

# Classification of LungCT scan images using Image Processing and Convolutional Neural Networks

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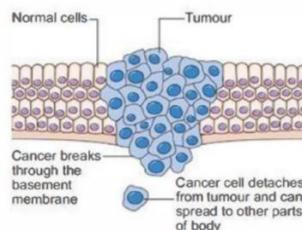
## ABSTRACT

*Lung cancer is the second most common disease in men and women. The mortality rate of lung tumour is the highest among all other types of tumour. Early detection of lung cancer can increase the possibility of survival among people. Lung cancer is also found by imaging tests such as chest computed tomography scan because it provides more elaborate picture. Computed Tomography (CT) are said to be more effective than plain chest X-ray in detecting and diagnosing the lung cancer. To classify the samples of lung CT scan images into normal, benign and malignant categories, a method is developed by implementing image processing and soft computing techniques. In this work, new algorithm is developed using image processing and machine learning technique to observe the cancer at early stage with additional accuracy. Image processing involves the pre-processing that is image smoothing, enhancement and segmentation. Once pre-processing of images is done, they are provided to Convolutional Neural Network classifiers for classification into cancerous or non-cancerous image. The implemented system gives an accuracy of 98.6 % for classification of samples into normal and abnormal classes and an accuracy of 99.5 % for the classification of samples into benign and malignant categories.*

**Keywords:** Image Processing, Convolutional Neural Network classifier, CT scan, Lung Cancer Detection

## 1. INTRODUCTION

Lung Cancer is the disease that begins in the lung. Lung cancer is the uncontrolled growth of abnormal cells that starts off in one or both of the lungs. People who smoke have the greatest risk of lung cancer. When symptoms are seen in person, lung cancer tests are done to determine the type of lung cancer and if it has spread. The excessively high prevalence of lung cancer has encouraged attempts for earlier detection, which is more substantial in clinical practice. The mortality rate of lung tumour is the highest among all other types of tumour. The general 5-year survival rate for lung cancer combining all stages is roughly 15 %. When cancer spreads, this is called metastasis. Around 24,730 people were diagnosed with lung cancer in 2016, that's around 68 people every day. The link between tobacco and cancer was established more than 50 years ago. Also smoking is by far the leading risk factor for lung cancer. The risk increases with the number of cigarettes smoked per day. Exposure to chemicals or other factors in the environment, like pollution might increase cancer risk too [1]. The body is made up of billions of small cells. Usually when the cells get old or damaged, they die and are replaced by new cells. Sometimes, cells continue to grow and divide when they aren't needed, causing an abnormal growth called a tumour. There are two main types of lung cancer, non-small cell lung cancer and small cell lung cancer. As for the stages, in general there are four stages of lung cancer; I through IV. Staging relies on tumour size [2]. Lung cancer patients don't feel any symptoms at initial stages however it can lead to death if not detected and treated in time. In order to detect it at its early stages, regular screening is necessary which may eventually reduce the number of deaths due to lung cancer. Automated systems may be helpful for this purpose and might offer time and cost-efficient solution. Presently, Computed Tomography (CT) are said to be more effective than plain chest X-ray in detecting and diagnosing the lung cancer. There are two kinds of tumour, benign tumour and malignant tumour. Cancerous cell spread by breaking from the original tumour. Figure 1 shows the structure of normal cell and how the way tumour is produced.



**Figure 1** Structure of Tumour[3]

Cancer treatments aim to kill or control cancerous cells. Though surgery, radiation therapy and chemotherapy have been used in the treatments of lung cancer, the five-year survival rate for all stages combined is only 14%. Various methods like Computed Tomography (CT) scan, chest radiography, Sputum analysis, microarray data analysis is used for lung cancer detection [4]. Mass screening by Computed Tomography (CT) scan of chest is a promising technique for lung cancer detection. However, this technique is not recommended because of its cost and long-term safety of this technique is not established due to the risk of exposure to radiation [5].

As lung cancer is a major health issue in the 21st century, numerous studies are done on the lung cancer related to cause of lung cancer, its statistics, detection of lung cancer its classification etc. Some of those techniques are presented as below,

**S. Kanitkar et.al.** [6] proposed a system which is having stages such as pre-processing stage, segmentation stage, feature extraction stage and classification. For smoothing, Gaussian filter is applied on the input image because Gaussian smoothing is very effective for removing noise, it removes high frequency components from the image. Gabor function is used for image enhancement. Watershed segmentation is used to extract the region minimum value from an image. It determines the corresponding to the demarcation with the least value. Watershed gives 100 % accuracy compared to the thresholding algorithm. So it is efficient for segmentation.

**R. Agarwal et.al.** [7] proposed a computer aided lung cancer detection system. A Computer Aided Diagnosis system is studied for detecting the lung cancer at early stage here. The CAD system makes use of Computer Tomography images. Firstly, the lung region extraction technique is done from those CT images. Several processing methods are studied in the lung region extraction such as GLCM. In the second stage, segmentation is done on the lung with the region-based segmentation approach. The next stage is feature extraction technique in which the features are extracted from the partitioned image for the diagnosis. At last, classification method is done to identify the presence of cancer in the lung using SVM with different kernels. This process shows the benefits of this system to detect the cancer in the lung. Thus, we can distinguish between the images and help in diagnosis. It is observed that the efficiency is above 80 %.

The techniques presented by **Sruthi Ignatious et.al.** in [8] identify the various stages within the lung cancer detection systems. The different combinations of these techniques will produce accurate prediction of cancer. They used Median filter, Gabor filter, Auto enhancement and FFT for enhancement purpose. Segmentation is done by using thresholding, region growing and marker-controlled watershed segmentation. Features such as area, perimeter, eccentricity, entropy, mean and standard deviation are calculated. Classification was done by using Neuro-fuzzy model. It proves that combination of Gabor filter, watershed algorithm and features such as area, perimeter and eccentricity give best result of about 90 %.

The paper presented by **T. Aggarwal et.al.** [9] have a computational based system for detection and classification of lung nodules from chest CT scan images. In their study they consider the case of a primary lung cancer. Optimal thresholding and gray level characteristics are used for segmentation of lung nodules from the lung volume area. After detection of lung mass tissue, geometrical features are extracted. Simple image processing techniques like filtering, morphological operation etc. are used on CT images collected from Cancer Imaging Archive database to make the study effective and efficient. To distinguish between the nodule and normal pulmonary structure, geometrical features are merged with LDA (linear discriminate analysis) classifier. GLCM technique is used for calculating statistical features. The results show that the methodology proposed by them successfully detects and provides prior classification of nodules and normal anatomy structure effectively, based on geometrical, statistical and gray level characteristics. Results also provide 84 % accuracy, 97.14 % sensitivity and 53.33 % specificity.

**B.V.Ginneken et.al.** [10] has explained the general pre-processing and enhancement technique. He has classified the lung region extraction approaches in two different categories; either rule based or pixel classification-based category. Techniques employed are thresholding, region growing, edge detection; morphological operation. The watershed algorithm from mathematical morphology is powerful for segmentation.

**Nguyen et.al.** [11] has explained some methods of segmentation techniques giving impotence of watershed segmentation technique. It includes properties of watershed algorithm such as topographical distance, watershed line, watershed from selected maxima etc. He also compares watershed with other energy-based segmentation methods

One more method of automatic detection of lung nodule is explained by **A.Amuthaet.al** [12], for enhancement technique wiener filter also gives better results. Sobel edge detection method marks segmented parts more accurately. Area of interest, calcification, size and shape of nodule, perimeter and eccentricity are some of the considered features to be extracted.

**Camarlinghi et.al.** [13] have used three different computer aided detection techniques for identifying pulmonary nodules in CT scans for lung nodule classification.

**Abdulla and Shaharum** [14] used feed forward neural networks to classify lung nodules in X-Ray images albeit with only a small number of features such as area, perimeter and shape.

**In Riccardi et al.** [15] the authors presented a new algorithm to automatically detect nodules with an overall accuracy of 71 % using 3D radial transforms.

**Jun Lai and Ming Ye** worked on active contour-based lung field segmentation in [16]. The algorithm comprised pre-processing and segmentation stages with lung area profile. The segmentation results had been significantly improved by active contour using shape energy control mechanism. Nevertheless, performance of this algorithm was not perfect and there was an expectation in providing adequate results with further experimentation. Image segmentation is processed with colour and object characteristics, and there was a study focusing watershed segmentation.

**Chen et al.** [17] gave Computer aided diagnosis for distinguish the cancerous cells and normal cells by cellular automata and evolutionary learning. In this study authors used pattern recognition technique, evolutionary learning and cellular automata to detect differences between cancerous cell and normal cell. The purposed of this study was manufacturing an autonomous feature detection system. According to this paper analysis the microscope image with computer include three steps such as recognition of the cells contour with segmentation, feature extraction and the last step is classification. In the first step after removing the noise by image enhancement method, the contour of cells was detected. The images were saved with bit mapped format and then were converted to ASCII format. Some possible feature detector (FD) is generated according to patterns of cancerous cells. If generated features match a cell, this cell diagnosis is a cancerous cell and if not, the cell diagnosis is a normal cell. A feature detector is suitable as it matches with minimum one cancerous cell and didn't have adaptation with any normal cell. The FDs that do not have high performance are improved by cellular automata. This study used 80 cells; 40 of those for training and another 40 were used for test. The results show that the proposed system has a high ability to separate the cancerous and normal cells.

Technique implemented by **Anuradha C Phadke and Priti P Rege** [18] uses local as well as global features along with Support Vector Machine classifier for classifying region of interest (ROI) of breast mammogram into normal and abnormal classes. The localfeatures used are Chebyshevmoment and GLCM features whereas globalfeatures used are Laws texture energy measures of original ROI and of Gabor magnituderesponse of ROI and fractal dimension. This technique has shown an accuracy of 93.17%. Similar techniques can be developed for classification of lung CT scan ROI into normal and abnormal classes.

The paper by **Anushriet.al.** [19] discusses various deep learning-based methods for breast cancer detection. The survey paper concludes that CNN are being widely employed for the feature extraction in the deep learning systems. The important features determined by the convolution layer of the CNN may contain features which are not expected by radiologists and this may result in improved accuracy.

From the literature studied it can be concluded that CNN based machine learning techniques are not yet explored for detection and classification of lung cancer. Convolutional Neural networks are well-suited for image classification as they use filters that automatically detect features and classify the images based on them. Hence a system is proposed to classify CT scan images of lung cancer patients using CNN.

## **2.DATABASE GENERATION**

The database collection is the first stage of system development. The CT images are having low noise when compared to X-ray and MRI images; hence the diagnosis of lung cancer is easier using CT images. The main advantage of using Computed Tomography image is that, it gives better clarity and less distortion. For research work CT images arecollected from Lung Image Data Consortium (LIDC) [20]. DICOM (Digital Imaging and Communications in Medicine) has become a standard for medical imaging. Its purpose is to standardize digital medical imaging and data for easy access and sharing. For the purpose of this work, a total of 11069 images out of which 4512 are benign,5277 are malignant and 1280 are normal CT images of lungs have been used.The input image is in RGB color format. For further processing, the RGB is converted into a grayscale image.

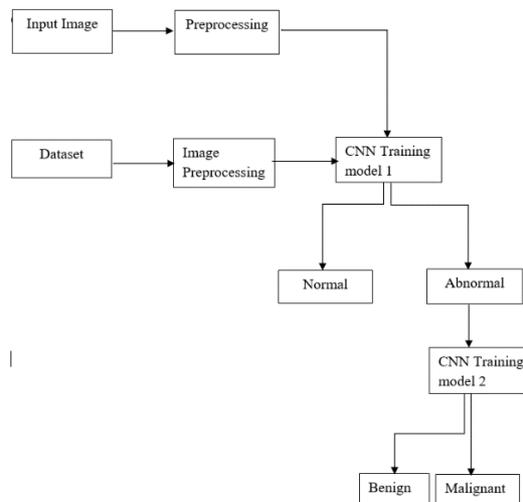
## **3.METHOD**

Primary focus of this work is to develop a system to classify abnormality from normal samples at a very early stage. Figure 2 demonstrates the methodology adopted for the design of the system. For the proposed system, two different

approaches have been considered. The first approach uses two separate classifiers to classify between normal and abnormal, and to further classify abnormal into benign and malignant. The second approach uses a single classifier to classify the image as normal, benign and malignant.

The database acquired is first separated into three parts namely benign, malignant and normal CT images. All the images in the database are then processed to obtain a form suitable for training the model. The database is divided into two parts- 80% images are used for training and 20% images are used for testing. Considering the first approach, the training dataset of first classifier comprises of normal and abnormal (benign and malignant) images which are filtered and segmented. These images are fed to the classifier along with a validation dataset (testing data) so that accuracy and loss of the model can be noted. After training is over, the model can classify any input lung CT image given to it into abnormal and normal. Similarly, for training classifier 2, a dataset comprising of abnormal i.e. benign and malignant images is used. All the images are first filtered and segmented, and then fed to the classifier along with a validation dataset to observe accuracy and loss of the model.

After training is over, the model can classify any abnormal CT image given to it into benign and malignant. Similarly, a single classifier can be trained to classify an input image into normal, benign or malignant.



**Figure 2** System Block Diagram

**3.1 Image Acquisition**

The database collection is the first stage of system development. The CT images are having low noise when compared to X-ray and MRI images; hence the diagnosis of lung cancer is easier using CT images. The main advantage of using Computed Tomography image is that, it gives better clarity and less distortion. For research work CT images are collected from Lung Image Data Consortium (LIDC). DICOM (Digital Imaging and Communications in Medicine) has become a standard for medical imaging. Its purpose is to standardize digital medical imaging and data for easy access and sharing.

**3.2 Image Processing**

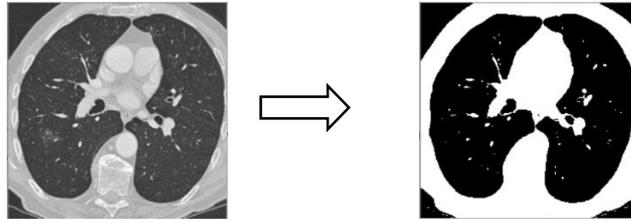
Image processing is a technique through which certain operations like filtering the image, suppressing noise, geometric transformations, etc, can be performed on image so that a suitable form of the image can be obtained that can be used further in the classifier. Image Processing used in the proposed system is explained by the following steps:

**3.2.1 Image Segmentation**

Image Segmentation is the process of segmenting the image into different parts. For this system, we have used Binary Thresholding for segmenting the images.

**Binary Thresholding:**

This operation converts an image into its binary form. In this, a threshold value is considered. If the value of image pixel is higher than the threshold value, it gets converted into a white pixel, if value of an image pixel is less than this threshold value, then it gets converted into a black pixel. Binary Thresholding is usually used to separate foreground pixels from background pixels.



**Figure 3** Binary Thresholding

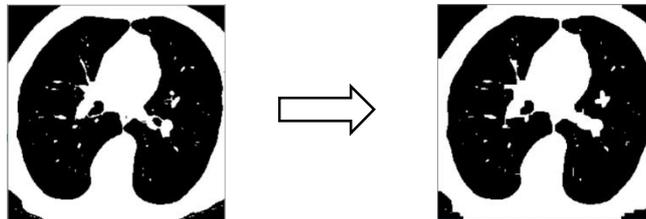
**3.2.2 Image Filtering**

In this system, morphological closing operation has been used to filter out noise in the image. The output image Is then further segmented and provided to a classifier.

Closing operation is a process in which dilation is followed by erosion on an image. Mathematically, it can be represented as

$$A \cdot B = (A \oplus B) \ominus B$$

Here, A is the binary image, B is the structuring element.  $\oplus$  and  $\ominus$  are dilation and erosion respectively.



**Figure 4** Morphological closing operation

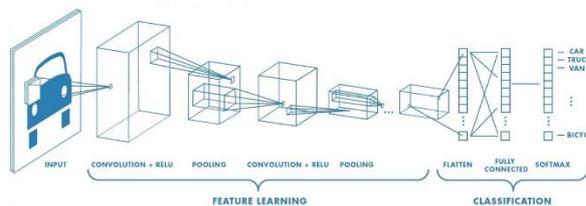
Closing operation is performed on a segmented image to remove noise and other irregularities. The results of closing operation are shown in Figure 4.

**3.3 Classification**

For the first approach, there are two stages of classification. First the segmented images are classified into normal and abnormal images. In the second stage, the abnormal images are further classified into benign and malignant. In this work, machine learning technique used for classification is Convolutional Neural Network (CNN).

**3.3.1 CNN**

CNN's are a category of Neural Networks that have proven very effective in areas such as image recognition and classification. CNN's are a type of feed-forward neural network made up of many layers. CNN's consist of filters or kernels or neurons that have learnable weights or parameters and biases. Each filter takes some inputs, performs convolution, and optionally follows it with a non-linearity. A typical CNN architecture can be seen as shown in Figure 5 The structure of CNN contains Convolutional, pooling, Rectified Linear Unit (ReLU), and Fully Connected layers.



**Figure 5** Basic architecture of CNN [21]

**Convolutional Layer:**

The Convolutional layer performs the core building block of a Convolutional Network that does most of the computational heavy lifting. The primary purpose of the Convolution layer is to extract features from the input data which is an image. Convolution preserves the spatial relationship between pixels by learning image features using small squares of the input image. The input image is convoluted by employing a set of learnable neurons. This produces a feature map or activation map in the output image and after that, the feature maps are fed as input data to the next Convolutional layer.

**Pooling layer:**

The pooling layer reduces the dimensionality of each activation map but continues to have the most important information. The input images are divided into a set of non-overlapping rectangles. Each region is down-sampled by a non-linear operation such as average or maximum. This layer achieves better generalization, faster convergence, robust to translation, and distortion and is usually placed between Convolutional layers.

**Fully Connected Layer:**

Adding a FC layer is a cheap way of learning non-linear combinations of high-level features as represented by the output of the convolutional layer.

**4.SYSTEM IMPLEMENTATION**

**4.1 Database Resource**

The CT scan images used in this experiment are obtained from the lung cancer database of LIDC(Lung Image Database Consortium). The images in the database were available in DICOM(Digital Imaging and Communications on Medicine) format with each image having size 512 pixels by 512 pixels. In this work, all the images have been converted to jpeg format with a size of 256x256. A set of 14757 images is used wherein 11069 images are used for training and 3688 images are used for testing purpose. In training the model, 4512 benign, 5277 malignant and 1280 normal images are used. For testing, 1503 benign, 1759 malignant and 426 normal images are used.

**4.2 Classification of Cancerous Image**

Following steps are used to convert the image into a suitable format that can be used to classify it.

**Algorithm 1- Image Pre-processing**

- Separate the acquired dataset into two parts namely normal, and abnormal (Benign and malignant).
- Crop the image to a size of 256x256.
- Perform binary thresholding to remove irrelevant pixel intensities.
- Perform morphological closing operation to remove noise from the image.
- Isolate biggest contour along with its bounding rectangle.
- This procedure will be repeated until all the images in the database are segmented.

**Algorithm 2- Training CNN**

- Create a training set and testing set of the segmented images. In the proposed system, 80% of the images are used for training and 20% are used for testing.
- Train classifier 1 by providing training dataset so that it classifies images into normal and abnormal.
- Test the validation of CNN by providing testing dataset to classifier 1 by noting accuracy and loss of the model.
- Train classifier 2 by providing training dataset so that it further classifies abnormal images into benign and malignant.
- Test the validation of CNN by providing testing dataset to classifier 2 and note accuracy and loss of the model.
- Note accuracy and loss of the model. This information can be used to change parameter values of the model accordingly, to obtain high accuracy.

Considering approach 2, a single classifier can be trained in a similar way to classify images into normal, benign and malignant. Test validation of the single classifier by feeding it testing dataset.

**Algorithm 3- Testing CNN**

- The trained model is used to classify images that are provided to it.
- The class of the output image will be annotated on the top left corner of the image.

**5.RESULTS**

For the proposed system, two approaches have been implemented and tested for classification of samples into normal, benign and malignant classes. The first one uses two CNN classifiers, one to classify normal and abnormal CT scan images and second to further classify abnormal images into Benign and Malignant. The second approach uses a single classifier to classify the images into Benign, Malignant and Normal.

**Approach 1: Two Stage Classifiers**

In the first approach, there are two stages of classification. First the images are classified into normal and abnormal images. Then the abnormal images are further classified into benign and malignant. The accuracy, sensitivity and specificity of both classifiers is given by Table 1(a) and Table 1(b) respectively.

**Table 1(a)** Performance of Approach1 Classifier 1

TP	TN	FP	FN	Sensitivity	Specificity	Accuracy
3248	391	14	35	98.63	96.54	98.67

**Table 1(b)** Performance of Approach1 Classifier 2

TP	TN	FP	FN	Sensitivity	Specificity	Accuracy
1501	1747	2	12	99.20	99.88	99.57

**Approach 2: Normal vs Benign vs Malignant**

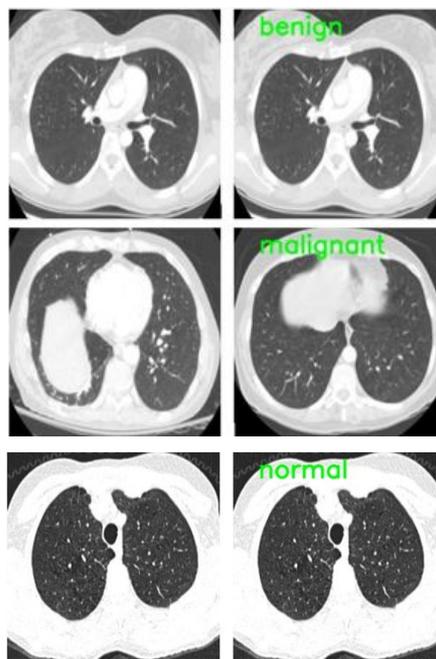
In the second approach, only one classifier is used to classify the images into benign, normal and malignant classes. Results of this classification is shown in table 2.

**Table 2** Performance of Approach 2

TP	TN	FP	FN	Sensitivity	Specificity	Accuracy
1302	2120	65	201	86.62	96.02	92.78

It can be seen that in approach 1, accuracy for classifying normal and abnormal is 98.67%, and that for classifying benign and malignant is 99.57%. The accuracy of single classifier in approach 2 is 92.78%.

The final results of the system for three sample test images belonging to benign, malignant and normal class are given by Figure 6.



**Figure 6** Results of classifier

LHS section shows the sample input images that are provided to the classifier. RHS section indicates the class of the image annotated on it in green colour by the system.

## **6.CONCLUSION**

Lung cancer is the second most cause of death from all types of cancer. According to survey done by American Cancer society its occurrence is high in both male and females. In this system, detection and classification of lung cancer nodule is done using CT images in jpg format. Total 14757 images are used in the system for implementation. The CT images are first pre-processed to enhance the outcomes.

Smoothing of the images is done by using morphological operations. Segmentation is performed by using Binary Thresholding. Total 11069 images are used for training and 3688 for testing. The feature database is provided to Classifier 1 which uses CNN algorithm to classify the images into two categories namely: Normal and Abnormal.

For further classification, the obtained abnormal dataset is then provided to Classifier 2, which also uses CNN algorithm to classify the images into two categories: Benign and Malignant. The accuracy, specificity and sensitivity of first classifier is 98.6%,96.5%,98.9% respectively. Similarly, for the second classifier, the parameter values are 99.5%,99.8%, and 99.2% in the same order. For a second approach, a single CNN classifier is used to classify the input images into three categories i.e. Benign, Malignant and Normal. The accuracy, specificity and sensitivity of this classifier is 92.7%,97% and 86.6% respectively. Out of these two approaches it is observed that the performance of the first approach is better. So, it can be concluded that the individual classifiers have better accuracy than single classifier system. This system will help radiologist for diagnosis of cancer.

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## **REFERENCES**

- [1] Statistics about lung cancer available at, [www.cancer.org](http://www.cancer.org)
- [2] D. Lin and C. Yan, Lung nodules identification rules extraction with neural fuzzy network", IEEE, Neural Information Processing, Vol. 4, 2002.
- [3] Malignant Tumour, digital image, available at <https://www.cancerresearchuk.org/about-cancer/what-is-cancer/how-cancer-can-spread>
- [4] Mokhled S. Al-Tarawneh, Lung cancer detection using image processing techniques", Leonardo Electronic Journal of Practices and Technologies, June 2012.
- [5] A. Amutha, Dr.R. Wahidabanu, Lung tumor detection and diagnosis in CT scan images", IEEE, International conference on Communication and Signal Processing, April 2013.
- [6] S. S. Kanitkar, N. D. Thombare, S. S. Lokhande, Detection of lung cancer using Marker-Controlled Watershed transform", IEEE, International Conference on Pervasive Computing, 2015.
- [7] R. Agarwal, A. Shankhadhar, R. Sagar, Detection of lung cancer using content based medical image retrieval", IEEE, International Conference on Advanced Computing & Communication Technologies, 2015
- [8] S. Ignatious, R. Joseph, Computer aided lung cancer detection system", IEEE, Global Confrence on Communication Technologies, 2015.
- [9] Taruna Aggarwal, Asna Furqan, Kunal Kalra, Feature extraction and LDA based classification of lung nodules in chest CT scan images", IEEE, International Conference on Advances in Computing, Communications and Informatics, 2015.
- [10] Bram van Ginneken, Bart M. HaarRomeny and Max A. Viergever, Computer- Aided diagnosis in Chest radiography: A survey", IEEE Transactions on medical imaging, Vol. 20, no. 12, December 2001.
- [11] Hieu Tat Nguyen, Marcel Worring, and Rein van den Boomgaard, Watersnakes: Energy-Driven Watershed Segmentation", IEEE transactions on pattern analysis and machine intelligence, vol. 25, no. 3, Pp.330-342, March 2003.
- [12] A. Amutha, Dr.R. Wahidabanu, Lung tumor detection and diagnosis in CT scan images", IEEE, International conference on Communication and Signal Processing, April 2013.
- [13] N. Camarlinghi, I. Gori, A. Retico et al., Combination of computer-aided detection algorithms for automatic lung nodule identification", International journal of computer assisted radiology and surgery, vol. 7, pp. 455464, 2012.

- [14] A. A. Abdullah and S. M. Shaharum, Lung cancer cell classification method using artificial neural network", Information Engineering Letters, vol. 2, pp. 49-59, 2012.
- [15] A. Riccardi, T. S. Petkov, G. Ferri, M. Masotti, and R. Campanini, Computer- aided detection of lung nodules via 3-D fast radial transform, scale space representation, and zernike MIP classification" Medical physics, vol. 38, pp. 1962-1971, 2011.
- [16] Jun Lai and Ming Ye, Active Contour based lung field segmentation" International Conference on Intelligent Human- Machine Systems and Cybernetics, 2009.
- [17] J.-C. Chen, C.-M. Yeh, and J.-E. Tzeng, Pattern differentiation of glandular cancerous cells and normal cells with cellular automata and evolutionary learning", Expert Systems with Applications, vol. 34, pp.337-346, 2008.
- [18] Anuradha C Phadke, Priti P Rege, "Fusion of Local and Global Features for Classification of Abnormality in Mammograms", Springer Sadhana - Academy Proceedings in Engineering Science, Vol. 41 No. 4, pp 385-395, April 2016, DOI 10.1007/s12046-016-0482-y
- [19] Anushri Angal, Sayali Bapat, Swarada Sathe, Mangesh Bedekar and A. C. Phadke, "A Fresh Look at Deep Learning Approaches for Breast Cancer Detection", International Conference on Machine Learning and Data Science ICMLDS 2018 at Mahindra Ecole Centrale, Hyderabad, India. held between December 21st and 22nd, 2018, will be published on IEEE Explorer
- [20] The Lung Image Database Consortium image collection (LIDC-IDRI), available at <https://wiki.cancerimagingarchive.net/display/Public/LIDC-IDRI>
- [21] Neural Network with many convolution layers, digital image, available at <https://medium.com/@RaghavPrabhu/understanding-of-convolutional-neural-network-cnn-deep-learning-99760835f148>