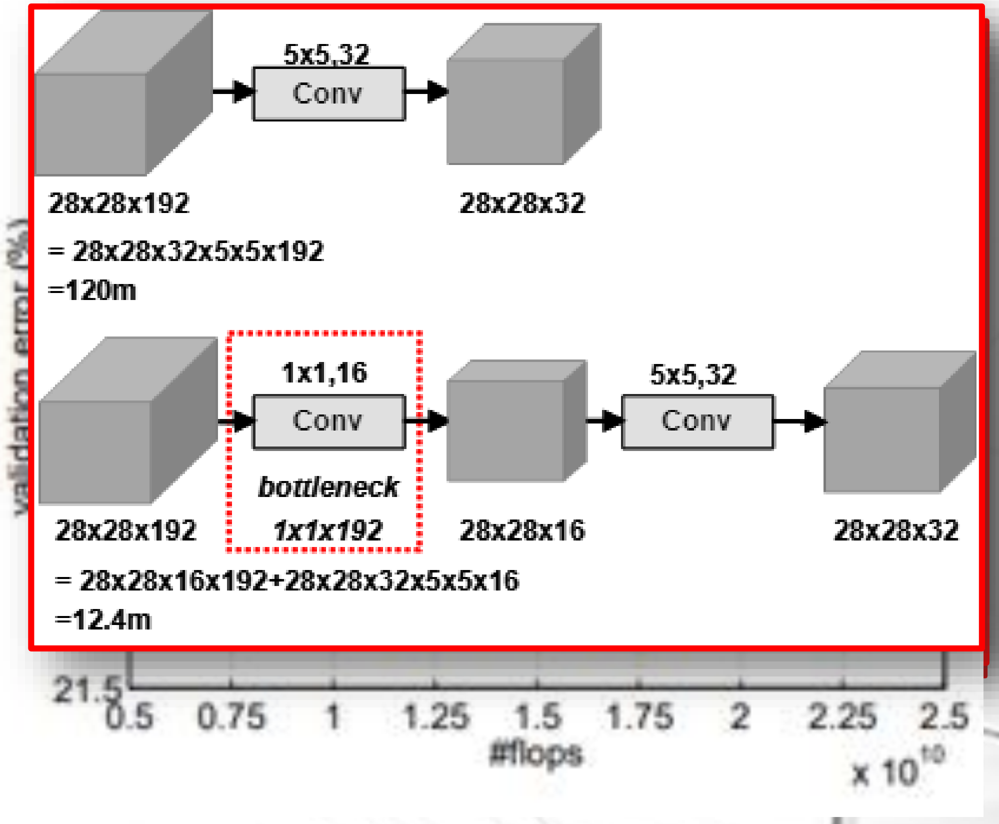


Tan, Mingxing, and Quoc V. Le, "Efficientnet: Rethinking model scaling for convolutional neural networks," arXiv preprint arXiv:1905.11946, 2019.

Related Work – Backbone Network

- [





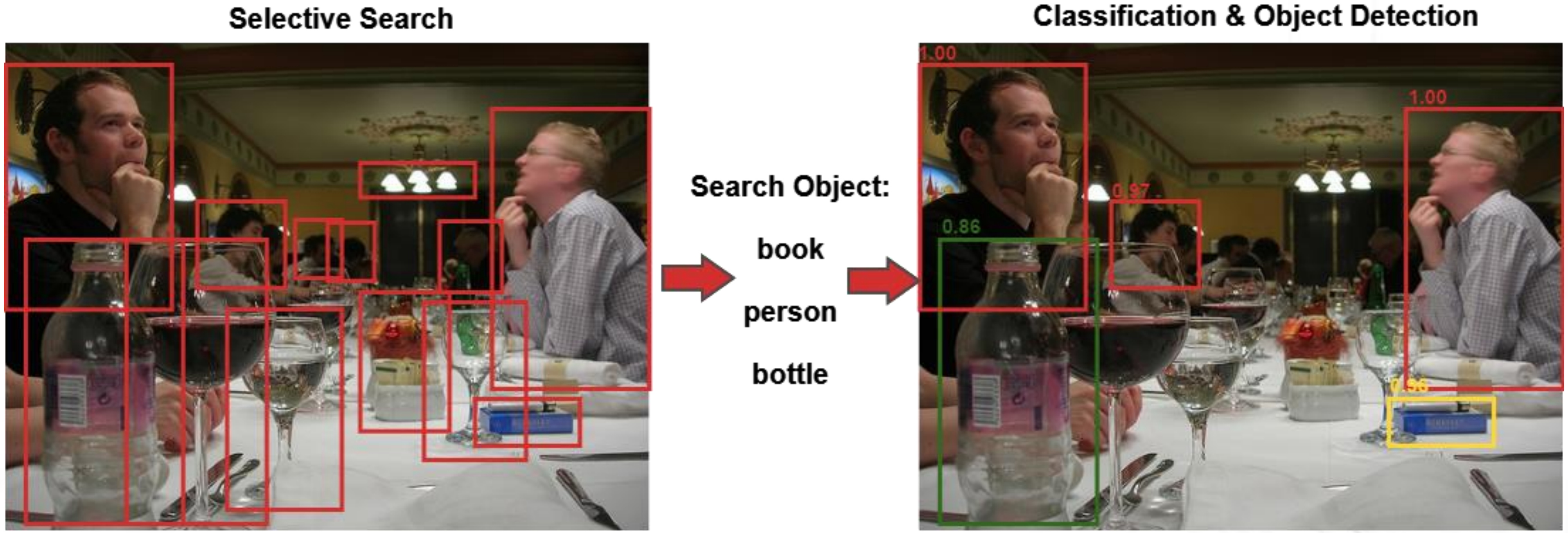
Huang, Gao, et al., "Densely connected convolutional networks," Proceedings of the IEEE conference on computer vision and pattern recognition, pp. 4700-4708, 2017.

Related Work – Object Detection

- Object Detection Network

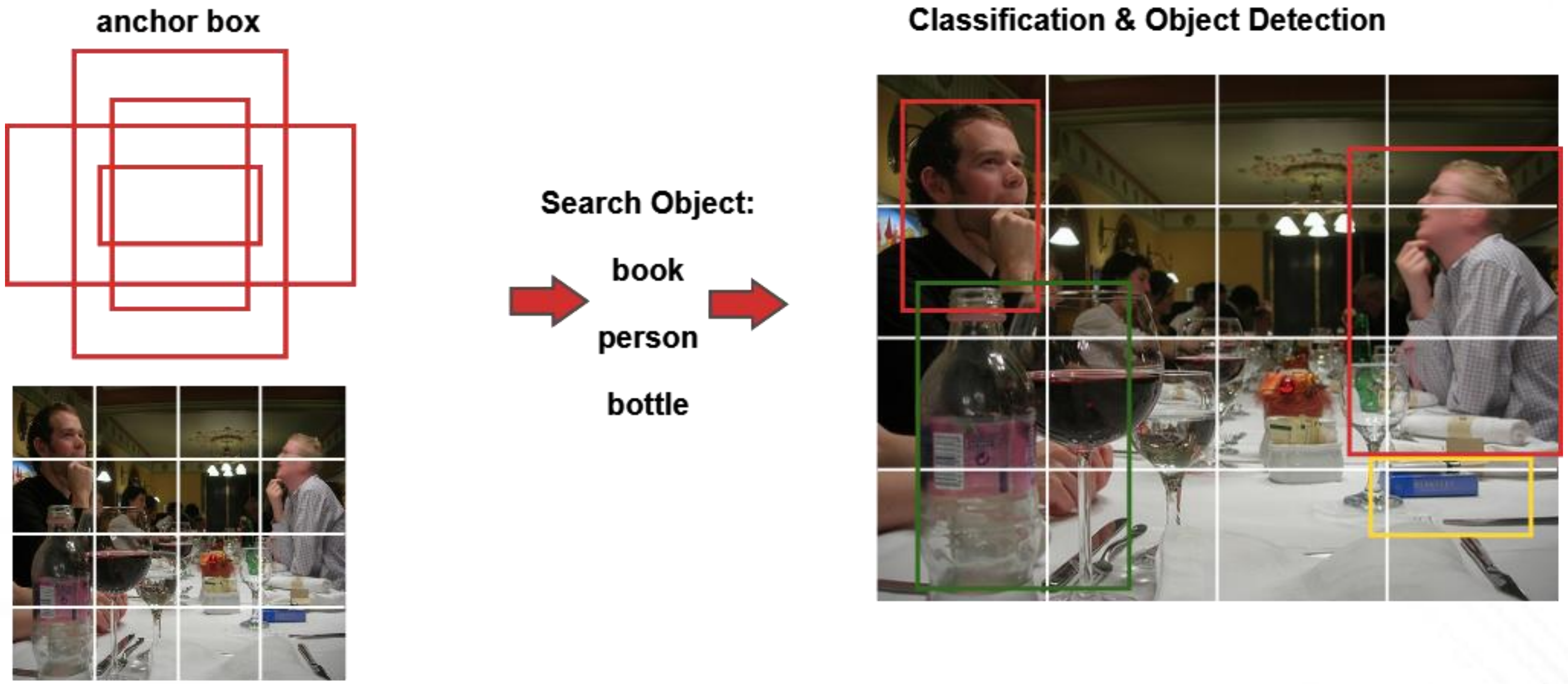
Related Work – Object Detection

- Object Detection Network – Two Stage



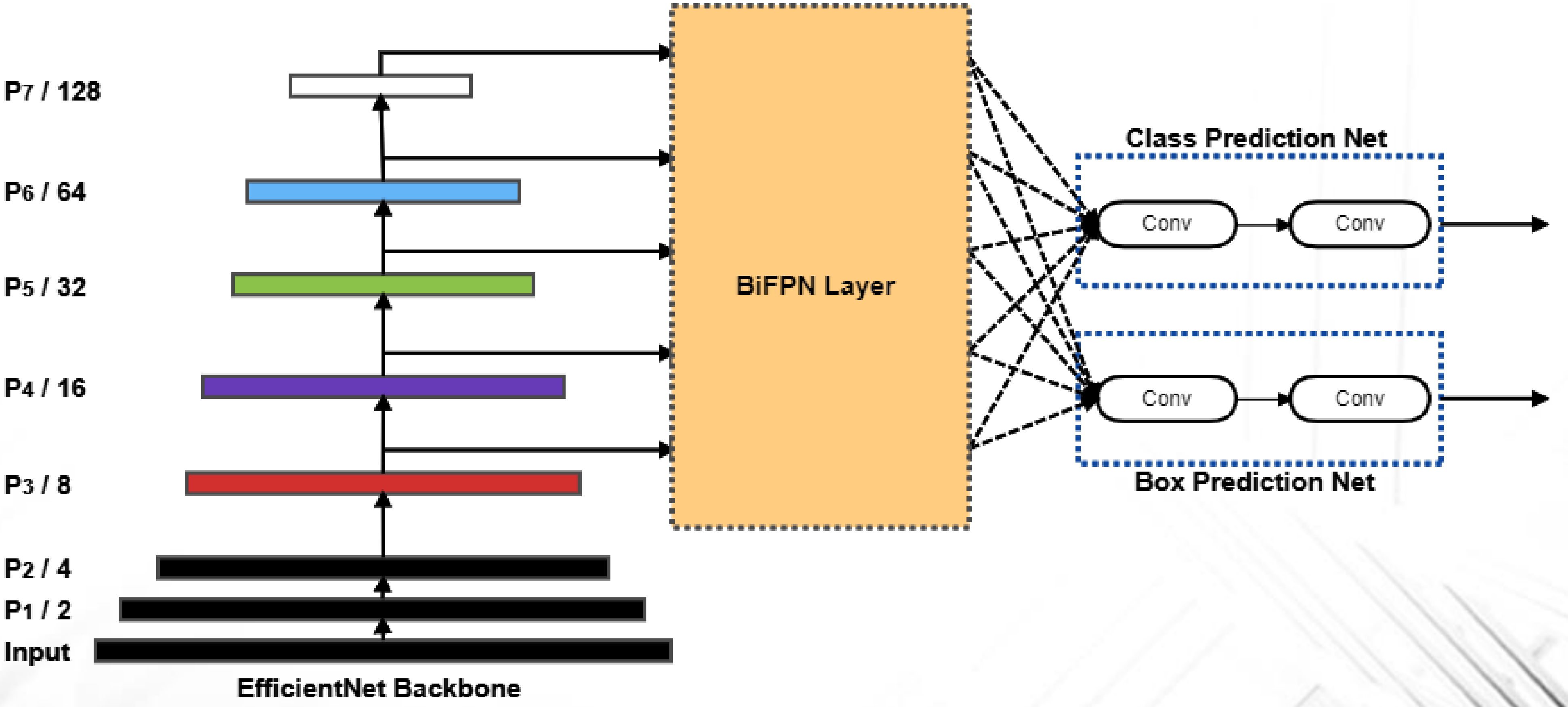
Related Work – Object Detection

- Object Detection Network – One Stage



Related Work – Object Detection

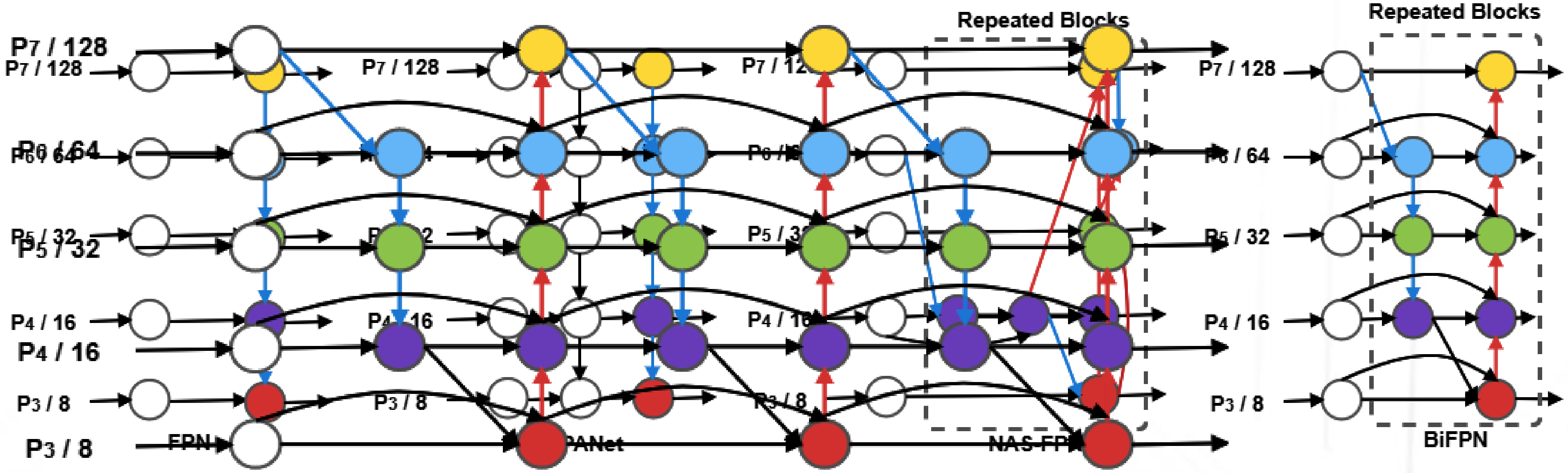
- Object Detection Network – EfficientDet



Tan, M., R. Pang, and Q. V. Le, "Efficientdet: Scalable and efficient object detection. arXiv," arXiv preprint arXiv:1911.09070, 2019.

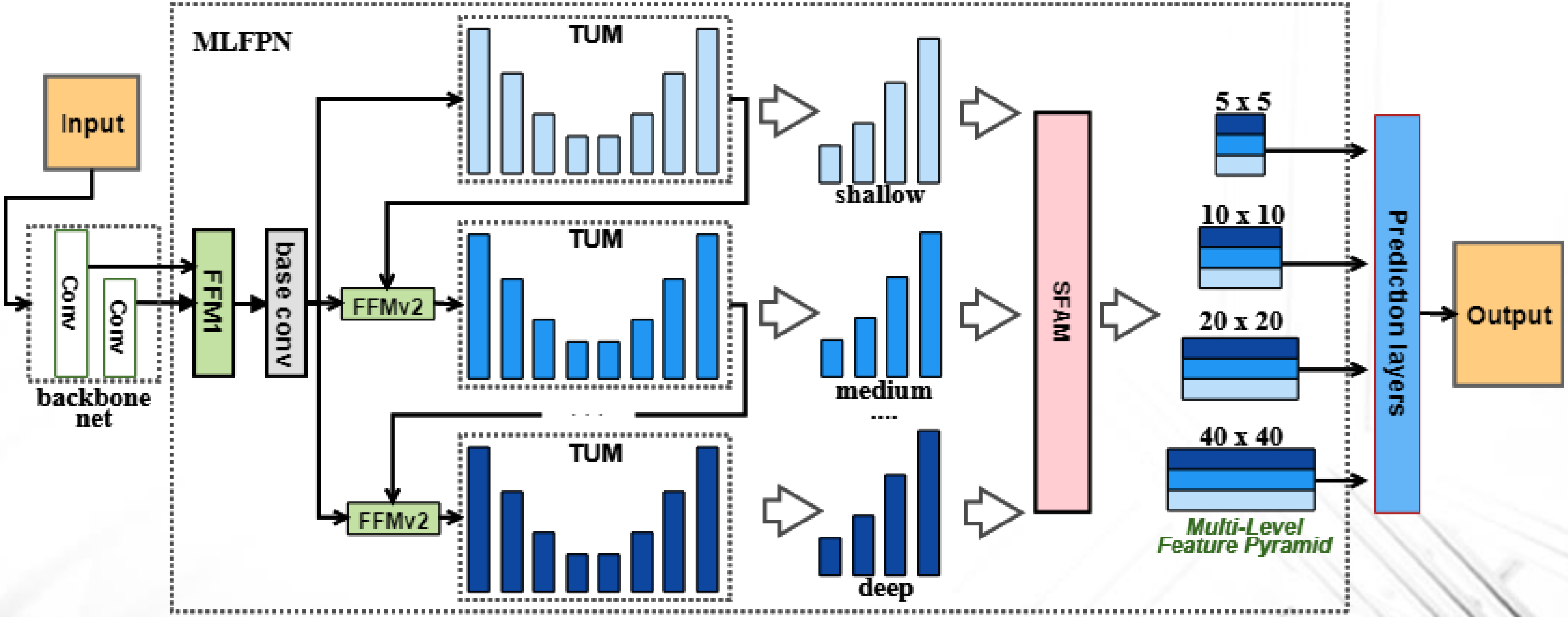
Related Work – Object Detection

- Object Detection Network – EfficientDet



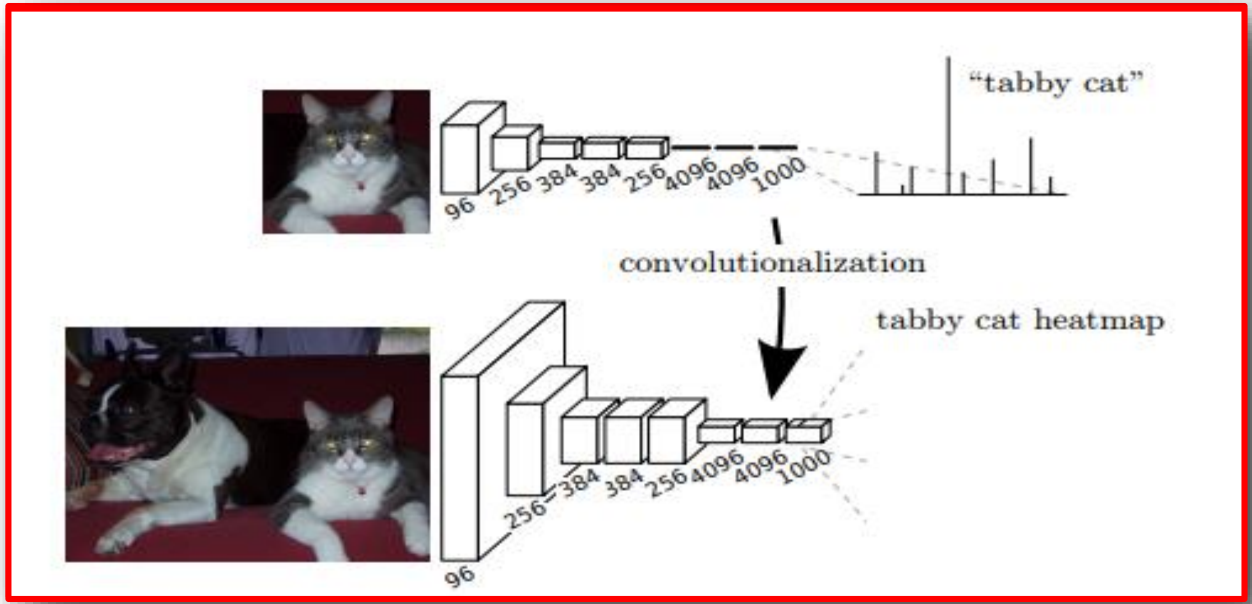
Related Work – Object Detection

- Object Detection Network – M2Det



Related Work – Semantic Segmentation

- Fully Convolutional Network



Flattening

001000110000010000100

Spatial Info

0	0	1	0	0
0	1	1	0	0
0	0	1	0	0
0	0	1	0	0

Long, Jonathan, Evan Shelhamer, and Trevor Darrell, "Fully convolutional networks for semantic segmentation," Proceedings of the IEEE conference on computer vision and pattern recognition, pp. 3431-3440, 2015.

Motivation

Model	backbone	fps	accuracy
Object Detection Network (COCO dataset，1280×1080)			
EfficientDet-D1	EfficientNet	27 ± 5	45% (mAP)
YOLOv3	Darknet53	40 ± 5	31% (mAP)
Semantic Segmentation Network (COCO dataset，1280×1080)			
R-FCN	VGG16	5.9 ± 5	29% (mIoU)
DeepLab v3+	Xception	8 ± 5	85% (mIoU)

Motivation

- Need to improve the current method of Data Augmentation.

  ※Generate more datasets.

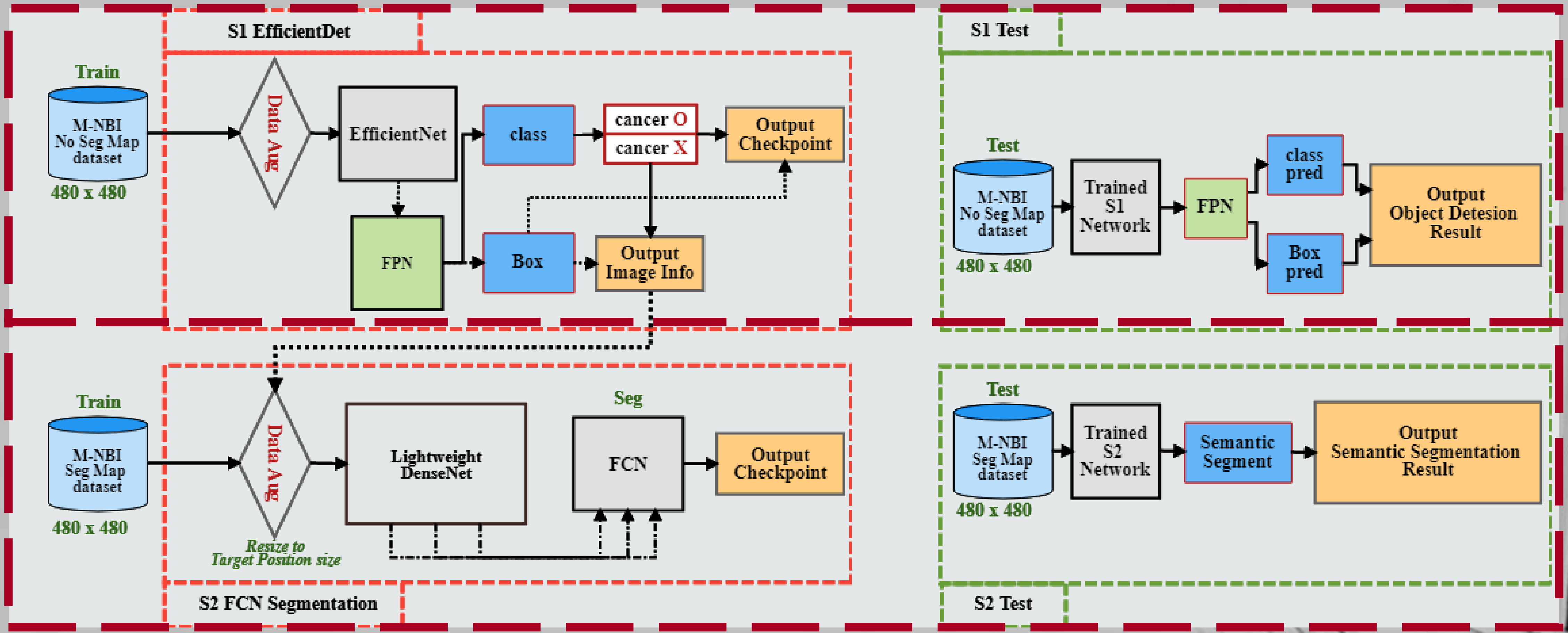
Experiment Result – Limitations of Study

- All training dataset only use the data of the planned doctor.
- Research aims to assist doctors, not replace them.
- Current experimental equipment can only achieve limited experimental results

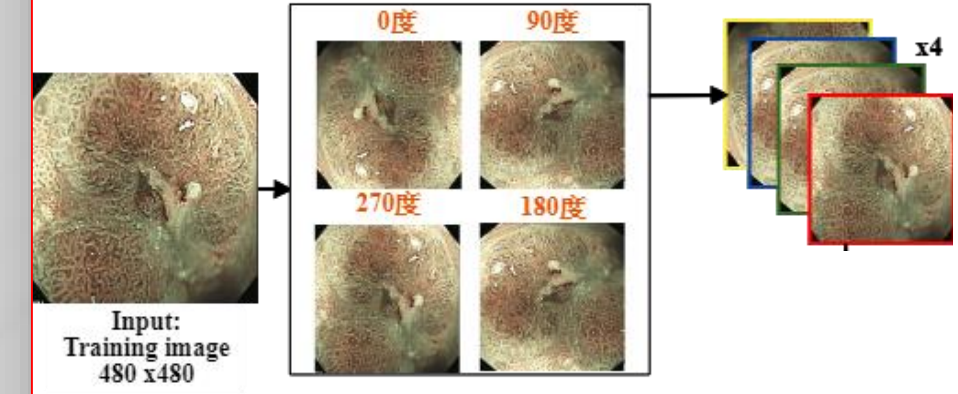
Method

- Propose Method – S1 and S2
  - S1 Stage : Use EfficientDet for Object Detection and Classification.
  - S2 Stage : Use the adjusted FCN Net and Dense Net for Semantic Segmentation.
- Combined Two Network (S1+S2)
- Data Augmentation
  - Use special pre-process method to increase the number of samples before starting training.

Method – End-to-End Training Framework



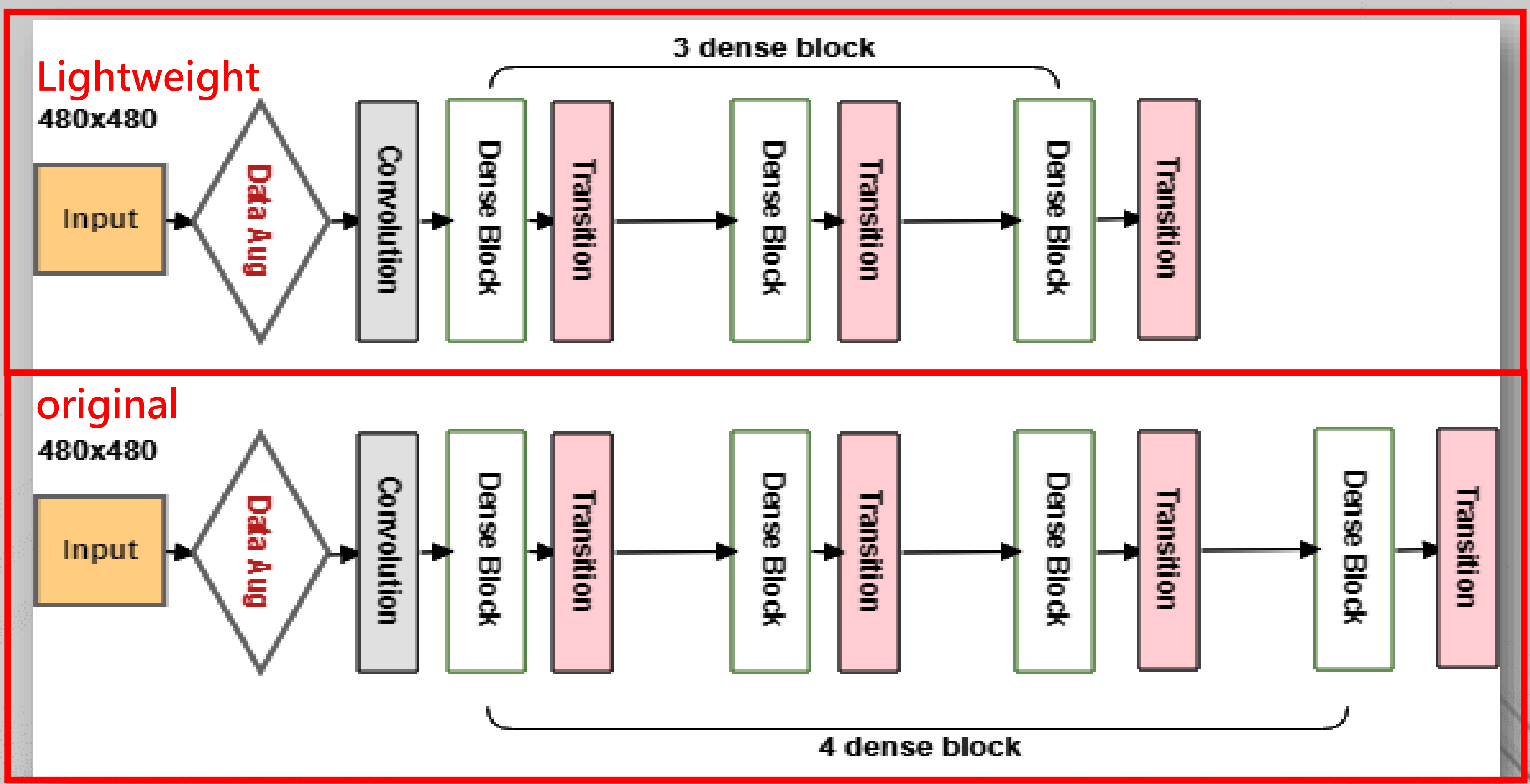
Method – Special Data Augmentation



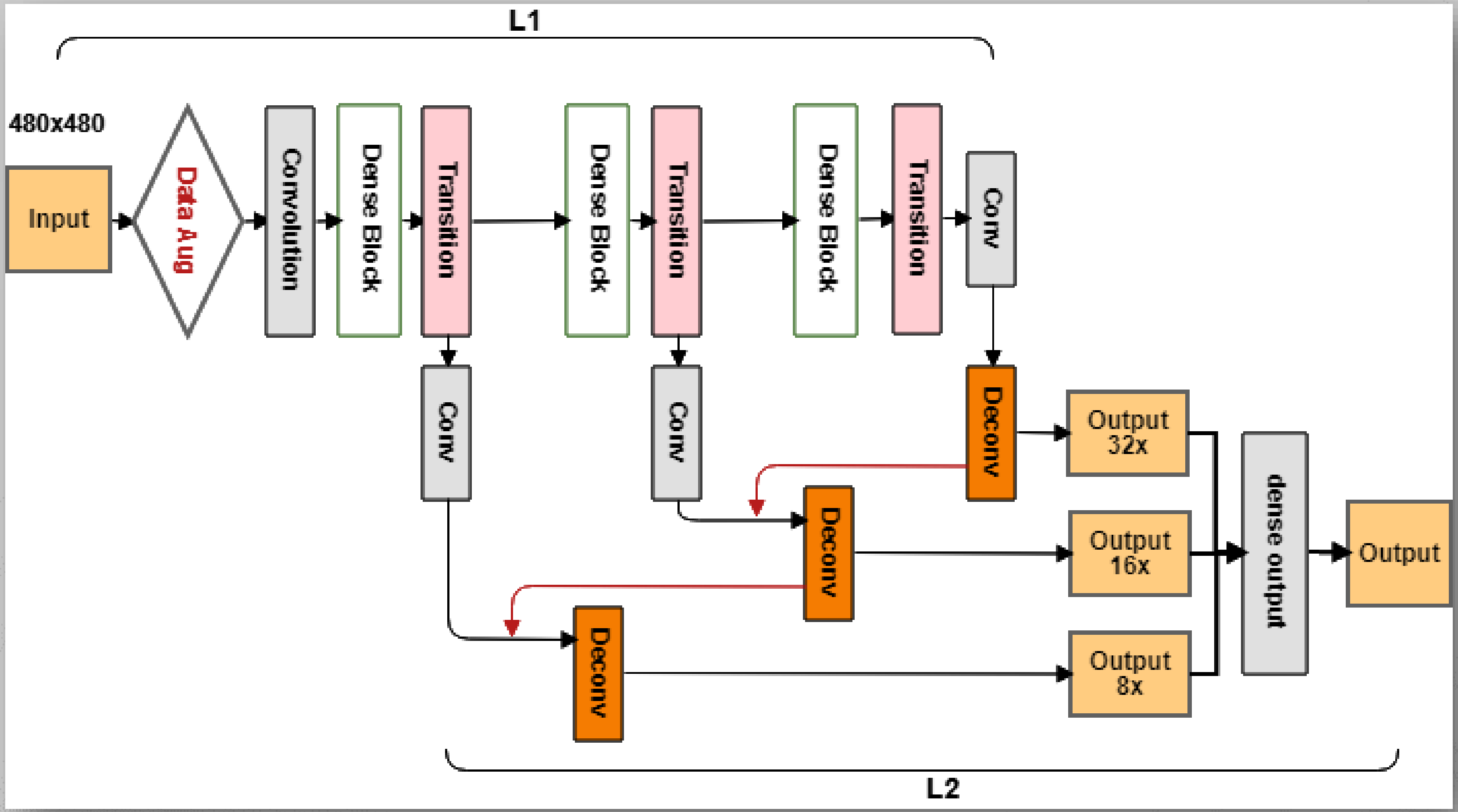
Method – EfficientDet

Model (Backbone)	Top-1 Acc	Top-5 Acc	Params	FLOPS	Detection Network
EfficientNet-B0	76.3%	93.2%	5.3M	0.39 B	EfficientDet-D0
EfficientNet-B1	78.8%	94.4%	7.8 M	0.70 B	EfficientDet-D1
EfficientNet-B2	79.8%	94.9%	9.2 M	1.0 B	EfficientDet-D2
EfficientNet-B3	81.1%	95.5%	12 M	1.8 B	EfficientDet-D3
EfficientNet-B4	82.6%	96.3%	19 M	4.2 B	EfficientDet-D4
EfficientNet-B5	83.3%	96.7%	30 M	9.9 B	EfficientDet-D5
EfficientNet-B6	84.0%	96.9%	43 M	19 B	EfficientDet-D6
EfficientNet-B7	84.4%	97.1%	66 M	37 B	EfficientDet-D7

Method – Lightweight DenseNet



Method – Lightweight FCN



Method – Evaluation Metrics

Fast Normalized Fusion

$$O = \sum_i \frac{w_i}{\epsilon + \sum_j w_j} \cdot I_i \quad , \quad w_i = \max(0, x)$$

Cross Entropy

$$H = \sum_{i=1}^{n} -y_{C,i} \log_2(p_{C,i})$$

Method – Evaluation Metrics

Confusion Matrix

		Actual Class	
Predicted Class		True	False
	Positive	True Positive (TP)	False Negative (FN)
	Negative	False Positive (FP)	True Negative (TN)

True Positive	是癌症圖像且模型判斷是癌症圖像
False Negative	是癌症圖像但模型沒有判斷出來是癌症圖像
False Positive	不是癌症圖像但模型判斷是癌症圖像
True Negative	不是癌症圖像且模型沒有判斷是癌症圖像

Method – Evaluation Metrics

$Specificity = \frac{TN(nocancer)}{FP + TN} \times 100\%$	$Sensitivity = \frac{TP(cancer)}{TP + FN} \times 100\%$
$F1 - score = 2 \times \frac{Specificity \times Sensitivity}{Specificity + Sensitivity} \times 100\%$	$\text{Accuracy} = \frac{TP + TN}{TP + TN + FP + TN}$
$\text{mAP} = \frac{\sum_{th=\{0.5,0.55,\ldots,0.75\}} AP(IoU_{th} = th)}{x}$, $\text{AP} = \frac{1}{n}\sum_{r} P_{interp}(r)$	

Experiment Result

First stage network parameter setting						
Parameter	Input size	Optimizer	Learning Rate	momentum	Activation Function	iteration
Value	480	Adam	10^{-4}	0.997	Relu	1000

Second stage network parameter setting						
Parameter	Input size	Optimizer	Learning Rate	momentum	Activation Function	iteration
Value	480	Adam	5×10^{-5}	0.9	Relu	1000

Experiment Result - Outline

- Experiment Result (Multiple box and Single box)
- Experiment Result I (S1 - Object Detection Network Result)
- Experiment Result II (S2 - Semantic Segmentation Network Result)
- Experiment Result III (S1+S2 - Combined Network Result)

Experiment Result

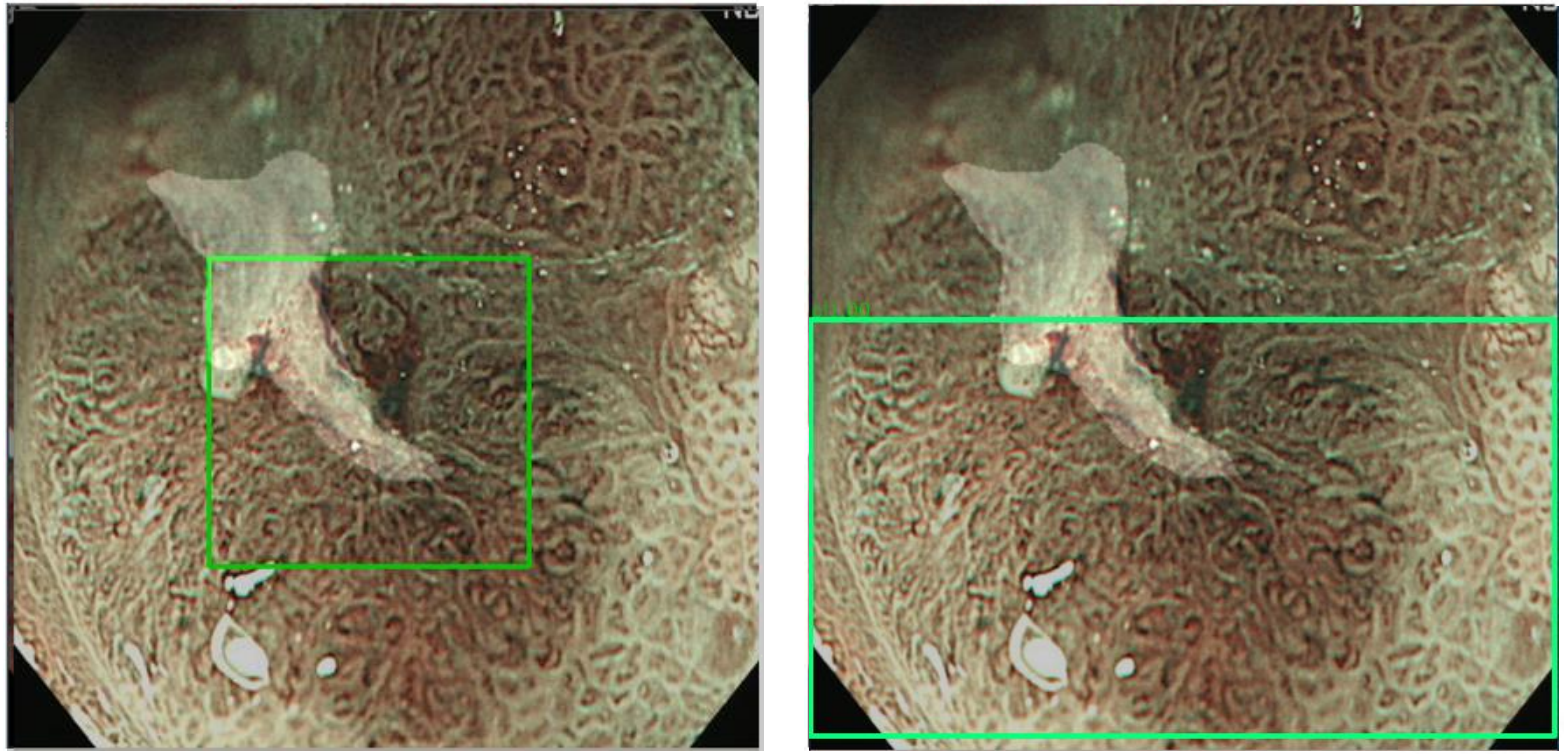


Fig 1. Multiple box function and Single box function.

Experiment Result I

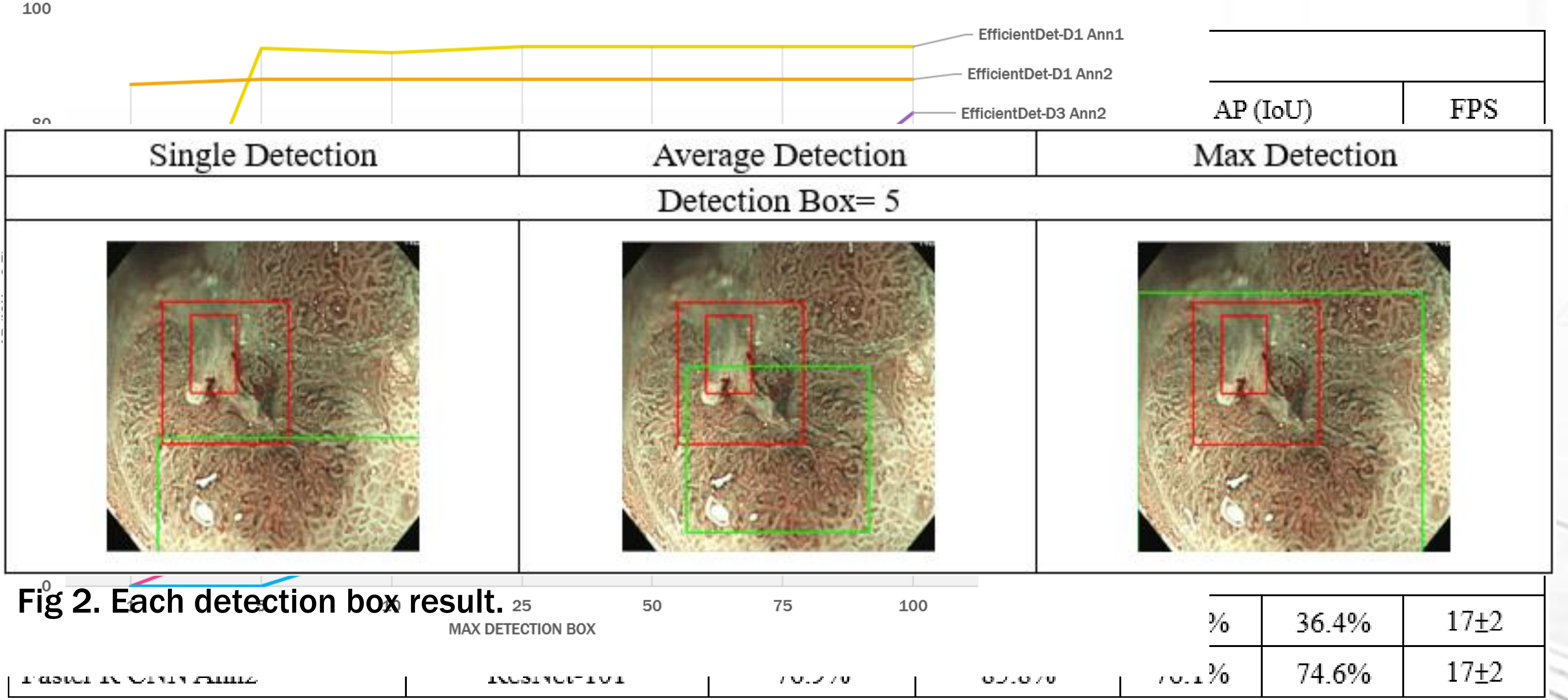
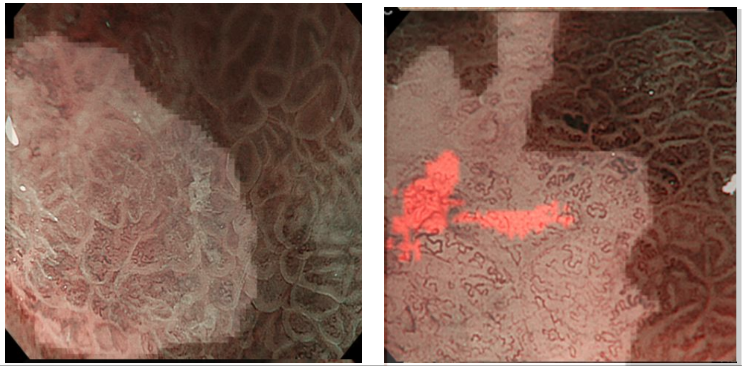


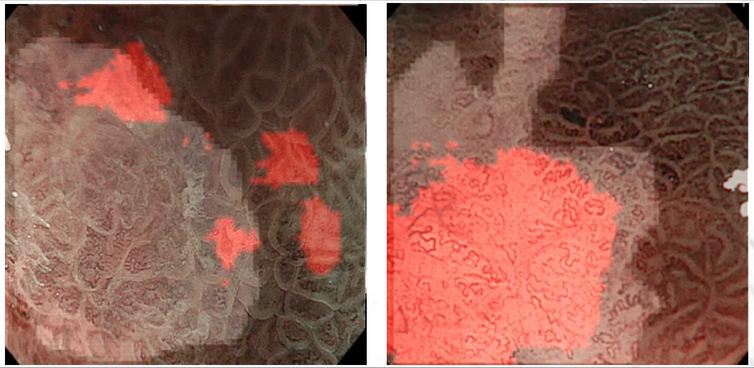
Fig 2. Each detection box result.

Experiment Result II

Model	My Data Augmentation	Sensitivity	F1-socre	Accuracy	TP	FN	FPS
Epoch=1200, Input Size=480×480, Test data = 20 張							
Lightweight DenseNet	X	42.8%	59.1%	60%	6	8	60
Lightweight DenseNet	V	64.2%	72.5%	70%	9	5	60
Epoch=900, Input Size=480×480, Test data = 20 張							
Lightweight DenseNet	X	40%	57%	55%	6	9	60
Lightweight DenseNet	V	28.5%	42.5%	45%	4	10	60



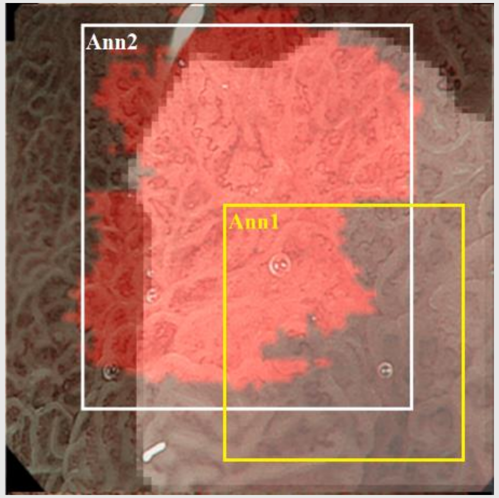
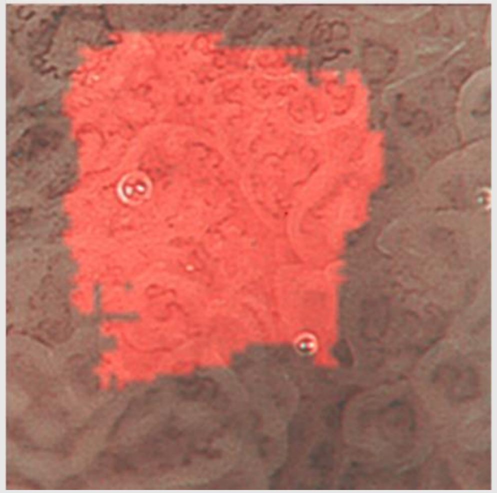
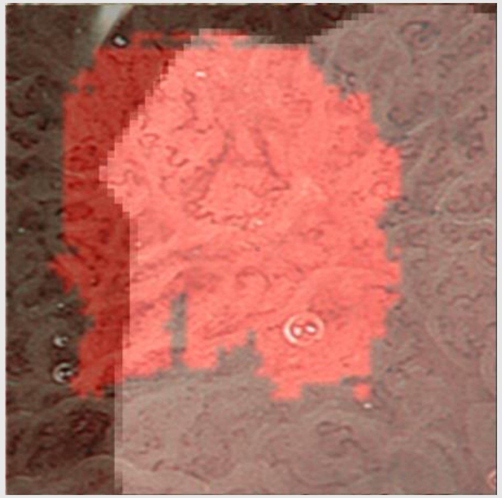
None Data Augmentation



Data Augmentation

Experiment Result III

Model	Sensitivity	F1-score	TP	FN	Accuracy
Semantic Segmentation Network	64.2%	72.5%	9	5	70%
Two Stage Detection Network-Ann1	83.3%	85.3%	10	2	87.5%
Two Stage Detection Network-Ann2	84.6%	91.6%	11	2	89.7%

		
Semantic Segmentation Network	Two Stage Detection Network-Ann1	Two Stage Detection Network-Ann2

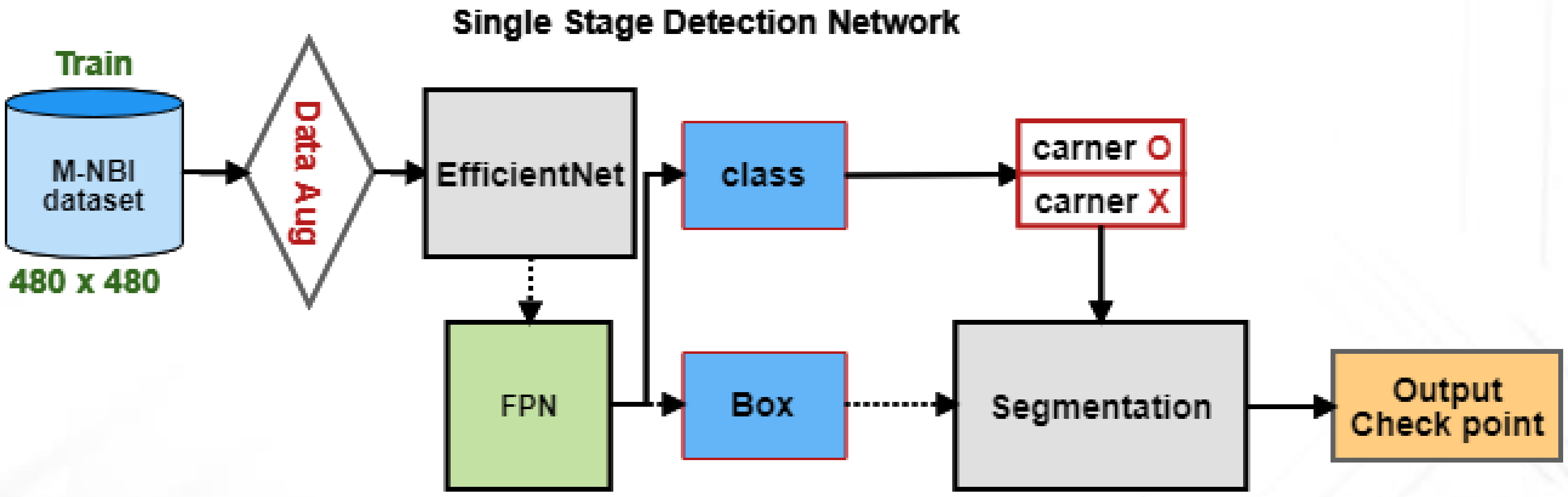
Conclusion

- Build a two-stage high-performance cancerous detection network based on EfficientDet and lightweight DenseNet.
- Using 「Special Data Augmentation」 method can make Small-Datasets comparable to Large-Datasets.

- EfficientDet || AP=90% ; FPS=70
- Lightweight DenseNet FCN || Accuracy=70% ; FPS=60
- Combined Network || Accuracy=89% ; FPS=50

Conclusion

- The accuracy of the combined network is less than 90%



The End

Thank you for your listening !!!