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# SIMULTANEOUS ACCURATE DETECTION OF PULMONARY NODULES AND FALSE POSITIVE REDUCTION USING 3D CNNS

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## Overview

**Pulmonary nodule diagnosis:** In this paper, we propose a CAD system for simultaneous nodule candidates detection and false positive reduction.

**Problems:** The intra-class variations of nodules' size, shape, texture, sharpness, brightness, compactness and its surrounding tissues make nodule detection difficult.

**Drawbacks of conventional method and 2d CNN method:**

(1)Traditional CAD systems use assumptions and experience. All these methods fail to adapt to variable shape, size and texture of nodules. Therefore, their performance may degrade drastically on large datasets.

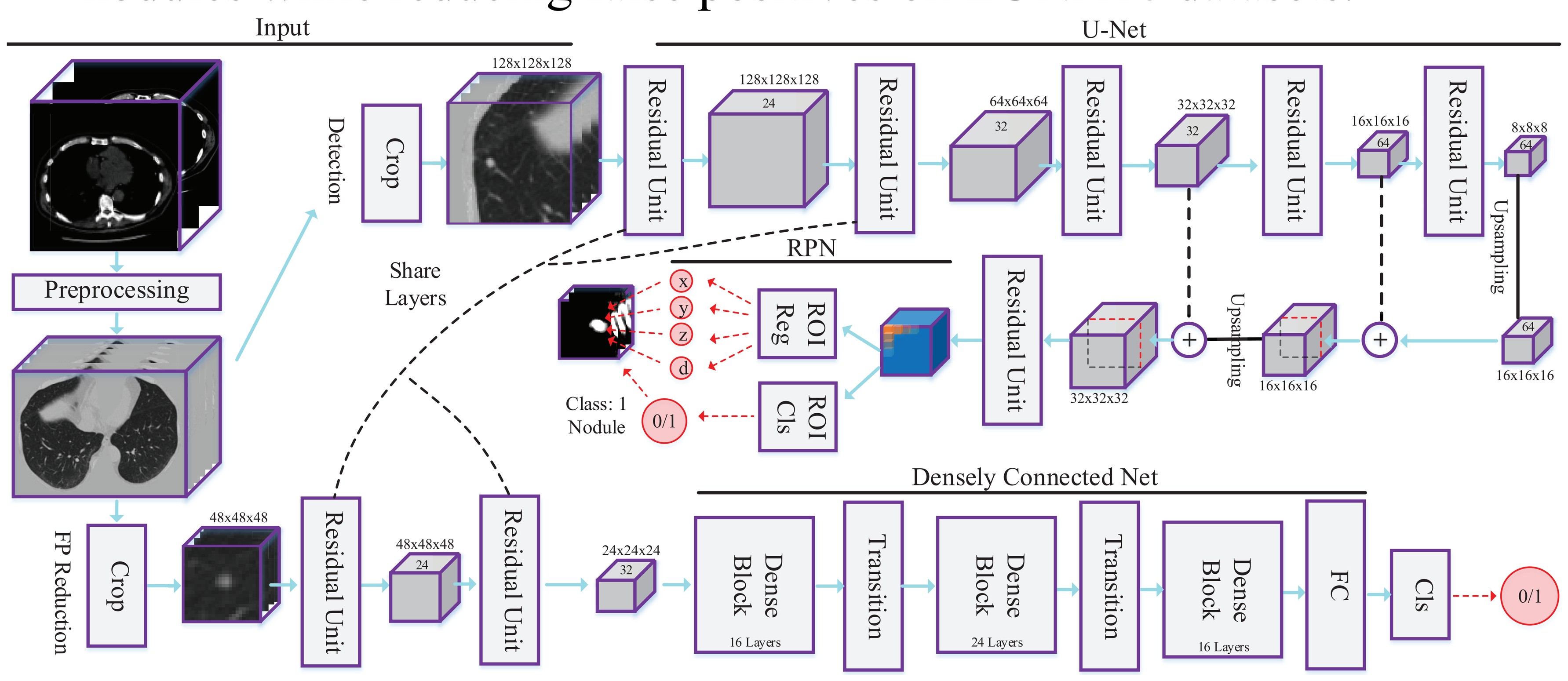
(2)2D CNN models have inherent limitations of processing CT images. Only 3 consecutive slices are not enough for CNNs to effectively learn volumetric representation from 3D contexts.

**Novelties:**

(1)We propose a full 3D CNN framework that accurately detects pulmonary nodules. To generate nodule candidates, we introduce the 3D U-Net structure to the region proposal network (RPN) for region of interests (ROI) classifier and regression.

(2)We propose a DenseNet based 3D CNN for false positive reduction. The structure of densely connected net strengthens nodule feature propagation and encourages feature reuse.

(3)The proposed CAD system achieves accurate detection of pulmonary nodules while reducing false positives on LUNA16 datasets.

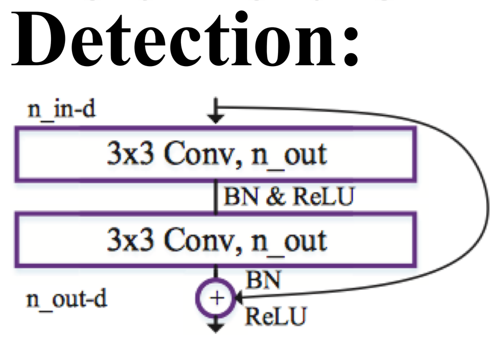



An overview of the proposed CAD system.

## Methods

### Nodule Candidate Detection:

**Key Components:**




**Multi-task learning with weighted loss:** The total loss function is classification loss plus location regression loss. Given a set of training pairs {(xi , yi)} i=1,2,...,Ncls , the WBCE loss between the label target yi and prediction output oi is:

$$\mathcal{L}_{cls} = -\frac{1}{N_{cls}} \sum_{i=1}^{N_{cls}} w y_i log(o_i) + (1-y_i) log(1-o_i),$$

$$w = \frac{N_{cls} - \sum_{i=1}^{N_{cls}} y_i}{\sum_{i=1}^{N_{cls}} y_i},$$

The regression loss of location information is given by:

$$\mathcal{L}_{reg} = \frac{1}{N_{reg}} \sum_{i=1}^{N_{reg}} \sum_{\gamma \in \{x,y,z,d\}} y_i \, \mathrm{smooth}_{L_1}(t_\gamma - t^*_\gamma),$$

$$\mathrm{smooth}_{L_1}(x) = \begin{cases} 0.5x^2 & \text{if } |x| < 1 \\ |x| - 0.5 & \text{otherwise,} \end{cases}$$

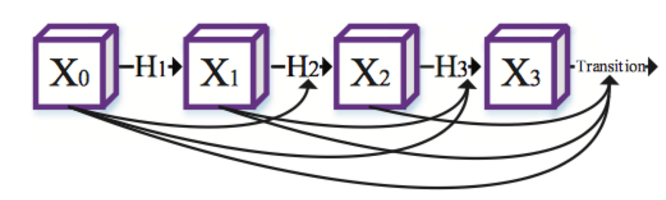
## Methods (Continued)

$$t_x = (x - x_a)/d_a, t_y = (y - y_a)/d_a,$$
$$t_z = (z - z_a)/d_a, t_d = log(d/d_a),$$

**Online hard negative example mining:** Since hard examples contain more valuable information than simple ones, we adopt an online hard negative example mining strategy (OHNEM) during training.

### False Positive Reduction:

**Key Components:**




The loss function of false positive reduction is WBCE loss. Since the overwhelming easy negatives will give rise to degenerative models, OHNEM is also used to avoid the situation where training is dominant by easy negative examples.

## Results

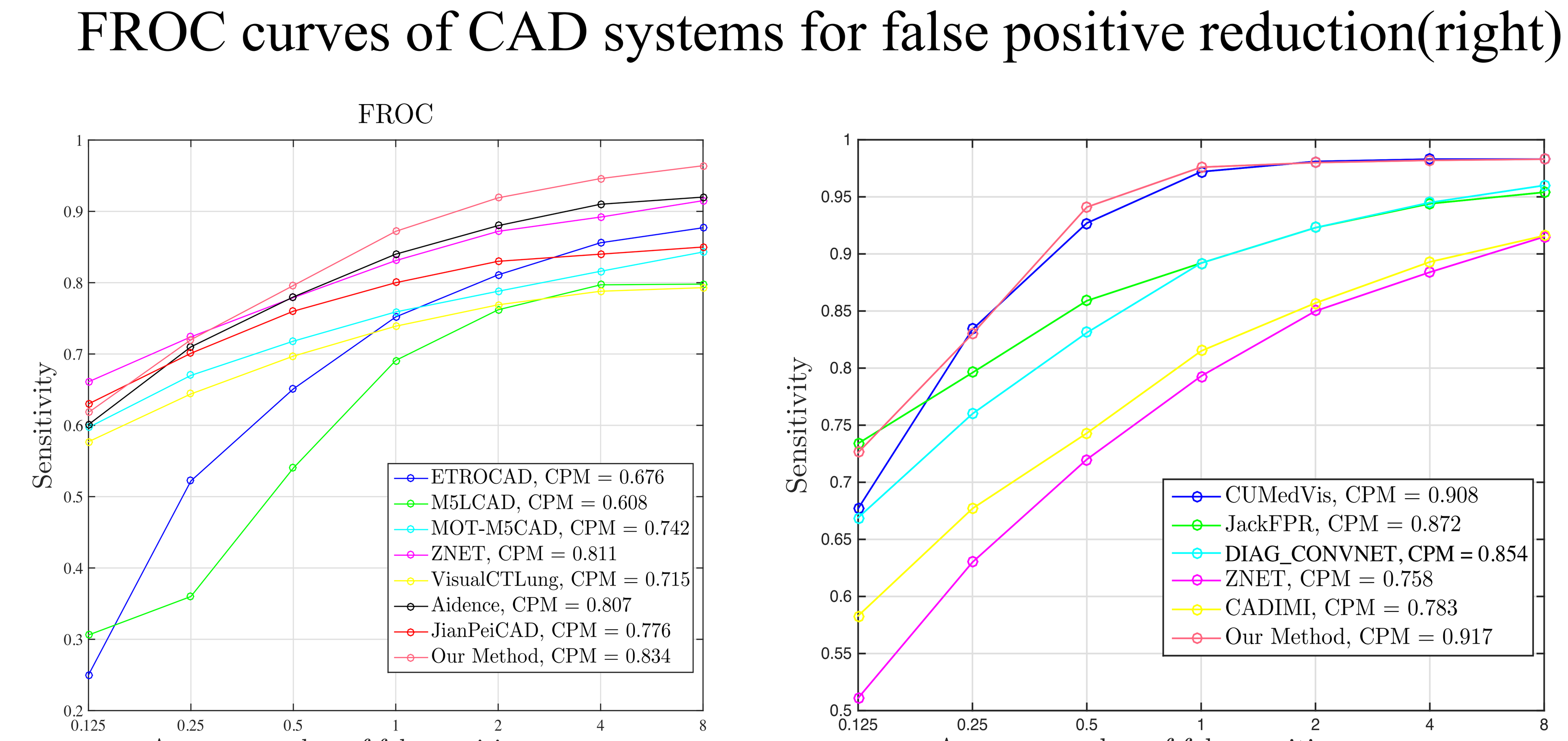
**Datasets:** We use LUNA16 datasets to validate the proposed CAD framework. The datasets are divided into 10 subsets for 10-fold cross validation and they contain 888 scans in total. We preprocess the images to obtain minimum bounding boxes of lung area cubes and then use augmentation methods of flipping, swapping, random rotation and random scaling.

Comparison of CAD systems for nodule detection

| System name | Sensitivity | Avg. candidates/scan |
|---|---|---|
| ISICAD | 0.856 | 335.9 |
| SubsolidCAD | 0.361 | 290.6 |
| LargeCAD | 0.318 | 47.6 |
| M5L | 0.768 | 22.2 |
| ETROCAD | 0.929 | 333.0 |
| Our method | **0.967** | 25.9 |

FROC curves of CAD systems for nodule detection(left)

FROC curves of CAD systems for false positive reduction(right)




Ablation studies of OHNEM

| Stage | Nodule detection | |
|---|---|---|
| Sensitivity | without OHNEM 0.925 | OHNEM **0.967** |
| Stage | False positive reduction | |
| Sensitivity | without OHNEM 0.934 | OHNEM **0.983** |

## Conclusions

We have proposed a full 3D framework for pulmonary nodule detection. A RPN model is built based on U-Net backbone to generate nodule candidates. Then a 3D DenseNetbased model is developed for false positive reduction. Experimental results on LUNA16 dataset demonstrate that the proposed method achieves accurate detection of pulmonary nodules while reducing false positives, thus suggesting its potential for clinical applications.