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Computer Aided Detection of Lung Cancer Pulmonary Nodules from CT Images: A Recent Survey

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***Abstract*— among all cancers, lung cancer is a major cause of death in both women and men. 1.2 Million People are estimated to have diagnosed with this disease every year. About 1.1 million people have died of this disease in a year. Many lives can be saved if cancer is detected at early stages. However, early detection of lung cancer is not an easy task. Most of the correct detection (i.e.80%) in patients is diagnosed at the middle or advanced stage of cancer. Radiologist with help of Computer aided diagnosis system (CAD) can detect and diagnose the abnormalities quickly and at earlier stages. Lung cancer is diagnosed with detection of pulmonary nodules. The detection work on pulmonary nodule is carried out using Computer Tomography (CT) scan images. CT scan images have better clarity, low noise and distortion. Extensive research work is done in this area. Various research focuses are seen on different sections of the CAD system. In this paper, efforts are put to compile different techniques of image acquisition, preprocessing, segmentation, lung nodule detection, false positive reduction and different lung nodule classification. This paper presents a review of available research work on detection of lung nodule for last five years.**

Keywords – ***Characterization, Computer tomography, Computer-aided diagnosis, Nodule, Nodule detection.***

1. INTRODUCTION

LUNG cancer is the second most commonly diagnosed cancer in both men and women. In INDIA every year 63,000 new lung cancer cases are reported [3]. According to the statics from the American Cancer society, lung cancer is the primary cause of cancer-related death in United States [1]. Estimated 224,390 (i.e. 117,920 cases of Men and 106,470 cases of female) new cases of lung cancer are expected to occur in 2016. The estimate accounts for about 14% of all cancer diagnoses [1]. Lung cancer records more deaths than any other cancer in both men and women. From SEER Cancer Statistics Review the Five-year (2006-2012) Relative Survival Rates when combined is 17.7%, 14.9% in males and 20.8% in females [1]. Pulmonary nodules are potential manifestation of lung cancer. Early diagnose of the lung tumor is the key to increase the survival rate of 1 to 5 years. It can be further increased up to 65 to 80%. Hence major research efforts are made in early detection of lung nodules to win the war against lung cancer [2]. Cigarette smoking is the most important risk factor for lung cancer; 80% of lung cancer deaths in the US are caused by smoking. There is high increase in risk with both quantity and duration of smoking [1]. Death rates have declined by 2.9% per year in men and by 1.9% per year in women from 2008 to 2012 due to the drop in smoking prevalence [1].

The lung tumor is formed due to an abnormality in body cell. The normal human body checks and maintains the growth of cell. The unbalance of the system results in uncontrolled division and proliferation of cells due to which a mass is formed, known as a tumor. Tumor can be benign or malignant. Benign tumor is a non-cancerous growth in the body. It can be removed and its spread in other parts of the body is stopped. Whereas, tumor that grows aggressively and spread into the other parts of the body tissues are classified as Malignant. Lung nodules are the tissue abnormalities that are roughly spherical with round opacity and a diameter of up to approximately 30mm [1]. Medical Imaging is more accurate and efficient method for the diagnosis and hence is widely used for the nodule detection and treatment of lung cancer.

There are various types of images available in medical imaging. However Computed Tomography (CT) images are being preferred because of better clarity, low noise and less distortion for the detection of lung cancer. Another advantage of CT scan images is that it is very easy to calculate the mean and variance of CT scan images.

A pulmonary nodule in the CT images is identified with approximately round opacity, moderately well margin and maximum diameter not greater than 3cm [5]. Lung nodules can be classified into four main categories based on the location and connection with surrounding pulmonary structure,

1. Well-circumscribed nodule – These nodules are centrally located in the lung and has no connection to its neighboring vessels and structures.
2. Juxta-vascular nodule – This type has significant connections to its neighboring vessels.
3. Pleural tail – Nodule has thin connection to its neighboring pleural wall, where the pleural tail belongs to the nodule itself.
4. Juxta-pleural nodule – This has some degree of attachment to the chest and its neighboring pleural surface [2], [9] as shown in Fig 1.

Based on the image intensity profile nodules are classified as, solid nodule and ground glass nodules (GGN). Solid nodules have uniform intensity distribution whereas GGN have indistinct increase in lung attenuation on CT images that is difficult to discover the underlying pulmonary parenchymal architecture shown in Fig 2. The growth rate of nodule is one of the important parameter for assessing its malignancy.

For this reason, most of the published CAD research has focused on detection of pulmonary nodule as well as estimation of the growth rate [2].

clinical applications of 2D and 3D CT imaging for analysis of HRCT pattern and pulmonary nodule respectively [6].

The current paper aims to provide an overview of the literature on lung nodules detection methods from year 2011–2016. This paper is organized in the following sections: section 1 gives an introduction, section 2 gives review of nodule detection methods, section 2.1 describes different image acquisition techniques section 2.2 gives a literature on

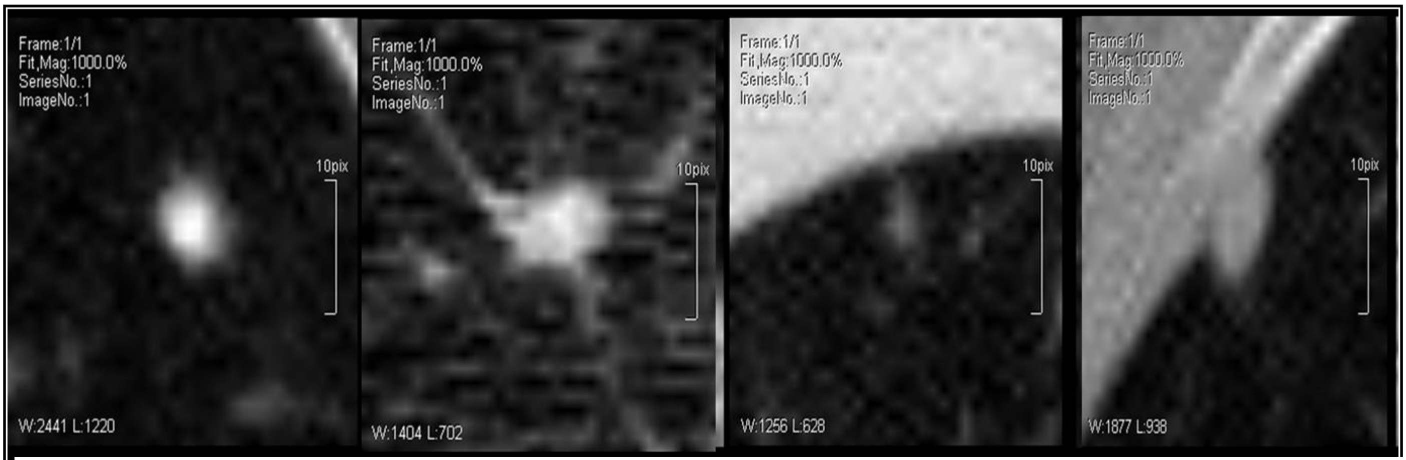

Fig 1 Typical lung nodule for different type; (a) well-circumscribed nodule; (b) juxta-vascular nodule; (c) nodule with a pleural tail; (d) juxta-pleural nodule.

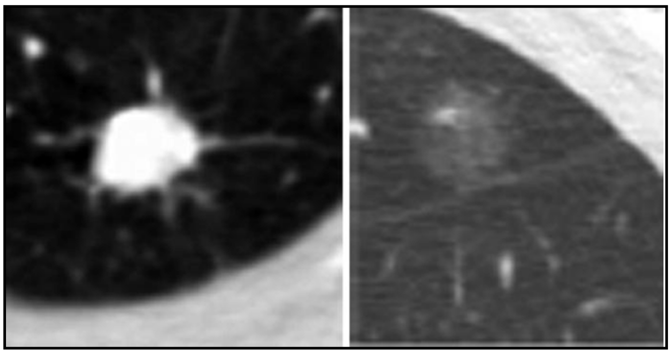

Fig 2 Classification of lung nodule depending on intensity profile; (a) solid nodule; (b) ground glass nodule [2]

There are several good review papers on lung nodule including [2–9], [14]. The focus of the review is on respective sets of the detection system. Dhara *et al.* have provided an overview of the literature on different components of automated nodule detection and analysis system and their evolution from 1998–2010 [2]. Sluimer *et al.* have given an extensive review on the performance of lung nodule detection and characterization system from 1999 to 2004 [7]. Li *et al.* gives a very extensive literature work on nodule detection and classification of lung nodules in thin-section CT images; published work is covered till 2006 [8]. S.L. Lee *et al.* cite the review on preprocessing, lung segmentation, pulmonary nodule detection, false positive reduction, and nodule characterization up to 2009 [9]. His work gives a comparative study of performance of the existing approaches and also gives a general framework of the computer-automated system for nodule detection and analysis. Salvolini *et al.* reported the

different preprocessing techniques, section 2.3 describes different lung segmentation methods, section 2.4 presents a review of existing methods of lung nodule detection (Subsection 2.4.1) and false positive reduction (Subsection 2.4.2). Section 2.5 describes different existing techniques on lung nodule classification. Section 2.6 describes the two public challenges for nodule detection are ANODE09, LUNA16 followed by Discussion, Conclusion, and Acknowledgments.

2. Review of Nodule Detection Methods

There are several research survey papers that have described nodule detection methods and have classified it into two types, semi automated and fully automated.

Computer-aided diagnosis (CAD) assists radiologists in the diagnosis of various diseases on medical images. The output from the system is considered as a second opinion in drawing the conclusions. Presently significant effort is being directed to the detection and classification of lung nodules. Thin-section CT images are preferred due to previously highlighted benefits. Due to large amount of data associated with number of images, radiologist may overlook some lung cancers because of either detection error (failure to detect a cancer) or interpretation error (failure to correctly diagnose a detected cancer). Hence, a CAD scheme for detection and for characterization of lung nodules would be particularly useful for the reduction of detection and interpretation errors. Missed cancers can be detected and classified through computerized scheme that provides quantitative information such as the possibility of malignancy to assist radiologists in diagnosing a detected nodule [8].

The CAD system is designed to automatically detect lung cancer through CT images and can provide valuable information on stages of lung nodules. The system consists of six stages 1) Acquisition 2) Pre processing, 3) Segmentation, 4) Nodule Detection and false positive reduction, 5) Nodule Classification. The general scheme of lung nodule detection system is shown in Fig 3.

The objective of CAD system is to:

- Improve accuracy in diagnosis
- Assist in early detection of cancer
- Reduce the evaluation time of the radiologist.

Following sub sections describes each block and existing methods relating to each component.

For each method, tables (2-6) are compiled to describe the performance of several existing nodule detection systems. Information on authors, publication year, and technique used data sets/sample images, and performance results/remarks is provided.

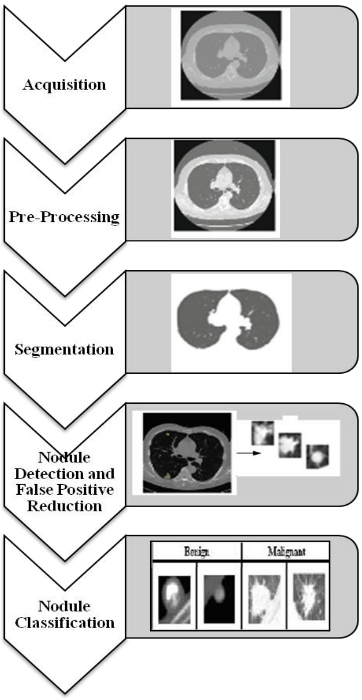

Fig 3 The general scheme of lung nodule detection system

2.1. Image Acquisition

Image acquisition is the process of acquiring medical images. For designing nodule detection system CT scan image is used because CT enables visualization of small volume or low-contrast nodules by decreasing the thickness of slices and the interval between consecutive slices. CT is preferred for the preliminary analysis of lung nodules screening comparing to other lung imaging methods.

There are several public and private databases of Lung CT images. Following are the popular public lung nodules databases available: Early Lung Cancer Action Program (ELCAP) Public Lung Image Database [10], Lung Image Database Consortium (LIDC) in National Imaging Archive [11], and Medical Image Database [12]. Beyond the public lung image database many researchers have referred private databases from their partner hospitals [2, 9]. Typical CT image of lung is shown in

In CT scanning, image quality depends on many technical parameters such as radiation exposure time, slice thickness, table speed, reconstruction algorithm detector efficiency etc. For reconstruction of 3D image from 2D, slice thickness must

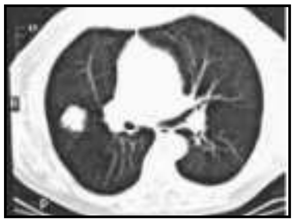

Fig 4 Typical CT image of Lung [5]

be greater than slice spacing otherwise reconstructed image will be erroneous because of lack of information in the inter

A comparative study among the four generation of CT scan machine with respect to slice thickness, table speed in second is described in TABLE I [2]. It can be seen that the fourth generation CT machines are more advanced in capturing the smaller slice thickness and with more speed per slice.

TABLE I Comparative study of CT scan machine. CT – Computer tomography; Gen. – Generation [2]

CT machine parameter	**First Gen.**	**Second Gen.**	**Third Gen.**	**Fourth Gen.**
Slice thickness in mm	10	5	1	0.75
Speed in s/slice	140	20	0.5	0.12

2.2. Preprocessing

Pre-processing image is the process of improving quality of displayed image and interpretability of the input lung image and boundary identification. The pre-processing reduces distortions and unwanted artifacts in the lung image. Here preprocessing phase is meant to remove the unwanted parts and to enhance the visibility of extracted pulmonary nodule [2, 9] (See Fig 5).

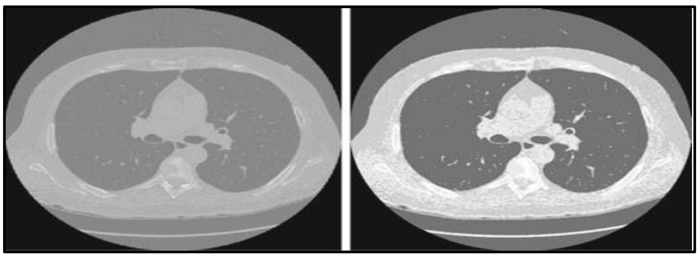

Fig 5 A sample pre-processed lung image: (left) original and (right) pre-processed images [9]

Different filtering techniques are proposed in literature to remove these noises compiled in TABLE II. Sharma *et al.* [20] and H. Shao *et al.* [19] both uses wiener filter for preprocessing [5]. Tan *et al.* proposed Isotropic re-sampling method to enhance CT image [64]. Ashwin *et al.* used an Adaptive Median filtering to improve contrast. The low frequency image is replaced by calculating median value from

5x5 matrixes. In order to enhance the contrast of the preprocessed lunge image the contrast limited adaptive histogram (CLAHE) equalization method is used [15]. T. Gao *et al.* have used high-pass filter for preprocessing [17]. Takahiro Miyajima *et al.* proposed selective enhancement filters to enhance blob like structures and to hide vessel like structures [21]. For preprocessing Prewitt filter was used by V. Vijaya Kishore *et al.* to enhance the horizontal edges [23]. To denoise and preserve the spherical structures 3-D Coherence-Enhancing Diffusion (CED) filter was used by Wook-Jin Choi *et al.* [24]. Tariq *et al.* [18] and S.Sivakumar *et al.* [22] proposed Median filter to denoise the CT image. The advantage of Median filter is that it doesn't distort the edges.

Vaibhav K. *et al.* have achieved improvement in the contrast of CT image using histogram equalization method [26]. G. Vijaya *et al.* compare performance of various filters used for pre-processing techniques and observed that bilateral filter has better results. [16]. Sunanda Biradar *et al.* suggested Median filter to increase the contrast of CT images [25]. Gangotri Nathaney *et al.* proposed Adaptive Thresholding and Morphological operations for pre processing. Adaptive Thresholding method was used to distinguish two values as foreground and background by changing all pixels values whose intensity values are more than a threshold to a foreground value and all the left over pixels to a background value. Morphological operations were used to remove the background noise and to remove small objects [27]. Eman Magdy *et al.* [28] and M. Obayya *et al.* [29] both have used a Wiener filter to remove noise, preserving the edges and fine details of lungs CT image. Ruchika *et al.* proposed Median filter to attenuate noise without blurring the images [52].

TABLE II Preprocessing method reported in the literature

Study	Reported	Method of preprocessing	Purpose
D. Sharma *et al.* [20]	2011	Wiener filtering	Denoising, smoothing
Tan *et al.* [64]	2011	Isotropic re-sampling	To enhance CT image
H. Shao *et al.* [19]	2012	Wiener filtering	To improve lung CT image
S. Ashwin *et al.* [15]	2012	Adaptive median filtering, contrast limited adaptive histogram (CLAHE) equalization	To correct the poor contrast, to enhance the contrast of preprocessed CT lung image
T. Gao *et al.* [17]	2012	High-pass filter	To reduce the noise from CT image
Takahiro Miyajima [21]	2012	Selective Enhancement filters	To enhance blob like structures and to hide vessel like structures
V. Vijaya Kishore [23]	2012	Prewitt filter	To enhance the horizontal edges
Wook-Jin Choi *et al.* [24]	2013	Coherence-Enhancing Diffusion (CED)	To denoise and preserve the spherical structures
Tariq [18]	2013	Median filter	Denoising
S.Sivakumar *et al.* [22]	2013	Median filter	To denoise CT image without distort the edges
Vaibhav K *et al.* [26]	2014	Histogram equalization	To improve the contrast of images
G. Vijaya [16]	2014	Bilateral filter	Better performances for pre-processing
Sunanda Biradar [25]	2015	Median filter	To increase the contrast of images
Gangotri Nathaney [27]	2015	Adaptive Thresholding, Morphological operations	Eliminates image distortion and enhances
Eman Magdy *et al.* [28]	2015	Wiener filter	To denoise image by maintaing edges and small details of lungs CT image
M. Obayya *et al.* [29]	2015	Wiener filter	To remove noise
Ruchika *et al.* [52]	2016	Median filter	To attenuate noise without blurring the images

2.3. Lung Segmentation

Lung Segmentation is the procedure of identifying the lung lobe region and separating the lung region from other portion of the body in chest CT image (See Fig 6). The segmentation distinguishes the nodule from background part of the lung CT image. An accurate segmentation will reduce the computational cost of detection [2], [9]. This process helps to improve accuracy and precision which helps in early diagnosis of lung cancer. It is prerequisite for Nodule detection and has important role In CAD system. Segmentation is partitioning the given input image into multiple segments. Segmentation is a process to extract other anatomical parts of the body in chest, like lungs from fats, muscles etc from the CT images.

H. Mahersia *et al.* [5] have classified lung segmentation into two main approaches; 2D and 3D. Authors have classified segmentation methods based on thresholding, multiple thresholding, adaptive thresholding, optimal thresholding, region growing, deformable boundaries, edge detection, shape models, fuzzy c means clustering, morphological operations and so on [14],[5].

Different segmentation techniques were proposed in literature presented in TABLE III such as Korfiatis et al. proposed 3D Histogram technique to segment vessel tree and

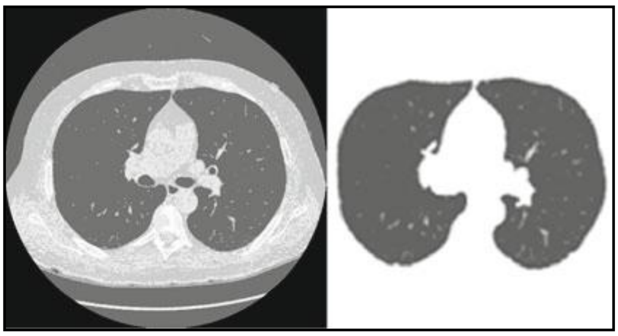

Fig 6 A segmented lung CT image: original (left) and segmented images (right) [9

reticular patterns [30]. Schuldause et a.l have used segmentation technique as region growing and local adaptive contrast enhancement technique [31]. P. Hua et al. suggested graph based search method with information about intensity, gradient and rib to automatically segment the lung [32]. D. Sharma et al. proposed Sobel edge detection method based algorithm to detect and extract the cancer nodules from the CT image [38]. Kubota et al. used Region-Based segmentation with a euclidean distance map [39]. Model based method is proposed by A. El-Baz et al. and A. Farag et al.in 2011. A. El-Baz et al. explained the model based method using energy minimization method [41]. A. Farag et al. explained model based method using a level sets solution [42]. S. Ashwin et al. in 2012 have suggested thresholding method to segment lung CT image and two value of threshold is found using image histogram [15]. Region growing segmentation method is suggested by Aggarwal et al. [35] and K. Devaki et al. [36] in 2013. K. Devaki et al. have also considered textural features [36]. A morphological operation for segmentation is proposed by Jinsa Kuruvilla et al. [44] and Y. Guo et al. [37] in year 2013. Jinsa Kuruvilla et al. achieved sensitivity of 88.24%, specificity of 93.33% and accuracy of 90.63% [44]. Y. Guo et al. used expectation-maximization (EM) analysis method along with morphological operations. Threshold value for lung segmentation is estimated from the computed image's histogram using EM algorithm [37]. Tariq et al. suggested gradient mean and variance based method to remove the lung background. Gradient operator is able to differentiate high values of pixels on the boundary of foreground and background [18].

Ashwin *et al.* [15], N. Birkbeck *et al.* [33], K. Z. Faizal *et al.* [34], Hong Shao *et al.* [19], Vaibhav K *et al.* [26] have proposed a segmentation technique to converts a gray-level image into a binary image. This was achieved by defining all pixels greater than some value to be foreground and rest pixels were considered as background. Hong Shao *et al.* have achieved initial segmentation of the pulmonary parenchyma using twice the adaptive iteration threshold technique [19]. Vaibhav K *et al.* have segmented the left and right region of lungs by using Thresholding method [26]. J. Gong *et al.* explained 3D region growing algorithm and then interested segments were extracted using the Otsu threshold algorithm [40] in year 2014. A morphological operation is suggested by Jinsa Kuruvilla *et al.* [62] and Sunanda Biradar *et al.* [25]. Morphological operation has advantage of speed and it's easy to implement. Jinsa Kuruvilla *et al.* have achieved average 98% segmentation correctly [62].

Dhara *et al.* in 2015 explained a robust segmentation workflow to segment solid, part-solid, and non-solid nodules. First nodules are classified into solid/part-solid and non-solid nodule. Then vasculature pruning technique is proposed for solid/part-solid nodules and selective enhancement filtering and adaptive thresholding is proposed for non-solid nodule to remove blood vessels form nodule [43]. Gangotri Nathaney *et al.* suggested the (ROI) Region of Interest method for segmentation. ROI is defined by creating a binary mask with ROI pixels to 1 and all rest pixels to 0 [27]. Eman Magdy *et al.* proposed a hybrid technique resulting from a combination of histogram analysis, thresholding, and morphological operation for automatic lung segmentation [28]. In 2015, M. Obayya *et al.* proposed region growing algorithm for partitioning a lung CT image [29]. Ruchika *et al.* proposed Mean shift algorithm to segment the image [52].

TABLE III Literature review of Segmentation Techniques of lung CT images

Study	Reported	Segmentation Technique	Dataset	Remark
Kortifias [30]	2011	3D Histogram Thresholding	210	Enhancement Technique Use Is Multiscale Filter Using Hessian Matrix
Schuldause [31]	2011	Region Growing	45	Enhancement Technique Use Is Local Adaptive Contrast Technique
P. Hua [32]	2011	Graph-Search	15 cases	Hausdorff Distance=13.3pixel Sensitivity=98.6% Specificity=99.5%
D. Sharma [38]	2011	Sobel Edge Detection Method	1000	Extract The Cancer Nodules
T. Kubota [39]	2011	Region-Based Segmentation	820	Euclidean distance map
A. El-Baz [41]	2011	model based method	200	energy minimization
A. Farag [42]	2011	model based method	--	Level Sets solution
S. Ashwin [15]	2012	Thresholding	40	Used image histogram
P. Aggarwal [35]	2013	Region-Based Segmentation	246	to segment lungs region
K. Devaki [36]	2013	Region-Based Segmentation	5	Involve Textural Features
Jinsa Kuruvilla [44]	2013	morphological operations	120	Sensitivity =88.24%, Specificity =93.33%, Accuracy =90.63%.
Y. Guo [37]	2013	Morphological Operation	58	Expectation-Maximization (EM) Analysis To Estimate The Threshold Value
Tariq [18]	2013	Gradient Mean And Variance Based	100	segment lungs
N. Birkbeck [33]	2014	Thresholding	260	Converts A Gray-Level Image Into A Binary Image
K.-Z. Faizal [34]	2014	Thresholding	--	segment lungs region
Hong Shao *et al* [19]	2014	Thresholding	--	Adaptive Iteration Threshold Method
Vaibhav K [26]	2014	Thresholding	--	To extract the lungs left and right region
J. Gong [40]	2014	region growing algorithm	--	Interested segments extracted using Otsu threshold algorithm
Jinsa Kuruvilla [62]	2014	Morphological operations	155	98% accurate segmentation

Sunanda Biradar [25]	2015	morphological segmentation	1,012	Segment lungs region from the CT images
Dhara *et al.*[43]	2015	robust segmentation framework	891	vasculature pruning technique for solid/part-solid nodules Selective enhancement filtering and adaptive thresholding for non-solid nodule
Gangotri Nathaney[27]	2015	ROI processing(ROI processing)	--	ROI pixels to 1 and all rest pixels to 0
Eman Magdy[28]	2015	combination of histogram analysis, thresholding, and morphological operations	83	to separate the lungs from both background and non lung regions
M. Obayya[29]	2015	Region Growing Algorithm	100	Simplicity and good performance
Ruchika [52]	2016	Mean shift algorithm	--	For faster execution and high accuracy

2.4. Lung Nodule Detection and False Positive Reduction

Lung nodule detection is a process of determining possibility of nodule patterns in the image, and identifying the nodule location within the lung field (see Fig 7). Lung nodule detection is essential and very important step to extract Region of interest (ROI). The result of lung nodule detection process depends on accuracy of lung field segmentation and the method used for false positive reduction.

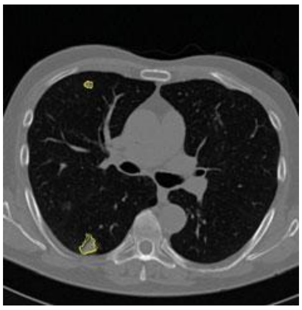

Fig 7 Sample detected nodules in a lung image [9]

Some existing nodule detection systems fail to detect the nodule patterns from the image due unavailability of the process. They depend on output of segmentation process.
However, there are some systems that determine nodule patterns and identify the location of the nodules more precisely. In this case, the nodule detection section is used to improve the output of the lung segmentation process.

Well-circumscribed nodules detection is relatively easy as they are isolated in nature. But the detection becomes more challenging if the lung nodule is placed at pleural of vascular attachment as these types generate mostly false positive results, so false positive reduction method must be used to correctly identify the pulmonary nodule.

Following section describes various proposed methods for lung nodule detection and different technique for false positive reduction.

2.4.1. Lung Nodule Detection

A pulmonary nodule is almost spherical shaped opacity measuring less than 3cm in diameter surrounded by lung parenchyma so basic characters of feature extraction are area, perimeter and eccentricity.

Different methods have been proposed by researchers for detecting the lung nodules such as Thresholding, Morphological processing, template matching, adaptive thresholding, watershed algorithm, region growing approach, wave front algorithm, grey level thresholding, rolling ball algorithm, rule based method, clustering, connected component analysis and a combination of these methods with methods of segmentation.

Different detection techniques were proposed in survey and are presented in TABLE IV. Wei Ying *et al.* proposed thresholding and multi scale morphological filtering [45]. Amal A Farag *et al.* proposed a variation level set segmentation where a signed distance function was used to represent a 2D contour followed by template matching algorithm to remove juxta pleural nodules [42]. Maria Evelina *et al.* used Channeler ant model used for segmenting candidate nodules [50]. Tan *et al.* had introduced a novel method for finding seed points based on the maxima of the Divergence of the normalized image gradient (DNG) The nodule centers are subsequently merged with the segmented nodule clusters and Finally implemented a cluster merging stage is to cluster overlapping nodules. This method achieves better estimation of location of the nodule centers and reduces the FP (False positive) rate [64].

V. Vijaya Kishore *et al.* suggested thresholding method followed by watershed algorithm and region growing method to attain more accurate segmentation of nodules [23]. Non Juxta pleural nodules and Juxta pleural nodules were segmented from a huge set of CT scans by Si Guang-lei *et al.* using morphological operations which extracted both small and large nodules [46]. Roozgard *et al.* adapted Kernel Rx algorithm to detect lung nodules. Median filters, morphological dilation and erosion filters were further used to improve the quality of segmentation of nodule [51].

Template matching technique was proposed by Hong Shao *et al.* [19], Amal Farag *et al.* [49], Mickias Assefa *et al.* [47].
Hong Shao *et al.* explained adaptive threshold technique. It was used on twice segmented lung filed to select candidate nodules [19]. Amal Farag *et al.* proposed an active appearance model (AAM) with template matching and registration to identify nodule [49]. Mickias Assefa *et al.* proposed both circular and semicircular templates to identify nodules residing inside and on the boundaries of lung region. This circular, spherical hypothesis is not enough to portray the actual geometry of nodules. Lesion's geometry can be irregular due to their attachment to the pleural surface or lung vessels [47].

Vaibhav K *et al.* detected the nodule by considering feature value as the nodule size, structure, volume and nodule spine values [26]. Brown *et al.* has proposed Euclidean Distance Transformation (EDT) method to detect lung nodule, which achieves sensitivities relatively high over 90 % with lower false positive rates. This Proposed CAD system provides comprehensive, clinically-usable lung nodule detection

[65].Gangotri Nathaney *et al.* suggested Gray level co-occurrence matrix method for feature extraction [27]. Eman Magdy *et al.* applied the Amplitude - Modulation Frequency - Modulation (AM-FM) modeling techniques to extract features from lung images that will be used further in classification. They have also used multiscale filter bank to isolate the AM-FM image components in model to perform demodulation [28]. M. Obayya *et al.* explained two sets of feature extraction techniques and evaluated their performance. These techniques used to calculate following features: (1) Geometric features (2) Radon transform. Geometric features achieved 98% accuracy [29]. Jacobs [66] used commercial Herakles CAD system, this was the first paper, which reports the performance of CAD systems on the full LIDC/IDRI database with high sensitivity of 82 %.

Ruchika *et al.* applied a series of morphological operations for edge detection. The proposed algorithm has faster execution time and average accuracy approximate of 90% [52].

TABLE IV Different review methods of lung nodule Detection process

Study	Reported	Detection method	Dataset	Remark
Wei Ying [45]	2011	Thresholding, Morphological Filtering, Boundary Extraction Morphological Filtering	20	Sensitivity 94.6%
Amal A Farag [42]	2011	Variational Level Set Segmentation, Template Matching	50	Accuracy 70%
Maria Evelina [50]	2011	3D Region Growing Method, Wavefront Algorithm, Morphological Operations	138	Sensitivity 80%
Tan [64]	2011	Divergence of the normalized image gradient (DNG)	235	Sensitivity 87.5%
V. Vijaya Kishore [23]	2012	Thresholding, Watershed Algorithm, Region Growing Segmentation	--	Extracts ROI i.e. lung region
Si Guang-lei [46]	2012	Thresholding, Morphological Processing	85	Accuracy 90.5%
Roozgard [51]	2012	Kernel Rx Algorithm	12	improve the quality using Median filters, morphological dilation and erosion filters
Hong Shao [19]	2012	Template Matching, Adaptive Threshold Technique	130	Accuracy 90.35 %, Sensitivity 89.47 %, Specificity 90.52%
Amal Farag [49]	2012	Template Matching, Registration	50	--
Mickias Assefa [47]	2013	Template Matching	165	Accuracy 81.21%
Vaibhav K [26]	2014	feature extraction method	--	To calculate feature value as the nodule size, structure, volume and nodule spine value
Brown[65]	2014	Euclidean Distance Transformation (EDT)	108	Sensitivities 90 % with lower false positive rates
Gangotri Nathaney [27]	2015	Gray Level Co-occurrence Matrix	--	for Feature Extraction
Eman Magdy [28]	2015	Amplitude-Modulation Frequency-Modulation (AM-FM)	83	to extract features from lung images
M. Obayya [29]	2015	Proposed two methods 1) Geometric Features 2) Radon transform	100	1) Accuracy 98%, Sensitivity 96 %, Specificity 100% 2) Accuracy 86 %, Sensitivity 80 %, Specificity 92%
Jacobs [66]	2015	Herakles System	888	Sensitivity 82 %
Ruchika [52]	2016	Series of morphological operations	--	accuracy 90%

2.4.2. False Positive Reduction

False positive reduction is the process of further eliminating the false positives (nodule like anatomical structure during detection of nodule). The different false positive reduction techniques are on lung segmented image. The main aim of false positive reduction method is to get maximum sensitivity or true positive rate. Not all existing system incorporates a false positives reduction section.

The False Positive Reduction review methods shown in TABLE V, Zhenghao Shi *et al.* proposed a two stage technique for the false positive reduction [53]. Mickias Assefa *et al.* extracted intensity based and multi resolution based features such as mean, energy, entropy etc. to reduce the false positive cases [46].

TABLE V Different methods of false positive reduction during lung nodule detection

Study	Reported	FP Reduction Method	Dataset	Remark
Zhenghao Shi [53]	2013	Two Stage Method	60	False Positive Reduction
Mickias Assefa[47]	2013	Multi resolution	165	False Positive Reduction

2.5. Nodule Classification

Nodule Classification is the process of classifying if the detected nodule is benign or malignant. The nodules with diameters less than 10 mm are very common and majority of them are benign. Whereas the nodules having diameter greater than 10 mm are at high risk for cancer and are classified as malignant. In a high risk population, the percentage of lung cancer with small nodules is below 10% [2]. The Benign nodule is a nodule with solid, round shape, and regular boundary and having low growth rate. The malignant nodules are persistent nonsolid ground glass opacity with diameter greater than 10 mm, solid nodule with speculated contour and high volumetric growth rate etc [2].

There is some overlapping feature between benign and malignant nodules but still characterization of the nodule is possible depending on few features such as multiple morphological features, texture features and growth rate of nodules [2]. Multiple morphological features include density, roundness, convexity, density distribution, circularity; irregularity and solidity of the nodule whereas, texture features include homogeneity, contrast etc.

Different available classification methods are Support vector machine (SVM), automated rule based method, K-nearest neighbor, feature based classifier method, artificial neural networks, K-nearest neighbor, minimum distance classifier, radial basis function network (RBF), Bayesian classifier, cascade classifier, multilayer perception, radial basis function network (RBF), Fuzzy logic etc.

Different classification techniques were proposed in literature is presented in TABLE VI. Wei Ying *et al.* proposed SVM (Support vector machines) to classify lung nodule [45]. Tan *et al.* developed a new feature-selective classifier based on ANNs and genetic algorithms (FD-NEAT) for the first time. Authors also compared the results with two commonly used classifiers like SVM classifier and a fixed-topology ANN. It shows that, the proposed method achieves better sensitivity 87.5% [64].In 2012, Bong *et al.* explained an automated rule-based classifier to classify benign or malignant. [54]. Mabrouk *et al.* suggested K-nearest neighborhood classifier to perform classification [55]. Feature based classification was suggested by Takahiro Miyajima *et al.* [21] and Amal Farag *et al.* [48]. Takahiro Miyajima *et al.* used feature based classification like statistical features; luminance features and Scale invariant feature transform (SIFT) for classification of nodules [21]. Amal Farag *et al.* proposed nine similarity measures for categorization [48]. Hong Shao *et al.* [19] and Hiram Madero Orozco *et al.* [58], Orozco *et al.* [56] explained SVM classifier in frequency domain.

In 2013, Mickias Assefa *et al.* extracted features like intensity based and multi resolution based to reduce the false positive [47]. Sheng Chen *et al.* proposed a SVM with Gaussian kernel method for lung nodule classification [59]. To enhance the accuracy of a lung nodule classification system Javed *et al.* suggested a weighted Support vector machines (SVM) classifier [57].

In 2014, Jinsa Kuruvilla *et al.* used neural networks for classification of nodule [62]. Han *et al.* compared three famous texture features such as Haralick, Gabor, and local binary patterns in the classification. They proposed 3D Haralick features and noted that the Haralick features provide better classification performance [60]. Vaibhav K *et al.* suggested the SVM (Support Vector Machine) classifiers to differentiate the non-cancerous (Benign) from cancerous (Malignant) lung nodules. It constructs a hyperplane in a high dimensional space, which can be used for classification. The hyperplane achieves the good partition [26].

In year 2015 literature, Sunanda Biradar *et al.* proposed SVM (Support Vector Machine) classifier to identify the cancerous and noncancerous nodules .The SVM polynomial has given the 96.6% accuracy and SVM quadratic function has given the 92% accuracy [25]. Gangotri Nathaney *et al.* have explained Neural network classifier for nodule classification [27]. Eman Magdy *et al.* used four different classifier are *K*-nearest neighbor (*K*NN), support vector machine (SVM), Naive Bayes, and linear classifier to correctly discriminate between normal and cancer lung images. Author further computed accuracy, sensitivity, and specificity for four different classifiers and declared that the linear classifier gives the best classification with 95% accuracy, 94% sensitivity, and 97% specificity. However found that, the *K*NN classifier is the worst classifier with only 64% accuracy, 55% sensitivity, and 72% specificity [28]. M. Obayya *et al.* proposed Artificial neural fuzzy interference system (ANFIS) classifier to classify nodules and non-nodules [29].

In year 2016, Ashis Kumar Dhara *et al.* [61] proposed SVM (Support vector machine) to distinguish nodules from benign or malignant. The suggested technique provides best classification accuracy. Author compared the proposed method with the recent classification work done by Han *et al.* [60]. P. Thamilselvan *et al.* explained EKNN (Enhanced k nearest neighbor) method for lung cancer cells classification by using MRI (Magnetic Resonance Images) images [63].

TABLE VI Different review methods of lung nodule Classification Techniques

Study	Reported	Classification Techniques	Data Set	Purpose
Wei Ying [45]	2011	Support vector machines	20	To nodule classification
Tan[64]	2011	A feature-selective classifier based on ANNs and genetic algorithms (FD-NEAT)	235	To classify nodules and non nodules
Bong [54]	2012	automated rule-based classifier	--	to differentiate the Benign from Malignant nodules
Mabrouk [55]	2012	K-Nearest Neighborhood classifier	2911	to categorize nodules and non-nodules

Takahiro Miyajima [21]	2012	Feature Based Classification	31	statistical features, luminance features and Scale Invariant Feature Transform (SIFT) features used
Amal Farag [48]	2012	Feature Based Classification	3 datasets used:ELCAP 50 sets, LIDC 1018 helical thoracic CT, LDCT 8 sets	to classify and reduce the false positive cases
Hong Shao [19]	2012	SVM based Classification	--	Classification in frequency domain
Hiram Madero Orozco [58]	2012	SVM based Classification	200	Classification in frequency domain
Mickias Assefa [47]	2013	Feature Based Classification	165	to classify nodules
Sheng Chen [59]	2013	SVM with Gaussian kernel	118	to nodule classification
Orozco *et al.* [56]	2013	Support Vector Machines	128	to classify nodules
Javed *et al.* [57]	2013	weighted Support vector machines (SVM)	600	Enhance the accuracy of a lung pulmonary nodule classification
Jinsa Kuruvilla [62]	2014	artificial neural network	155	correctly classified as cancerous nodule
Han F [60]	2014	Support vector Machine(3D texture-based)	1,012	3D Haralick provide better classification performance
Vaibhav K [26]	2014	Support Vector Machine classifier (Hyperplane)	--	to differentiate the Benign from Malignant nodules
Sunanda Biradar [25]	2015	Support Vector Machine (SVM)	1,012	to identify the cancerous and noncancerous nodules
Gangotri Nathaney [27]	2015	Neural Network Classifier	--	To classify nodules
Eman Magdy [28]	2015	four different classifiers: *K*-nearest neighbor (*K*NN), support vector machine (SVM), naive Bayes, and linear	83	to correctly discriminate between normal and cancer lung images
M. Obayya [29]	2015	Artificial Neural Fuzzy Interference System (ANFIS) classifier	100	to classify Benign from Malignant nodules
Ashis Kumar Dhara [61]	2016	Support vector Machine (classification is evaluated in terms of area under characteristic curve.)	891	Several shape-based, margin-based, and texture-based features are analyzed to improve the accuracy of classification
P. Thamilselvan [63]	2016	EKNN (Enhanced k nearest neighbor)	300 MRI Images	for lung cancer cells classification by using MRI images

ELCAP (Early Lung Cancer Action Program), Lung Image Database Consortium (LIDC), low-dose CT (LDCT)

2.6. Two public challenges for nodule detection are ANODE09, LUNA16

2.6.1. ANODE09: The ANODE09 is first study, the framework for the evaluation of CAD algorithms to compare and combine a large group of CAD systems for nodule detection with new database of 55 CT scans. The combination of six CAD algorithms is able to detect 80% of all nodules at the expense of only two false positive detections per scan and 65% of all nodules with only 0.5 false positives. The ANODE09 set contained a limited number of larger nodules, which generally have a higher suspicion of malignancy.

2.6.2. LUNA16: LUNA16 is the framework for automatic nodule detection algorithms using the largest publicly available reference database of chest 888 CT scans, the LIDC-IDRI data set. This framework having the two tracks: 1) the complete nodule detection track where a complete CAD system was developed, or 2) the false positive reduction track where a provided set of nodule candidates was classified.
Seven systems have been applied to the complete nodule detection track and five systems have been applied to the false positive reduction track. When multiple candidate detection algorithms were combined, the sensitivity substantially improved up to 98.3% which is higher than the sensitivity of any individual system. This illustrates the potential of combining multiple candidate detection algorithms to improve the sensitivity of CAD systems.

3. DISCUSSION

The use of CAD systems improves the performance of radiologists in the detection process of pulmonary nodules.

However, the system to be used regularly in the radiology department these systems must meet the following requirements: improve the performance of radiologists providing high sensitivity in the diagnosis, a low number of false positives, have high processing speed, present high level of automation, low cost (of implementation, training, support and maintenance), the ability to detect different types and shapes of nodules, and software security assurance.

Based on literature research, it was observed that many, if not all, systems described in this survey have the potential to be important in clinical practice. Various techniques have been used in the lung cancer detection methods to improve the efficiency of cancer detection. Each method has its own uniqueness, advantages and limitations.

However, several systems showed promising results; for example, with regard to the parameters of sensitivity and number of FP likeTan et al. [64] validated his system with 235 CT scans and obtained a sensitivity of 87.5% with 4 FP per case. Jacobs et al. used commercial Herakles CAD system, this was the first paper, which reports the performance of CAD systems on the full LIDC/IDRI database with high sensitivity of 82 % [66].

Brown et al. Proposed CAD system which provides comprehensive, clinically-usable lung nodule detection with high sensitivity over 90 % and lower false positive rates [65]. Wei Ying et al. had achieved Sensitivity 94.6% [45].

Non Juxta pleural nodules and Juxta pleural nodules were segmented from a huge set of CT scans by Si Guang-lei et al. using morphological operations which extracted both small and large nodules with Accuracy 90.5% [46].

4. CONCLUSION

Developing an efficient CAD system for detection of lung nodules is necessary for early detection which increases the survival rate of lung cancer patients. This paper presented review of several work completed on automated lung nodules detection and analysis system. The performances of several algorithms in preprocessing, segmentation, detection and classification have been discussed in chronological order.

It is seen from survey that there is need to use 3D CT images processing. However it is inevitably not simple task. There are major challenges in terms of non availability of reference standards as in case of 2D images.

Improving performance of algorithm to detect the lung nodules of different geometrical shapes and sizes needs further research. There are difficulties observed in detecting nodule with vascular and pleural attachment. Many of the techniques presented have reported more number of false positives. Reducing them further is one of the open challenges. Computer analysis in tumor staging has not been explored much.

There is huge amount of scope for improvement in existing algorithm. Practically the algorithm needs to be fast, easy to use, reliable (easy adjustments in case the algorithm fails) and correctable (correct results in the vast amount of cases).

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REFERENCES

[1] Cancer Facts and Figure 2016 by American Cancer Society. Available from: http://www.cancer.org

[2] Ashis Kumar Dhara, Sudipta Mukhopadhyay and Niranjan Khandelwal, “Computer-aided Detection and Analysis of Pulmonary Nodule from CT Images: A Survey” IETE Technical Review, Volume 2, No 4, pp. 265-275, July -August-2012.

[3] Jaspinder Kaur, Nidhi Garg, Daljeet Kaur, “A survey of Lung Cancer Detection Techniques on CT scan Images” International Journal of Scientific & Engineering Research, Volume 5, Issue 6, pp. 377-380, June-2014.

[4] Jisha Krishnan, RejimolRobinson “A SURVEY ON LUNG SEGMENTATION TECHNIQUES”, International Journal of Computer Science & Engineering Technology (IJCSET), Volume 4 No., pp. 612-621, 05 May 2013.

[5] H. Mahersia, M. Zaroug, L. Gabralla “Lung Cancer Detection on CT Scan Images: A Review on the Analysis Techniques” (IJARAI) International Journal of Advanced Research in Artificial Intelligence, Volume 4, No.4, pp. 38-45, 2015.

[6] L. Salvolini, E.B. Secchi, L. Costarelli, and M.D. Nicola, “Clinical applications of 2D and 3D CT imaging of the airways - a review,” European Journal of Radiology, Volume 34, pp. 9-25, Dec. 1999.

[7] Sluimer, A. Schilham, M. Prokop, and B. V. Ginneken, “Computer analysis of Com- puted Tomography scans of the lung: A survey”, IEEE Trans. on Medical Imaging, Volume 25, pp 385-405, Apr. 2006.

[8] Q. Li, “Recent progress in computer-aided diagnosis of lung nodules on thin-section CT,” Computerizez Medical Imaging and Graphics, Volume 31, pp. 248-57, Feb. 2007.

[9] S.L. Lee, A.Z. Kouzani, and E.J. Huu, “Automated detection of lung nodules in CT images: A review,” Machine Vission and Application, Springer, Volume 138, no. 10, pp. 1-13, May 2010.

[10] Early Lung Cancer Action Program (ELCAP), available from: http://www.via.cornell.edu/lungdb.html.[Last cited on 2016].

[11] Lung Imaging Database Consortium (LIDC). Available from: https://imaging.nci.nih.gov/ncia/login.jsf.[Last cited on 2016].

[12] Medical image database, MedPix, available from: http://rad.usuhs.edu/medpixlindex.html. [Last cited on 2016].

[13] Korfiatis, P., Kalogeropoulou, C., Costaridou, and L.: “Computer aided detection of lung nodules in multislice computed tomography”. In: Proceedings of the International Special Topic Conference on Information Technology in Biomedicine (IEEE-ITAB 2006), p. 4. Ioannina, Epirus, Greece , 2006.

[14] Bhavanishankar .K and Dr. M.V.Sudhamani “Techniques for detection of solitary pulmonary nodules in human lung and their classifications -a survey” International Journal on Cybernetics & Informatics (IJCI) Volume 4, No. 1, pp.27-40, February 2015.

[15] S. Ashwin, S.-A. Kumar, J. Ramesh and K. Gunavathi, “Efficient and Reliable Lung Nodule Detection using a Neural Network Based Computer Aided Diagnosis System”, In Proceeding of the International Conference on Emerging Trends in Electrical Engineering and Energy Management (ICETEEEM'2012), pp. 135-142, Chennai, Dec. 2012.

[16] G. Vijaya and A. Suhasini, “An Adaptive Pre-processing of Lung CT Images with Various Filters for Better Enhancement”,

Academic Journal of Cancer Research, Volume 7, No. 3, pp. 179-184, 2014.
[17] T. Gao, X. Sun, Y. Wang and S. Nie, “A Pulmonary Nodules Detection Method Using 3D Template Matching, Foundations of Intelligent Systems”, AISC, Volume 122, pp. 625-633, 2012.
[18] Tariq, M.-U. Akram and M.-Y. Javed, “Lung Nodule Detection in CT Images using Neuro Fuzzy Classiffier”, in Proceeding of the Fourth International IEEE Workshop on Computational Intelligence in Medical Imaging (CIMI), pp. 49-53, 2013.
[19] H. Shao, L. Cao and Y. Liu, “A Detection Approach for Solitary Pulmonary Nodules Based on CT Images”, in Proceeding of the 2nd International Conference on Computer Science and Network Technology, pp. 1253-1257, 2012.
[20] D. Sharma and G. Jindal, “Identifying Lung Cancer Using Image Processing Techniques”, in Proceeding of the International Conference on Computational Techniques and Artificial Intelligence (ICCTAI'2011), pp. 115-120, 2011.
[21] Takahiro Miyajima et al., “Classification of Lung Nodules Temporal Subtraction Image Based on Statistical Features and Improvement of Segmentation Accuracy”, proceeding 12th IEEE International Conference on Control, Automation and Systems, Jeju Island, Korea, pp.1814-1817, 2012.
[22] S.Sivakumar et al., “Lung Nodule Detection Using Fuzzy Clustering and Support Vector Machines”, International Journal of Engineering and Technology (IJET), volume 5 Issue 1, pp. 179-185, 2013.
[23] V. Vijaya Kishore, R.V.S. Satyanarayana, “Performance Evaluation of Edge Detectors Morphology Based ROI Segmentation and Nodule Detection from DICOM Lung Images in the Noisy Environment”, proceeding 3rd IEEE International Advanced Computing Conference, pp. 1131-1137, 2012.
[24] Wook-Jin Choi et al., “Automated Pulmonary Nodule Detection System in Computed Tomography Images: A Hierarchical Block Classification Approach”, Entropy 2013, Volume 5, pp. 508-523, 2013.
[25] Sunanda Biradar, Kavya Agalatakatti “Lung Cancer Identification Using CT Images” International Journal Of Engineering And Computer Science ISSN: 2319-7242 Volume 4 Issue 7, Page No. 13022-13025, July 2015.
[26] Mr. Vaibhav K. Likhitkar, Prof. Ujwalla Gawande, Mr. Kamal O. Hajari “Automated Detection of Cancerous Lung Nodule from the Computed Tomography Images” IOSR Journal of Computer Engineering (IOSR-JCE), Volume 16, Issue 1, Version VIII, PP 05-11, Feb. 2014.
[27] Ms.Gangotri Nathaney, Prof.Kanak Kalyani, “Lung Cancer Detection System on Thoracic CT Images Based on ROI Processing”, International Journal of Advanced Research in Computer and Communication Engineering, Volume 4, Issue 4, pp. 173-176, April 2015.
[28] Eman Magdy, Nourhan Zayed, andMahmoud Fakhr , “Automatic Classification of Normal and Cancer Lung CT Images Using Multiscale AM-FM Features”, Hindawi Publishing Corporation International Journal of Biomedical Imaging Volume 2015, Article ID 230830, pp. 1-7, Sep. 2015, http://dx.doi.org/10.1155/2015/230830
[29] M. Obayya , Mohamed Ghandour , “Lung Cancer Recognition using Radon Transform and Adaptive Neuro Fuzzy Inference System”, International Journal of Computer Applications, Volume 124, No.2, pp. 25-30, August 2015.
[30] Panayiotis D. Korfiatis, Cristina Kalogeropoulou, Anna N. Karahaliou, Alexandra D. Kazantzi, and Lena I. Costaridou, “Vessel Tree Segmentation in Presence of Interstitial Lung Disease in MDCT”, IEEE Transactions On Information Technology In Biomedicine, Volume 15, No. 2, pp. 214-220, March 2011.
[31] Dominik Schuldhaus, Martin Spiegel, Thomas Redel,Maria Polyanskaya, Tobias Struffert, Joachim Hornegger, Arnd Doerfler, “ 2D Vessel Segmentation Using Local Adaptive Contrast Enhancement”, Bildverarbeitung für die Medizin, Informatik aktuell, Springer, DOI 10.1007/978-3-642-19,pp.109-113 , 2011.
[32] P. Hua, Q. Song, M. Sonka, E. A. Hoffman, and J. M. Reinhardt, “Segmentation of pathological and diseased lung tissue in CT images using a graph-search algorithm”, In Proceedings of the International Symposium on Biomedical Imaging (ISBI ’11), pp. 2072–2075, 2011.
[33] N. Birkbeck, M. Sofka, T. Kohlberger, J. Zhang, J. Wetzl, J. Kaftan and S. Kevin Zhou, “Robust Segmentation of Challenging Lungs in CT Using Multi-stage Learning and Level Set Optimization”, Computational Intelligence in Biomedical Imaging, pp. 185-208, 2014.
[34] K.-Z. Faizal and V. Kavitha, “An Effective Segmentation Approach for Lung CT Images Using Histogram Thresholding with EMD Refinement”, Proceedings of International Conference on Internet Computing and Information Communications, Advances in Intelligent Systems and Computing, Volume 216, pp. 483-489, 2014.
[35] P. Aggarwal, R. Vig and H.-K. Sardana, “Semantic and Content-Based Medical Image Retrieval for Lung Cancer Diagnosis with the Inclusion of Expert Knowledge and Proven Pathology”, In proceeding of the IEEE second international conference on Image Information Processing ICIIP'2013, pp. 346-351, 2013.
[36] K. Devaki, V. MuraliBhaskaran and M. Mohan, “Segment Segmentation in Lung CT Images- Preliminary Results”, Special Issue of International Journal on Advanced Computer Theory and Engineering (IJACTE), Volume 2, No. 1, pp. 84-89, 2013.
[37] Y. Guo, C. Zhou, H.-P. Chan, A. Chughtai, J. Wei, L.-M. Hadjiiski and E.-A. Kazerooni, “Automated iterative neutrosophic lung segmentation for image analysis in thoracic computed tomography”, Med. Phys., Volume 40, No. 8, pp. 081912/1-081912/11, 2013.
[38] D. Sharma and G. Jindal, “Identifying Lung Cancer Using Image Processing Techniques”, In Proceeding of the International Conference on Computational Techniques and Artificial Intelligence (ICCTAI'2011), pp. 115-120, 2011.
[39] T. Kubota, A.-K. Jerebko, M. Dewan, M. Salganico and A. Krishnan, “Segmentation of pulmonary nodules of various densities with morphological approaches and convexity models”, Medical Image Analysis, Volume 15, No. 1, pp. 133-154, 2011.
[40] J. Gong, T. Gao, R.-R. Bu, X.-F. Wang and S.-D. Nie, “An Automatic Pulmonary Nodules Detection Method Using 3D Adaptive Template Matching”, Communications in Computer and Information Science, Volume 461, pp. 39 - 49, 2014.
[41] A. El-Baz, G. Gimelfarb, R. Falk and M. Abo El-Ghar, “3D MGRF-based appearance modelling for robust segmentation of pulmonary nodules in 3D LDCT chest images”, in Lung Imaging and Computer Aided Diagnosis, chapter 3, pp. 51-63, Taylor and Francis edition, 2011.

[42] A. Farag, H. Abdelmunim, J. Graham, "Variational approach for segmentation of lung nodules", in Proceeding of the IEEE International Conference on Image Processing (ICIP 11), pp. 2157-2160, 2011.
[43] Dhara AK, Mukhopadhyay S, Das Gupta R, Garg M, Khandelwal N: "A segmentation framework of pulmonary nodules in lung CT images". J Digit Imaging, doi: 10.1007/s10278-015-9812-6, pp.86-103, 2015.
[44] Jinsa Kuruvilla, Dr.K.Gunavathi, "Detection of Lung Cancer using Morphological Operations", International Journal of Scientific & Engineering Research, Volume 4, Issue 8, 1636-1639, August-2013.
[45] Wei Ying et al., "Autonomous Detection of Solitary Pulmonary Nodules on CT Images for Computer- Aided Diagnosis", proceeding IEEE Chinese Control and Decision Conference, pp. 4054-4059, 2011.
[46] Si Guang-lei et al., "A Novel Method for Lung Nodule Segmentation Based on CT Images", proceeding 2nd IEEE International Conference on Applied Robotics for the Power Industry, pp. 826-830, 2012.
[47] Mickias Assefa et al., "Lung nodule Detection Using Multi Resolution Analysis", proceeding IEEE, International Conference on Complex Medical Engineering, ICME, pp. 457-461, 2013.
[48] Amal Farag et al., "Small – Size Lung Nodule Modeling and Detection with Clinical Evaluation", proceeding IEEE Cairo International Biomedical Engineering Conference, Cairo, Egypt, pp. 44-47, 2012.
[49] Amal Farag er.al, "An AAM Based Detection Approach of Lung Nodules from LDCT scans", IEEE, pp. 1040-1043, 2012.
[50] Maria Evelina et al., "Algorithms for automatic detection of lung nodules in CT scans", IEEE International Workshop on Medical Measurement and Applications, MEMEA, p.5, 2011.
[51] A Roozgard et al., "Malignant Nodule Detection on Lung CT Scan Images with Kernel RX algorithm", Proceeding IEEE-EMBS International Conference on Biomedical and Health Informatics, pp. 499-502, 2012.
[52] Ruchika, Archna Sharma, "Cad Implementation for Detection of Lung Cancerous Nodules", International Journal of Advanced Research in Computer Science and Software Engineering, Volume 6, Issue 4, pp.804-806, April 2016
[53] Zhenghao Shi et al., "A Computer Aided Pulmonary Nodule Detection System Using Multiple Massive Training SVMs", Appl. Math. Inf. Sci. Volume 7, No. 3, pp-1165-1172, 2013.
[54] C.-W. Bong, H.-Y. Lam and H. Kamarulzaman, "A Novel Image Segmentation Technique for Lung Computed Tomography Images", Communications in Computer and Information Science, Volume 295, pp. 103-112, 2012.
[55] M. Mabrouk, A. Karrar and A. Sharawy, "Computer Aided Detection of Large Lung Nodules using Chest Computer Tomography Images", International Journal of Applied Information Systems (IJAIS), Volume 3, No. 9, pp. 12-18, 2012.
[56] H.-M. Orozco and O.-O. Villegas, "Lung Nodule Classification in CT Thorax Images using Support Vector Machines", In proceeding of the 12th Mexican International Conference on Artificial Intelligence, pp. 277-283, 2013.
[57] U. Javed, M.-M. Riaz, T.-A. Cheema and H.-F. Zafar, "Detection of Lung Tumor in CE CT Images by using Weighted Support Vector Machines", In. proceeding of the 10th International Bhurban Conference on Applied Sciences and Technology (IBCAST), pp. 113-116, 2013.
[58] Hiram Madero Orozco et al., "Lung Nodule Classification in Frequency Domain Using Support Vector Machines", proceeding IEEE 11th International Conference on Information Sciences, Signal Processing and their Applications: Main Tracks, pp. 870-875, 2012.
[59] Sheng Chen et al., "Computerized Detection of Lung Nodules by Means of Virtual Dual-Energy Radiography", IEEE Transactions on Biomedical Engineering, Volume 60, no. 2, pp.369-378,2013.
[60] Han F, Wang H, Zhang G, Han H, Song B, Li L, MooreW, Lu H, Zhao H, Liang Z: "Texture feature analysis for computer-aided diagnosis on pulmonary nodules". J Digit Imaging 28(1):99–115, 2014.
[61] Ashis Kumar Dhara, Sudipta Mukhopadhyay, Anirvan Dutta, Mandeep Garg, Niranjan Khandelwal, "A Combination of Shape and Texture Features for Classification of Pulmonary Nodules in Lung CT Images", J Digit Imaging, DOI : 10.1007/s10278-015-9857-6, p.10, 2015.
[62] Jinsa Kuruvilla, K. Gunavathi, "Lung cancer classification using neural networksfor CT images ", Elsevier-Computer methods and programs in biomedicine 113, pp. 202-209, 2014
[63] P. Thamilselvan , Dr. J. G. R. Sathiaseelan ,"An enhanced k nearest neighbor method to detecting and classifying MRI lung cancer images for large amount data", International Journal of Applied Engineering Research, 11(6), pp. 4223-4229, 2016.
[64] Maxine Tan, Rudi Deklerck and Bart Jansen, Michel Bister and Jan Cornelis ,"A novel computer-aided lung nodule detection system for CT images", Medical Physics, Vol. 38, No. 10, October 2011.
[65] Matthew S. Brown ,Pechin Lo & Jonathan G. Goldin ,Eran Barnoy, Grace Hyun J. Kim, Michael F. McNitt-Gray & Denise R. Aberle," Toward clinically usable CAD for lung cancer screening with computed tomography", European Society of Radiology , 24,pp.-2719–27282014.
[66] Colin Jacobs, Eva M. van Rikxoort , Keelin Murphy, Mathias Prokop, Cornelia M. Schaefer-Prokop, Bram van Ginneken, "Computer-aided detection of pulmonary nodules: a comparative study using the public LIDC/IDRI database", Eur Radiol, September 2015.
[67] Bram van Ginneken, Samuel G. Armato III, Bartjan de Hoop, Saskia van Amelsvoort-van de Vorst, Thomas Duindam, Meindert Niemeijer, Keelin Murphy, Arnold Schilham, Alessandra Retico, Maria Evelina Fantacci, Niccolò Camarlinghi, Francesco Bagagli, Ilaria Gori, Takeshi Hara, Hiroshi Fujita, Gianfranco Gargano, Roberto Bellotti, Sabina Tangaro, Lourdes Bolaños, Francesco De Carlo, Piergiorgio Cerello, Sorin Cristian Cheran, Ernesto Lopez Torres, Mathias Prokop , "Comparing and combining algorithms for computer-aided detection of pulmonary nodules in computed tomography scans: The ANODE09 study", Medical Image Analysis, Volume 14, pp-707–722, 2010.
[68] Arnaud Arindra Adiyoso Setio, Alberto Traversog, Thomas de Bel, Moira S.N. Berens, Cas van den Bogaard, Piergiorgio Cerell, Hao Chen, Qi Dou, Maria Evelina Fantacci, Bram Geurts, Robbert van der Gugten, Pheng Ann Heng, Bart Jansen, Michael M.J. de Kaste, Valentin Kotov,
[69] Jack Yu-Hung Lin, Jeroen T.M.C. Manders, Alexander S´o˜nora-Mengana, Juan Carlos Garc´ıa-Naranjo, Mathias Prokopa,

Marco Salettah, Cornelia M Schaefer-Prokopa,c, Ernst T. Scholtena, Luuk Scholteno, Miranda M. Snoeren, Ernesto Lopez Torres, Jef Vandemeulebroucke, Nicole Walasek, Guido C.A. Zuidhof, Bram van Ginneken, Colin Jacobs , "Validation, comparison, and combination of algorithms for automatic detection of pulmonary nodules in computed tomography images: the LUNA16 challenge", Donate to arXiv, arXiv:1612.08012v2 [cs.CV], last revised 5 Jan 2017.

[70] A M Sapkal, V K Bairagi, "Telemedicine In India: Challenges and Role of Image Compression", American Scientific Publishers: Journal of Medical Imaging And Health Informatics. Vol. 1, No 4, Dec 2011, pp300–306.

[71] V K Bairagi, A M Sapkal, "Automated Region Based Hybrid Compression for DICOM MRI Images for Telemedicine Applications", The IET Science, Measurement & Technology, Vol 6, No 4, July 2012, pp. 247 – 253

[72] P. Bhor, R. Gargote, R. Vhorkate, R.U.Yawle, V. K. Bairagi, "A No Reference Image Blur Detection Using Cumulative probability Blur Detection(CPBD) Metric", International Journal of Innovative Science and Modern Engineering, Vol 1, No 5, April 2013, pp 76-80.

[73] Shrikhande Rohini,Vinayak Bairagi : Lossless Medical Image Security, International Journal Of Applied Engineering Research, Dindigul Volume 1, No 3, (2010) ISSN 09764259.

[74] V. K. Bairagi, A. M. Sapkal & M. S. Gaikwad, "The Role of Transforms in Image Compression", Journal of The Institution of Engineers (India): Series B, Vol. 94, No. 2, June 2013, pp. 135-140.

[75] T. G. Shirsat and V. K. Bairagi, "Lossless Medical Image Compression by Integer Wavelet and Predictive Coding", Hindawi: ISRN Biomedical Engineering, Volume 2013, june 2013, pp. 1-6.

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