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Lung Cancer Detection and Classification Using Deep CNN

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Abstract: Lung cancer is one of the most killerdiseases in the developing countries and the detection of the cancer at the early stage is a challenge. Analysis and cure of lung malignancy have been one of the greatest difficulties faced by humans over the most recent couple of decades. Early identification of tumor would facilitate in sparing a huge number of lives over the globe consistently. This paper presents an approach which utilizes a Convolutional Neural Network (CNN) to classify the tumors found in lung as malignant or benign. The accuracy obtained by means of CNN is 96%, which is more efficient when compared to accuracy obtained by the traditional neural network systems.

Key Words: Lung cancer, Computed Tomography, Chest CT image, Neural Network, Deep Learning, Convolutional Neural Network

I. INTRODUCTION

Lung cancer is one of the most dreadful diseases in the developing countries and its mortality rate is 19.4% [1]. Early detection of lung tumor is done by using many imaging techniques such as Computed Tomography (CT), Sputum Cytology, Chest X-ray and Magnetic Resonance Imaging (MRI). Detection means classifying tumor two classes (i)non-cancerous tumor (benign) and (ii)cancerous tumor (malignant)[2]. The chance of survival at the advanced stage is less when compared to the treatment and lifestyle to survive cancer therapy when diagnosed at the early stage of the cancer. Manual analysis and diagnosis system can be greatly improved with the implementation of image processing techniques. A number of researches on the image processing techniques to detect the early stage cancer detection are available in the literature. But the hit ratio of early stage detection of cancer is not greatly improved. With the advancement in the machine learning techniques, the early diagnosis of the cancer is attempted by lot of researchers. Neural network plays a key role in the recognition of the cancer cells among the normal tissues, which in turn provides an effective tool for building an assistive AI based cancer detection. The cancer treatment will be effective only when the tumor cells are accurately separated from the normal cellsClassification of the tumor cells and training of the neural network forms the basis for the machine learning based cancer diagnosis [3].This paper presents a Convolutional Neural Network (CNN) based echnique to classify the lung tumors as malignant or benign.

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II. PROPOSED METHODOLOGY

This paper presents lung cancer detection based on chest CT images using CNN. In the first stage,lung regions are extracted from CT image and inthat region each slices are segmented to get tumors. The segmented tumor regions are used to train CNN architecture. Then, CNN is used to test the patient images. The main objective of this study is to detect whether the tumor present in a patient's lung is malignant or benign.Figure1 shows the block diagram of the proposed system. As shown in the figure, the trained system will able to detect the cancerous presence in lung CT image.

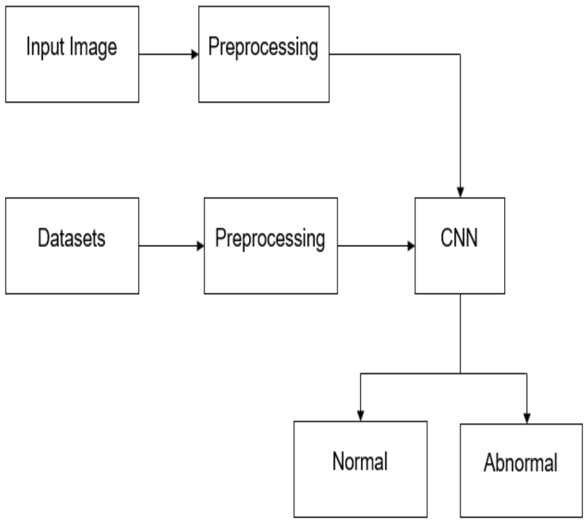

Fig 1. Block Diagram of the Proposed System

III. DATASET

Dataset for training is obtained from Lung Image Database Consortium (LIDC) and Image Database Resource Initiative (IDRI). LIDC and IDRI consist of 1000 CT scans of both large and small tumors saved in Digital Imaging and Communications in Medicine (DICOM) format [5].

IV. PREPROCESSING

In preprocessing stage, the median filter is used to restore the image under test by minimizing the effects of the degradations during acquisition. Various preprocessing and segmentation techniques of lung nodules are discussed in [6].The median filter simply replaces each pixel value with the median value of its neighbors including itself. Hence, the pixel values which are very different from their neighborswill be eliminated
[7].

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Fig 2.a Input image

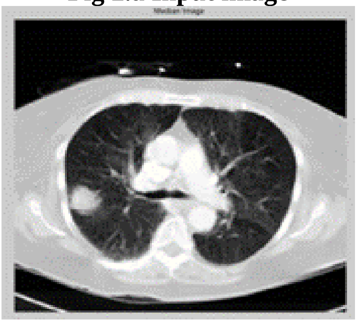

Fig 2.bMedian filtered

Fig 2.c Input image

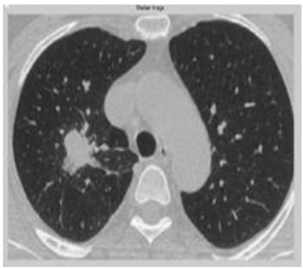

Fig 2.d Median filtered

V. DEEP LEARNING

Deep learning composed of several layers of nonlinear nodes, combine input data with a set of weights so that assigning significance to inputs for the corresponding task the algorithm is attempting to learn in supervised and/or unsupervisedbehavior. The sum of product of these input and weights is passed through activation function of nodes. [10][12].The output of each layer's is fed simultaneously as input to the subsequent layer starting from input layer [8]. Learning can be performed in multiple levels of representations correspond to various levels of abstraction [9].

VI. CONVOLUTION NEURAL NETWORKS (CNNS)

A CNN is type of a DNN consists of multiple hidden layers such as convolutional layer, RELU layer.Pooling layer and fully connected a normalized layer. CNN shares weights in the convolutional layer reducing the memory footprint and increases the performance of the network. The important features of CNN lie with the 3D volumes of neurons, local connectivity and shared weights. A feature map is produced by convolution layer through convolution of different sub regions of the input image with a learned kernel. Then, anon-linear activation function is applied through ReLu layer to improve the convergence properties when the error is low. In pooling layer, a region of the image/feature map is chosen and the pixel with maximum value among them or average values is chosen as the representative pixel so that a 2x2 or 3x3 grid will be reduced to a single scalar value. This results a large reduction in the sample size. Sometimes, traditional Fully-Connected (FC) layer will be used in conjunction with the convolutional layers towards the output stage.

In CNN architecture, usually convolution layer and pool layer are used in some combination. The pooling layer usually carries out two types of operations viz. max pooling and means pooling. In mean pooling, the average neighborhood is calculated within the feature points and in max pooling it is calculated within a maximum of feature points. Mean pooling reduces the error caused by the neighborhood size limitation and retains background information. Max pooling reduces the convolution layer parameter estimated error caused by the mean deviation and hence retains more texture information. Figure 2 shows the architecture of CNN.

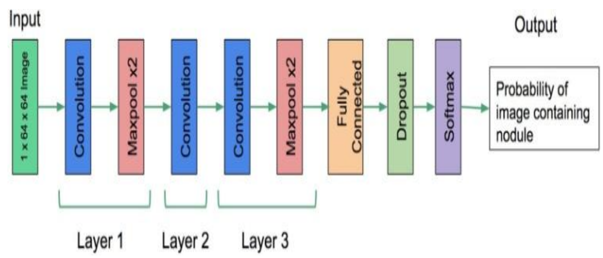

Fig 3.Architecture of CNN

The input to a convolutional layer is an image of size m x m x r, where r is the number of channels. There are k filter kernels of size n x n x q where $n < m$, $q \leq r$ and may vary for each kernel in convolutional layer, which are convolved with the input image to produce k feature maps. Each map is then subsampled with mean or max pooling over p x p contiguous regions (p – ranges from 2to5) and an additive bias and sigmoidal nonlinearity is applied before or after the subsampling layer. The figure 3shows the layer of a CNN.

VII. LAYERS USED TO BUILD CONVNETS

A simple ConvNet is a sequence of layers; each layer alters one volume of activations to another through a differentiable function. Convolutional Layer, Pooling Layer, and FC Layer are used to build ConvNet architectures. Pixel values of the raw input image is used as the input and CONV layer computes the output of neurons that are connected to local regions in the input.

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RELU layer applies an element wise activation function and leaves the size of the volume unchanged. A down-sampling along the spatial dimensions will be performed by POOL layer. Theclass scoreswill be computed by FC layer.

VIII. TRAINING

Back-propagation algorithmis used to train the Deep CNN to detect lung tumors in CT image of size 5×20×20. It consists oftwo phases. In the first phase, a CNN consists of multiple volumetric convolution, rectified linear units (ReLU) and max pooling layers is used to extract valuable volumetric features from input data. The second phase is the classifier.It has multipleFC and threshold layers, followed by a SoftMax layer to perform the high-level reasoning of the neural network. No scaling was applied to the CT images of the dataset to preserve the original values of the DICOM images as much as possible. During training, the randomsub-volumes extracted from the CT images of the training set and are normalized according to an estimate of the normal distribution of the voxel values in the dataset.

IX. RESULTS

The neural network based on convolutional and watershed segmentation has been implemented in MATLAB and the system is trained with sample data sets for the model to understand and familiarize the lung cancer. A sample image has been fed as an input to the trained model and the model at this stage is able to tell the presence of cancer and locate the cancer spot in the sample image of a lung cancer. The process involves the feeding the input image, preprocessing, feature extraction, identifying the cancer spot and indicate the results to the user. In case of the malignancy is present, a message indicating the presence of will be displayed on the screen along with the given input image as shown in Figure 4.

Input image Result display

Fig 4. Output for Cancerous Image

Lung cancer detection using the convolutional neural network which model by the end to end learning, i.e. Initialize the weights, Learning rate, gradient moment and hidden neurons. In the neural network, hidden units to form a zero matrix whatever weights will change to be hidden units would change the matrix value. Some of the parameter used for training the model of the neural network is shown in Table 1

Parameter	**Value**
Learning rate	0.0001
Weight	0.0002
Bias	0.1
Gradient moment	0.9
Hidden neurons	250
Epoch	100

Table 1:f FC layer with compute the class score

CNN has two layers such as 2 convolution layers and 2 subsampling layer which is used to increase the accuracy of detection. The confusion matrix parameters derived from CNN output are given in Table.2

S.No	Parameters	Values
1	Training images	70
2	Test images	30
3	True Positive	7
4	True Negative	22
5	False Positive	0
6	False Negative	1
7	Specificity	1
8	Sensitivity	0.875
9	Overall Accuracy	0.96

Table 2:Confusion matrix

The confusion matrix shows the true positive, true negative, false positive and false negative. From the analysis true positive gives the correctly classified the lung cancer images and false positive gives the misclassification of images which means that the lung cancer is wrongly predicted as non-cancerous image.

X. CONCLUSIONS AND FUTURE WORK

A convolutional neural network based system was implemented to detect the malignancy tissues present in the input lung CT image. Lung image with different shape, size of the cancerous tissues has been fed at the input for training the system. The proposed system is able to detect the presence and absence of cancerous cells with accuracy of about 96%. The accuracy of Lung cancer detection with the proposed convolutional neural network based method was compared with that obtained by previous works in Table 3

Table 3 Comparison of Results with the Previous Works

Authors	**Sensitivity**	**Specificity**
Albrt Chon. et al	43%	85%
Devi Nutiyasari, et al	86.30%	###
Proposed Method	100%	###

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In addition to deep convolutional network, the same dataset was classified by multilayer perceptron network Backpropagation algorithm with using GLCM features. The results show only 93% accuracy [10].

In this proposed work, the specificity obtained is 100% which shows that that there is no false positive detection. Also, the accuracy, sensitivity and specificity of the proposed system is high when compared to previously available conventional neural network based systems.

In the near future, the system will be trained with large datasets to diagnose the type of cancer with its size and shape. The overall accuracy of the system can be improved using 3D Convolutional Neural Network and also by improving the hidden neurons with deep network.

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