Classification of Lung Nodules from Low Radiation CT Images

Hansori Chang, Shuming Cui, Yuhao Xue

Machine learning and imaging

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Introduction

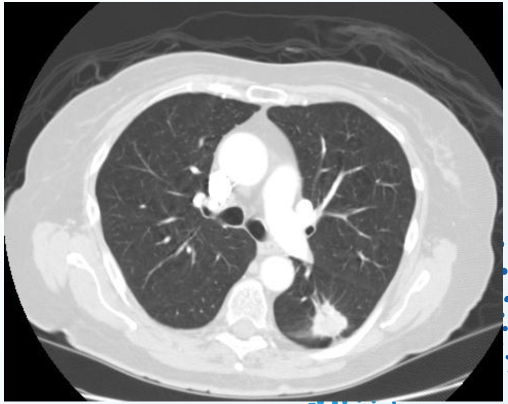
- Lung cancer is second most common cancer and leading cause of cancer death(24%)[3]
- 5-year relative survival[4]
  - At distant stage: 6%
  - At localized stage: 61%
- CT scan is read by radiologist (Need computer-aided detection)
- CT uses X-rays (7mSv)[5]
- Low dose CT scan is critical

Lung Cancer[1]

A person getting a CT scan[2]

Data Description

- Lung Nodule Analysis 2016, using LIDC-IDRI[6]
- Cancer screening Ct scans with annotated lesions
- Lung nodule with a thickness over 2.5mm are excluded
- 888 CT scan mdh files
- Categorized lesions
  - Non-nodule
  - nodule<3mm
  - nodule>3mm



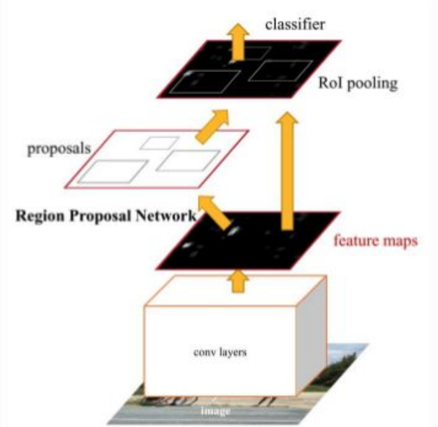
Sample image of the dataset [6]

The Project Goal

"

Classifying presence of lung nodule on CT scanned images with poisson noise

Related Work

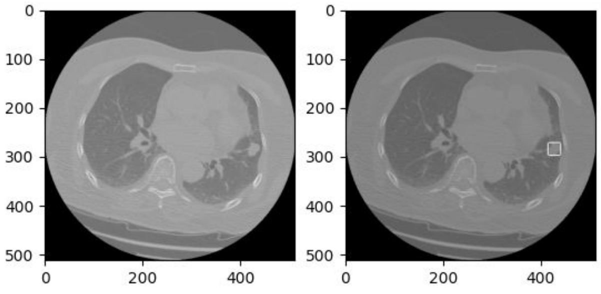


Faster R-CNN with RPN [9]

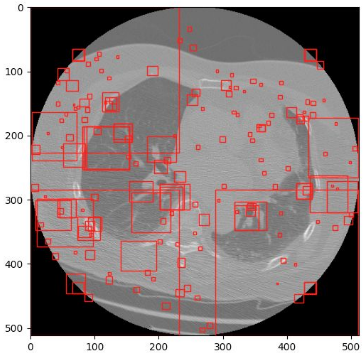
- Uses RCNN with two stages
  - Region Proposal Network(RPN)
  - Region based Convolutional Neural Network (RCNN)
- Li et al. used faster R-CNN [7]
  - 3 different feature extraction model
  - VGG16, ResNet50, ResNet100
- Kopelowitz et al. used Mask R-CNN [8]
  - sensitivity: 0.936
- Krizhevsky et al. [11]
  - Introduced R-CNN with Alexnet
  - 30% improvement on the best result on PASCAL VOC in 2012

Preprocess of Data

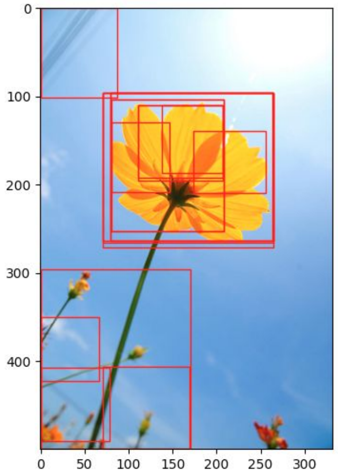
- Raw image original Size: 512 × 512
- Cropped after selective search to train by R-CNN
- Unbalance between lung nodule and non-lung nodule images
    - Increase the number of lung nodule images manually
- Resize the cropped images into 64 × 64 for training, to reduce the memory usage of our training.



Lung CT images with lung nodule



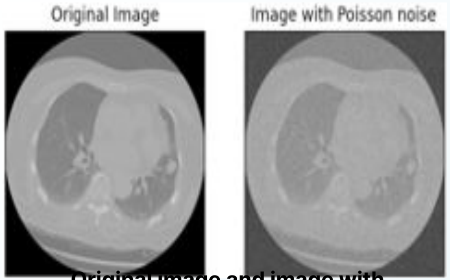
Selective search for lung nodule



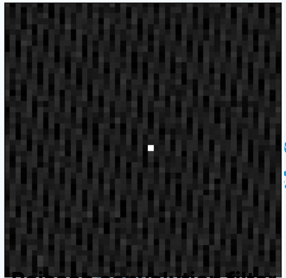
Selective search for normal object

Poisson Noise

- A layer with random Poisson noise is designed to simulate the result from low-dose CT
- Import skimage and used random noise function
- A convolution filter that can generate Poisson noise, which should be consistent for all cropped image from one CT image.



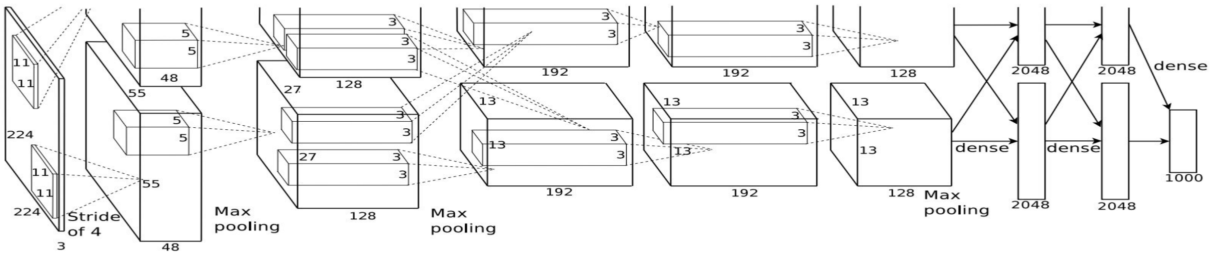
Original image and image with Poisson noise



Poisson convolution filter

R-CNN with AlexNet

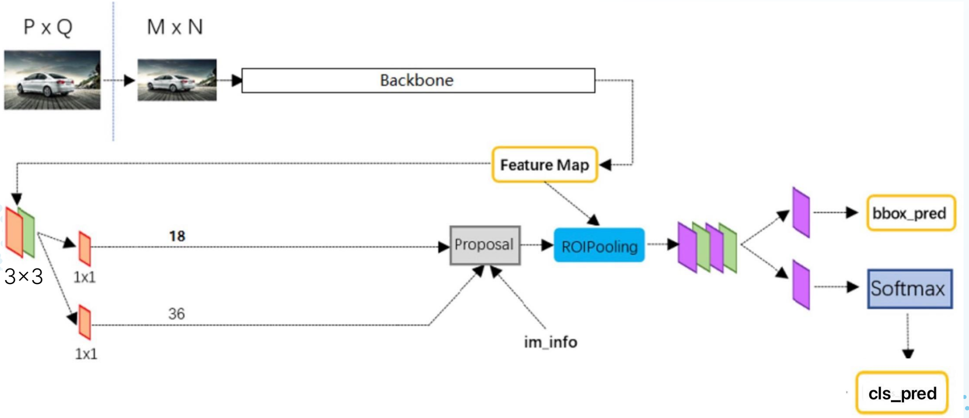
- AlexNet: 8 layers, including 5 convolution layers and 3 fully-connected layers[11]
- ReLU, dropout, overlapping pooling, local response normalization, and data augmentation
- Input size: 64×64, stride 1, kernel 10 (instead of 224×224, stride 4, kernel 11)
- Batch Normalization for tensorflow
- Addition of dense model with 1 channel as the last layer
- Classification: “Nodule” & “No nodule”



Structure of Alexnet[10]

Localization: Faster R-CNN with ResNet 50

- Faster R-CNN model: a more complex model with both feature map and proposal regions used for bbox prediction and classification [7]
- Backbone: VGG, ResNet50, etc.



Faster R-CNN[12]

Faster R-CNN with ResNet 50 Result

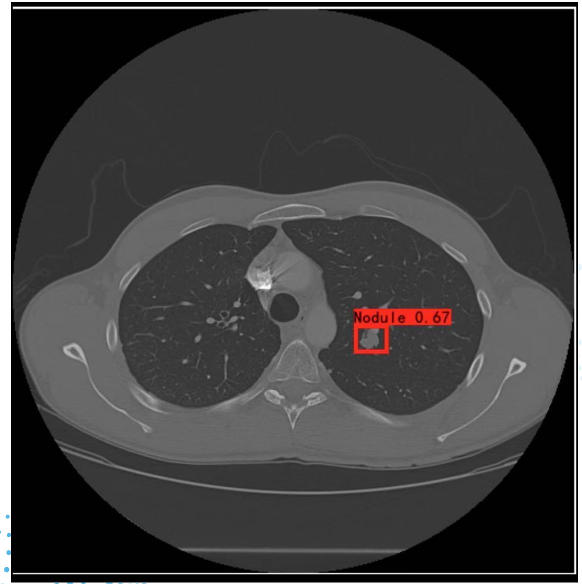


Figure 1. Localization of Lung Nodule

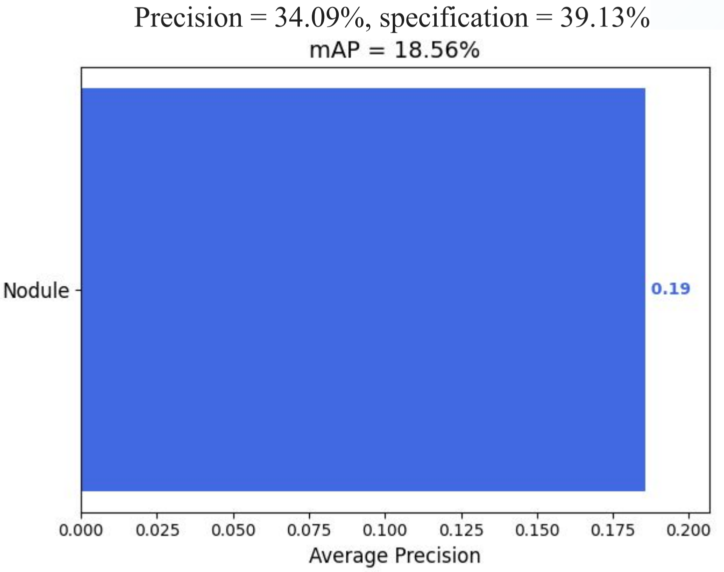
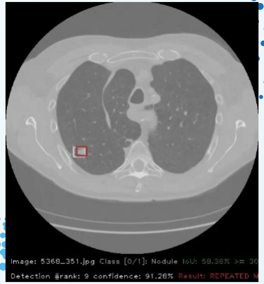


Figure 2. Average Precision of the model



Data illustration of mAP calculation

Classification Result of Images w/o Noise

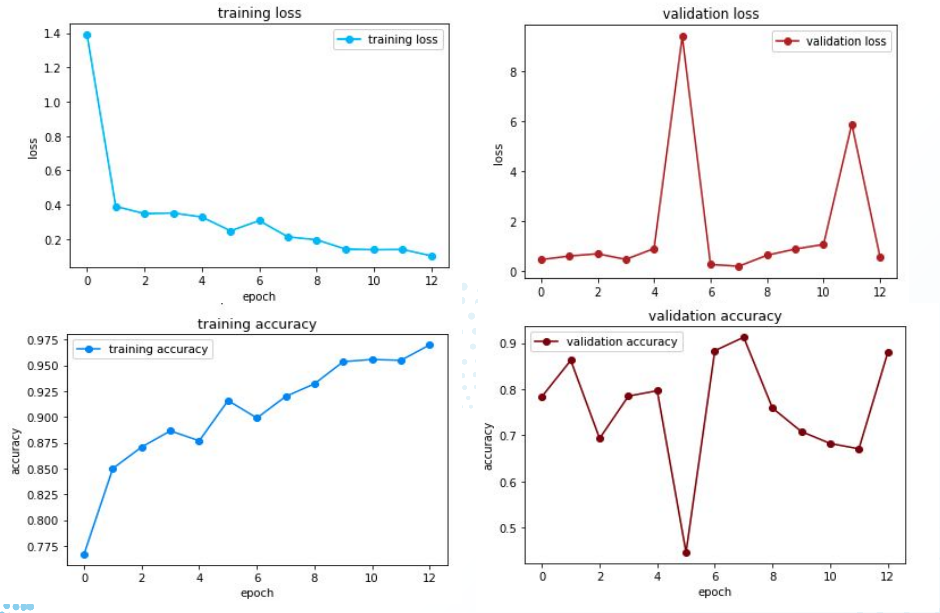


Figure 3. Classification result of images without noise

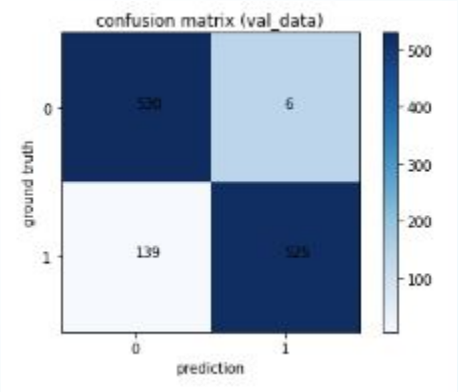


Figure 4.Confusion matrix for original images

Training accuracy: 0.9805

Validation accuracy: 0.9358

Sensitivity: 0.9202

Precision: 0.9445

Classification Result of images w/ noise

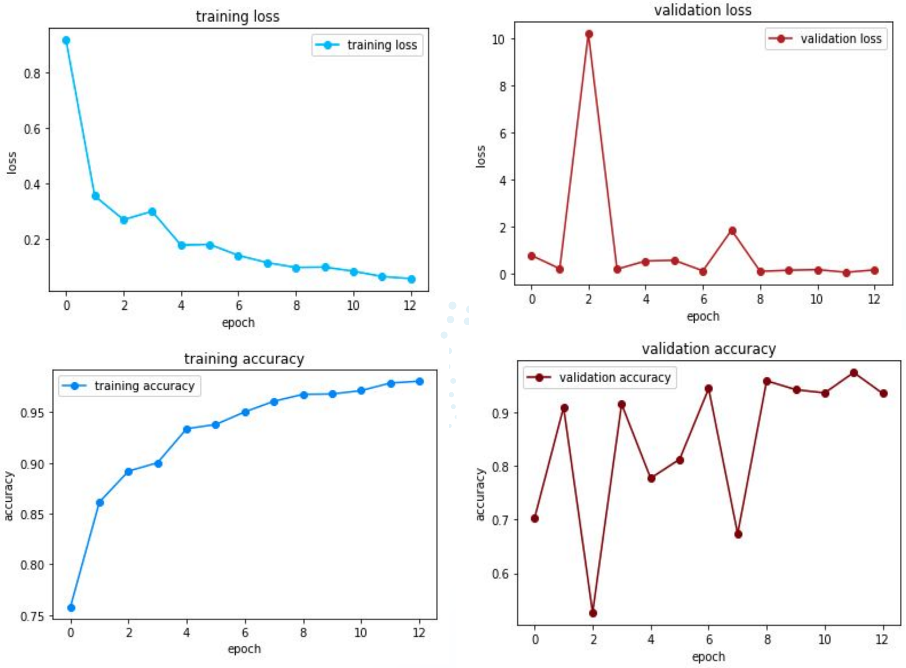


Figure 5. Classification result of images with noise

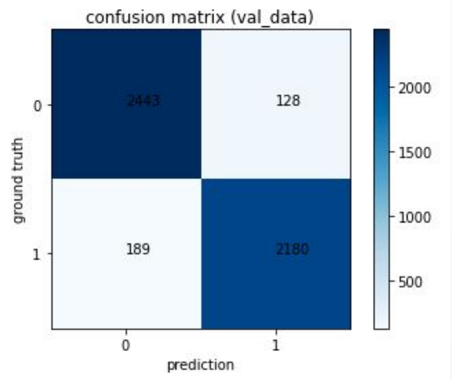


Figure 6. Confusion matrix for images with noise

Training accuracy: 0.9698

Validation accuracy: 0.8792

Sensitivity: 0.7907

Precision: 0.9887

Conclusion

- R-CNN with Alexnet are successful in classifying a lung nodule with poisson noise.
- Fail to localize the lung nodule with the advanced model.

Limitation and Further Investigation

- Memory and Time for running the model
- Size of the dataset
- False positive reduction and SVM

- Localization of the lung nodule.
- Compare between different models
- Data Augmentation

Thank you for listening!
Q&A

Sources

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