

# A review on Lung Segmentation of CT Images using Different Techniques

Manjula.T<sup>1</sup>

Assistant Professor, Department of BCA,  
Seshadripuram Degree college, Research scholar,  
Department of CSE, SSAHE,  
Tumkur, Karnataka, India.

Dr.Ramesh.D<sup>2</sup>

Professor, Department of CSE,  
Sri Siddhartha Institute of Technology,  
Tumkur, Karnataka, India

**Abstract:** Medical imaging represents the use of technology in biology to reveal the internal structure of the organs of the human body. It is a way to improve the patient's quality of life through a more accurate and rapid diagnosis, and with limited side effects, leading to an effective general treatment process. The main goal is to propose new tumor differentiation techniques that cover both microcomputers and macroscopic textures found on computed tomography (CT).

Detection of lung nodules based on CT imaging is the most widely used and accepted method for the detection of lung cancer. Most CT imaging methods are based on supervised learning, which has a large number of false positives and requires a large number of predefined training samples. These problems can be solved if an optimal number of training sample images can be generated, where each sample has lung nodules similar in size and shape to the patient's actual image. CAD systems must meet the following requirements: improving the performance of radiologists by providing high diagnostic sensitivity, low number of false positives (FP), high processing speed, high level of automation, low cost (implementation, training, support and maintenance), the ability to detect different types and shapes of nodules and guarantee software security.

Keywords : tomography, threshold, sensitivity, nodules

into computer diagnostic assistance (CAD) systems. Some of the parameters used to determine the effectiveness of a CAD system are

I. Sensitivity: Sensitivity is defined as

$$\text{Sensitivity} = \frac{TP}{TP+FN}$$

Where, TP = True positive, i.e., a positive output for a sample that has the disease and

FN= False negative, i.e., a negative output for a sample that has the disease.

2. False positives (FP), a positive result for a sample that does not have disease.

3. Processing time.

4. Level of automation.

5. Implementation costs.

6. Ability to detect different types, sizes and shapes of nodules, such as individual nodules, micro-nodules, partially solid, nodules attached to the edges of the lungs or cavities of the lungs.

## I. INTRODUCTION

Lung cancer is one of the leading causes of death in the world and the second most common cancer in the United States. Lung cancer is caused by uncontrolled cell growth in the lung, and early detection of uncontrolled cell growth can significantly increase the survival rate of cancer patients. Advances in computed tomography (CT) technology have offered a great opportunity for such early detection and thus helped lung cancer patients receive early treatment.

Focal opacity between 3mm and 30mm is defined as a nodule. There are lung nodules of different sizes. Anything smaller than 3 mm is called a microscope and anything larger than 30 mm is called a mass. CT technology has made it possible to visualize very small low-contrast nodules that are difficult to see on conventional radiographs.

Careful observation of CT images by an experienced radiologist is a common practice for detecting pulmonary nodules. Since 1980, many efforts have been made to create an automated system for the detection of lung nodules in order to save time and costs. None of these systems are completely successful in automatically detecting pulmonary nodules, but some of them have been instrumental in helping radiologists reduce their workload. These systems are generally grouped

## II. COMPUTER TOMOGRAPHY

Computed tomography (CT) is a widely used method of creating an image of the inside of a living human body. Figure 1-1 shows a typical setup for a CT scan. In the CT technique, X-ray beams pass through a section of the human body from different directions. X-ray sensors are placed on the opposite side of the body. Today's CT scanners can obtain up to 320 CT slices at a time. A 2.5 mm (2D) cut is the standard for a routine chest protocol. A typical chest CT scan can contain 400 slices, where each slice is a 512 × 512 pixel frame. In fact, MDCT produces high-quality volumetric (3D) images. Figure 1-2 shows three MDCT sections of the chest from three different planes.

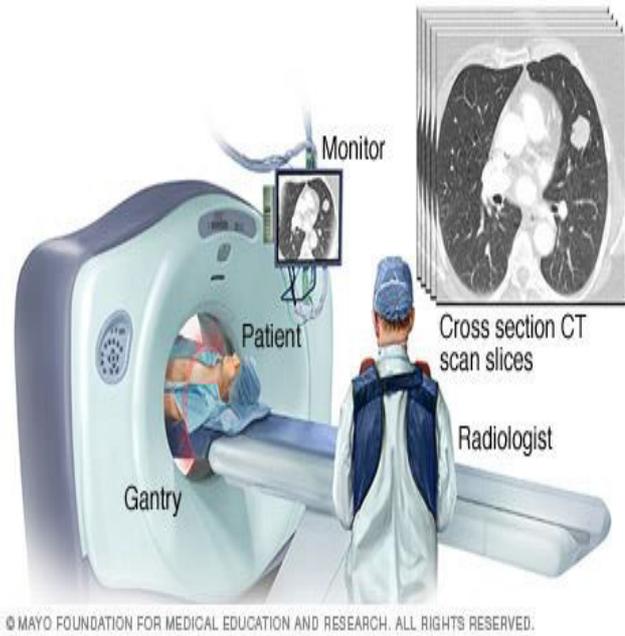
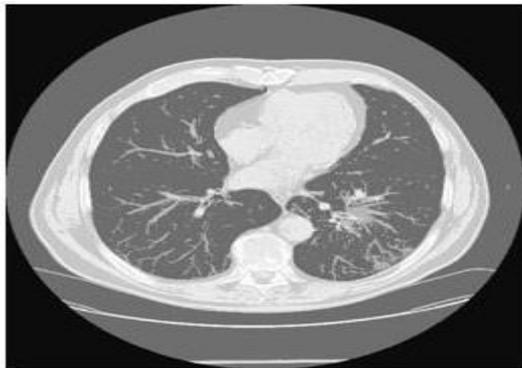


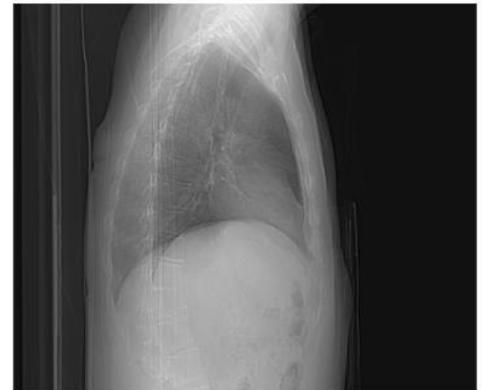
Figure 1: A typical CT scan setup



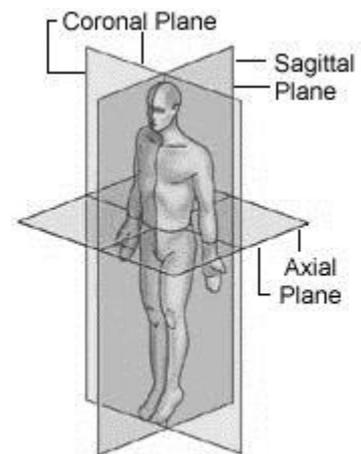
(a) Axial slice



(b) Coronal slice



(c) Sagittal slice



(d) Body Planes

### III. LITERATURE REVIEW

#### Cancer detection:

There is a large body of literature on the detection and segmentation of lung nodules from 2D and 3D CT images. Each article follows an algorithmic structure with different steps. Some of the steps are common to most articles. These common steps are: imaging, pretreatment, lung segmentation, nodule detection, and reduction of false positives.

The first step in the process is to take pictures of the lungs. There are several public databases available for research purposes. Examples include the Therapy Response Evaluation Reference Database (RIDER) [1], the Lung Imaging Database Consortium (LIDC) [2], the Lung Imaging Database Consortium, and the Imaging Database Resource Image Initiative (LIDC) -IDRI [1], Early Lung Cancer Action Plan (ELCAP) on the Internet [3], etc.

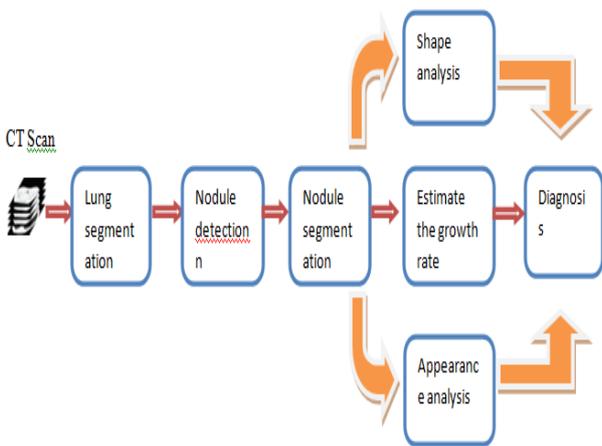


Figure 2: Typical Computer Aided Diagnosis(CAD) system for lung cancer

FIGURE 2: Typical computer-aided diagnosis (CAD) system for lung cancer. CAD entry is medical images taken using an appropriate method. A lung segmentation step is used to find space for lung nodules, while nodule detection is used to locate the location of the lung nodules. The nodules found are fragmented. Then, a set of candidate features, such as tumor, shape and / or appearance features, are extracted and used for diagnosis.

The second step in dividing the lungs is pretreatment. Preprocessing helps reduce noise and objects in CT images. Pre-processing steps may also be required because different CT scanners produce different images of different sizes and intensities. These are not necessary steps and therefore not all articles on preprocessing are mentioned. Different methods are used for pretreatment. Cascio, Donato et al. [4], Pu et al. [5], Wei et al. [6] Selected Gaussian filtering to remove objects, The algorithm of Namin et al. [7] had several steps for pretreatment: the first was to unify the size of the voxel and the second was to normalize the volume range. They also implemented a Gaussian filter to remove noise from the image.

The third step is to divide the lungs. Lung segmentation refers to the segmentation of the lung area from muscle and adipose tissue. Healthy lung tissue forms darker areas on CT images compared to other parts of the chest, such as the heart and liver. This fact has encouraged many researchers to look for an optimal boundary that separates the lungs from all other tissues. Hu et al. [8] repeatedly calculated this threshold to obtain an initial area of the lungs. The initial segmentation was then improved by opening and closing morphological features. Armato et al. [9] used a gray border to segment first the thoracic thorax and then the thoracic lungs. In addition, a rolling ball filter was applied to the segmented margins of the lung to prevent the loss of parallel lateral nodules. The identified lung fields were used to narrow the search space of the lung nodule detection frame. In Pu et al. Study [10], the

threshold is automatically selected as described by Armato et al. [9] A threshold area filling methodology was then used to segment the lung fields as a first step in a lung segmentation framework. Pu et al. [11] setting a threshold for the initial segmentation of lung regions. To improve segmentation and include the jute lateral nodules, a gait tip algorithm was used to walk along the margins of the lungs with an adaptive gait step to improve the curved traces.

The fourth step is to detect the candidate nodule. El-baz et al. [12] implemented a standard based on genetic algorithms for the detection of candidate nodules. In his method, in the first step, a genetic algorithm was developed to determine the position of the target and the appropriate radius in an observed image. In the second step, they used pattern matching. Ted W. Way et al. [13] Four sets of features were used in this study: M morphological features, texture features extracted from RBST T images, recently developed image features based on gradient and radius G characteristics, and D demographic characteristics. , the subscription indicates which feature groups were included in the function space, for example, feat MTG is the feature space that contains the new forms of morphology, texture and display.

The fifth step is to reduce false positives by using entity classifiers. Choi and Choi [14] and Santos et al. [15] developed support vector classifiers for nodule classification. El-baz et al. [16] developed a Bayesian supervised classifier to reduce false positives. Matsumoto et al. [17] rule classifiers were applied. In their method, seven characteristics were calculated for 9 of each candidate nodule. For each characteristic, a cut-off value was selected above which the candidate nodule was designated as a true nodule.

Comparison of different approach for nodule detection based on the performance:

Healthy Healthy lung tissue forms darker areas on CT images compared to other parts of the chest, such as the heart and liver. This fact has encouraged many researchers to look for an optimal boundary that separates the lungs from all other tissues. Hu et al. [18] repeatedly calculated this threshold to obtain an initial area of the lungs. The initial segmentation was then improved by opening and closing morphological features. Mendonca et al. [19] automatically selected the ROIs of PA chest X-rays as rectangular areas surrounding each lung field as closely as possible through a repeat procedure. Boundary points (i.e., mediastinal, lateral, upper, and lower border points) were identified using spatial boundary detection filters and combined to define a closed contour for the lung boundaries. Korfiatis et al. [20] used 2D waveform to mark the ends of the lungs in a stack of 2D images. Gao et al. [21] proposed another threshold-based segmentation approach consisting of four processing steps: (i) removal of the large airway from the lung area using isotropic diffusion to smooth the extremities followed by area development; (ii) finding an optimal threshold for elimination of the pulmonary vessels, (iii) separation of the left and right lungs by detecting anterior

and posterior connections using the greater threshold; and (iv) morphological normalization of the pulmonary border along the mediastinum and lung wall according to the structure of the airway tree. Silveira et al. [22] used a 2D geometrically active LS contour initialized at the border of the thoracic region, which was then automatically divided into two regions representing the left and right lungs. Pu et al. [23] sets a threshold for the initial segmentation of lung areas. To improve segmentation and include jute lateral nodules, a gait tip algorithm was used in March along the lungs at an adaptive gait rate to improve curved traces. El-Baz et al. [24] proposed an iterative segmentation frame based on Markov-Gibbs random fields (MGRF-) for segmenting lung fields from LDCT images. Kockelkorn et al. [25] used an interactive user framework to segment the lungs into extremely irregular CT

scans, where a user corrected the results obtained from a k-nearest neighbor classifier (KNN) trained in previous data. Sofka et al. [26] aligned a shape scheme using a set of automatically identified anatomical landmarks and improved the shape model through an iterative surface deformation approach in lung sections containing pathologies. The main limitation of shape-based segmentation techniques is that their accuracy is highly dependent on the precision with which the model is recorded anteriorly relative to the CT image. Hua et al. [27] presented an automated method for segmenting pathologic lung fields using a graph-based search for a cost function that incorporates intensity, gradient, boundary smoothness, and ribinformation

Table 1: Overview of current approaches to lung segmentation

Study	Database	Dim	Image Size	Approach	AL	GS	Performance
Hu et al[3]	24 datasets from 8 subjects	3D	512x512, 3mm thin	Iterative Threshold, Dynamic programming, Morphological Operations	A	229 manual traced images	RmsD=0.54mm(0.8 pixel)
Mendonca et al.[43]	47 image radiographs	2D	512x512, 3mm thin	Spatial edge detector	A	47 manual traced data	Sen.=0.9225,PPV=0.968
Korfiatis et al.[44]	23 scans	3D	512x512	Wavelet edge Detector	A	22 manual traced data	OM=0.983.AD=0.77mm, RmsD=0.52mm
Gao et al.[13]	8 subjects	2D	512x512x240	Thresholding	A	8 manual traced datasets	DSC=0.9946
Silveira et al.[18]	1 subject	2D	512x512, 1mm thin	Deformable model	A	-	Qualitative Assesment
Pu et al.[12]	20 datasets	2D	512x512, 1.25mm thin	Thresholding	A	20 manual traced datasets	FP/GT=0.43% FN/GT=1.63%
El-Baz et al[35,36]	10 image datasets	3D	512x512x182, 2.5mm thin	Statistical MGRF model	A	1820 manual traced images	Accu.=0.968
Kockelkorn et al.[32]	22 scans	3D	0.9-1.0mm	Prior training, Statistical classifier	UI	12 manual traced data	OM=0.96, AD=1.68mm
Sofka et al.[31]	260 scans	3D	0.5-5.0mm	Shape based	A	68 manual traced data	SCD=1.95
Hua et al.[33]	15 scans	3D	0.3-0.9mm	Graph search	A	12 semiautomated traced data	HD=13.3 pixel, Sen.=0.986, Spec.=0.995

AL indicates level of automation (A: automatic, UI: interactive user; Dim indicates approach dimension (2D or 3D). GS means gold standard; NA means non-applicable. DSC indicates the similarity coefficient of the dice.  $DSC = 2TP / (2TP + FP + FN)$   
 Accu. states accuracy,  $Accu. = (TP + TN) / (TP + TN + FP + FN)$   
 OM indicates overlap measure,  $OM = TP / (TP + FP + FN)$   
 Sen. indicates sensitivity,  $Sen. = TP / (TP + FN)$   
 Specifications Indicates Specialty,  $Spec. = TN / (TN + FP)$   
 PPV indicates positive predictive value,  $PPV = TP / (TP + FP)$   
 RmsD denotes the root mean square difference of the distance between segmentation and ground truth.  
 AD denotes the mean absolute surface distance.  
 HD indicates the Hausdorff distance, the average maximum distance of one set to the nearest point of the other set.

SPD indicates the average signed border detection error.  
 SCD indicates symmetric point-to-grid comparison error.

#### IV. OVERVIEW

Figure below shows the different methods used in nodule detection in various papers

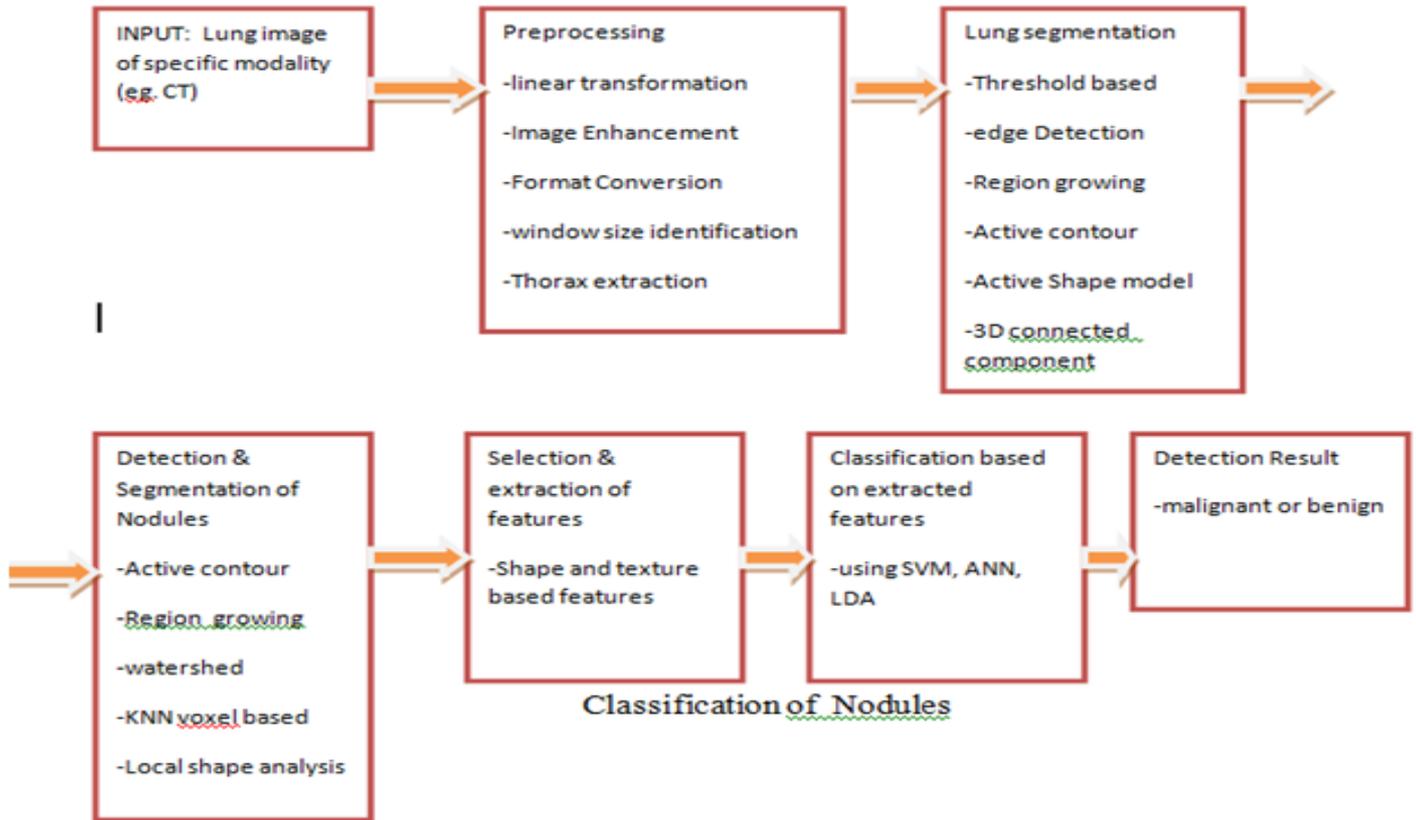


Figure 3: Overview of different approaches for lung nodule detection

### V. CHALLENGES

More research is needed to improve existing systems and propose new solutions. Therefore, we believe that collaborative efforts through the creation of software communities are essential for the development of a CAD system with all the above requirements and a short development cycle. Therefore, the challenges of new CAD systems for the detection of pulmonary nodules are:

1. Develop a CAD system, preferably an open source system, that displays all operational requirements with zero licensing costs and allows the source code to be modified according to local needs.
2. Development of new techniques or improvement of existing ones, to segment the image of the lungs to allow a higher level of automation, including cases of serious pathology, small nodules ( $\leq 3\text{mm}$ ). □ Develop standards that allow CAD systems to be integrated with other systems in the hospital environment (electronic patient record)
3. Development of systems that detect nodules, determine their characteristics (malignancy, tumor, presence of calcifications and their pattern, contours, boundaries and internal structures) and evaluate the development of oncological treatment and its possible prognosis.

4. Larger databases should be provided for effective validation of the proposed systems.

The sensitivity of CAD systems is relatively high, but the number of FPs is high compared to the performance of radiologists. Therefore, further improvement of the specialty in future research is required

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