Research Article

Identification of Lung Cancer Using Convolutional Neural Networks Based Classification

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Abstract: Identification of lung cancer is an efficient way to minimize the death rate and maximize survival rate of patients. It is an essential step to screen out the computed tomography (CT) images for pulmonary nodules towards the efficient treatment of lung cancer. However, robust nodule identification and detection is a most critical task due the complexity of the surrounding environment and heterogeneity of the lung nodules. The use of machine learning to detect, predict, and classify disease has grown exponentially in the past few years, especially for complex tasks such as lung cancer detection and recognition. Deep Convolutional neural networks (DCNN) have exploded in popularity for transforming the field of computer vision research. In this paper, we are using Deep Convolutional Neural Network for lung cancer classification using CT images based lung cancer image dataset consortium (LIDC) for detecting cancerous and noncancerous lung nodules for measuring the accuracy of classification better than existing methods.

Keywords: Lung Cancer, DCNN, Computed Tomography, computer vision

1. Introduction

Lung cancer is one of the important reasons to increase death rate in the world, since every year it is seen that many deaths were occur due to lung cancer as compare to other types of cancer. Both men and women are being affected from this deadly disease. Hence suitable mechanism should be adopted to detect and identify this disease in the initial stage to save the life of large number of peoples suffering from lung cancer. If it is detected and identified in primary stage then survival rate of many number of patients can be improved. Later after disease identification, by providing proper diagnosis can reduce the death rate of patients. So in order to avail a suitable and instantaneous outcome the importantly, applying recent techniques of machine leaning in the medical image processing field by enhancing the amount of duplication for the methods use can increase the accuracy of the classification. Therefore proper timely detection and identification in the prior stage will definitely improve the level of survival and can decrease the death rate.

The medical images taken in most of the earlier studies comprise of computed tomography (CT), magnetic resonance, and mammography images. The expert doctor of this domain uses these images for analysis to detect and identify the various levels of lung cancer by using suitable techniques. The different laboratory and clinical steps are being used including chemical treatment to destroy or stop the duplications of malignant cell, targeted therapy and also radiotherapy. All these procedures adopted to identify and detect the cancer diseases are lengthy, costlier and more painful for the patients. Thus, to overcome all these problems suitable machine learning techniques for processing these medical images were used which comprise of CT scan images. CT scan images are preferred compared to other images because as comparable to other medical images such as MRI and X-Ray, CT images are less noisy.

In the process of lung cancer classification, the images applied at the input layer of Deep Convolutional neural networks are classified into cancerous or non-cancerous at the output layer after processing in all hidden layers of the network. DCNN is a deep learning algorithm that takes an input image, and then marks significance for each object in the image. The network further classifies each object in the image one from the other when it is trained precisely with more number of dataset. Deep learning methods needs minimum pre processing steps in comparable to the other image processing algorithms. The objective of DCNN is to convert input images suitable for processing with minimum permissible loss of image features for achieving the best level of accuracy. To design and to attain better accuracy of classification in the DCNN, the parameters used are size of filters, more no of hidden layers and extracted number of feature maps. As the network layers are deeper, there is high detection level with high level of abstraction of features can be achieved. Deeper the network leads to increase in computation time due to more number of Convolutional operations. The most suitable size of the Convolutional filters is 3 x 3 or 5 x 5. The performance of the network may minimize as the size of the Convolutional kernel increases. The Paper is organized as follows: literature review is summarized in section II. Section III describes the details of methodology used. Section IV describes about results and discussions and section V summarizes about conclusion and future work.

2. Literature Review

The Convolutional neural network were used for classification by using 1006 images of LIDC dataset [1], 94% of accuracy results found with 90% training and 10% of testing images. Identification of lung nodules by applying computed tomography images is proposed by the author [2] where it produces the sensitivity results of 90%, thereby patient survival rate becomes higher. The region of interest are retrieved by using methods such as wiener filter, image slicing. The nodule size of 3mm is obtained to recognize lung cancer in the primary stage.

The author [3] proposed a method to classify the lung nodule by computed tomography images where the lung segmentation take place by applying thresholding and region growing technique, thereby the image features are extracted. The extracted features were used to apply as input to the various classifiers such support vector machine, KNN, then the classifier decides and classify benign and malignant images. The author proposes Convolutional neural network classifier for identifying lung nodules [5] which gives an accuracy of about 84.6%. Also sensitivity of 82.5% and specificity of 86.7% are achieved. It is noted that the degree of treating the diseases will be higher as the dataset quantity increases. The author proposes a model [6] which is used to identify cancerous part of the lung by applying the methods of deep learning of neural network; the model gives an accuracy of classification of about 90% and also the model unable to find the nature and category of cancer disease. The author [7] proposes a model which gives an accuracy of 83.11% which classifies benign and malignant images using support vector machine form computed tomography images. The classification is achieved depends on the collected fractal features from Brownian motion model. Recognition of lung cancer nodules from CT images is presented [8] where the model uses various classifiers to detect the cancer, the classifiers such as support vector machine were utilizes which improves the efficiency and thereby reduces the error rate.

The author [9] presented a system which classifies the lung cancer nodules depends on the size of nodules between 3mm-10mm from LIDC dataset. The system uses the methods of machine learning such as K-Nearest Neighbor, Random Forest; the system gives an accuracy of classification of 82%. Deep Convolutional neural network is trained from CT images of LIDC dataset to classify the malignant and benign images. The network provides a sensitivity of 78.9% using back propagation methods by extracting the image features. The author [11] presented a classification model based on principal component analysis using CT images which achieves an accuracy of about 90% by applying principal component analysis method. The model uses lung organ segmentation as a first step, lung nodule segmentation as next step and classification of cancerous and non cancerous images in the last step. The system identifies the malignancy of disease in the primary stage [12] by undergoing different steps of the disease. The detecting phase first step consists of preprocessing and segmentation which improves the accuracy of classification by adopting support vector machine and fuzzy logic classifiers. The classifier identifies and classifies the images based on the degree intensities of images as benign and malignant tumor.

Convolutional neural network by employing deep learning techniques does lung segmentation in CT images [13] were used. The challenging task for the radiologist is to identify malignancy of lung diseases hence deep CNN model assist much in this task as lung cancer images have different degree of opacities in region of interest. This is texture based problem which employs 42 CT images with high degree of cancerous and low degrees of cancerous images are collected. The machine learning methods are utilizes to classify the lung images [14]. The classification accuracy can be enhanced by deep learning techniques, thereby cancerous and non cancerous image classification can be performed. In the work [15], the different classifiers were employs which includes decision trees, support vector machine as these provides higher accuracy of classification. The accuracy of classification can be improved further by large data input images at the input of the network model. The model achieves an accuracy of 94% by using Convolutional neural network classifier and also SVM classifier gives an accuracy of 86%. Compare to these results of classification, CNN provides the more accuracy then SVM classifier.

The hybrid segmentation network based CNN is designed [16] which use hybrid 2D and 3D features to train CNN model. This model provides a good performance of accuracy of 88%, average sensitivity of 87.2% and average precision of 90.9%. The author proposes Convolutional neural network [17] that minimizes the false positive rate and enhances the sensitivity in identifying lung cancer diseases from CT images. The classification accuracy of 91.23% was achieved. The proposed method gives an improved accuracy of 97% using deep neural network [18] and hence reduces the complexity of time with greater accuracy by employing Mobile Net. From the literature review it is seen that many authors had used many techniques for classification of lung nodules to find malignant and benign images to predict and identify the lung cancer in the early stage. It is evident from the review that one of the most powerful tools to classify the cancerous images is Convolutional neural networks and its deep learning features. When a Convolutional neural network utilizes the deep learning principles of classification of cancerous images will form a Deep Convolutional Neural Networks (DCNN). Deep CNN does more number of computations by utilizing many hidden layers, Convolutional layers, softmax layer and fully connected layer. Deep CNN does the classification task efficiently and takes much computation time as it employs many hidden layers. DCNN perform two major functions that are feature extraction and classification

3. Methodology Used

A. Convolutional Neural Networks(CNN)

A Convolutional Neural Network (CNN) is a type of feed forward neural network which is inspired by biological visual system models [15], where the individual neurons are lined in such a way that they respond to overlapping regions in its receptive field and continues to be reliable with the modern perceptive of the structure of the image system [21]. When neurons with the same parameters are applied on overlapping regions of the previous layer, at different locations, a form of translational invariance is obtained.

This allows CNNs to detect objects in their receptive field in a way that is invariant to their size, location, orientation, and other visual properties. Besides this restricted connectivity of CNNs minimizes the computational requirements of training compared to fully connected neural networks [26]. The architecture of a Convolutional neural network as shown in the figure.1 is a multi-layered feed-forward neural network, made by stacking many hidden layers on top of each other in sequence. It is this sequential design that allows Convolutional neural networks to learn hierarchical features. The hidden layers are typically convolutional layers followed by activation layers, some of them followed by pooling layers.

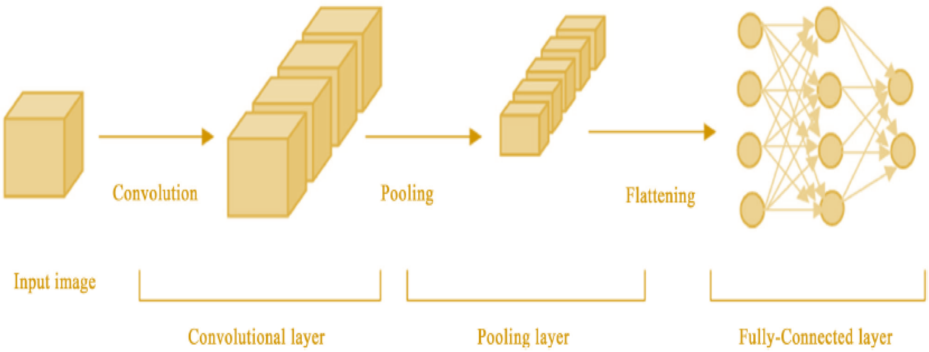

Figure 1: Architecture of CNN

Figure 1 Represents the Basic Blocks a Architecture of CNN comprise of three major layers such as an input, Convolutional, pooling and fully-connected layers.

1 Convolutional layer: This layer accepts the input images of specified size suitable for the network training, which is then, translated into feature maps by using filters or Convolutional kernels. The filters used in this layer are moved through the dimensions.

2 Pooling layer: The important function of this layer is to downsize the matrix and to minimize the parameters hence this layer does down-sampling from the feature maps of Convolutional layers. This layer calculates maximum value or weighted average by moving filters across the output of Convolutional layer.

3 Fully-connected layer: The objective of this layer is to classify the resulting images of the previous two layers into a label. Since this layer utilizes the sofmax layer so as to find the probabilities of values in between 0 and 1. Besides it uses Batch normalization to enhance the training rate and to minimize over fitting.

The Identification of lung cancer using Deep CNN, comprise of two categories. The first category does preprocessing functionalities suitable to train and process the images in DCNN, thus feature extraction can be performed and second category performs the classification of input CT images where it identifies the type of nodule as benign or malignant.

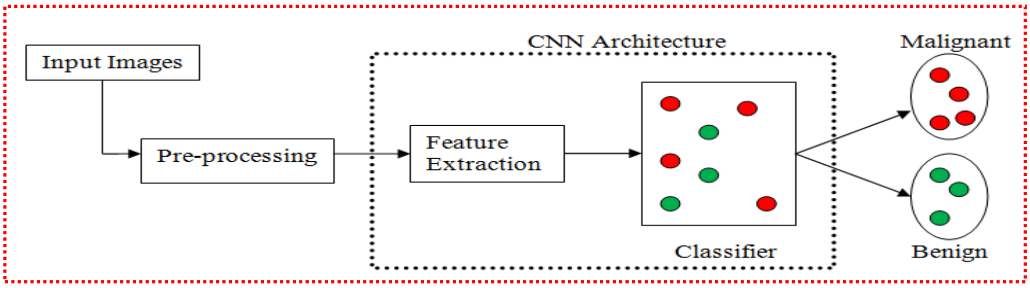

Fig.2. DCNN for lung cancer nodule identification.

The Architecture of Deep CNN as presented in Figure.4 with block diagram shown in figure.2 which comprise of 25 layers such as Eight convolution layer, eight ReLu layers, seven max- pooling layers and one fully-connected layer with softmax layer. From the Figure 1, it is seen that the first layer input layer consists of images of suitable network size. The convolution layer is the second layer which accepts the input images of size 256 x 256 size and then it converts the input images into feature maps by applying the Convolutional kernel of size 3 x 3. Each Convolutional layer followed by activation rectified linear unit (Re-Lu) layers for converting image to feature maps. The next layer after Convolutional layer is max pooling layer, the size of the filter or kernel used is 2 x 2 and 2 pixels stride. Finally the outputs of previous two layers are applied to the fully-connected layer to generate a 1024 output dimensions. The resultant outputs are then applied to another fully connected layer followed by softmax layer. The fully connected layer along with softmax layer gives the classification probability of benign or malignant cancer type. From the figure 3(a) and 3(b), the output sample of images after classification into malignant or benign are presented from the experimental work.

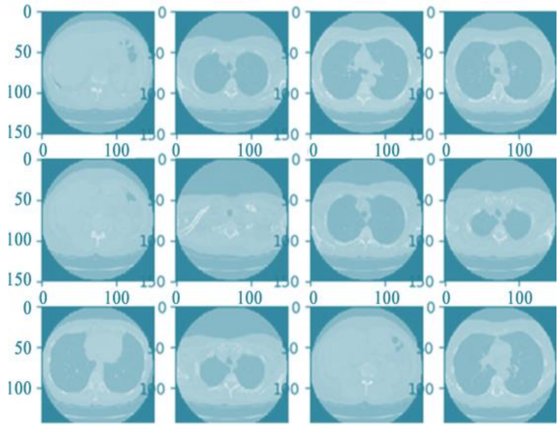

Figure 3(a) Benign Images

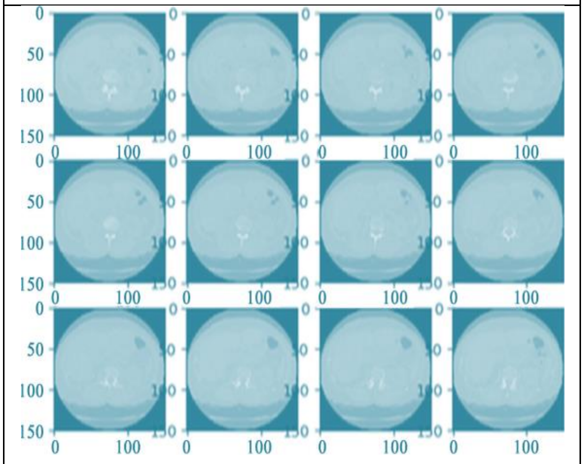

Figure3(b) Malignant Images

Figure.3 Experimental Images

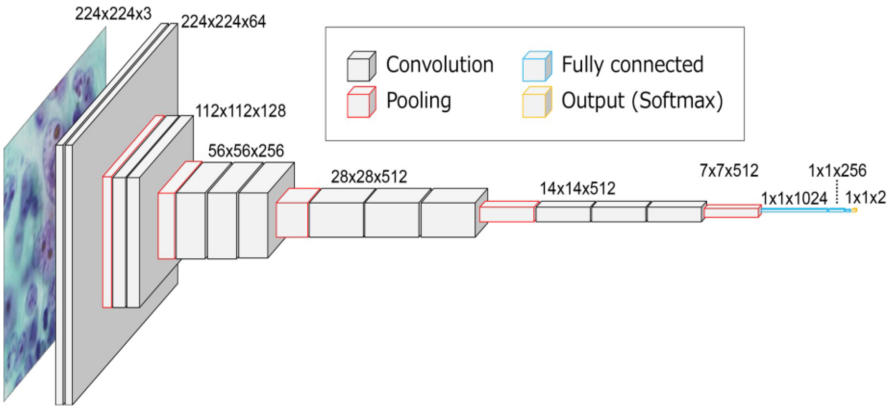

Fig.4. Architecture of Deep CNN

B. Training a deep CNN

Back-propagation algorithms are used to train the Deep CNN using CT images of size 256x256x3. It consists of two phase, training phase and testing phase. In the first phase DCNNs are trained using CT images where 900 images are being used to train the network for the classification of lung as either cancerous or non-cancerous. In the testing phase an image unknown to the network is applied as input to classify as cancerous or noncancerous. For minimum loss of features images are trained and tested in the DICOM format itself by modifying the network parameters such that it can take DICOM images. The proposed designed network accuracy can be achieved by suitable evaluation.

C. Performance Measures parameters

The performance of a medical image can be analyzed, by using performance evaluation parameters such as Accuracy, Loss and Computation Time.

- Accuracy: it is one of the important performance measure parameter to evaluate the model. It gives correctly classified number of pixels from the given image.

- Loss Function : The error in the neural network can be predicted by Loss which is calculated by Loss function. This is another performance measure parameter of the network.

- Computation Time: Time required for the process to complete its computation or its operations. If the process is simple then time taken for processing is less compared to the complex process whose computation time is more.

4. Results And Discussions

The dataset of the Lung Image Database Consortium image collection (LIDC-IDRI) is an international image resource for evaluating and identifying lung cancer. It consists of CT images in DICOM format of 1018 cases. The size of the original images are 512 x 512 but it is difficult to train large size images in DCNN so preprocessed the images to reduce size suitable for the network. Hence training and testing images are categorized for evaluating the network for efficient classification of images into cancerous and non cancerous images and helps for diagnosing the patient in the early stages [5][6].

From the given dataset, the input images are applied to the Deep CNN model for training the model using 90% training images. After training, the model is evaluated by 10 % of testing image dataset collected from the same dataset. Here the images samples are used to feed the network model which classifies into cancerous or Non Cancerous Images.

TABLE.1 (a) DCNN Results

Resultant Curves of Deep CNN for 900 CT Images (A)		
Epoch	*Loss*	*Accuracy%*
1	0.8171	48.44
13	0.0336	100
25	0.0108	100
38	0.0091	100
50	0.0051	100
63	0.0033	100
75	0.0037	100
88	0.0024	100
100	0.0028	100
113	0.0019	100
125	0.0023	100
138	0.0015	100
150	0.0019	100
163	0.0013	100
175	0.0016	100
188	0.0011	100
200	0.0014	100
213	0.0014	100
225	0.0010	100
238	0.0013	100
250	0.0009	100

Epoch, Loss and Accuracy data collected from experimental work which is carried on CT image dataset is shown in Table.1 (a).

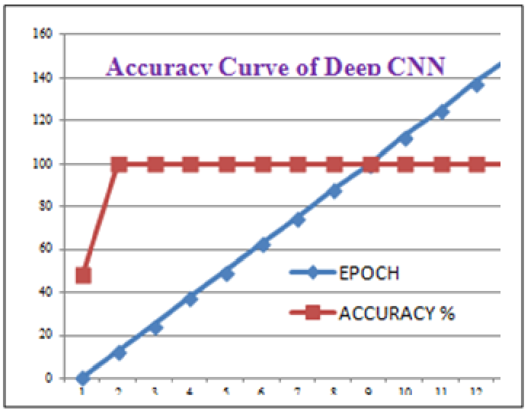

Figure.5 Epoch Verses Accuracy Curve

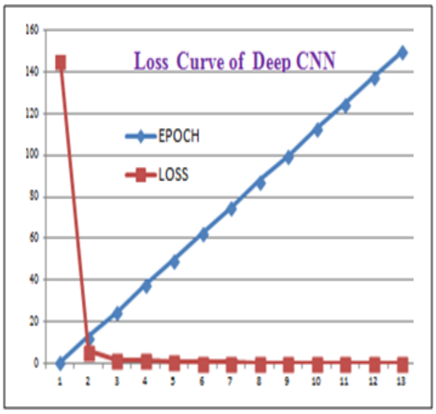

Figure.6 Epoch verses Loss Curve

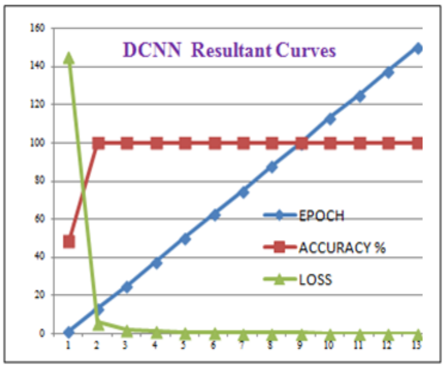

Figure.7 Epoch verses Accuracy & Loss Curves

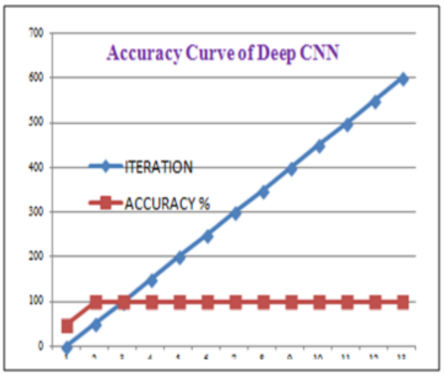

Figure.8. Iteration verses Accuracy Curve

Table.1(b) DCNN Results

Resultant Curves of Deep CNN for 900 CT Images(B)		
Iteration	Accuracy (%)	Loss
1	48.44	0.8171
50	100	0.0336
100	100	0.0108
150	100	0.0091
200	100	0.0051
250	100	0.0033
300	100	0.0037
350	100	0.0024
400	100	0.0028
450	100	0.0019
500	100	0.0023
550	100	0.0015
600	100	0.0019
650	100	0.0013
700	100	0.0016
750	100	0.0011
800	100	0.0014
850	100	0.0014
900	100	0.0010
950	100	0.0013
1000	100	0.0009

Iteration, Loss and Accuracy data collected from experimental work which is carried on CT image dataset is shown in Table.1 (b)

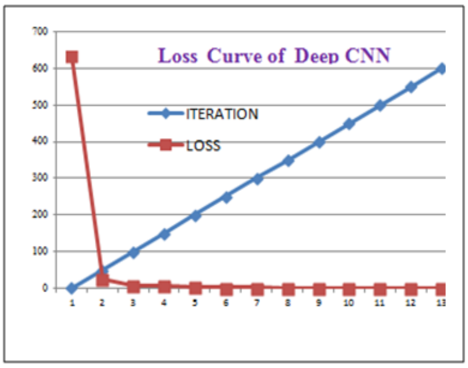

Figure.9 Iteration verses Loss Curve

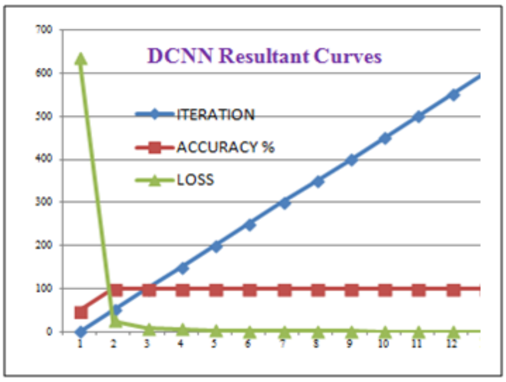

Figure.10 Iteration verses Accuracy & Loss Curves

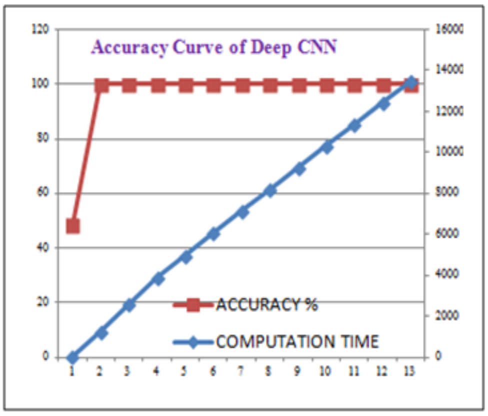

Figure.11 Computation Time verses Accuracy Curve

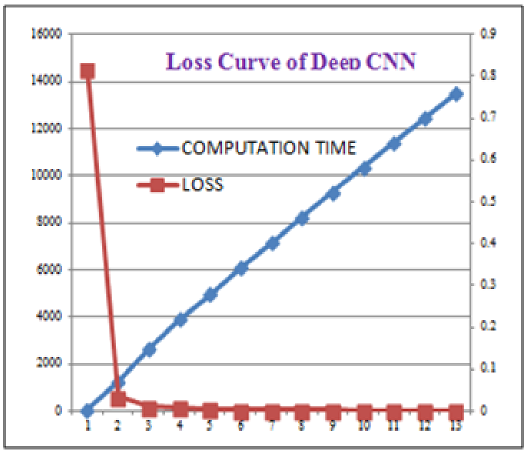

Figure.12 Computation Time verses Loss Curve

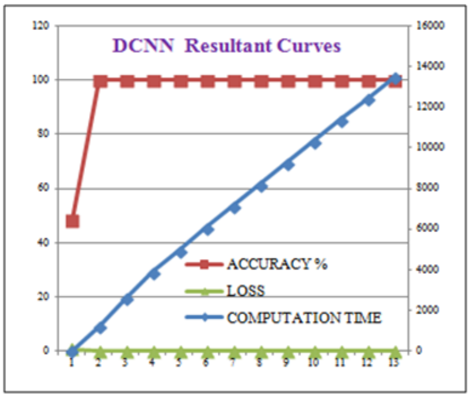

Figure.13 Computation Time verses Accuracy & Loss Curves

Table.1(c) DCNN Results

Resultant Curves of Deep CNN for 900 CT Images (C)		
Computation time (sec)	*Accuracy (%)*	*Loss*
27	48.44	0.8171
1238	100	0.0336
2616	100	0.0108
3902	100	0.0091
4960	100	0.0051
6085	100	0.0033
7152	100	0.0037
8224	100	0.0024
9289	100	0.0028
10344	100	0.0019
11392	100	0.0023
12422	100	0.0015
13473	100	0.0019
14537	100	0.0013
15610	100	0.0016
16618	100	0.0011
17695	100	0.0014
18746	100	0.0014
19818	100	0.0010
20832	100	0.0013
21877	100	0.0009

Computation Time, Loss and Accuracy data collected from experimental work which is carried on CT image dataset is shown in Table.1 (c)

In our research work, Lung nodule classification has been implemented in MATLAB 2018b and the dataset used for training and testing purposes are taken from LIDC-IDRI to get familiarize with lung cancer. Here the images samples are used to feed the network model which is able to detect and identify the presence of cancer that is cancerous images (Malignant Images) and Non Cancerous Images (Benign Images). As it is observed from the results that as training proceeds further classification accuracy will be increases with increase in the computation time, thereby decreases the percentage of loss as shown in above output graphs.

The complete process of DCNN gives 100% of accuracy with computation time of 45,141 seconds in single CPU workstation, which is the best level of accuracy obtained compare to the work done in earlier research papers [19][20]. In this research work, there are 900 ct images were used for training and testing purposes which are greater number of images used comparable to the previous research papers [21][22]

TABLE.2 accuracy OF CLASSIFICATION

Accuracy (%)	Year	Citation
78.9	2017	[10]
82	2016	[9]
83.11	2016	[7]
84.6	2016	[5]
90	2011	[2]
90	2016	[6]
90	2017	[11]
90	2019	[16]
91.23	2019	[17]
94	2017	[15]
94	2018	[1]
97	2016	[19]
97	2019	[18]
98	2014	[20]

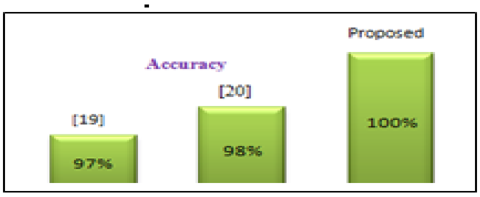

Figure.14 Accuracy comparison

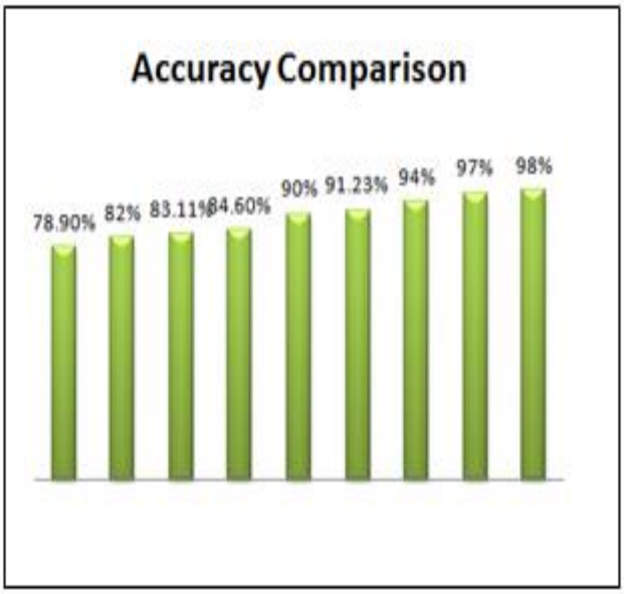

Figure.15 Comparison of Accuracy from Literature Review

The Accuracy is one of the important performance measure parameter of DCNN, hence accuracy percentage level from the various papers of literature review is depicted in table.3 with graphical representation in figure.15 and also figure.14 gives the accuracy comparison of previous papers and proposed method. The computation of this model is performed by using a Computer with Intel Core i3-2330M CPU, 2.20 GHz, 4 GB RAM, 64-bit Windows 10 OS. Thus a better classification accuracy is achieved which is greater than that of [19] [20].

5. Conclusion And Future Work

In our research work, we have used deep Convolutional neural networks for classifying the ct images of lung nodules into cancerous (malignant) and non cancerous (benign). Thus preprocessing has been done before applying input ct images to network model to make equal sizes and format of the images. The dataset used in our research work belongs to LIDC dataset. Hence we achieved an accuracy of 100% which is the better results comparable to previous research papers as mentioned. As a future work, the experiments could be performed by using Deep CNN architecture for other types of cancer.

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