

# Medical Image Seminar

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- ① (MICCAI 2017) Accurate Pulmonary Nodule Detection in Computed Tomography Images Using Deep Convolutional Neural Networks
- ② (ISBI 2019) An End-to-End Framework for Integrated Pulmonary Nodule Detection and False Positive Reduction

# Accurate Pulmonary Nodule Detection in Computed Tomography Images Using Deep Convolutional Neural Networks

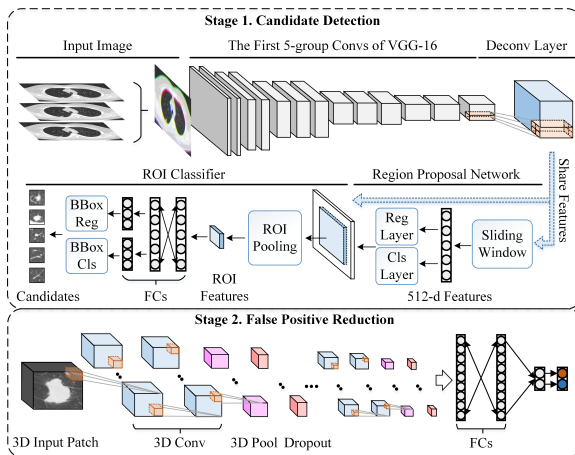


Figure 1: The framework of the proposed CAD system.

# Objective Function

$$\mathcal{L}_t = \frac{1}{N_c} \sum_i \mathcal{L}_c(\hat{p}_i, p_i^*) + \frac{1}{N_r} \sum_i \mathcal{L}_r(\hat{t}_i, t_i^*) + \frac{1}{N_{c'}} \sum_j \mathcal{L}_c(\tilde{p}_j, p_j^*) + \frac{1}{N_{r'}} \sum_j \mathcal{L}_r(\tilde{t}_j, t_j^*)$$

- $\hat{p}_i$  and  $p_i^*$  respectively denote the predicted and true probability of anchor  $i$  being a nodule
- $\hat{t}_i$  is a vector representing the 4 parameterized coordinates of the predicted bounding box of RPN,  $t_i = (t_z, t_y, t_x, t_d)$
- $\tilde{p}_j$ ,  $p_j^*$ ,  $\tilde{t}_j$  and  $t_j^*$  denote the corresponding concepts in the ROI classifier
- $L_c$  is softmax loss,  $L_r$  is smooth L1 loss

# Data Augmentation

- **Crop** For each  $40 * 40 * 24$  patch, we crop smaller patches in the size of  $36 * 36 * 20$  from it, thus augmenting 125 times.
- **Flip** For each cropped  $36 * 36 * 20$  patch, we flip it from three orthogonal dimensions, thus finally augmenting  $8 * 125 = 1000$  times.
- **Duplicate** To balance the number of positive and negative patches in the training set, we duplicate positive patches by  $8 * 1000 = 8000$  times.

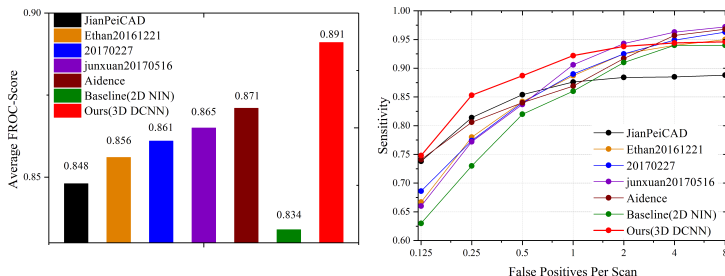


Figure 4: Comparison of performance among our CAD system and other submitted approaches on the LUNA16 Challenge. (a) Average FROC-scores (b) FROC curves

# Contribution

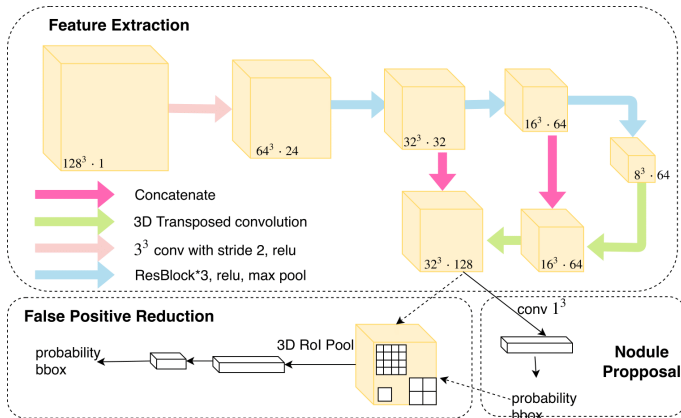
An End-to-End Framework for Integrated Pulmonary Nodule Detection and False Positive Reduction (ISBI 2019)

- Present an end-to-end framework for nodule detection, integrating nodule candidate screening and false positive reduction into one model, trained jointly.
- Improves the performance by 3.88% over the two-step approach, while at the same time reducing model complexity by one third and cutting inference time by 3.6 fold.

## 2 stage

- ① Generating nodule candidates using 3D Nodule Proposal Network (adapted from Faster-RCNN).
- ② Nodule candidate classification for false positive reduction.  
(Nodule proposal is then used to crop features using 3D Region of Interest (RoI) Pool layer, fed as input to the nodule false positive reduction branch.)





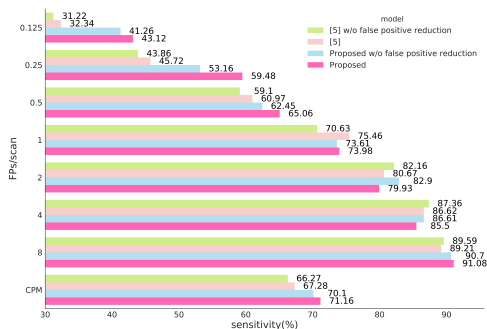
**Fig. 1.** End-to-end pulmonary nodule detection framework

# Objective Function

$$L(\{p_i\}, \{t_i\}) = \frac{\sum_i L_{cls}(p_i, p_i^*)}{N_{cls}} + \lambda \frac{\sum_i L_{reg}(t_i, t_i^*)}{N_{reg}} \quad (1)$$

- $i$  is the index of an anchor in one mini-batch
- $p_i$  is the probability that anchor contains a nodule candidate
- $\lambda$  is a hyper-parameter for balancing classification and regression losses (set it to 1 in this case)
- $t_i$  is a vector representing the four parametrized coordinate offsets of the predicted bounded box,  $t_i = (t_z, t_y, t_x, t_d)$
- $L_{cls}$  is binary cross entropy loss,  $L_{reg}$  is L1 loss

- Train the whole network in an end to end fashion.
- First train the nodule proposal network using Stochastic Gradient Descent (SGD) for 60 epochs and then we train both network together for another 100 epochs.
  - This is because, in the beginning the nodule proposal network predicts random nodule candidates which would be time-consuming for training the false positive reduction branch.
- To improve the generalization ability of the network, input volume is randomly shifted, randomly flipped along all 3 axis, and randomly scaled between 0.9 and 1.1.



**Fig. 2.** Performance comparison

	# Parameters	Inference Time
[5]	15903490	10.2s/CT
Proposed	9618523	2.8s/CT

**Table 1.** Comparison of number of parameters and time for inference between separate two stage framework [5] and the proposed framework

[5] Automated pulmonary nodule detection using 3d deep convolutional neural networks. (ISBI 2018)

# Comparison

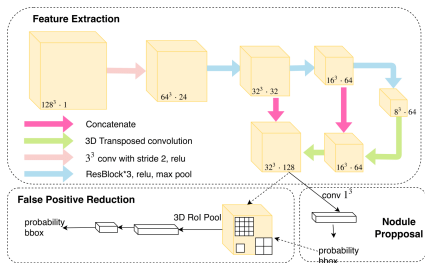


Fig. 1. End-to-end pulmonary nodule detection framework

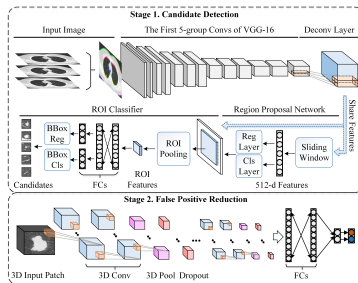


Figure 1: The framework of the proposed CAD system.

# The End