Automatic Classification and Accuracy by Deep Learning Using CNN Methods in Lung Chest X-Ray Images

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Abstract. Automatic image segmentation and classification of medical images plays significant role in detection and diagnosis of various pathological process. Normally chest radiography is a basic representation to find many abnormalities present in the chest. Radiology services delayed due to proper detection, segmentation and classification of diseases. Automatic segmentation and classification of medical images improved both pathological and radiological process. In recent days the deep learning with CNN methods provides remarkable successes in medical image diagnosis with in time limit and with minimum cost. The proposed method handles CNN for automatic classification of lung chest x-ray images as normal and non-normal. Applying these modern techniques to lung chest x-ray images face more challenges while using small dataset. For testing JSRT dataset used which contains 247 images. Preeminent performance achieved using 180 images of nodule and non-nodule images. This method produce expected classification accuracy with the help of faster computation of CNN within fraction of seconds and attain 86.67% in classification accuracy.

1. Introduction
Lung cancer is most dangerous type of cancer among all other cancer types in human society. Chest radiographs are essential for basic examination of various diseases in radiology. Lung nodule detection is a challenging process even for computer aided diagnosis and detection tools. Most of the radiographs concentrated on common pathological identification of chest diseases and struggle to find lung nodules. [4], [5] Modern works has revealed that Deep learning techniques produce effective result on lung nodule detection, segmentation and classification than machine learning algorithms. The strength of deep learning methods only used in this proposed system in the form of Convolution Neural Network (CNN)[1].

CNN is kind of deep learning method it accept image as batches or pixel groups. It solves many computer vision problems which include image identification, localization, segmentation, classification, etc. In this paper CNN works well based on group of pixels and it is very simple method
of classification. Jonathan Long et al examined fully convolution neural network and different classification networks for segmentation [4]. Yaniv Bar et al used deep learning methods to examined different pathological diseases and tested 433 images and identified CNN with GIST features gives better performance [5]. Geoffrey Hinton et al trained large deep neural network to classify 1.2 million high resolution images with 1000 image classes and used dropout for regularization [6]. Dan C. Cire et al proposed convolutional neural network for object classification. [7], Yann Le Cun et al described new unsupervised learning algorithms and trained ConvNet for visual object recognition and vision navigation for off-road mobile robots [8], Rupesh Kumar Srivastava et al produced high way network to process hundreds of layers without any delay by using simple gradient descent and used adapting gating unit to regulate information flow [9], Dan Ciresan et al trained huge DNN within hours and reduce error rate 30-40% by combining DNN columns into Multi- Column DNN and improve recognition rates on MNIST, traffic signs, NIST SD 19, Chinese characters, NORB AND CIFAR10 [10].

2. Lung Nodule Classification using DNN

2.1. Data Acquisition
The Japanese Society of Radiological Technology (JSRT) dataset consist of 247 images of 154 nodule images and 93 non nodule images. Totally 180 images of 90 nodule and 90 non-nodule images used for this classification. The image original size 2048 × 2048 reduced to 512 × 512 for classification and mask created by using original and ground truth image. Final resultant segmented image used for further process. The following Figure 1. shows the extracted lung portion.

![Original image, Ground truth, Extracted Lungs](image)

Figure 1. LungsExtraction

2.2 Methodology
The working methodology of Deep Neural Network (DNN) involves Convolution neural network, Batch Normalization, RELU activation function, Fully connected layer, softmax function and it used 90 images in each class 0 and 1. It train 18 images and It randomly select 2 images from 90 images for classification. There is a chance to increase and decrease training images, based on this result going to vary and also chance to change the value of filter size .This paper gradually increased value of filter and also increased number of training images to validate classification accuracy. Figure 2 shows CNN working methodology.
2.2.1 CNN Model

Convolutional neural network (CNN) need only little work of pre-processing when compared to other techniques. It has filters to pre-process the image. It has trained itself to fit the image. Here CNN used $512 \times 512 \times 1$ as image size. Basically it need large amount of data to avoid over fit problem, technically medical images have no such large dataset. To overcome this problem it used data augmentation technique. Data augmentation used batch normalization to solve this problem.

The goal of Convolution is to extract high level features from input image. In CNN each layer has some responsibility to extract features, based on number of layers which gives better performance. The increased number of layer understands the dataset well and always results two types of operation.

1. The convolved feature decrease the dimensionality by using Valid Padding
2. The convolved feature Increase the dimensionality or same by using Same Padding

The CNN used same padding for classification. Spatial size of convolved layer is reduced with the help of pooling layer. It is also used to extract dominant features like rotational and positional invariant with the help of max pooling and average pooling. This paper CNN used max pooling to return the maximum value of image portion which is covered by kernel. The max pooling also accomplishes denoising in the image. To get more basic features from image, increase the combination of convolved and pooling layers. Finally CNN totally understand the dataset and capture features.

2.2.2 Batch Normalization

Batch Normalization normalizes each input layer. Normalization done with the help of scaling and adjusting the activation. [2] It permits each layer learn itself independent of other layers and also it reduces dropouts there by increase the stability of neural network. Normally it used between convolution layer and RELU activation function to speed up the training. It has two parameters standard deviation($\gamma$) and mean($\beta$) for each layer, the denormalization done simply by changing these two weights for activation.

Figure 2. CNN working Methodology
2.2.3 RELU activation
Rectified linear unit most commonly used activation function and it has easily implemented in hidden layers of neuron. It simply back propagates the errors. Computationally it is less expensive and it learns faster than other activation functions. RELU equation \( A(x) = \max(0,x) \). The output is \( x \) if \( x \) is positive else it gives 0.

2.2.4 Classification by fully connected layer
Fully connected layer is used to learn the high level features from output of the convolution layer. The input image is converted to fix the multi-level perceptron and flatten output is passed through feed forward neural network and for each training back propagation is applied. Based on the number of epochs, it easy to identify high level and low level features in an image. This model used 4 epochs and 4 iteration for training cycle. Softmax classification technique used for classification. It used in the output layer of classification. To handle multiple classes 0 and 1 softmax function is used.

3. Result and Discussion
The Figure 3 shows sample lung portion extracted by applying mask which are given as input in the input layer of the CNN for classification.

![Sample Lung Portions](image)

Figure 3. Sample Lung Portions

Figure 4 shows the graphical representation of the training and validation process using CNN. In this experimental set up, 90 nodule and non-nodule images with size of 512 X 512 used for Training. Validation accuracy obtained is 86.67. This validation accuracy is got by using 4 epoch, 30 iteration.

![Training Progress](image)

Figure 4. Validation accuracy
The Table 1 shows the classification accuracy at different experimental setup. Number of input images and the training files have been changed during each setup. It is done for 180 images by changing number of train files, epochs and iteration. Validation accuracy improves by increasing number of train files.

Table1. Classification Accuracy

| S.No. | No of Images | Train files | Accuracy |
|-------|--------------|-------------|----------|
| 1.    | 180          | 150         | 86.67%   |
| 2.    | 176          | 120         | 82%      |
| 3.    | 170          | 90          | 80%      |
| 4.    | 166          | 50          | 79%      |
| 5.    | 160          | 20          | 78%      |

4. Conclusion
Radiographs are best public screening mechanism for lung cancer. Due to different nature of lungs it takes more time for segmentation and classification. Normal computer aided techniques provides more methods for pathological diagnosis, segmentation and classification which takes more time and tedious work. DNN provide outstanding performance in medical image processing. This paper proposed a basic and simple mechanism for classification of lung images and attain accuracy of 86.67%. It’s a very first attempt which tried in deep learning classification with limited dataset, with more images it is possible to attain high accuracy. In future extend this type of work for segmentation and classification execute in various CNN methods and activation functions.

5. References
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