Using Deep Learning for Classification of Lung Nodules on Computed Tomography Images

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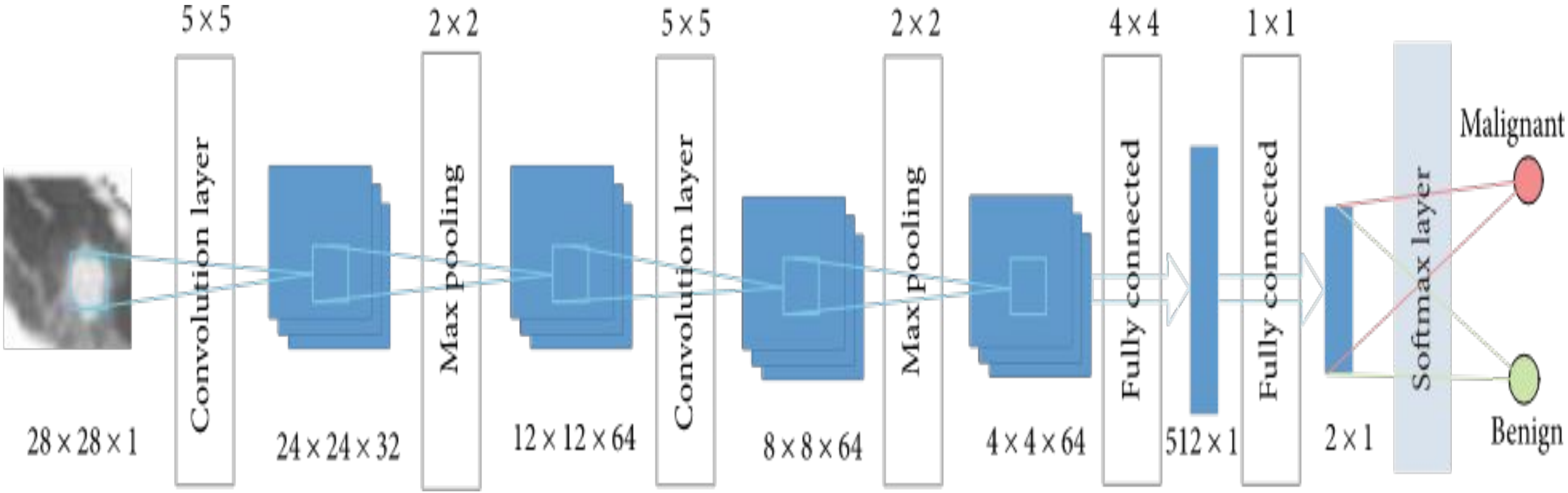
Introduction

- Lung cancer which is the most common cancer in both men and women is a major burden of disease worldwide
- Lung nodules need to be examined and watched closely when it might be at an early stage. By early detection, the 5-year survival rate of patients with lung cancer can be improved.
- Currently, CT scan can be used to help doctors detect lung cancer in the early stages. In many cases, the diagnosis of identifying lung cancer depends on the experience of doctors, which may ignore some patients and cause some problems.
- In this paper, the problem of classification of benign and malignant is considered. It is proposed to employ, respectively, the convolution neural network (CNN), deep neural network (DNN), and stacked autoencoder (SAE).
- The work can be used as input directly to reduce the complex reconstruction of data in the process of feature extraction and classification.

Methodology

Convolution Neural Networks (CNNs)

- A convolution neural network (CNN) is a multilayer neural network, which consists of one or more convolution layers and then followed by one or more fully connected layers as in a standard multilayer neural network.
- CNN architecture is usually used in collaboration with the convolution layer and pool layer.
- The pooling layer operation consists of max pooling and mean pooling.
- Mean pooling calculates the average neighborhood within the feature points, and max pooling calculates the neighborhood within a maximum of feature points.
- The error of feature extraction mainly comes from two aspects: the neighborhood size limitation caused by the estimated variance and convolution layer parameter estimated error caused by the mean deviation.



The architecture of the CNN in this paper is shown in Figure

DNN (Deep Neural Network)

- A simple extension of the fundamental neural network by increasing the number of hidden neurons in the network forms a deep neural network.
- For enhancing the ability of DNN, a nonlinear activation function should be employed.
- In the training phase of DNN, weights are initialised randomly and bias is kept to 0. The output value is propagated forward while the parameters are updated using backpropagation.
- However, fine-tuning, regularization and increase in data volume are required to overcome overfitting issue in the DNN.

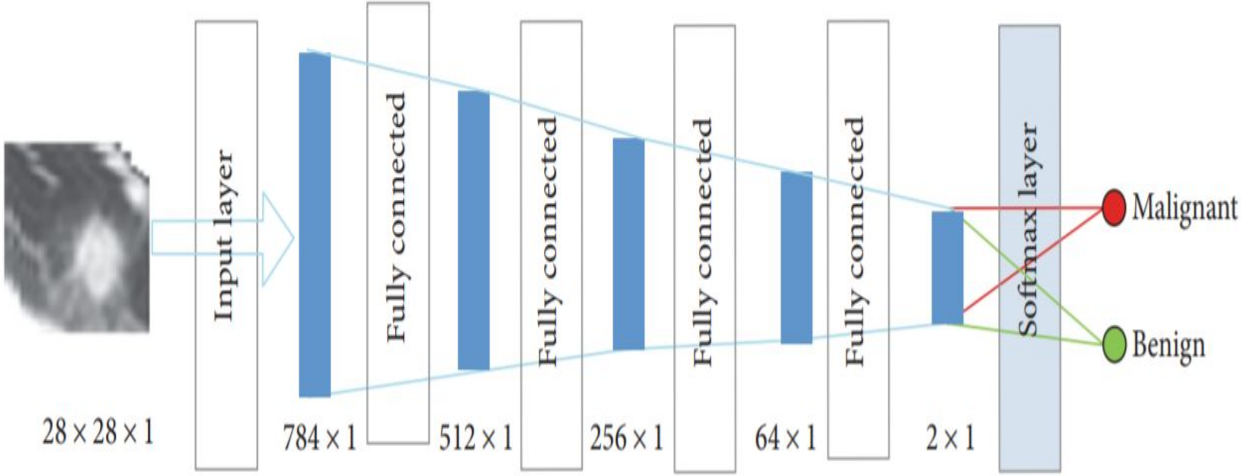


FIGURE 2: The architecture of the DNN.

Stacked Autoencoder

- A multilayer sparse autoencoder of a neural network forms the stacked autoencoder.
- Sparse autoencoder has the same number of neurons in the input and output layers. Also, the number of neurons in the hidden is less than that of the input layer.
- Each sparse encoder skips the decoding part and directly employs the encoding process for the next sparse autoencoder training.
- Multiple autoencoders combine with softmax classifiers form the SAE architecture.

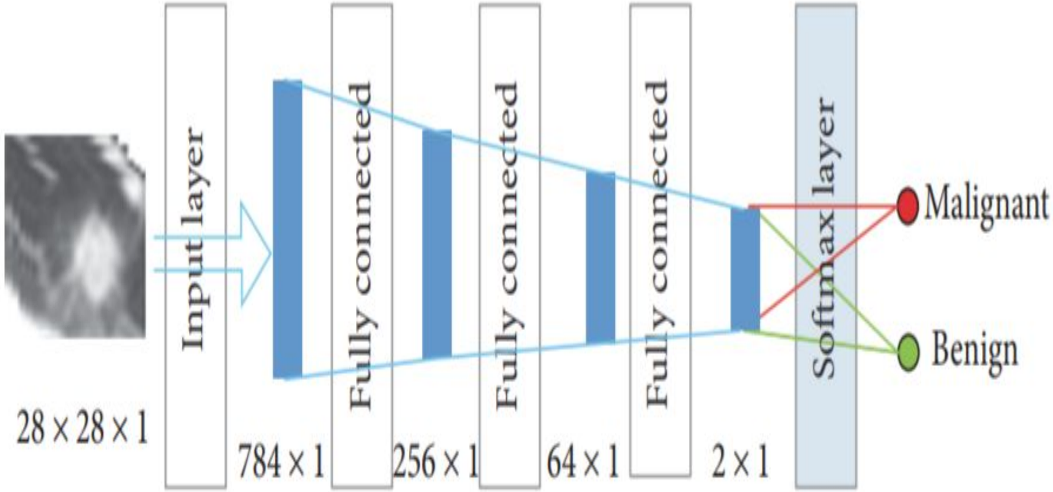


FIGURE 4: Architecture of the SAE.

Loss Function of the Neural Network

- The cost function is as follows:

$$C(w,b) \equiv \frac{1}{2n}\sum_x \|y(x) - a\|^2 + \frac{1}{2n}\lambda\sum_w w^2,$$

- The last term in the loss function is used to prevent overfitting.
- DNN carries out the backpropagation operation to update the weight and paranoid b in order to improve the accuracy.
- The activation function used in the training process is Leaky ReLU.
- The formula for Leaky ReLU is as follows:
  Here, a is fixed to 0.1.

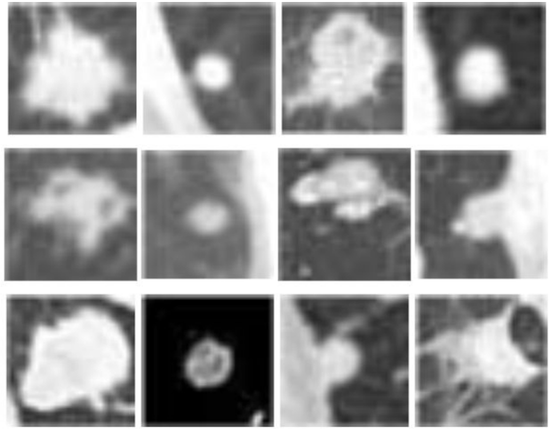
$$y = \begin{cases} x & \text{if } x \geq 0 \\ ax & \text{if } x < 0, \end{cases}$$

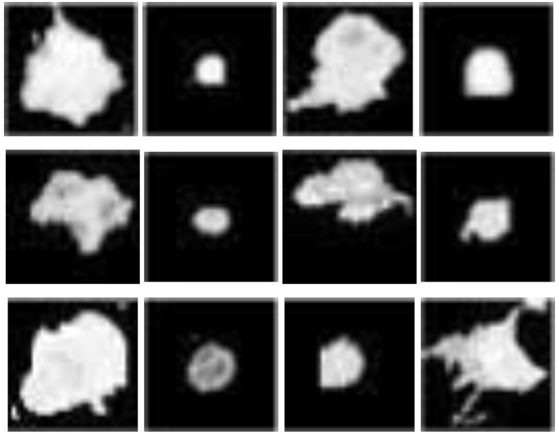
LIDC-IDRI

- 244527 images and an XML file
- Lung Nodules: 1 mm, 1.25 mm, 2.5 mm
- Pulmonary Nodules: 3 mm to 30 mm
- Degree of malignancy of pulmonary nodules:
    - Highly unlikely for cancer
    - Moderately unlikely for cancer
    - Indeterminate likelihood
    - Moderately suspicious for cancer
    - Highly suspicious for cancer

Data Augmentation

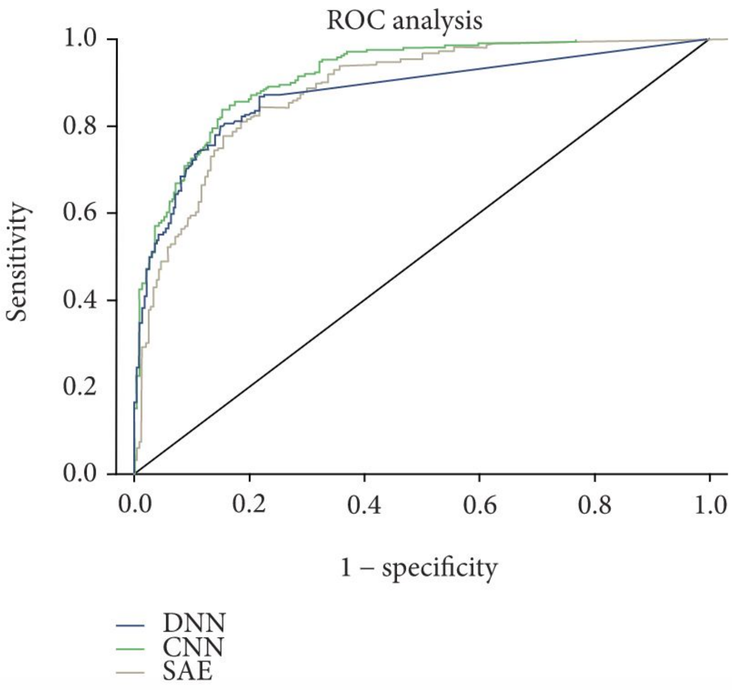
- Pulmonary nodule images are set to a size of 28*28
- Steps to achieve this:
    - Binary processing
    - Restoring the image
    - Eliminating noise disturbance





Results

Models	Accuracy	Sensitivity	Specificity
CNN	84.15%	83.96%	84.32%
DNN	82.37%	80.66%	83.9%
SAE	82.59%	83.96%	81.35%



Thank You