

Lung Nodule Classification Using Deep Learning Algorithm

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ABSTRACT

Lung cancer is one of the major cause of death among people throughout the world. Early detection of lung cancer can increase the chance of survival among people. The reason for failure in detecting lung cancer in early stages is that there is only a dime-sized lesion growth known as nodule, inside the lung. Hence, a lung cancer detection system using deep learning algorithm is used to classify the presence of lung cancer in CT- images. Images are taken from LIDC (Lung Image Database Consortium) which contains 193 CT images of thoracic regions of patients. The proposed technique uses simulated annealing for segmentation, convolutional neural network for feature extraction and classification. The model classifies 93.04% of actual nodules and significantly reduces the false positive rates.

Keywords: Computer Aided Diagnosis (CAD), Simulated annealing, Convolutional neural network (CNN).

1. INTRODUCTION

Lung cancer is the leading cause of cancer deaths in both men and women. The number of deaths caused due to lung cancer is more than prostate, colon and breast cancers combined. Also, most patients detected with lung cancer today are already at an advanced stage as lung cancer is hard to detect in early stages. The small lesions cannot be detected by X-rays and are only detectable by a CT scan. Even after the detection, it takes a considerable amount of effort and experience on the part of radiologists to detect and label the nodules as benign or as a probable case of malignancy.

On considering the more number of cases encountered by radiologists every day there is a constant pressure on them to analyse a huge amount of data and make a decision as quickly as possible based on the analysis. To detect and analyse lung nodules in CT images and to reduce the burden of radiologists Computer Aided Diagnosis(CAD) is used. There is always a need for a reference standard dataset to create such CAD systems, that can be used to obtain ground truths and can also act as a basis for comparison of different CAD algorithms. To effectively represent the structure and characteristics of region of interest in images CAD system is used for classification. To obtain more abstract and useful representations of data, deep learning architectures are effectively formed.

The objective of this research work is to classify potential pulmonary lesions as nodule or non nodule using convolutional neural networks. The main aim is to develop a fast, reliable and cost-effective program using MATLAB, which would enable detection of cancerous or tumorous lesions in CT images of the lungs of affected patients.

2. METHODOLOGY

In this article, the system uses three steps. The first step starts with collection of CT images of lungs. The second step is image segmentation which uses simulated annealing algorithm and the third step is feature extraction and

classification using convolutional neural networks. Fig.2.1 illustrates the block diagram of lung nodule extraction and classification of this system.

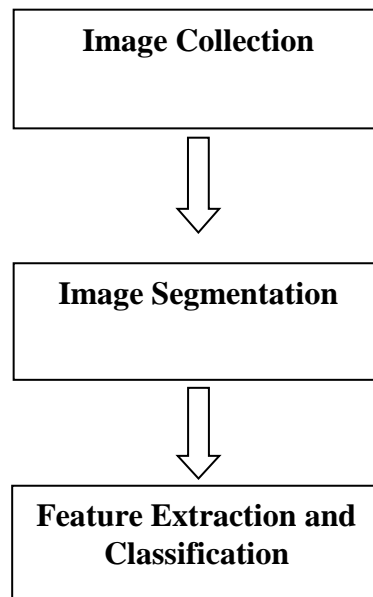


Fig.2.1 Block diagram of lung nodule extraction and classification of this system.

2.1 IMAGE COLLECTION

The foremost step in medical image processing is collection of images. The lung CT images are collected from LIDC data base. The medical data is usually in DICOM format, which is the standard for storage and transfer of medical images. Computed tomography (CT) images have better clarity, low noise and distortion for lung diagnosis. So, CT scan of lung images are given as input for this system. Dimensions of images are 512x512 pixels in size. Fig.2.2 shows the original CT lung image with nodule.



Fig.2.2 Original CT lung image

2.2 IMAGE SEGMENTATION

The most important part of medical image processing is image segmentation. Image segmentation is a procedure for extracting the region of interest (ROI) through an automatic or semi-automatic process. Many image

segmentation methods have been used in medical applications to segment tissues and body organs. Segmentation can be used in separating different tissues from each other, through extracting and classifying features in medical researches. One of the efforts is classifying image pixels into anatomical regions.

Image segmentation has been a long-standing problem in computer vision. It is a very difficult problem for general images, which may contain effects such as highlights, shadows, transparency, and object occlusion. Segmentation in the domain of medical imaging has some characteristics that make the segmentation task easier and difficult at the same time. On the one hand, the imaging is narrowly focused on an anatomic region. The imaging context is also well defined.

In particular, many of the existing techniques for image description and recognition depend highly on the segmentation results. The aim of segmentation is to simplify or change the representation of the image into something that is more easier to analyse and meaningful in representation. Image segmentation is usually used to locate boundaries (lines, curves, etc.) and objects in images. The pixels with the same label share certain visual characteristics when a label is assigned to every pixel in an image is referred as image segmentation.

A set of contours extracted from the image (edge detection) or a set of segments that collectively represents the whole image is the result of image segmentation process. In a specified region all pixels are similar with respect to some characteristics or computed property, such as intensity, colour, or texture. Adjacent regions are almost different with respect to the same characteristics.

Segmentation algorithms are based on one of two basic properties of intensity values: discontinuity and similarity. The first category is to partition the image based on abrupt changes in intensity, such as edges in an image. The second one is based on partitioning the image into regions that are similar according to a predefined criterion.

2.2.1. SIMULATED ANNEALING ALGORITHM

A probabilistic technique for approximating the global optimum of a given function is Simulated annealing . Specifically, it is a meta heuristic to approximate global optimization in a large search space. When the search space is discrete it is often used. Finding an approximate global optimum is more important than finding a precise local optimum for problems in a fixed amount of time, simulated annealing may be preferable to alternatives such as gradient descent.

The Simulated Annealing algorithms in general work as mentioned below: The algorithm randomly selects a value close to the current one, measures its quality, and then decides to move to it or it stays with the current value based on either one of the two probabilities between which it chooses on the basis of the fact that the new solution is better or worse than the current one at each time step. The value is progressively decreased from an initial positive value to zero and affects the two probabilities: at each step, the probability of moving to a better new solution is either kept

to 1 or is changed towards a positive value; instead, the probability of moving to a worse new solution is progressively changed towards zero during the search.

From the original CT lung image binary mask and the closed binary mask are determined using this algorithm. Fig 2.3 shows the binary mask of the input image.

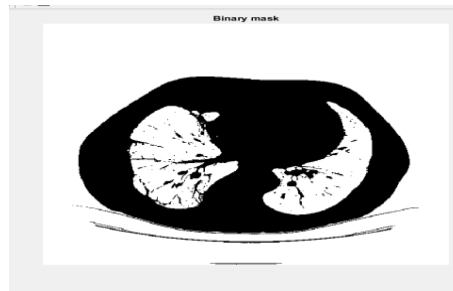


Fig.2.3. Binary mask

Fig 2.4 shows the closed binary mask of the input image.

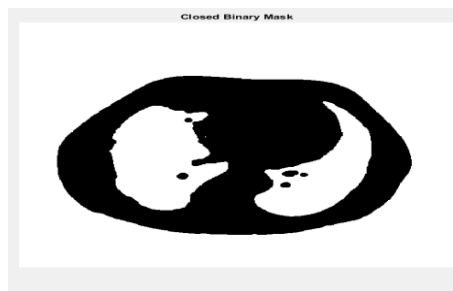


Fig 2.4. Closed binary mask

Thresholding is one of the most powerful tools for image segmentation. The segmented image obtained from thresholding has the advantages of smaller storage space, fast processing speed and ease in manipulation, compared with gray level image. A binary image is obtained from gray scale image by thresholding. In a non-linear operation two values are defined to pixels that are below or above the specified threshold value is referred as thresholding. Fig 2.5 shows the threshold extraction of the input image.



Fig 2.5 Threshold Extraction

2.2.2 CONVOLUTIONAL NEURAL NETWORK

After the segmentation is performed, the segmented lung nodule is used for feature extraction. A feature is a significant piece of information extracted from an image which provides more detailed understanding of the image. The features like geometric and intensity-based statistical features are extracted. Classification of the features is done. Feature extraction and classification is done using Convolutional neural networks. Fig 2.6 shows the architecture of convolutional neural network.

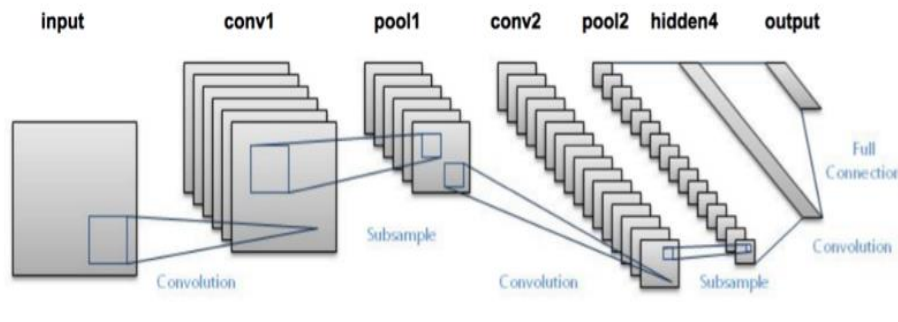


Fig 2.6 Architecture of convolutional neural network

Convolution neural network is a multi-layer neural network, which comprised of one or more convolution layers and then followed by one or more fully connected layers as in a standard multilayer neural network. The benefit of CNNs is that they are easier to train and have many fewer parameters than fully connected networks with the same number of hidden units. Convolution neural network architecture is usually used in combination with the convolution layer and pool layer. The affection of pooling layer is to confuse the features of the specific position. Since some location features are not important, it just need other features and the relative position. 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 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; convolution layer parameters estimated error caused by the mean deviation. The first error is reduced by mean pooling layer, retaining more image background information. Max-pooling can reduce the second error, retaining more texture information. Fig 2.7 shows the mask for regions in the grey boundary of input lung image.

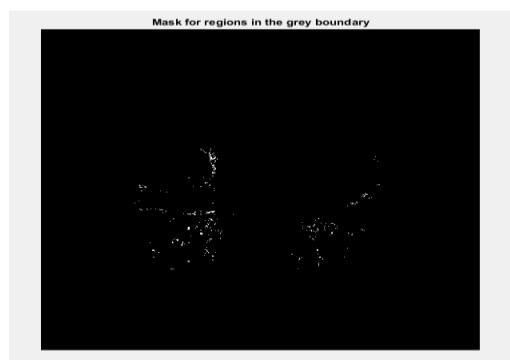


Fig 2.7.Mask for regions in grey boundary

After the extraction of the masks in the grey boundary, the pixels that are larger than 5×5 is considered and then the features are extracted. Fig 2.8 shows the masks for candidates that are larger than 5×5 pixels.

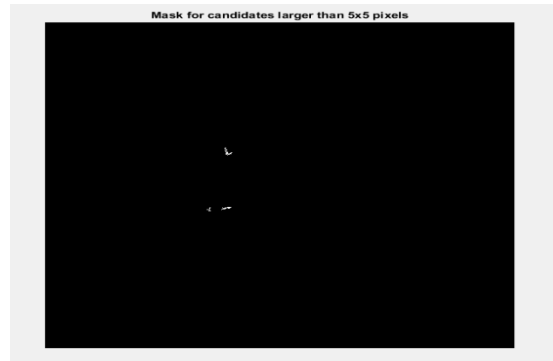


Fig 2.8 Masks for regions larger than 5×5 pixels.

The nodules that are larger than 5×5 is obtained. A linearity graph is drawn for the classified lung image. Fig 2.9 shows the linearity graph in which nodules and non nodules are shown.

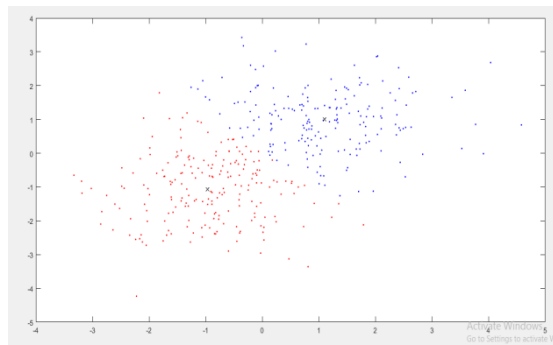


Fig 2.9 Linearity graph

More number of iterations are done until the loss is minimized. For the minimization of the loss iterations are increased. Fig 2.10 shows the CNN training loss. Here the loss is minimized with more iterations.

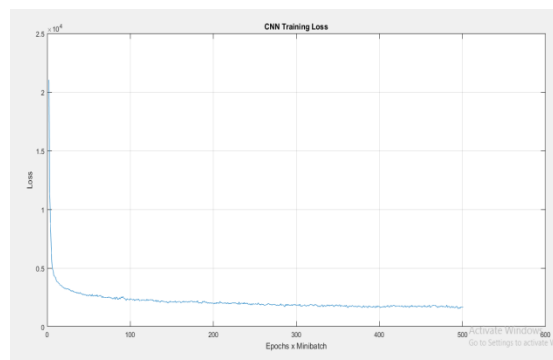


Fig 2.10 CNN training loss

Also the image is tested with the artificial neural network and the classification of features is done. The accuracy values are obtained. Table 1 shows the classification accuracy of the artificial neural network.

ANN	Accuracy
Correct classification	90%
Incorrect classification	10%

Table 1 Classification accuracy of ANN

In the proposed work (CNN) the network calculates the true positive rate and the false positive rates along with the area of the cancer cells. The accuracy is improved compared to ANN. The number of epochs is increased for better training accuracy. The network is tested for various datasets and the corresponding true positive rate and the false positive rate is obtained. Table 2 shows the comparison of different datasets along with the accuracy values.

CNN	LIDC Dataset1	LIDC Dataset2	LIDC Dataset3
Total number of images	193	160	133
Number of images tested	40	30	25
True positive rate	86.76%	86.83%	86.63%
False positive rate	13.24%	13.27%	13.37%
Overall accuracy	93.04%	92%	92.5%

Table 2. Comparison table for different datasets

3. CONCLUSION

The CT captured images are processed. The region of interest i.e., nodule is identified from the original image. From the extracted region of interest, the features are given to the classifiers which classifies the nodule based on the size. The dataset1 contains 193 images. The number of images tested are 40. The true positive rate obtained is

86.76%. The false positive rate is 13.24%. The overall accuracy obtained is 93.04%. For future work, we can implement this technique on some more images. Increasing the number of images can improve the accuracy.

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