EMERGING TRENDS IN LUNG CANCER DETECTION SCHEME- A REVIEW

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ABSTRACT—Recent technology in Medical imaging techniques has made the physicians to see the interior portions/parts of the human body for easy diagnosis of a particular disease. Lung cancer is proving to be a catastrophic threat to the human beings and it is main cause of deaths in both men and women among other cancer related casualties. Examination of lung cancer is done by using the various medical imaging techniques such as X-rays, Computed Tomography, Magnetic Resonance Imaging, Positron Emission Tomography etc. Among the above techniques, Computed tomography is widely used technique because it has been identified as an accurate and robust imaging technique in the diagnosis of the lung cancer. A good amount of research work has been carried out in the past towards CAD system for lung cancer detection. This paper presents a detailed literature survey on various image processing techniques that have been used in pre-processing, nodule segmentation and classification. Now-a-days nanotechnology displays huge advantages for cancer diagnosis .Finally, we can conclude by focusing one of the best method and simple unsupervised nano technique that may have high level accuracy.

Keywords – Computer-Aided diagnosis (CAD), Nano technique, Image segmentation, CT Image, Medical Image Processing, Region of Interest(ROI),Solitary Coin Lesion (SCL),Nano imaging.

I. INTRODUCTION

Nowadays, lung tumour has become one of the main causes for increasing mortality among children and adults. In addition, lung cancer is an ailment of abnormal cells increasing in large number and developing into a tumour [1]. Among the several kinds of cancers that are present in the human body the most dreaded forms of cancer with a very high death rate is lung cancer. The major issues with this organ are the difficulty in diagnosis and the time taken to identify it, thus reducing the living rate after diagnosis. In the current clinical platform medical imaging is becoming a very important aspect for numerous applications from diagnosis and treatment planning. At present, the diagnosis of cancer and disease patient is not done without the use of medical imaging modalities [2]. In recent medical field has various medical image modality such as MRI ,Ultrasound, CT, SPECT, PET, X-ray etc., play an important role in process of disease diagnosing and treatment planning and have become major evidence to ensure disease. Lung cancer affects both men and women, compare between young and old age person above 50 years person greatly affected by lung cancer Fig 1 Shows Pie-chart of age distribution for lung cancer.

![Figure1: Age distribution of lung cancer](image-url)
Computed Tomography (CT) or Computed Axial Tomography (CAT) scan imaging has useful isotropic acquisition technique for assisting in clinical diagnoses, due to its entire field of view high resolution view and ability to provide huge human soft tissue’s information. Fig-2; represents bar-chart for 5 years survival rate of lung cancer.[3] The performance of a CAD system depends on imaging systems, process of segmentation, and process of feature extraction, process of detection sensitivity.

![Bar Chart]

**Figure 2: Survival rates of Lung cancer**

**II. OVERALL REVIEW TECHNIQUES**

The purposes of this study an automated detection and segmentation techniques for the extraction of lung mass region and separation of tumour on the CT image accurately. This CT image helps to overcome the time taking process of manual segmentation of large datasets.

1. **DATASETS**

LDCT (Low Dose Computed Tomography) scan is highly effective modality of medical image to spot tiny lung nodules [4]. LIDC database image consist slice of CT scan images. By interacting with biological molecules at nano scale, nanotechnology broadens the field of research and application. In nano CT imaging is another area where Nano imaging tools and measure tools are being developed for in nano CT imaging.

2. **PREPROCESSING**

Random noise is the major source of noise present in the CT image however Gaussian noise is also present. They are further enhanced by pre-processing the images. For this purpose at first step, noise content is removed to improve the image quality with median filter.
The purpose of using median filtering is to remove the noise that has degraded the image. It is a statistical approach that uses nonlinear operation to reduce “salt and pepper” noise. The remarkable use of this filter is that it reduces noise by simultaneously preserving edges. The most challenging and critical task in a CAD system is segmenting the lung region since it reduces the search space for detecting the nodules. Lung segmentation is a challenging task. Pulmonary organs such as arteries, veins, bronchi and bronchioles have similar intensity values.

3. SEGMENTATION

Various types of Lung segmentation techniques: thresholding, deformable boundaries, shape models and edges based methods.

3.1 THRESHOLDING

Based on the fact that healthy lung tissues form darker region compared to other organs like heart and liver, thresholding technique can be used to separate lung tissues from other parts. Selecting the optimum threshold value is the crucial step in thresholding based methods since the intensity values are almost similar for tissues, vessels and lung lobes. Hu et al [5] proposed an iterative thresholding algorithm for lung segmentation followed by opening and closing operations using morphological operations for refining the segmentation output. Yim et al [6] used region growing method with connected component analysis for extracting lung fields. Pu et al [7] used an initial threshold for segmenting the lung region and for improving the segmentation process a border marching algorithm is used. Gao et el [8] used a threshold based method for separating the pulmonary vessels, lung airways, left and right lungs separately. Jibi et al [9] used multiple levels of thresholding to segment the lung from other parts of the CT image. In their studies they included irregular lung walls. Their work well suited for CT images with solitary nodules. The major drawback of this thresholding method is that the accuracy depends on the quality of the image which is determined by the acquisition method and scanner type. Also the densities of the different parts are similar and hard to differentiate.
3.2 DEFORMABLE BOUNDARIES

The next class of lung segmentation method includes the use of deformable boundary models including snakes, active contours and level sets. Deformable boundary models starts from one initial point and follows the shape based on internal or external assisting factors to fix the shape to any of the objects. Itai et al [19] used the deformable models to fit the lung boundaries. Silveria et al. [20] proposed the Level Set active contour model the major drawback of this method is that the initial point selection is highly sensitive and failure to adapt the boundaries because of the inhomogeneities in the lung region.

3.3 SHAPE-BASED MODELS FOR IMAGE SEGMENTATION

To improve the accuracy of segmentation, pre-information about the shape of the lungs is stored in the CAD system. Annangi et al [10] used this shape based deformable model with the prior information of shape of the lung for segmenting the lungs. Shi et al. [11] proposed a method that uses the prior knowledge of the shape of the lungs and Principal Component analysis for extracting the prime feature points. Sun et al. [12] suggested a lung segmentation process in which Active Shape Models are first used to extract rough lung borders later global optimal surface finding method is used for refining the lung segmentation. Graph based shape models to segment the lung fields [13]. Sofka et al [14] developed an automatic detection CAD system that used graph based shape for anatomical landmarks and refined through an iterative surface deformation approach. Hua [15] proposed a graph based search algorithm. The image is treated as weighted directed graph.

Table 1: The segmentation methods that use shape based deformable models

<table>
<thead>
<tr>
<th>S.NO</th>
<th>Study</th>
<th>Number of sample images</th>
<th>Method</th>
<th>Performance Results</th>
</tr>
</thead>
<tbody>
<tr>
<td>1.</td>
<td>Annangi et al.,[10]</td>
<td>1130 image</td>
<td>Shape-based deformable model</td>
<td>DSC =0.88</td>
</tr>
<tr>
<td>2.</td>
<td>Shi et al.,[11]</td>
<td>247 image</td>
<td>Shape-based model and PCA</td>
<td>OM=0.92 AD=1.78 pixel</td>
</tr>
<tr>
<td>3.</td>
<td>Sun et al.,[12]</td>
<td>30 scans</td>
<td>Active Shape Models and Optimal Surface finding methods</td>
<td>DSC=0.975</td>
</tr>
<tr>
<td>5.</td>
<td>Sofka et al.,[14]</td>
<td>260 scans</td>
<td>Graph-based shape with iterative surface deformation</td>
<td>SCD=1.95</td>
</tr>
<tr>
<td>6.</td>
<td>Hua et al.,[15]</td>
<td>15 scans</td>
<td>Graph-Search</td>
<td>Sensitivity=0.986 Specificity=0.995</td>
</tr>
<tr>
<td>7.</td>
<td>Kockelkorn et al.,[16]</td>
<td>22 scans</td>
<td>Prior training, Statistical Classifier using UI</td>
<td>OM=0.96 AD=1.68mm</td>
</tr>
<tr>
<td>8.</td>
<td>El-Baz et al.,[17 &amp; 18]</td>
<td>10 image sets</td>
<td>Statistical MGRF model</td>
<td>Accuracy=0.968</td>
</tr>
</tbody>
</table>

The algorithm operates on a cost function which incorporates intensity, gradient and boundary smoothness that minimizes the cost to segment the lung region. [16] Introduced a user interface framework for lung segmentation which corrects the results obtained from K-nearest neighborhood approach. [17, 18] proposed a method in which the initial lung segmentation is done using Bayesian classification and the
refinement is through Markov Gibbs Random Field (MGRF) method. The major limitation with this shape based approach is that the prior shape models of the organs should be registered accurately.

### 3.4 REGION GROWING

This method uses one pixel as a seed point and identifies the connected component region where the pixels are iteratively added to the seeded pixel. Diciotti et al. [21] proposed a hybrid approach of combining region growing with geodesic distance as fusion segregation criteria. This method applies to all types of nodules. Kubota et al. [22, 23] used Euclidean distance map along with region growing method to handle juxta pleural nodules. The overall maximum success rate is 86.3%, and the volumetric RMS error varies from 1.0 – 6.6%.

### 3.5 DEFORMABLE MODEL

The next category of segmentation method is based on the repeated progression of the outline curve that forms the edge of the expected object. This class of segmentation is called Deformable model segmentation. [24] and [25] used MRF and bimodal LCDG for prior information and current shape for segmentation. Yoo et al. [26] adopted multiphase level set framework for segmenting partly solid nodules. The mean segmentation error is 0.96% but the median percentage volume error is as high as 40%.

### 3.6 SPHERICAL/ELLIPSOIDAL MODEL FITTING

This is the next method under interest. A comparison is done between the manifestation of the CT nodules and the standard Gaussian intensity model. Okato [27,28] used a Robust model for fitting anisotropic Gaussian model and Mean Shift algorithm for fitting at each scale. In Diciotti et al. [29] the nodules are segmented using multiscale LoG filtering. The maximum success rate achieved in this method is only 89.6%.

### 3.7 PROBABILISTIC CLASSIFICATION

This is next familiar method which uses probability distribution for detecting a pixel as nodules or not. Likelihoods and prior distributions for each class are first estimated from data. At that point in light of that a conclusion is made for that pixel using MAP, maximum likelihood (ML), and likelihood ratio test (LRT). [30, 31] proposed a MAP approach for both offline and online training using Markov Random Field and Gaussian Mixture Model. Okato et al. [32] used Likelihood Ratio Test for estimating foreground and background probabilities. In Tao et al. [33] approach likelihoods are derived using GMM and segmentation is done using prior shape. In Zhou et al. [34, 35], Kernel Density Estimators are used for estimating likelihood distributions and Bhattacharya distance is used for neighborhood estimation.

### Table 2. Review of Lung Segmentation Methods on CT images

<table>
<thead>
<tr>
<th>Study</th>
<th>Method</th>
<th>Dataset</th>
<th>Performance</th>
</tr>
</thead>
<tbody>
<tr>
<td>Hu et al. [41]</td>
<td>Iterative threshold, Morphological operations</td>
<td>24 Datasets from 8 subjects</td>
<td>Root mean square difference=0.54mm</td>
</tr>
<tr>
<td>Mendonca et al. [45]</td>
<td>Spatial Edge Detector</td>
<td>47 image radiographs</td>
<td>Sensitivity=92.25% Positive predictive value=96.8</td>
</tr>
<tr>
<td>Yim et al. [42]</td>
<td>Region Growing &amp; Connected Component labeling</td>
<td>10 cases</td>
<td>Root mean square difference=1.2 pixel</td>
</tr>
<tr>
<td>Gao et al. [43]</td>
<td>Thresholding</td>
<td>8 cases</td>
<td>Dice Similarity Coefficient=99.46%</td>
</tr>
<tr>
<td>Hua et al. [44]</td>
<td>Graph-search</td>
<td>15 cases</td>
<td>Hausdorff Distance=13.3pixel</td>
</tr>
<tr>
<td>Study</td>
<td>Method</td>
<td>Dataset</td>
<td>Performance</td>
</tr>
<tr>
<td>---------------</td>
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</tr>
<tr>
<td>Filho et al., [49]</td>
<td>SVM with RBF</td>
<td>140 exams from LIDC-IDRI</td>
<td>Sensitivity=98.6% Specificity=99.5%</td>
</tr>
<tr>
<td>Cascio et al., [47]</td>
<td>Double Threshold Cut &amp; Neural Network</td>
<td>LIDC 84 scans and 148 Nodules</td>
<td>Sensitivity=97.66% FPs/case=6.1%</td>
</tr>
<tr>
<td>Keshani et al., [46]</td>
<td>SVM</td>
<td>63 scans including 8 clinical sets, 5 datasets from ANODE 50 sets by LIDC</td>
<td>Detection Rate=89% FP/case=7.3</td>
</tr>
<tr>
<td>Messay et al., [48]</td>
<td>Fisher Linear Discriminant Classifier</td>
<td>LIDC Database Consisting of 84 CT scans</td>
<td>Sensitivity=82.66% FPs per scan/case=3</td>
</tr>
<tr>
<td>Tan et al., [57]</td>
<td>Phased Searching with NEAT</td>
<td>LIDC 360 CT scans</td>
<td>Detection Sensitivity=83% FP/case=4</td>
</tr>
<tr>
<td>Choi et al., [53]</td>
<td>Genetic Programming based Classifier</td>
<td>Private Database containing 165 CT scans with 192 nodules</td>
<td>Sensitivity=94.1% FP rate/scan=5.45</td>
</tr>
<tr>
<td>Lin et al., [58]</td>
<td>SVM</td>
<td>Private Database 107 CT scans including 48 benign &amp; 59 malignant</td>
<td>Accuracy=88.82% Sensitivity=93.92% Specificity=82.9% Mean Square Error=0.998</td>
</tr>
<tr>
<td>Wang et al., [59]</td>
<td>SVM based on 3D matrix patterns</td>
<td>Private database contains 196 scans that consist of 8428 sections (108 nodules)</td>
<td>Accuracy=98.2% FPs/scan=9.1</td>
</tr>
<tr>
<td>Kuruvilla et al., [52]</td>
<td>Feed Forward Neural Network</td>
<td>LIDC CT scans of 155 patients containing 110 nodules.</td>
<td>Accuracy=93.3% Specificity=100% Sensitivity=91.4% Mean Square Error=0.998</td>
</tr>
<tr>
<td>Chen et al., [56]</td>
<td>ANNs and Multivariable logistic regression</td>
<td>Private CT scans Database of 200 patients</td>
<td>Using ANN: Accuracy=90% Area under ROC Curve=0.955</td>
</tr>
<tr>
<td>Netto et al., [55]</td>
<td>Ensemble of SVM, Nearest Mean Classifier (NMC) &amp; Linear Classifier based on Normal Density (LDC)</td>
<td>LIDC Database containing 58 scans</td>
<td>Accuracy =80%</td>
</tr>
<tr>
<td>El-BAz et al., [54]</td>
<td>K-Nearest Classifier</td>
<td>LDCT Database</td>
<td>Accuracy=93.7% Area Under ROC Curve=0.9782</td>
</tr>
<tr>
<td>Wu et al., [51]</td>
<td>BP Artificial Neural Network</td>
<td>1573 ROIs from 202 cases</td>
<td>Accuracy=91%</td>
</tr>
</tbody>
</table>


| Wook et al.,[50] | SVM | LIDC Test Data:58 Scans | Sensitivity=95.28%  
|----------------|-----|-------------------------|---------------------|
|                |     |                         | False Positives per scan =2.27  
|                |     |                         | Accuracy=97.61%  

3.8 DISCRIMINATIVE CLASSIFICATION

Discriminative Classification (DC) is another segmentation method similar to Probabilistic Classification except that the classification is done using generic supervised machine learning and not probabilistic distributions [36]. [37] Proposed a delicate division technique by utilizing a choice tree classifier with an arrangement and relapse tree (CART) calculation. The average soft overlap obtained using this technique is only 0.66.

3.9 MEAN SHIFT SEGMENTATION

This is another method for segmentation that employs iterative feature space analysis [38]. The average segmentation overlap achieved using this technique is 0.83. Performance wise it takes more time.

3.10 GRAPH CUTS (GC)

Graph cuts are applied in [39, 40] to obtain their early nodule segmentation using joined segmentation-registration method. The mean error boundary of distance between automatic segmentation and manual segmentation is 3.5 pixels as against the expected value of 0.

![Figure 4](image_url)

**Figure 4.** Steps involved in the segmentation of lung nodules:  
(a) Input image, (b) Gaussian filtered image and (c) Segmented lung and lung nodules

4. CLASSIFICATION

Once the nodules are detected and segmented, it has to be diagnosed into benign or malignant nodule. Diagnosis is based on the contour and boundary of the nodule. Commonly used classifiers are linear discriminant classifiers and neural network classifiers. Features used for classification include Geometrical features, Texture features, Histogram features, Gradient features and spatial features. Geometric features include features such as spherical disproportion, circularity etc. Texture features include features like contrast, energy, entropy, etc.

Histogram features are average, standard deviation, Skewness etc. Gradient features describe the average, standard deviation, kurtosis, etc. Spatial features are the location of the nodule. Mc Nitty-Gray et al. [60] developed a CAD system which is based on pattern classification approach for determination of the nodules. The features used are nodule attenuation, shape and texture. The Az value obtained is 0.92 for 35 nodules. Classification based on morphological and textural features is developed by Way et al [61,62]. This system achieved an Az of 0.85 with 152 patients. The initial neural network-based CAD system was developed by [63]. They used the nodule border smoothness, speculation, and lobulation as the features for classification. Henschke et al. [64] developed their CAD system that will automatically detect and extract
features along with it to classify the nodules. Neural network’s clustering technique is used for extracting and grouping the features into clusters. In their classification of 28 benign and malignant nodules, only three benign nodules were misclassified.

Lo et al. [65] in their work used a combination of Radio graphical parameters and shape indices. Their results showed the value of Az as 0.89. Suzuki et al [66] classified the nodules using trained MTANN classifier with nodules and non-nodules. The Az value obtained for 415 patients is 0.89. [67] Used ANN collection method to group the nodules and achieved a Az value of 0.915. Nakurama [68] test the effectiveness of different feature set with two different networks. Other network is trained with matched features that are automatically obtained from chest radiographs. Matched features include effective diameter, degree of circularity, mean gradient, mean pixel etc. Both networks used shape based features also. A high degree of performance Az =0.854 is achieved with objective features compared to subjective features. Iwano et al [69] CAD system is to automatically classify the nodules based on shape features and the results were as accurate as the radiologist’s classification.

Combining the genetic algorithm with a random subspace method Lee et al [70] developed a two-step supervised learning scheme and achieved an accuracy of 0.889. A 2D approach was proposed by El-Baz et al [71] for diagnosing malignant nodules. They also proposed [72] a 3D work in which the nodules are represented with spherical harmonics. Special harmonic analysis approximates the 3D surfaces of the detected nodules. The accuracy achieved is Az =0.97.

III. CONCLUSION

The review highlighted that all the proposed methods of different researchers has variable level of accuracy in lung cancer diagnosis for medical science. From the literature survey, it is concluded that contrast stretching technique and histogram binning concept improves quality and interpretability of images. Storing of source images in DICOM format increases processing time and provides better results than other non-medical image formats. Numerous studies for lung nodules detection scheme have been going on in research in medical field. In this paper, some recent research work done on the Lung tumour detection and segmentation is reviewed. Some conventional methods and other segmentation techniques are described. By this review we found that automation of Lung tumour detection and segmentation from the CT images and the present challenges and trends in this field, suggested that the search of more effective and accurate CAD for lung cancer diagnosis and false positive reduction scheme will remain an active research area. Now-a-days with the advancement of nanotechnology, self-assembled biocompatible nano technique can be created which will detect the tumour area. Our future method to focus the nanotechnology based approach for lung cancer detection and segmentation technique would help both the expert pathologists and the patients.

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