# Lung Cancer Diagnosis Using Deep Convolutional Neural Network

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## Abstract

In this paper, a method of diagnosing lung cancer from low-dose CT (computed tomography) scan images of high-risk patients using deep 3d convolutional neural network is described. Previously, diagnosis of lung cancer was performed by pulmonary radiologist based on malignant lung nodules from the CT images. However, with great success of neural network in various fields, the diagnosis potentially can be aided by deep learning. In Kaggle Data Science Bowl (DSB) 2017 challenge, which motivated this paper, encouraged participants to solve lung cancer detection problem by offering CT scans data of potential lung cancer patients. On this challenge, a whole pipeline was designed to predict whether the patients have lung cancer within 1 years of scanning. The proposed system is composed of three major stages, preprocessing of raw CT scan images, nodule detection and lung cancer prediction. Finally, a binary cross entropy loss score of 0.51092 was achieved on the test set which ranked 35 out of 1972 teams.

## 1. Introduction

According to American Cancer Society [1], Lung cancer is the second most common cancer in both men and women. It is one of the most cancer which has low survival rate for patient, and 1 out of 4 cancers which lead to death. In 2017, it was accounted for over 225,000 cases of lung cancer patient and 150,000 deaths in the United States. It is important to predict lung cancer in early stage because this often gives patients more treatment options and chances at survival.

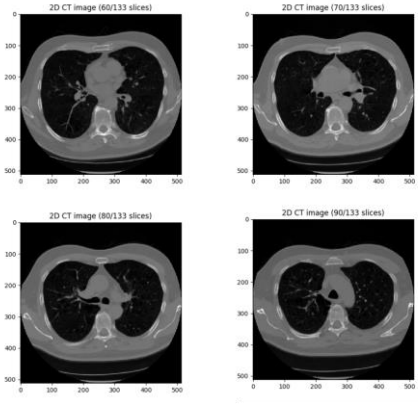



Figure 1. Examples of lung CT scan images in DSB dataset

Along with the great success of neural network in various computer vision application fields, there also have been many trials to solve various problems on bio-medical images using deep learning. Not only attempts for replacing conventional image processing techniques like lung segmentation, but also attempts for solving recognition problem like nodule classification, malignancy classification and lung cancer prediction have been made. Data Science Bowl (DSB) [2] is an annual machine learning competition held on Kaggle. Motivated by DSB 2017 challenge, we designed the automatic lung cancer prediction system based on deep 3d convolutional neural networks. It takes patient CT scan images as input and predicts the probability whether the patient will be diagnosed to have lung cancer within one year from the date the scan was taken.

Our pipeline is composed of following three steps. First, input raw CT scan images are preprocessed and stacked to 3d chunks. Preprocess includes Hounsfield Unit (HU)

transform, resampling for normalizing voxel spacing, thresholding and binarization. Second, with nodule classifier trained on LUNA16 [13] datasets, we predict nodule candidates by searching out all possible regions in 3d chunk with sliding windows. Finally, the nodule candidate features are fed to lung cancer classifier which predict binary class of lung cancer patient. More details for each stage will be described on below section.

## 2. Related Works

### 2.1 Nodule classification with Convolutional Neural Network

Lung nodule detection using convolution neural network was proposed in early years [4], [5]. Architecture of multiple streams of 2D CNN was proposed [6], using feature set of 2D patches from differently oriented planes. Considering variate size of the nodules from 3mm to 30mm, a Multi-scale Convolutional Neural Network (MCNN) [19] was introduced to classify the nodules with using different input patches. [8] generate nodule candidates in the form of 3D cubes with local geometric-model-based filter. Then, the candidates are classified by forwarding to deep 3D CNN model. [10] compared sliced-level 2d CNN, nodule-level 2d CNN and 3d CNN showing that result of 3d CNN is slightly better than other approach. [7] trained 3D CNN using extracted volumes of interest with generated hard negatives. They proposed screening FCN (fully convolutional network) which is used to generate candidates for entire volume at once and to make hard negative samples.

### 2.2 Convolutional Neural Network

In nowadays, Deep Convolutional Neural Network (CNN) has become a dominant approach for visual recognition. As layer depth of CNNs become deeper, vanishing gradient problem was emerged. When deep network is trained with backpropagation, gradient passing through all deep layers can be vanished. Many recent publications attempt to solve this problem. ResNets [12] and Highway Networks [11] made shortcut with identity connections which passes features from previous layer to the next. With the connection, gradient can more easily reach all the layers of a deep network.

## 3. Methodology

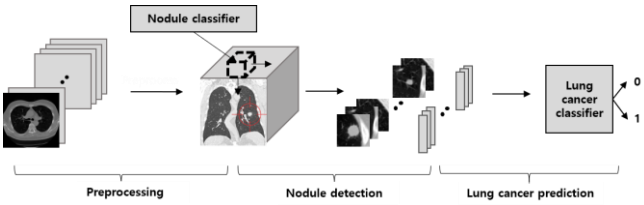



Figure 2. Overview of our lung cancer diagnosis system

The pipeline is composed of three stages, preprocessing, nodule detection and lung cancer prediction as shown in Figure 2. Preprocessed CT images are stacked into 3d shape in the first stage. Second, nodule classifier which is pre-trained on external dataset, extracts 16 candidates of nodules by sliding over all possible regions on the 3d images. In this process, the 256-dimension features of selected nodules are stored. Finally, nodule features are fed into lung cancer classifier and outputs the probability whether the patient will have lung cancer or not.

### 3.1 Preprocessing

#### 3.1.1 HU (Hounsfield Unit) transform

Hounsfield Unit (HU) is a linear transformation of raw attenuation coefficient measurement into relative value with the radio density of water in STP and air, which is set to 0 HU and -1000 HU respectively. As DICOM format provide rescale intercept and rescale slope, we can directly transform raw scan image to HU scale by Equation 1.

is the rescale slope, $R$ is stored raw pixel value, and $b$ is the rescale intercept. Finally, 2d slice scan images are stacked into 3d shape.

$$HU = m \times R + b \quad \text{Equation 1.}$$

### 3.1.2 Resampling

Some CT parameters, for example, the slice thickness and pixel spacing are different between each patient sample. It means that one may have 2.5mm×0.5mm×0.5mm and another may have 1.5mm×0.75mm×0.75mm of voxel spacing. A simple method to deal with these problem is to resample all data with the same scale. We resample every sample to 1mm×1mm×1mm voxel size with nearest neighbor interpolation. By doing this, we overcome slice thickness invariance and pixel spacing invariance problem. We choose 1mm as a good balance between accuracy and computational load.

### 3.1.3 Segmentation and Binarization

As nodules are located on lung tissues, we are only interested in lung region of 3d images. There were several 2D lung segmentation techniques based on traditional image processing and deep neural network. However, they still have some failure cases where a small nodule, especially, attached to the lung outside edge is disappeared. Furthermore, they take a lot of time to be processed. Instead, we made binary masks using simple and fast thresholding method with proper HU value. [3] investigated the effect of different HU threshold range from -400 to -200 with 50 intervals. They found that -300 HU threshold is beneficial for nodule detection task. With reference to [3], we threshold image with -300 HU and binarize it by replacing pixel value to one. Experimentally, we found that the binarized patches are easier to be trained and they do not need to be normalized from HU scale, which has different range for each patient. Figure 3 shows example of segmentation result with -300HU threshold.

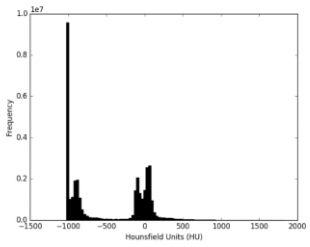



Figure 3. Distribution of HU value in CT scan sample image

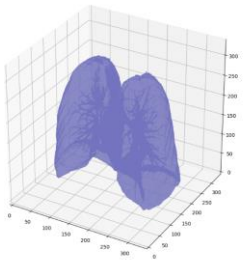


Figure 4. Segmentation with -300 HU thresholds

## 3.2 Nodule Detection

DSB 2017 Bowl only provides CT scan images and binary label for lung cancer patient. On the other hand, LUNA16 gives more information about nodules in CT scans, including coordinates and diameters. So, we used this dataset to make the nodule detector. We regarded the nodule detection problem as a classification problem with attempt to find all locations of the nodules by searching all possible area using pre-trained classification networks, 3D convolutional neural network. In other words, we can find position of the nodules by classifying candidates and scanning all the areas in 3d voxels with sliding window and threshold.

### 3.2.1 Training nodule classification network

First, we extracted all the positive and negative nodule candidates as a 3d cubic shape from LUNA16 dataset from coordinate and diameter information. We selected the cube sizes with three scales as 16×16×16, 24×24×24, and 32×32×32. When training network, we rotated, flipped

both vertically and horizontally, and shifted the positive samples. The positive and negative ratio are set to proper ratio, 1:1, for data balancing by randomly sampling negative candidates. We used 3d convolutional neural network, the 3d version of ResNet, for the nodule classifier as shown in Figure 5. Except for first residual block, each residual block has down sample layer which also is 3d convolution layer. All 3d convolution layers have 3×3×3 kernel size. Each output channel dimension of residual block is 16, 64, 128 and 256 respectively. We trained three classification models which receive 16×16×16, 24×24×24 and 32×32×32 patch as input with the same architecture except for final average pooling size.

### 3.2.2 Nodule detection and feature extraction

Using nodule classification network (Figure 5), we can extract locations and features of nodules from 3d CT scan image. We spectate all possible regions in 3d shape with sliding window, where the stride is half of the cubic size. 3d patches which have high confidence score are collected during inference time and finally sorted by the score value. 256-dimension features of fully connected layer are stored together. Then, we selected only 16 nodule candidates with highest scores. Practically, the confidence score was calculated by averaging outputs of the three networks. Finally, each patient has 16×256 nodule features which are used to classify lung cancer.

## 3.3 Lung Cancer Classifier

In previous step, we extracted features of 16 nodules for one patient with 256-dimension vector which comes from last fully connected layer of the network. Then, 16×256 nodule features are fed into lung cancer classification network. The basic network structure is showed in Figure 6. It is composed of three convolution blocks, which of them use 1d convolution.

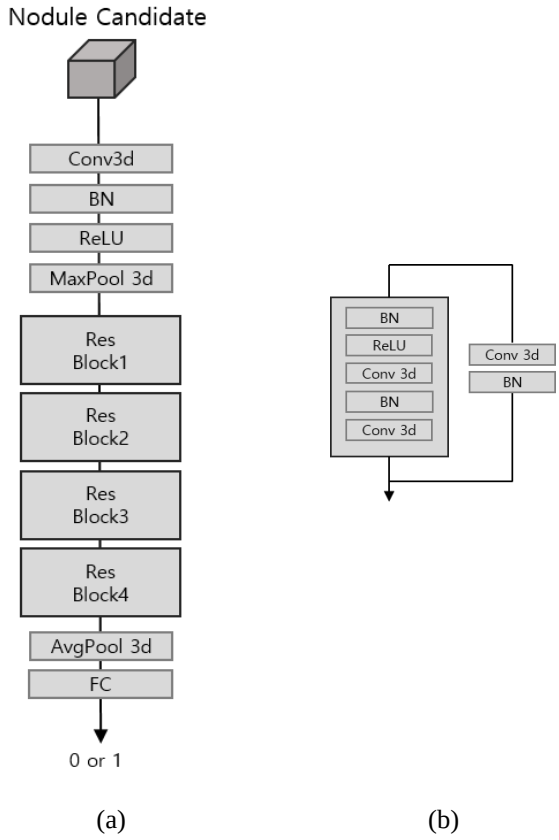



Figure 5. 3D residual network for nodule detection.

(a) nodule classification network

(b) each residual block in nodule classification network.

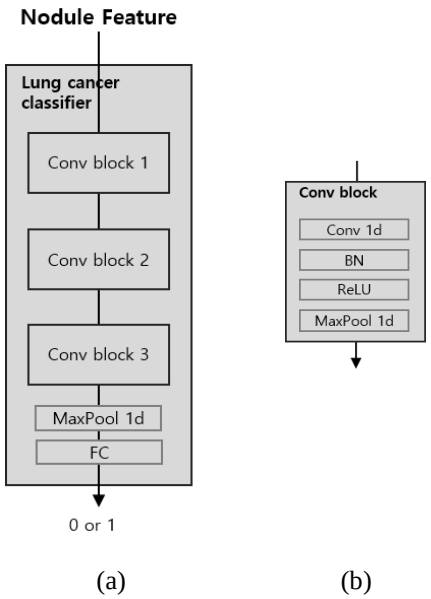
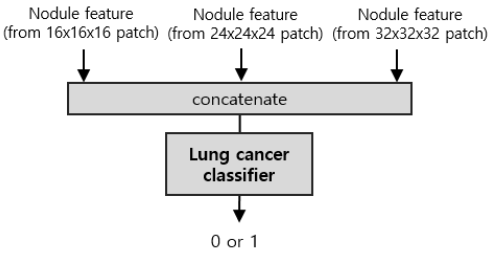



Figure 6. Basic lung cancer classification network.

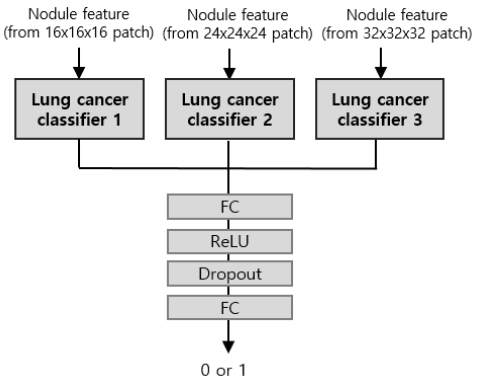
(a) basic lung cancer classification network

(b) each convolution block in lung cancer classification network

For better performance, we composed multi-scale lung cancer classifier depicted in Figure 7 with two types. Since we used three detectors in previous stage, which have different scale cube size as input, the classifier can use these three types of features. Type-A concatenates input nodule features each other before forwarding to lung cancer classifier. In type-B, on the other hands, input nodule features are first represented by each lung cancer classifier, and then concatenated together. Although, performance on validation set of type-B was slightly better than type-A, we use both to make ensemble results.




(a) Type-A lung cancer classifier




(b) Type-B lung cancer classifier

Figure 7. Two types of multi-scale lung cancer classification networks

## 4. Experiments

The competition uses binary cross entropy loss as an evaluation metric and we want to minimize Equation 2. $n$ is the number of patients and $\hat{y}_i$ is the predicted probability of the image if a patient has lung cancer. $y_i$ is 1 if the ground truth is labeled with 1, 0 otherwise

$$Loss = -\frac{1}{n}\sum_{i=1}^{n}\left[y_i \log(\hat{y}_i) + (1-y_i)\log(1-\hat{y}_i)\right] \quad \text{Equation 2.}$$

Table 1 shows lung cancer classification result on 198 validation samples. For comparison, we trained classifier of Random Forest, XGBoost and SVM as baselines with the concatenated features of 3d patches from different three scales. Our multi-scale classifier type-A and type-B both superior than above three classifiers. We ensembled results of those two types and it showed 0.47869 binary cross entropy loss on validation set. The confusion matrix of this ensemble model is shown on Table 2. It has total 74.75% accuracy on validation set with 93.61% on non-cancer patient and 28.07% on cancer patient. Consequently, this model showed 0.51092 loss on 508 test set. Using this score, we ranked at 35 out of 1972 teams.

Table 1. Lung cancer classification results

| Data | Classifier | Loss |
|---|---|---|
| Validation | Random forest | 0.58229 |
| | XGBoost | 0.52864 |
| | SVM | 0.52558 |
| | multi-scale classifier type-A | 0.49700 |
| | multi-scale classifier type-B | 0.49147 |
| | Ensemble (type-A + type-B) | 0.47689 |
| Test | Ensemble (type-A + type-B) | 0.51092 |

Table 2. Confusion matrix of lung cancer prediction on DSB 2017 validation set with ensemble of type-A and type-B

| | No Cancer (prediction) | Cancer (prediction) |
|---|---|---|
| No Cancer (G.T) | 132 | 9 |
| Cancer (G.T) | 41 | 16 |

## 5. Conclusions

Motivated by Kaggle DSB 2017 challenge, we designed automatic lung cancer diagnosis system using deep 3d convolutional neural network. Proposed system is divided into three stages, preprocessing, nodule detection and lung cancer classification stage. On the leader board, we ranked on 35th out of 1972 teams with 0.51092 loss on test set.

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