COMPUTER-AIDED DETECTION OF LUNG NODULES USING MULTI-LEVEL CONTEXTUAL 3D CNNS

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ABSTRACT

Lung cancer is one of the main causes of cancer-related deaths worldwide. The detection of pulmonary nodules during lung cancer screening through CT scanning is of high importance since they may indicate early stage of lung cancer. In the last years, Computer-Aided-Detection (CAD) systems have been developed to automatically detect pulmonary nodules. A CAD system consists of three parts; preprocessing, nodule candidate detection and false positive reduction. Existing systems tend to have high false positive rates and often lead to unnecessary and high interventional treatments.

The main purpose of our research is to optimize the false positive reduction task by determining the true nodules from a given long list of potentially cancerous lesions. Towards this purpose, we employ 3D convolutional neural networks (CNNs). It has been proved that 3D CNNs can better encode spatial information than equivalent 2D architectures and are able to extract better representative features. Moreover, we implement a framework with three different network architectures which take into account three different levels of contextual information. To manage the highly class imbalance, we use data augmentation techniques to produce more positive samples. We employ rotation, translating and flipping patches in the 3 axes of the extracted 3D patches. We present the results of classifying the candidate nodules using the two out of three architectures. Each of the three networks can output a probability of being a nodule for every candidate patch and by fusing them a more accurate probability can be calculated.

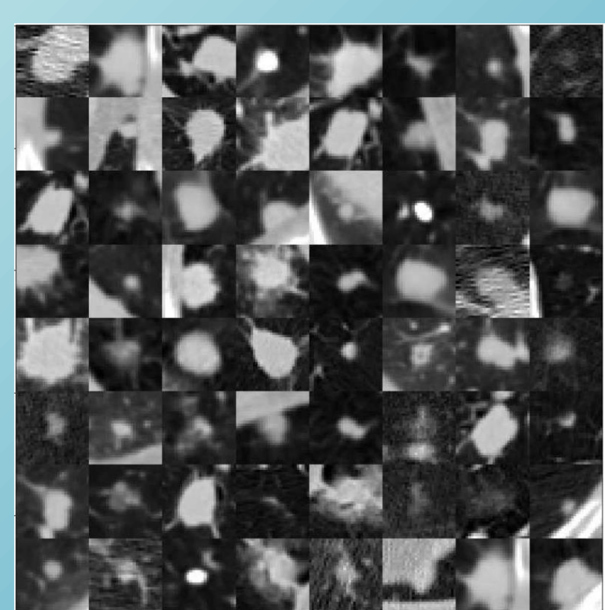
Although this implementation is used for pulmonary nodule detection, it is general enough and can be easily adapted to any other 3D object detection tasks using volumetric medical images where the desired objects can vary a lot and they can be very similar with other components.

DATA AUGMENTATION

Highly unbalanced dataset:
- 1351 nodules : 549,714 non-nodules → 1 : 400 ratio
- Need of balanced data for convolutional neural networks.

Data augmentation methods (of a 3D candidate patch):
- Rotation 90, 180, 270 over x, y, z axis
- Flipping over x, y, z axis
- Translation of one voxel left and right over x, y, z

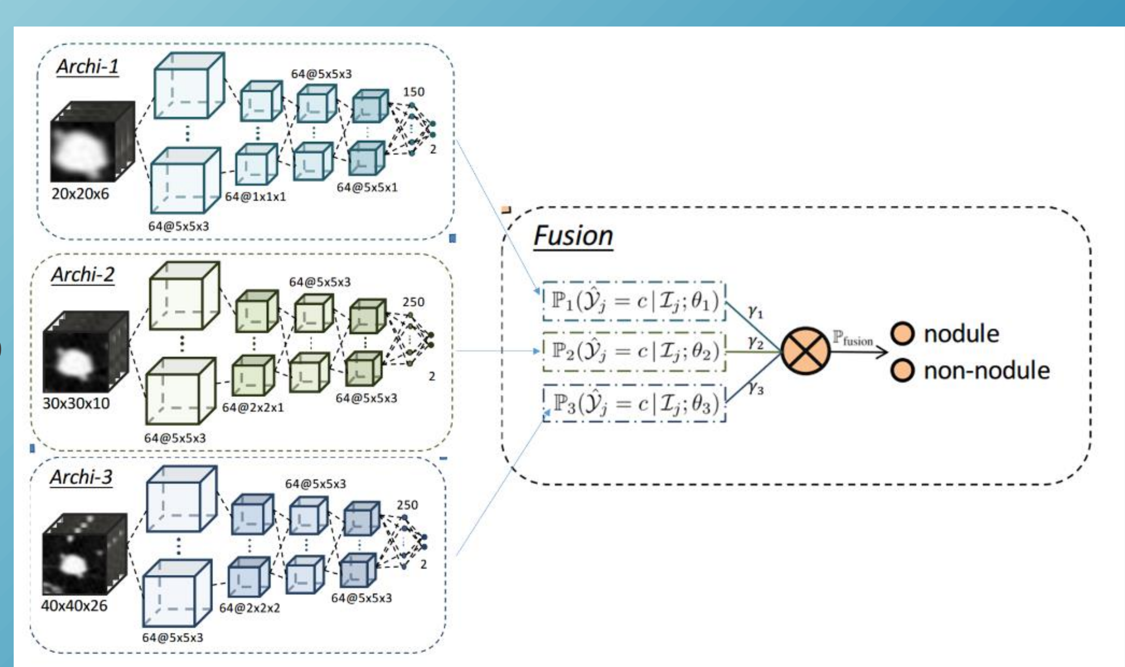
Mainly for the positive samples: 112 new patches for each positive patch



Examples of Positive Samples (nodules).

FALSE POSITIVE REDUCTION USING 3D CNNS

For every candidate, multi-level patch extraction:
- Small-sized patch: **20x20x6**
- Medium-sized patch: **30x30x10**
- Large-size patch: **40x40x26**



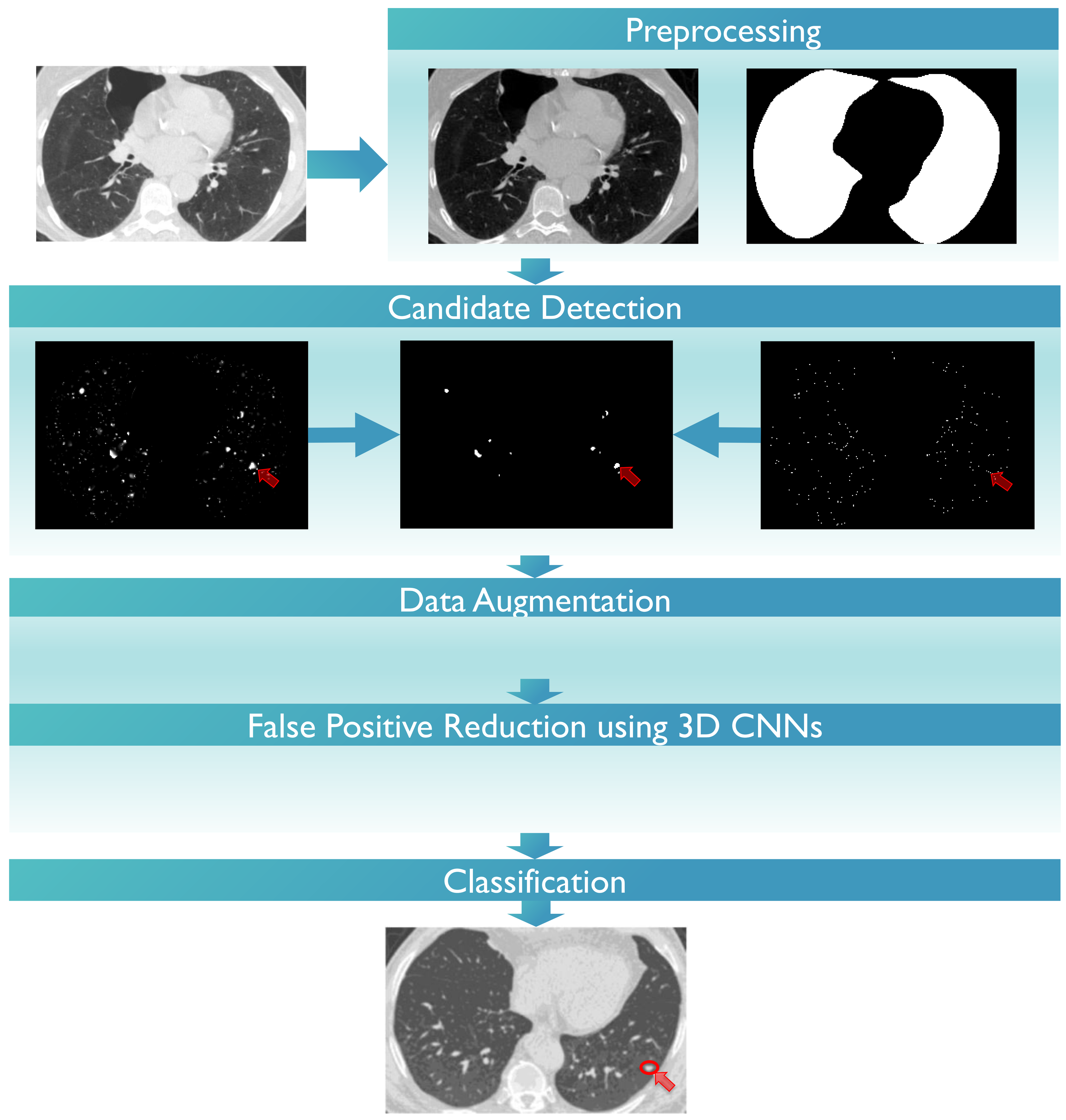
The multi-level contextual 3D CNNs framework [1].

Archi-1			Archi-2			Archi-3		
layer	kernel	channel	layer	kernel	channel	layer	kernel	channel
Input	-	1	Input	-	1	Input	-	1
C1	5×5×3	64	C1	5×5×3	64	C1	5×5×3	64
M1	1×1×1	64	M1	2×2×1	64	M1	2×2×2	64
C2	5×5×3	64	C2	5×5×3	64	C2	5×5×3	64
C3	5×5×1	64	C3	5×5×3	64	C3	5×5×3	64
FC1	-	150	FC1	-	250	FC1	-	250
FC2	-	2	FC2	-	2	FC2	-	2
Softmax	-	2	Softmax	-	2	Sofrmax	-	2

C: convolution, M: max-pooling, FC: fully-connected

The architectures of the multi-level contextual 3D CNNs [1].

APPROACH

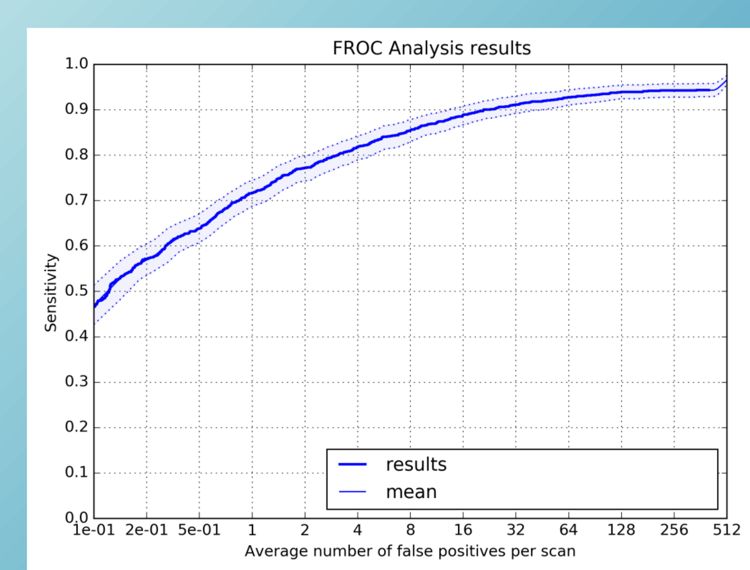


RESULTS

False positive reduction track of the LUNA16 Challenge
- Binary classification problem

Small-sized candidate patches (20x20x6):
- Mean sensitivity over (0.125 – 8 false positives): 0.65

Medium-sized candidate patches (30x30x10):
- Mean sensitivity over (0.125 – 8 false positives): 0.7



FROC curve for the medium-sized patches (30x30x10).

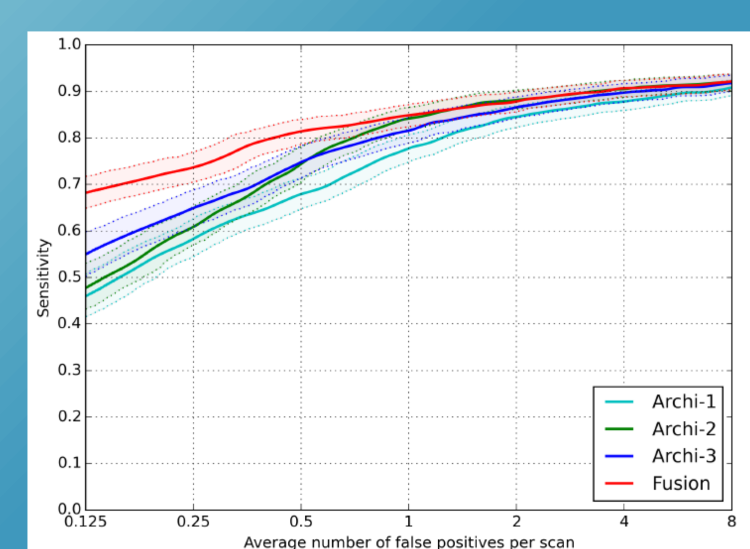
FUTURE WORK

Large-sized candidate patches (40x40x26) and fuse the probabilities.

Combine probabilities from all the patch-sizes, using:
- fixed weights ($\mathbf{0.3}P_1 + \mathbf{0.4}P_2 + \mathbf{0.3}P_3 = P$)
- a classifier (e.g. SVM)
- a neural network (1 or 2 fully-connected layers)

More data augmentation
- Positive and negative samples
- More sophisticated methods.

Explore:
- Combine with handcrafted features.
  - Handcrafted features (~ prior knowledge)
  - Learnt features (~ CNNs)
- Candidate generation using convolutional neural networks.
- Transfer learning:
  - Pretrain in various medical imaging datasets first
  - First layers as a fixed feature extractor
  - Finetune only with relevant data



FROC curves of different architectures and their fusion result [1].

REFERENCES

1) Dou et al., "Multilevel Contextual 3-D CNNs for False Positive Reduction in Pulmonary Nodule Detection," in *IEEE Transactions on Biomedical Engineering*, vol. 64, no. 7, pp. 1558-1567, July 2017.

2) Arnaud Arindra et al., "Validation, comparison, and combination of algorithms for automatic detection of pulmonary nodules in computed tomography images: the LUNA16 challenge", Medical Image Analysis, Volume 42, 2017.

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