Multitask Universal Lesion Analysis Network

for Joint Lesion Detection, Tagging, and Segmentation

MULAN

2020. 06. 06. SAT
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Tagging

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CT (Computed Tomography)

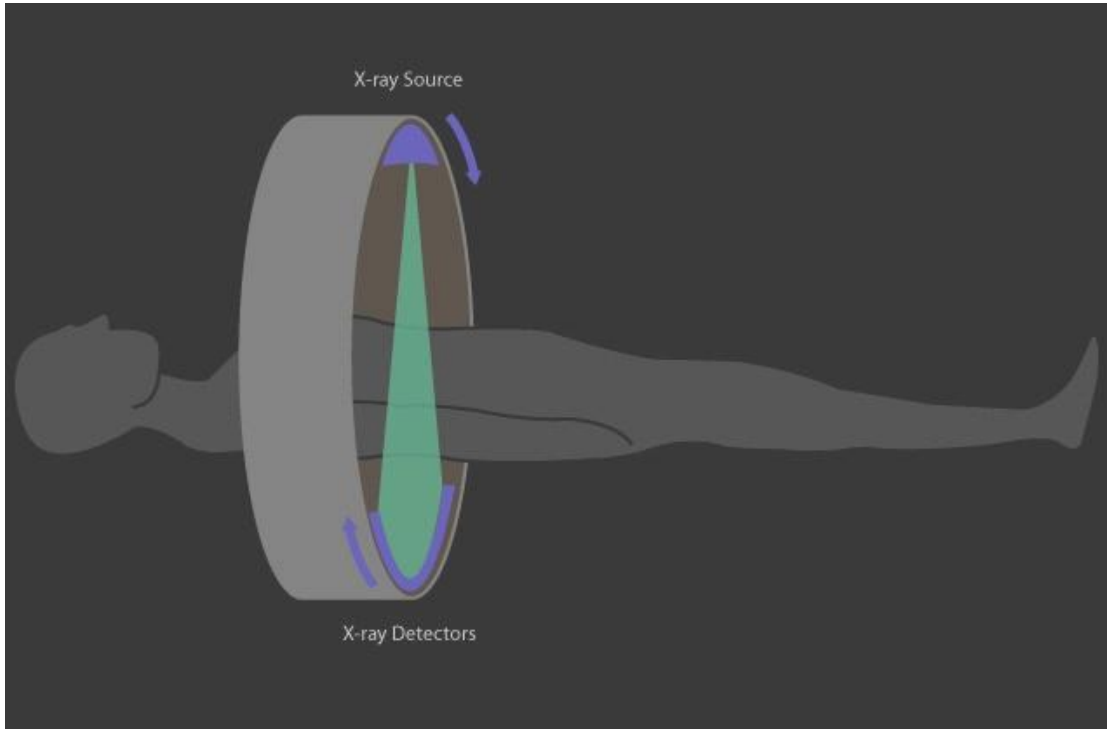
CT Scan Image

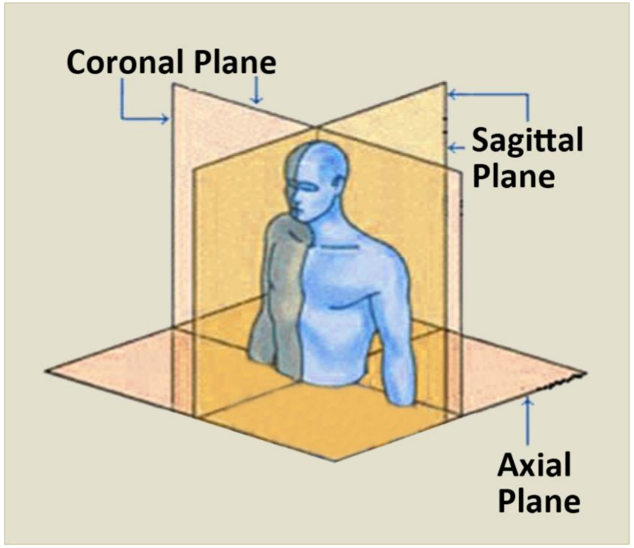
Lesion

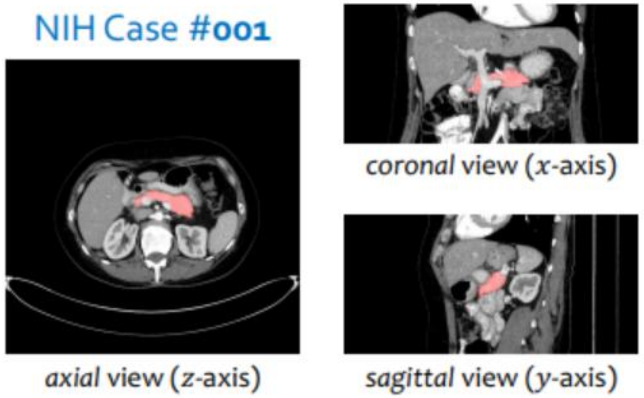
Detection

Tagging

Segmentation







CT란 X-선을 인체에 투과해 그 흡수차이를 컴퓨터로 재구성하여 인체의 단면영상을 얻거나 3차원적인 입체영상을 얻는 영상진단법

A lesion is any damage or abnormal change in the tissue of an organism

CT Scan Image

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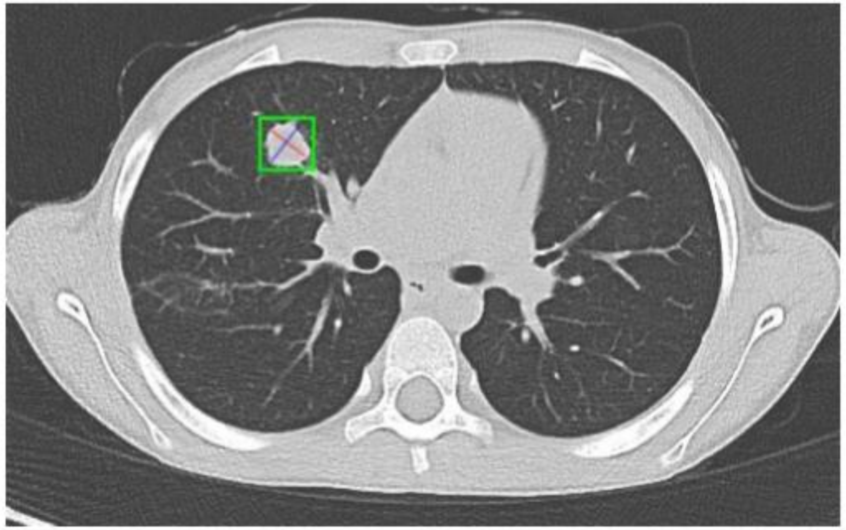
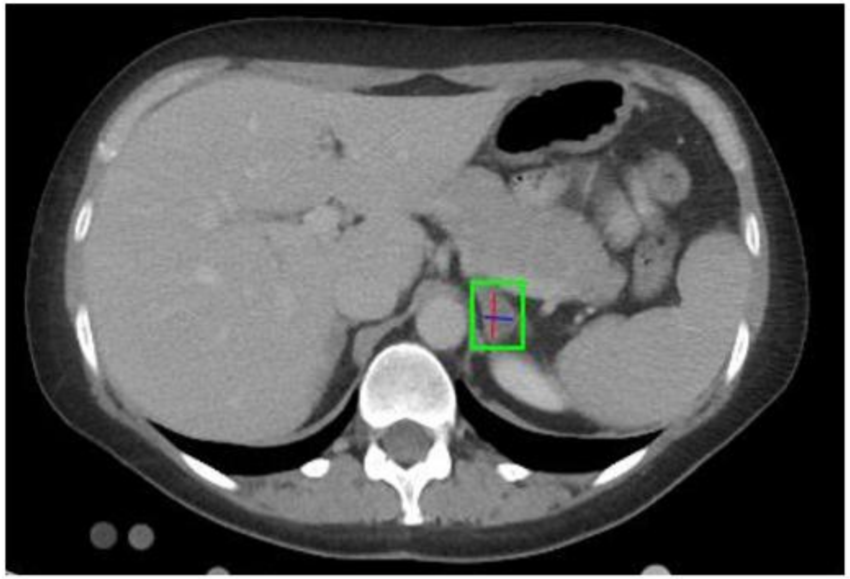


Sentence: Within the right middle lobe there is a stable nodule that measures BOOKMARK.

Tags: Right mid lung, nodule



Sentence: Low density left adrenal nodule BOOKMARK, likely adenoma.

Tags: Hypoattenuation, left adrenal gland, nodule, adenoma

DeepLesion Dataset

CT Scan Image

Lesion

Detection

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Segmentation

DeepLesion Dataset

- National Institutes of Health(NIH) Clinical Center, USA

- Contains 32,735 lesions on 32,120 **axial** computed tomography (CT) slices from 10,594 CT scans (studies) of 4,427 unique patients.

- lesions in each image with accompanying bounding boxes and size measurements, adding up to 32,735 lesions altogether.

- Semantic labels (tags) for the lesions mined from radiological reports. The labels describe the lesions' body part, type, and attributes. (2019. 4. added, the label with tags = Train : 20,266 / Valid : 1,976 / Test : 1879)

- Lesion size : 0.2mm ~ about 340 mm

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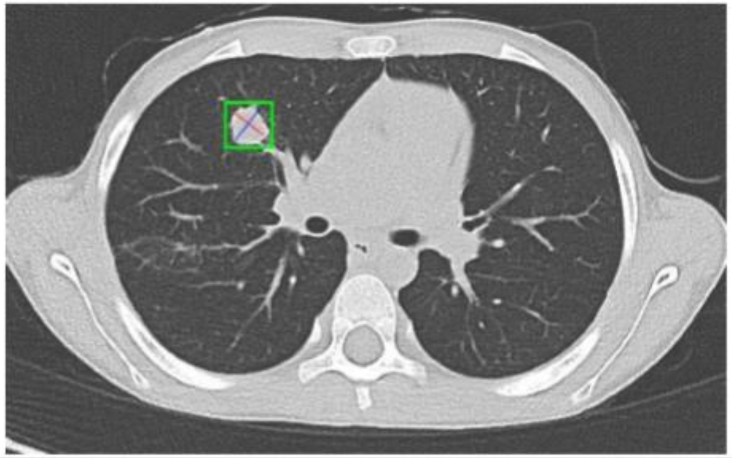
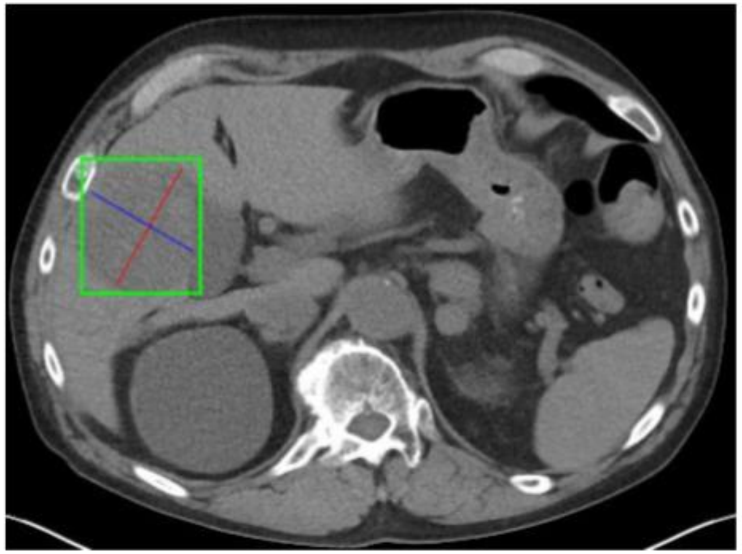
DeepLesion Dataset



Sentence: Within the right middle lobe there is a stable nodule that measures BOOKMARK.

Tags: Right mid lung, nodule



Sentence: A large right hepatic mass, incompletely characterized BOOKMARK.

Tags: Large, liver, liver mass, mass

Abstract

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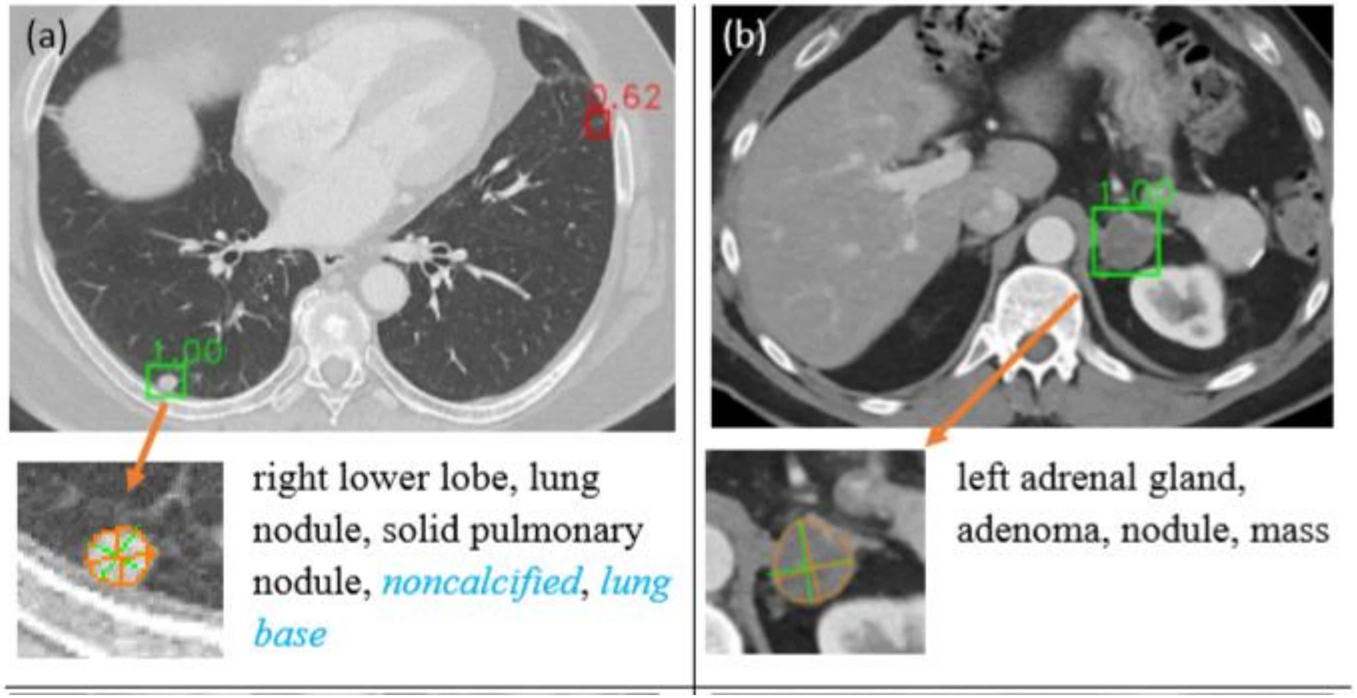


Whole Framework

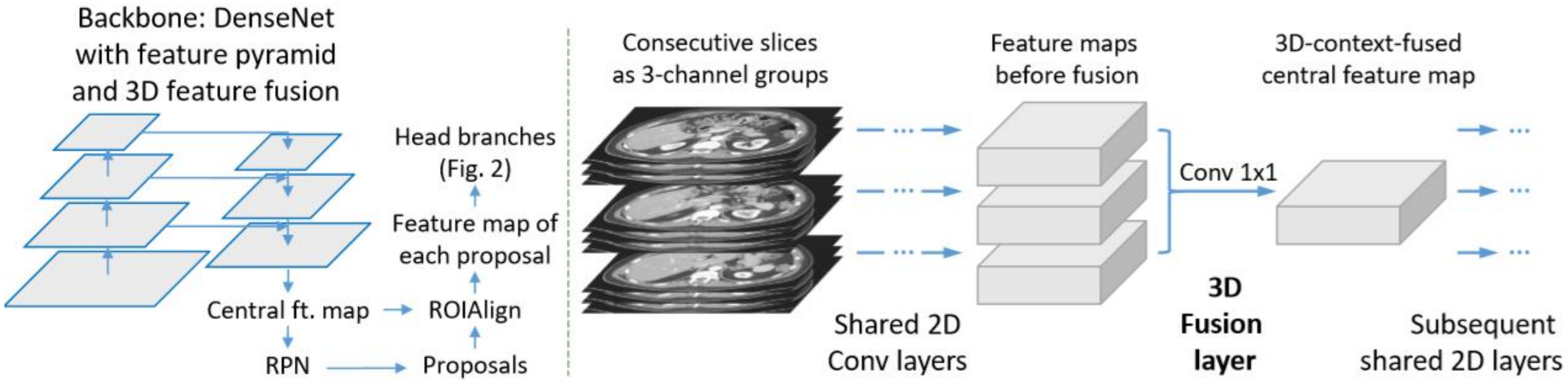
[1] Backbone

[2] 3D feature fusion

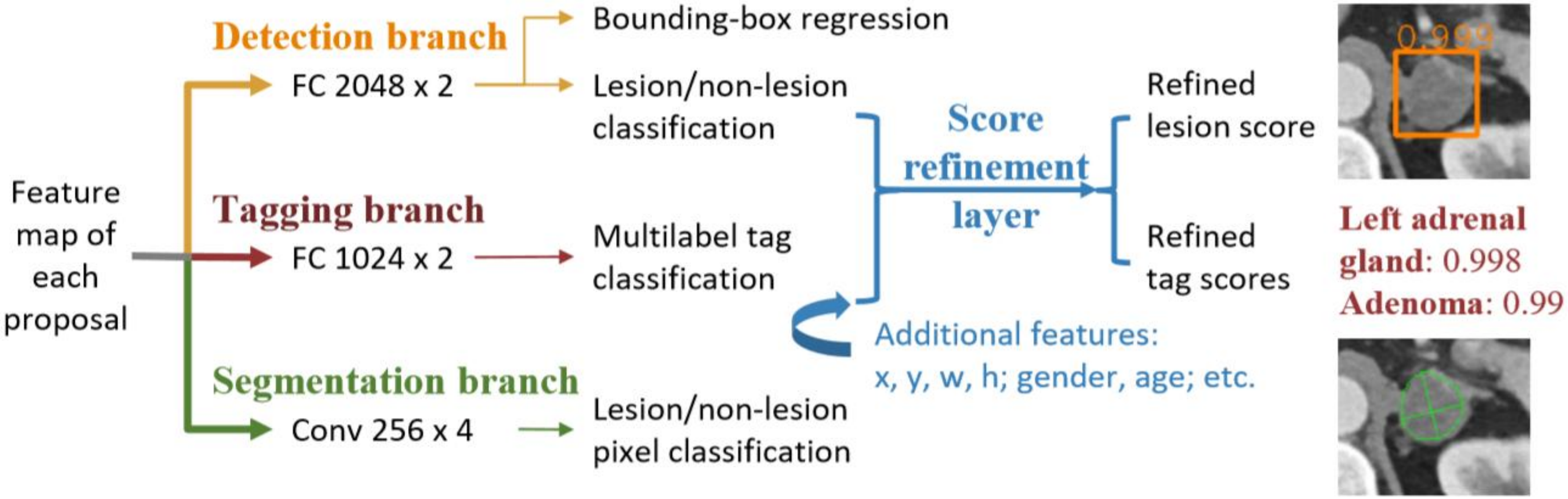
[3] Mask R-CNN

[4] 3 branches

[5] Refinement



(a) Flowchart **(b) 3D feature fusion**



Method

[1] Backbone

[2] 3D feature fusion

[3] Mask R-CNN

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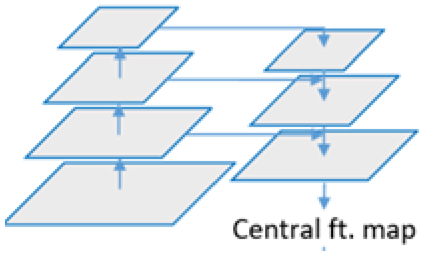
[5] Refinement



- DenseNet-121 with the last dense block and transition layer removed
- ImageNet pretrained
- Feature pyramid strategy (increase the size of final feature map, which will benefit the detection and segmentation of small lesions)
- Attach the head branches only to the finest level

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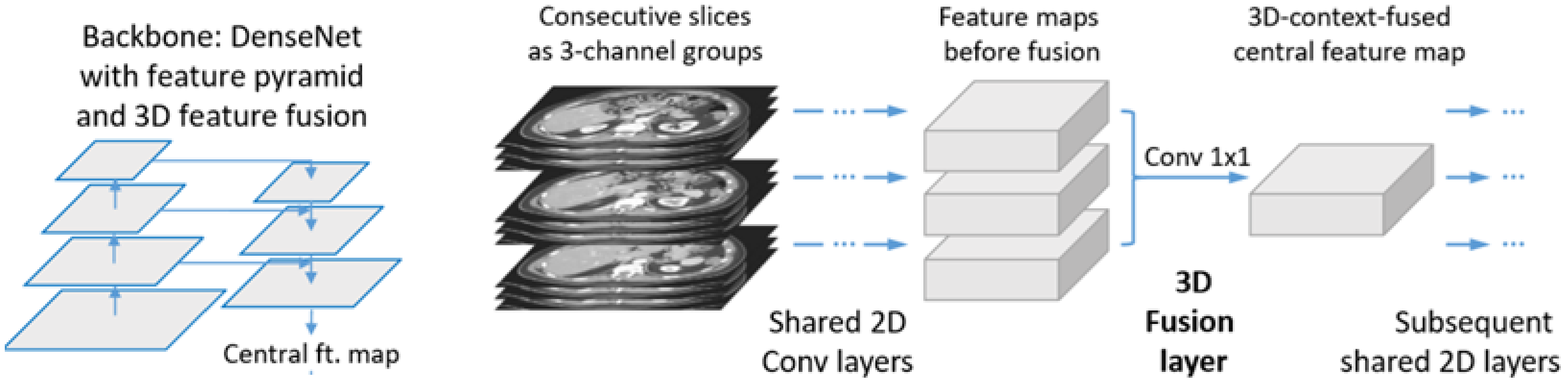

(b) 3D feature fusion

- **3D context information is very important!!**
- First, group consecutive axial slices in a CT volume into 3-channel
- With a 1x1 Conv layer (3D fusion layer)
- Fuse features of multiple slices(9) in eariler Conv layers. (after dense block 2 and the last layer of the feature pyramid)
- All FMs are fed to subsequent Conv layer, with Central FM is replaced by the FM(feature map)s are fused with the 3D fusion layer, upper FM and lower FM.

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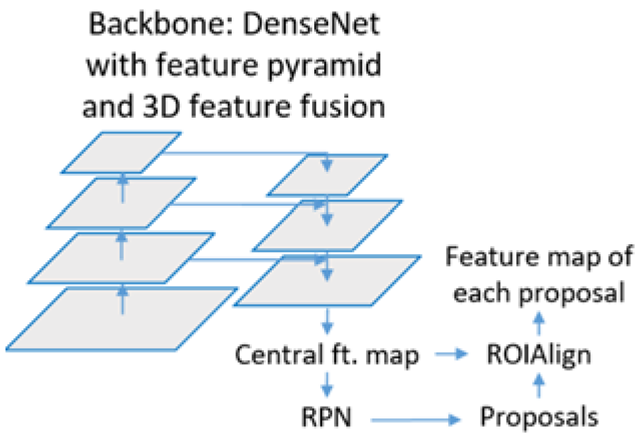

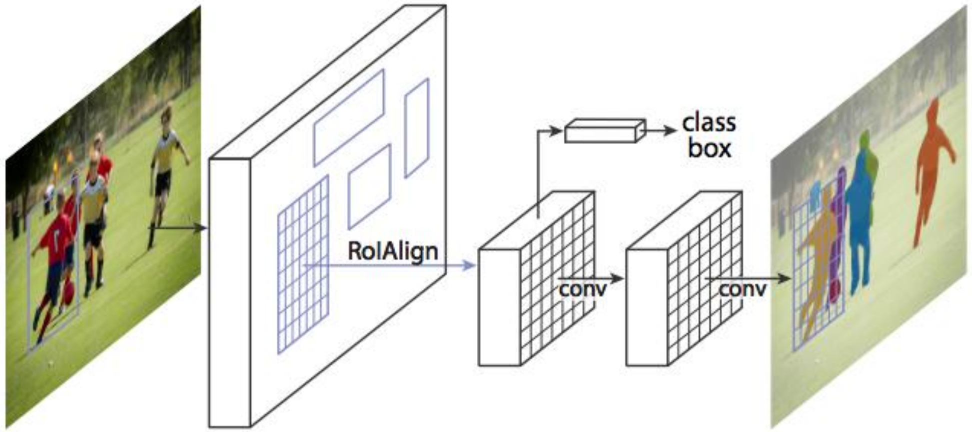

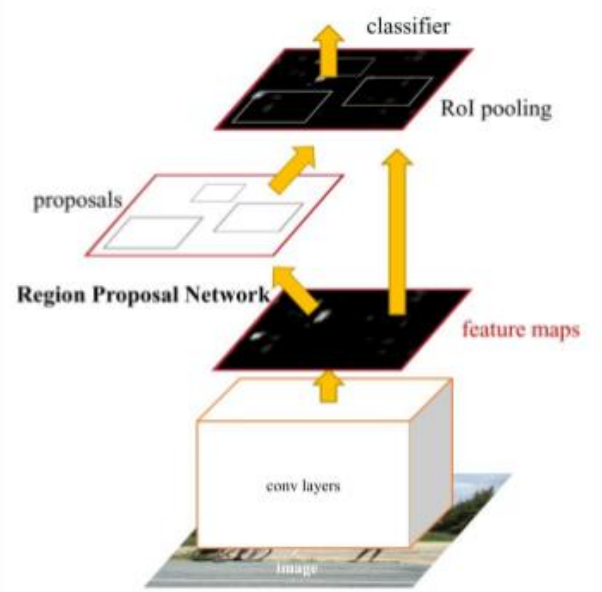

1. Faster R-CNN : bbox + class → bbox + class + seg
2. ROI Pooling 대신 ROI Align 을 사용함
3. Mask prediction 과 class prediction 을 decouple 함 (클래스 상관없이 masking)

출처: https://mylifemystudy.tistory.com/82 [ENCAPSULATION]

https://www.youtube.com/watch?v=RtSZALC9DlU

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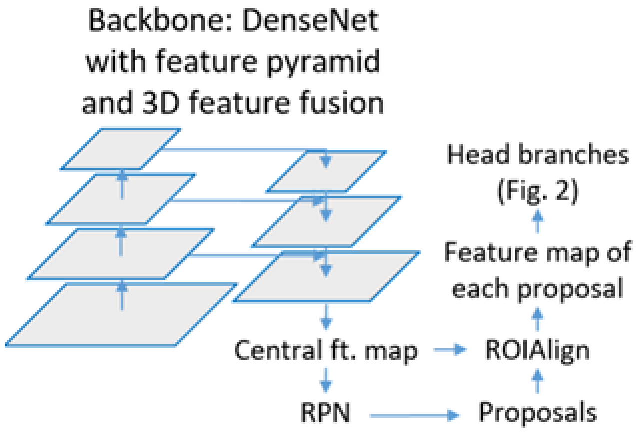

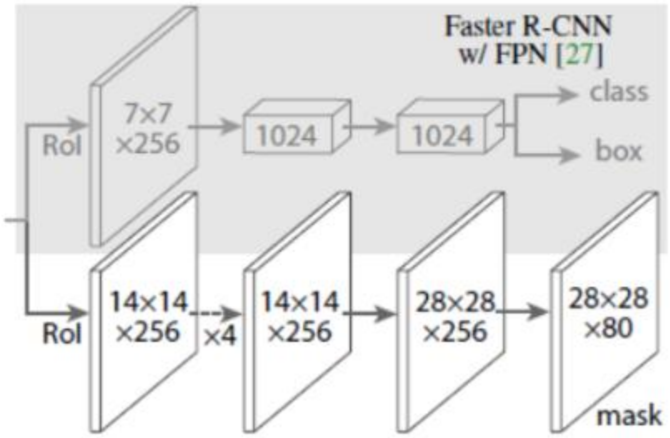

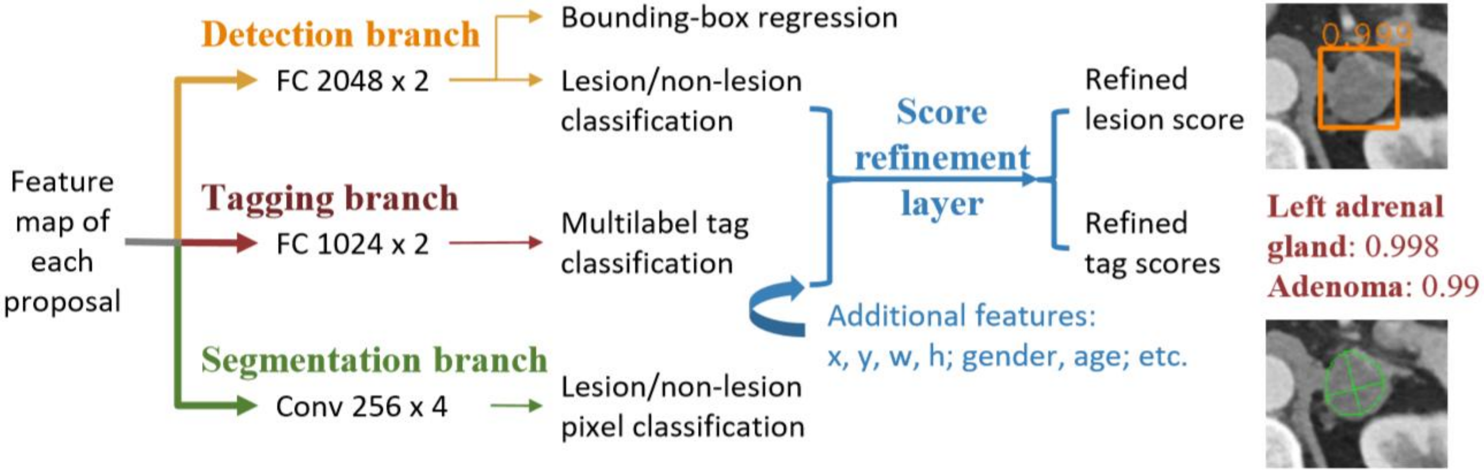

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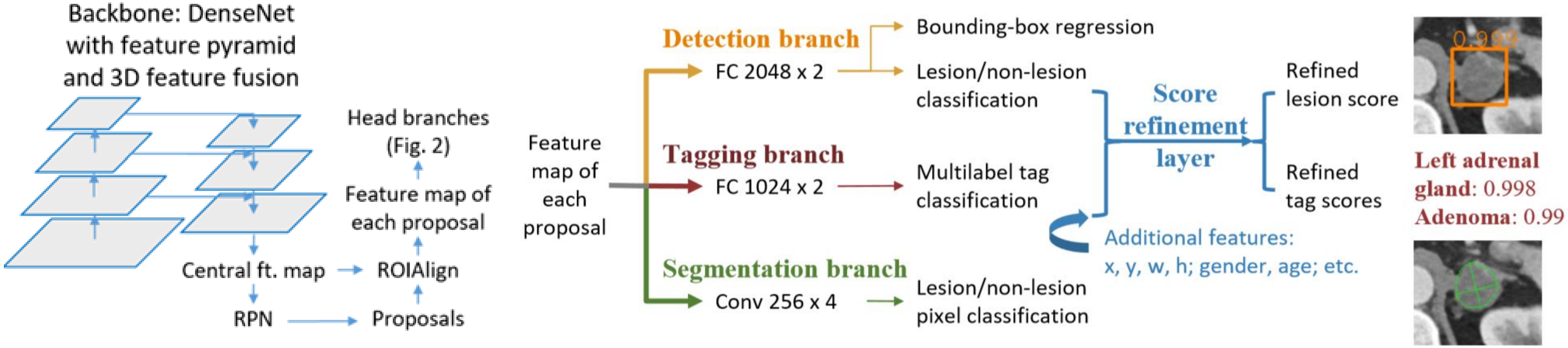


$$L = L_{\mathrm{det,seg}} + L_{\mathrm{tag,WCE}} + L_{\mathrm{tag,RHEM}} + L_{\mathrm{cls,SRL}} + L_{\mathrm{tag,WCE,SRL}}$$

$$L_{\mathrm{det,seg}} = L_{\mathrm{RPN,cls}} + L_{\mathrm{RPN,box}} + L_{\mathrm{det,cls}} + 10L_{\mathrm{det,box}} + L_{\mathrm{seg,dice}}$$

$$L_{\mathrm{tag,WCE}} = \sum_{i=1}^{B}\sum_{c=1}^{C}\left(\beta_c^{\mathrm{p}} y_{i,c}\log\sigma_{i,c} + \beta_c^{\mathrm{n}}(1-y_{i,c})\log(1-\sigma_{i,c})\right)$$

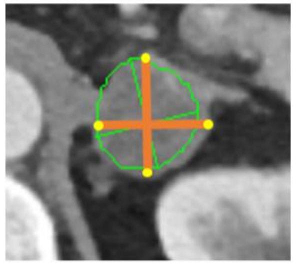
*relational hard example mining (RHEM)

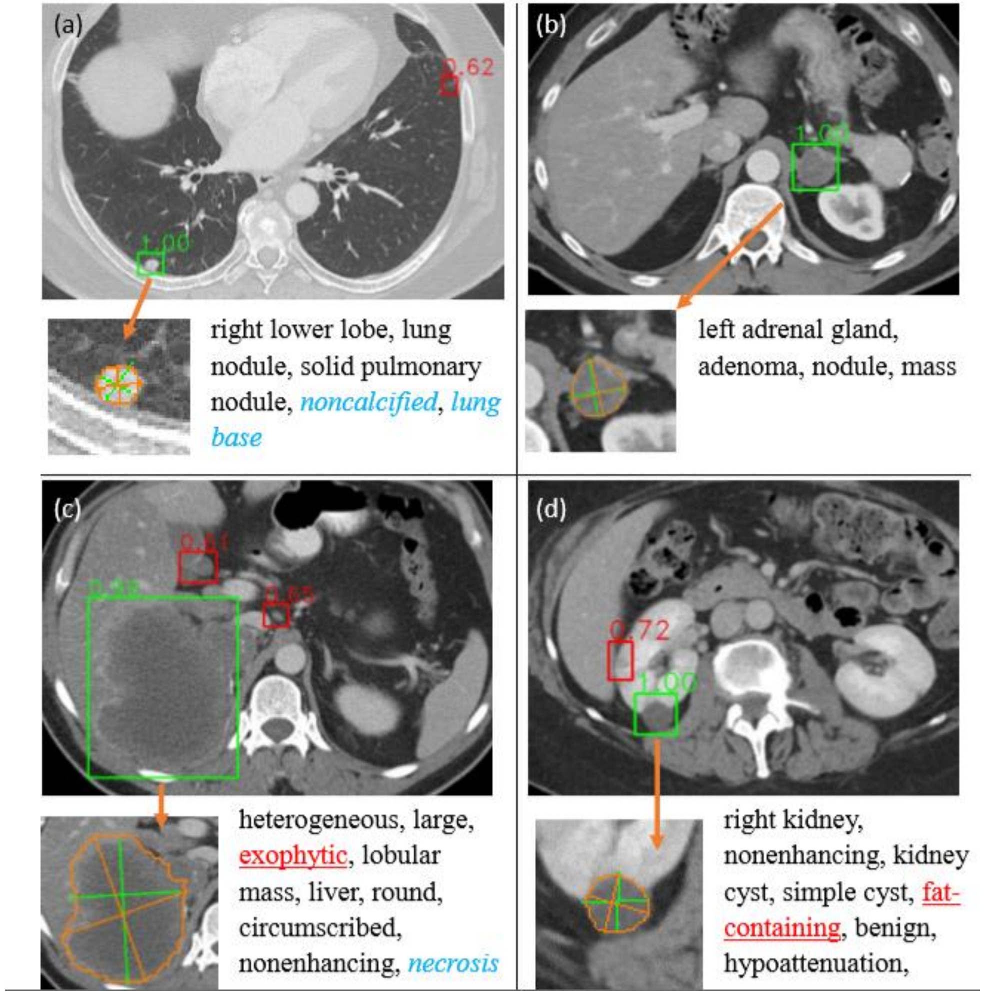
Result

	Detection (%)	Tagging (%)		Segmentation (mm)	
	Avg. sensitivity	AUC	F1	Distance	Diam. err.
ULDor [13]	69.22	–	–	–	–
3DCE [15]	75.55	–	–	–	–
LesaNet [16] (rerun)	–	95.12	43.17	–	–
Auto RECIST [11]	–	–	–	–	**1.7088**
MULAN	**86.12**	**96.01**	**45.53**	1.4138	1.9660
(a) w/o feature pyramid	79.73	95.51	43.44	1.6634	2.3780
(b) w/o 3D fusion	79.57	95.88	44.28	1.4120	1.9756
(c) w/o detection branch	–	95.16	40.03	**1.2445**	1.7837
(d) w/o tagging branch	84.79	–	–	1.4230	1.9589
(e) w/o mask branch	85.21	95.87	43.76	–	–
(f) w/o score refine. layer	84.24	95.65	44.59	1.4260	1.9687

Table 3. Sensitivity (%) at various FPs per image on the test set of DeepLesion (the 171 tags were used for training MULAN).

FPs per image	0.5	1	2	4	8	16	Avg. of [0.5,1,2,4]
3DCE [15]	62.48	73.37	80.70	85.65	89.09	91.06	75.55
ULDor [13]	52.86	64.80	74.84	84.38	87.17	91.80	69.22
MULAN	**76.12**	**83.69**	**88.76**	**92.30**	**94.71**	**95.64**	**85.22**





Conclusion

2 stage Object detection algorithm **– MASK-RCNN**

An effective **3D feature fusion** strategy

Jointly learning to automate radiologists' process

!!!

THANK YOU