A NEW METHOD FOR DETECTION AND EXTRACTION OF LUNG NODULES BASED ON ESTIMATION OF BOUNDARY AND ANALYZING THE SURFACE

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Abstract

CAD system plays a major role in assisting the radiologists in diagnosing the lung cancer nodules. However, the existing detection and extraction algorithms in CAD systems endure accuracy issues as it yields more number of false positives. Thus, comprehending the importance of CAD systems, algorithms for efficiently isolating the INC and extraction with high accuracy are of great interest. Automated detection of lung nodules includes detection of isolated nodules, juxta-pleural nodules, juxta-vascular nodules, and pleural-tail. The existing algorithms [1, 2] failto detect lung nodules attached to lung walls and blood vessels more accurately. Hence, there is need to design an automated system for accurate identification of nodules. In this direction, a new automated algorithm method is proposed to detect lung nodules based on boundary estimation and surface analysis.

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Related Work

Intensity-based segmentation [3,4] have applied to segment thenodules with the help of local density maximum and thresholding algorithms,however, decline in detaching tumors from the lung wall and blood vessels. T. Okumura [5] et al. implemented variable N-Quoit image filter to extract tumors from 2-dimensional images. R. Wiemker [6] applied thresholding for consecutive rendering and measuring the tumors. McCulloch [7] et al. proposeddifferent segmentation techniques to get different parts in the lungs, then applied a Bayesian statistical model to find the probability of various parts in the lungs and detects the lung tumors. Lakshmi Narayanan A et al. [8] have applied median filter, thresholding, morphological operations, labelling to extract lung nodule. Features such as area, perimeter, mean, equivalent diameter, centroid, irregularity index, eccentricity are extracted from the segmented lung nodule and features are given to ANN classifier as an input. The proposed method gives an accuracy as 92.2%.

Orozco et al. [9] applied Gray Level Co-occurrence Matrix (GLCM) to obtain features from input image to identify tumors withSVMclassifier and reliability index of 84% was achieved. Amjed S. Al-Fahoum et al. have used morphological operators, thresholding, region growing and shape features to extract lung nodules. Kaijun Zhou et al. have used morphological operators and active contour to extract the lung nodules. SruthiIgnatious et al. [10] have applied gabor filter, marker controlled watershed algorithm with area, perimeter and eccentricity features to detect lung cancer and the detection rate was found to be is 90.1%. P. Bhuvaneswari et al. [10] have used genetic algorithm with K-Nearest Neighbour (K-NN) algorithm for the detection of lung cancer with 90% accuracy in detection of lung cancer.Farag et al.[11] implemented an algorithm based on Gaussian templates, the algorithm identified tumors with 82.3% of sensitivity and9.2% of false positive rate.

The literature survey conveys that, accurate detection and extraction of lung nodules attached to the blood vessels, tail and pleura are challenging. Effective algorithms are proposed to extract nodules attached to the blood vessels, tail and pleura. The results from the proposed algorithms are compared with the state-of-the-art and the outcome is satisfactory.

Methodology

The proposed technique involves three stages as depicted in figure 1. Step 1 deals with detection of isolated nodule candidates from INC. In step 2, feature extraction and selection are applied on to the isolated nodule candidates. The features extracted are then provided as input to the Support Vector Machine (SVM) classifier in step 3, to classify the isolated nodule candidates as either nodule or non-nodule.

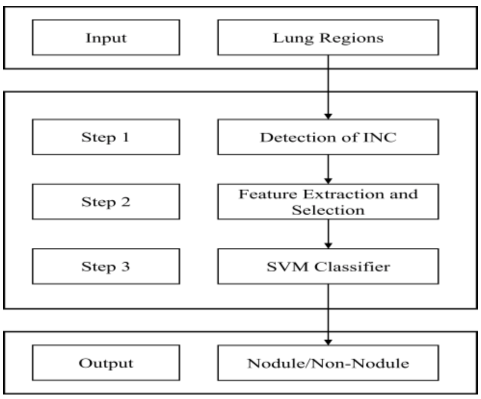


Figure 1: Block diagram for the detection of lung nodules

Detection of Isolated Nodule Candidates (INC)

Thresholding and run-length encoding techniques are applied on lung regions to get Connected Components (CCs) and these CC's are superimposed with the input image to get INC (which contains both the nodules and the non-nodules). Multiple kinds of INC exist in the segmented lung region like the isolated nodules, juxta-vascular nodules, pleura tail nodules and juxta-pleural nodule. Based on the type of INC, different techniques are applied to separate them as isolated nodule candidates as mentioned below.

Juxta-pleural Lung Nodules

Thresholding technique extracts INCs, but when the INC is attached to the wall, some partof it that is attached to the wall will be left out as shown in the figure 2 making cancer diagnosing difficult. To overcome this, a new technique is proposed based on boundary estimation. This information is important for classifying the isolated nodule candidate as cancerous or non-cancerous.

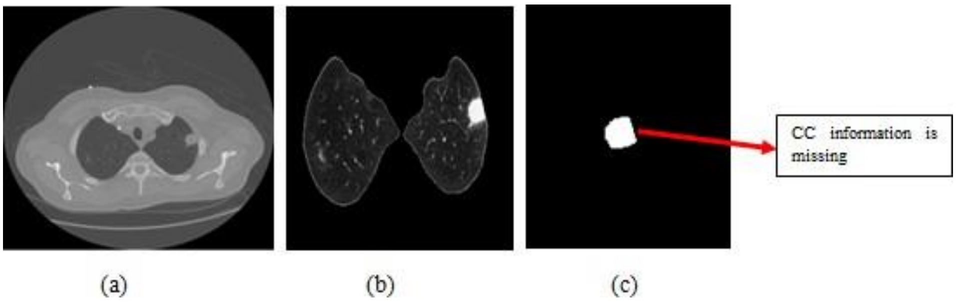


Figure 2: (a): Input Image (b) Lung Regions (c) Extracted CC

To solve the above problem, the original INC will be analyzed by calculating the centroidand radius. The extreme points of the INC (where the pixels are missing) are estimated and those points are connected by drawing lines. The lines should be equal to the length of the calculated original INC radius. It is as shown in the Figure 3. This additional connected component is filled with pixels (fig 3(c)) to get the isolated nodule candidate (3(d)). The algorithm for the same is discussed in step 3 of Algorithm 1.

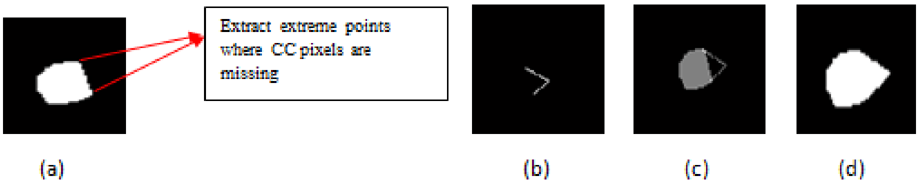


Figure 3: (a) Extracted INC (b) Line boundary of the INC (where the pixels aremissing)(c) Line boundary are attached to CC (2(c)) (d) Filled INC

Juxta-Vascular nodules and Pleural-Tail nodules If the INC is attached to the blood vessel or the tail of the lung wall, then erosion operation is performed to separate the INC from their respective blood vessel and tail as shown in step 4 of algorithm 1. Figure 4 shows the process of separation and isolation of INC from its attached blood vessel figure 5 shows the process of separation and isolation of INC from its attached tailof lung walls.

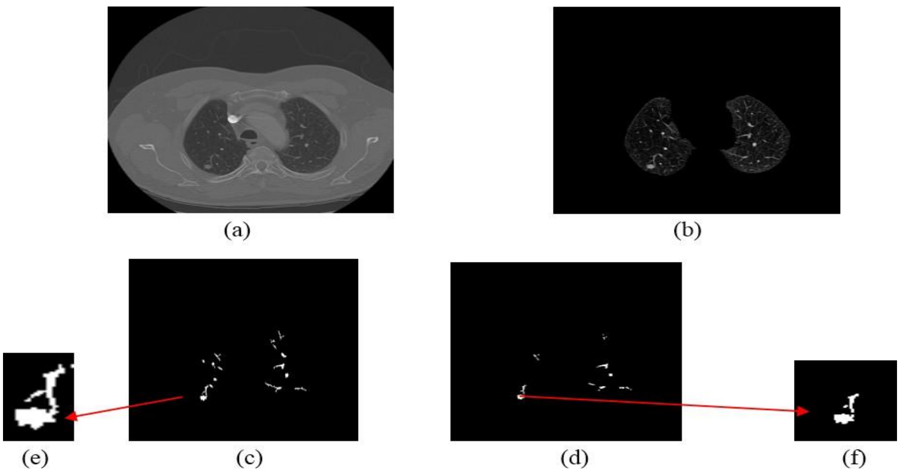


Figure 4: (a) DICOM Input image of the lungs (b) Extracted Lungs (c) Connectedcomponents (d) Separation of blood vessel from nodule (e) - (f) enlarged image

Algorithm 1 Pseudo code for the detection of Isolated Nodule Candidates using thresholding, boundary estimation and morphological operators
Input: Lung Regions
Output: Isolated Nodule Candidates
Method:
Step 1: All the INC's are extracted using thresholding technique. Step 2: Each INC is labeled using run-length encoding technique.
Step 3: If the INC is attached to wall, then perform
a) Calculate the centroid and radius for the original INC.
b) The extreme points (p and q)of this INC (where the information is missing)is estimated and are connected by drawing lines.
c) The length of the line must be equal to the radius of the original INC
d) The missing component is now connected with the original INC and filledwith pixels.
Step 4: If INC is attached to the vessels and tail of the lung then perform
(i) Erosion operation to isolate INC from the blood vessel and tail of the lung. Step 5: The isolated nodule candidates are superimposed with input image.

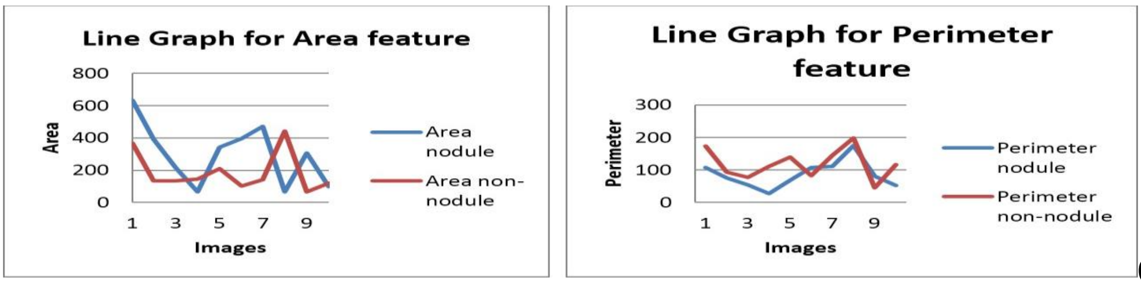
Feature Extraction and Feature Selection

The next step in detection of lung nodule is the application of feature extraction and selection on isolated nodule candidates obtained from algorithm 1. To select which feature is prominent in detecting a nodule, we experimented the various features extraction techniques on 150 LIDC-IDRI database images. The images in the database contain nodules and they are verified and marked by expert radiologists. Line graphs are plotted for nodules and non-nodules for each of the image. The x-axis in the graph represents the images and y-axis represents the feature values of both nodules and non-nodules. Based on the interaction of the plots of nodules and non-nodules in the line graph, it's decided whether the feature is prominent or not. The more the intersection between the plots of nodules and non-nodules, the less prominent the feature is, likewise less intersection implies more prominence of that particular feature.

First the existing feature extraction techniques like area, perimeter, solidity, circularity, equi-diameter, extent, eccentricity, major axis length, minor axis length, contrast, homogeneity, correlation, energy, orientation, skewness, kurtosis, mean, variance, standarddeviation is first applied to identify nodules. Above this, the research contributes two new feature extraction techniques based on surface analysis and mean intensity estimation. All these features contribute in deciding the accuracy of an isolated nodule candidate of being a nodule. The description and application of various features are explained as below.

Area: It is the total pixels present in nodule or non-nodule. A line graph depicting the area feature is plotted for nodule and non-nodule across multiple images. The figure 5(a)shows that the values of area overlap at images 3,4,7 and 9 and the corresponding values are shown in table 1. Hence it is considered as not a prominent feature.

Perimeter: Perimeter is the distance around tumor and non-tumor. The comparison of perimeter values for nodule and non-nodule is shown in the line graph figure 5(b) and table 1. As seen the graphs overlapped at 6th ,7th ,8th and 9th image numbers and henceit is not considered.



(a) (b)

Figure 5: Line graph showing comparison between nodule and non-nodule forfeature selection technique (a) Area and (b) Perimeter

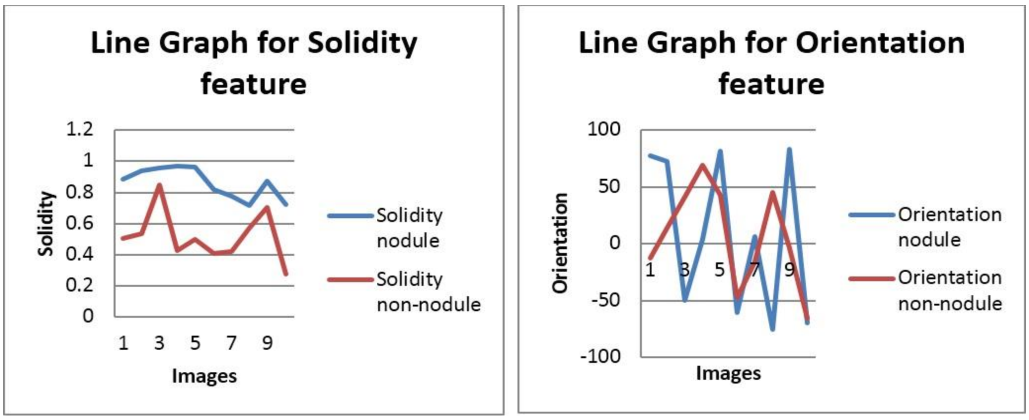
Table 1: Area and Perimeter values for

Image No	Image ID	Area		Perimeter	
		Non-Nodule	Nodule	Non-Nodule	Nodule
1	Image-0084	369	634	172.710	107.154
2	Image-0086	133	394	092.769	076.183
3	Image-0088	135	216	077.390	053.798
4	Image-0089	143	066	110.911	027.899
5	Image-0090	211	341	139.050	068.870
6	Image-0095	102	395	083.012	107.982
7	Image-0098	142	472	145.397	110.911
8	Image-0100	441	064	198.450	175.237
9	Image-0105	066	306	045.213	080.769
10	Image-0108	120	099	116.325	052.284

nodule and non-nodule across multipleimages.

Solidity: Solidity is that the quality or state of being firm or stable in structure. Since it can be observed from the comparison in the line graph for feature selection that there is no overlap as shown in the figure 6(a) with values in the table 2 and is therefore consideredas a prominent feature.

Orientation: Orientation of a rigid body is part of the description of how it is placed in the space it is in. The line graph comparison for orientation feature selection shows that it overlaps at images 2,4,6,7,8 and 10 as depicted in the figure 6(b) with the values in the table 2 and thereby gives an indication that it cannot be used as a prominent feature.



(a) (b)

Figure 6: Line graph showing comparison between nodule and non-nodule forfeature selection technique (a) Solidity and (b) Orientation

Table 2: Solidity and Orientation values for

Image No	Image ID	Solidity		Orientation	
		Non-Nodule	Nodule	Non-Nodule	Nodule
1	Image-0084	0.502	0.884	-12.558	77.044
2	Image-0086	0.536	0.938	13.623	72.190
3	Image-0088	0.849	0.955	41.320	-49.627
4	Image-0089	0.4255	0.970	69.448	03.751
5	Image-0090	0.496	0.960	42.921	81.252
6	Image-0095	0.406	0.819	-47.602	-60.901
7	Image-0098	0.423	0.777	-16.470	06.499
8	Image-0100	0.572	0.715	45.243	-75.493
9	Image-0105	0.702	0.871	-03.451	83.385
10	Image-0108	0.276	0.722	-65.781	-69.637

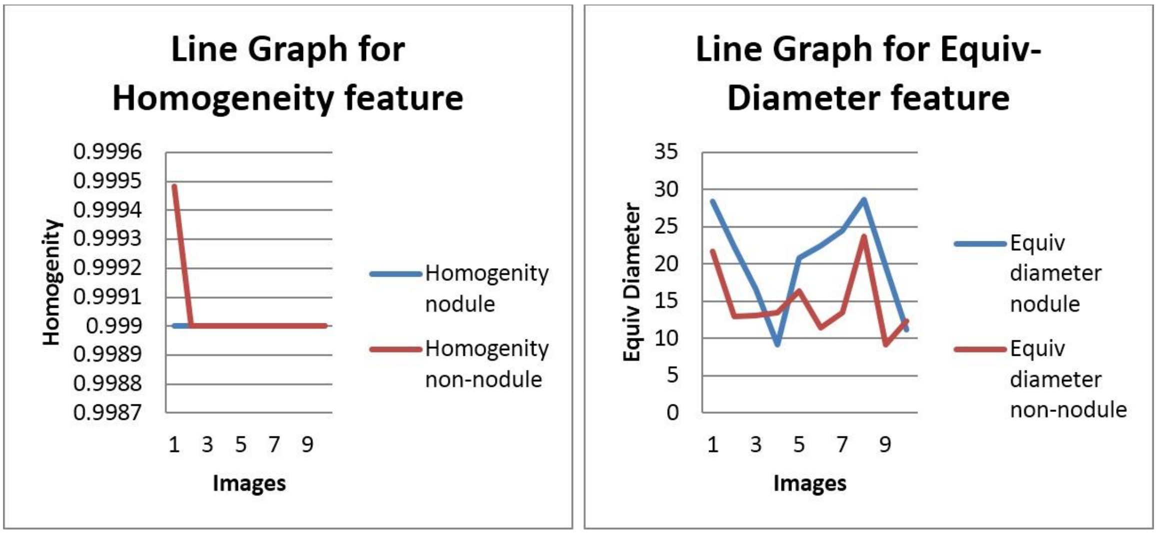
nodule and non-nodule across multipleimages.

Homogeneity: It is the state of having identical cumulative distribution function or values. As almost all the values in the comparison line graph for feature selection overlaps as shown in the figure 7 (a) with the values in the table 3, it proves to be a very poor feature to be considered.

EquivDiameter: It is a value which tells diameter of a circle with the similar size as the region. It is Computed as:

EquivDiameter= $\sqrt{(4 * Area/\pi)}$

The comparison graph for equivdiameter shows that it overlaps at 3 points as shown inthe figure 7(b) with the values in the table 3 and therefore it can be considered as a prominent feature.



(a) (b)

Figure 7: Line graph showing comparison between nodule and non-nodule for feature selection technique (a) Homogeneity and (b) Equiv-Diameter

Table 3: Homogeneity and Equiv-Diameter values for nodule and non-noduleacross multiple images.

Image No	Image ID	Homogeneity		Equiv-Diameter	
		Non-Nodule	Nodule	Non-Nodule	Nodule
1	Image-0084	0.999	0.999	21.675	28.411
2	Image-0086	0.999	0.999	13.013	22.397
3	Image-0088	0.999	0.999	13.110	16.583
4	Image-0089	0.999	0.999	13.493	09.166
5	Image-0090	0.999	0.999	16.390	20.836
6	Image-0095	0.999	0.999	11.396	22.426
7	Image-0098	0.999	0.999	13.446	24.514
8	Image-0100	0.999	0.999	23.695	28.635
9	Image-0105	0.999	0.999	09.166	19.738
10	Image-0108	0.999	0.999	12.360	11.227

Skewness: Skewness is a measure of the dissymmetry of the probability distribution of a real-valued random variable about its mean.

Extent: It is a value that indicates the proportion of pixels in the region to pixels in the total bounding box.

Table 4: Skewness and Extent values for nodule and non-nodule across multipleimages.

Image No	Image ID	Skewness		Extent	
		Non-Nodule	Nodule	Non-Nodule	Nodule
1	Image-0084	26.597	20.260	0.273	0.582
2	Image-0086	44.362	25.735	0.270	0.721
3	Image-0088	44.031	34.794	0.192	0.794

4	Image-0089	42.780	62.999	0.183	0.825
5	Image-0090	35.204	27.672	0.123	0.773
6	Image-0095	50.665	25.703	0.163	0.633
7	Image-0098	42.931	23.503	0.096	0.614
8	Image-0100	24.319	20.101	0.157	0.500
9	Image-0105	62.999	29.217	0.496	0.619
10	Image-0108	46.706	51.428	0.117	0.485

Contrast: It is the change between maximum and minumum pixel intensity in nodule or non-nodule.

Minor Axis Length: Minoraxislength is the shortest diameter length of the given elliptical figure.

Energy: It is the sum of squared elements in Gray Level Co-Occurrence Matrix (GLCM) and it can be inferred from the comparison graph that the values overlap at three points and hence can be considered.

Circularity: It is the calculation of how far the shape of an object tends to that of a circle.
$Circularity = 4 * \pi * Area/Perimeter^2$

MajorAxisLength: Majoraxislength is the largest diameter length of the given elliptical figure.

Variance: Variance is the expectation of the squared deviation of a random variable from its mean.

Standard Deviation: Standard deviation is a measure that is used to quantify the amount of variation or dispersion of a set of data values.

Mean: Mean is the average of nodule or non-nodule pixel values.

Correlation: Correlation gives values close to 1 shows that there is a positive linear link between the data columns

Kurtosis: Kurtosis is the sharpness of the peak of a frequency-distribution curve. (4.2)

Eccentricity: Using this parameter, object can be determined whether it is circular in shapeor not.

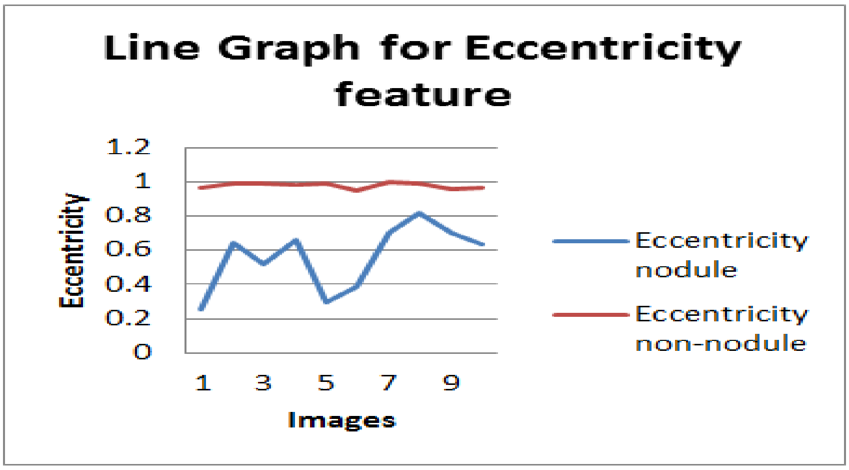


Figure 8: Line graph showing comparison between nodule and non-nodule forfeature selection technique Eccentricity

Surface analysis is one of the novel features contributed by this research that has benefited in improving the accuracy of nodule detection. It represents the intensity distribution on the surface of the INCs. The process for surface analysis is, first the surface of the extracted nodule is denoted by E and the polynomial surface curve fitting is denoted by Y. Y is computed using the equation (4.3). Polynomial surface curve fitting is then overlaid on the surface of the extracted nodules.

The difference (D) between surface of the extracted nodule (E) and the polynomial surface curve fitting (Y) is calculated using equation (4.4).

The frobenius norm for D is calculated to yield a value which shows whether the connected component is a nodule or not. If the value of D is more then it indicates that the connected component is a nodule. If the value of D is less than the connected component is a non-nodule.

$$Y = w_{00} + w_{10}x + w_{01}y + w_{20}x^2 + w_{11}xy + w_{02}y^2 + w_{30}x^3 + w_{21}x^2y + w_{12}xy^2 + w_{03}y^3 + w_{31}x^3y + w_{22}x^2y^2 + w_{13}xy^3 \quad (4.3)$$

$$D = Y - E \quad (4.4)$$

The frobenius norm for D is calculated using equation to yield a value which shows whether the connected component is a nodule or not. If the value of D is more then it indicates that the connected component is a nodule. If the value of D is less then the connected component is a non-nodule. The surface analysis process is described using theexample in figure 4.15 and the algorithm for the same is presented in Algorithm 4.2.

Mean Intensity Estimation

Another novel feature that contributed in reducing false positives is the mean intensity estimation and the process is as follows, both nodule and blood vessels inside the lungs are identified and they are dilated using a disk shaped structuring element. This dilated nodule and dilated blood vessel are superimposed on the original nodule and blood vessel respectively. By doing this, the region of the original nodule and original blood vessel are removed (subtracted) in the dilated images, thereby the region outside the nodule

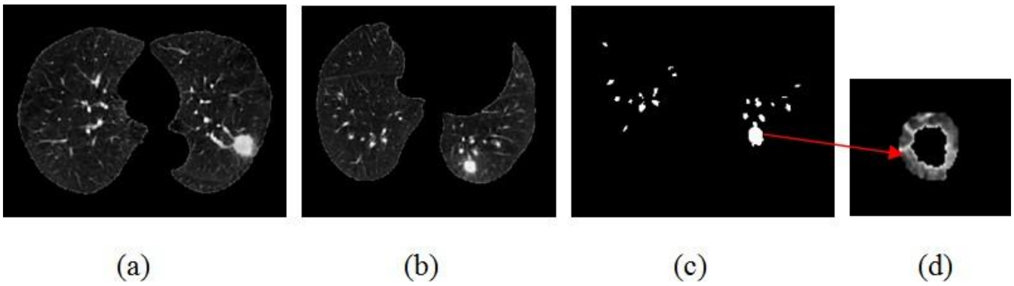


Figure 11: (a): Input DICOM image (b) Extraction of lung regions (c) INC fromlung regions (d) neighboring region of the nodule

Algorithm 3 Pseudo code for the detection of lung nodules using Mean Intensity feature

Input: Initial Candidate Nodules (INCs)

Output: Mean intensity of the surrounding pixels of the INCs

Method:

Step 1: The extracted nodule is dilated and then the dilated nodule is subtracted withextracted nodule to get Connected Component(CC)

Step 2: The CC is superimposed with lung regions to get a region Step 3: Mean intensity for that region is calculated

Based on above heuristics, the following features are considered prominent and hence taken up for detection. First, Solidity, Equiv-Diameter, Skewness, Extent, Contrast, Minoraxislength, Energy, Circularity, Majoraxislength, Variance, Correlation, Kurtosis, Mean, Standard Deviation, Eccentricity are applied. Above these as mentioned earlier, the two new techniques Mean Intensity and Surface Analysis are applied. The application of these new techniques has led to detect nodules with high accuracy.

Support Vector Machine (SVM) classifier

SVM is suitable to classify Initial Nodule Candidate (INCs) as nodule or non-nodule. Support vector machines can be used for multi-variable functions, provide approximations to the desired degree of accuracy for complex systems. They are used to classify a given input into either of the classes by separating the classes by a hyperplane, which is produced after training of SVM. SVM uses an optimal hyperplane to transform the input feature space into something linear for easy classification. In this research, 100 nodules and non-nodules are given as a training dataset to SVM and 50 nodules and non-nodules are given as testing datasets to SVM.

Results and Discussion

ROC Analysis

The analysis and validation of the proposed method is carried out on 50 images. Outof 50 images, 10 images contain juxta-pleural nodules, 05 images contain juxta-vascular nodules, 25 images contain isolated nodules and 10 pleural-tail nodules. Table 5 showsthe detection of lung nodules and figure 12 shows the comparative study among Amjed S. Al-Fahoum [82], Kaijun Zhou [90] and proposed method.

From the segmented nodule, Solidity, Equiv-Diameter, Skewness, Extent, Contrast, Minoraxislength, Energy, Circularity, Majoraxislength, Variance, Correlation, Kurtosis, Mean, Standard Deviation, Eccentricity, Mean Intensity and Surface Analysis features are considered. The performance of proposed approach is evaluated based on three performance metrics such as accuracy, sensitivity and specificity. The performance metrics are calculated based on following parameters:

True positive (TP): Lung nodules classified as cancerous tumors by the algorithm and the radiologist as cancerous tumor are known as True positive.

False positive (FP): Lung nodules categorized as cancerous tumor by the algorithm and non-cancerous tumor by the radiologist are known as false positive.

False negative (FN): Lung nodules classified as non-cancerous tumor by the algorithm and cancerous tumor by the radiologist are known as false positive.

True negative (TN): Lung nodules categorized as non-cancerous tumors by the algorithm and the radiologist as non-cancerous tumors are known as True negative.

Specificity is the number of correctly classified non-nodules out of actual non-nodules.

$$Specificity = (TN)/(TN + FP)$$

nodules.

$$Accuracy = \frac{(TP + TN)}{(TP + FP + TN + FN)} \quad (4.6)$$

Sensitivity is the number of correctly categorized nodules (nodule) out of actual positivenodules.

nodules.

$$Sensitivity = \frac{(TP)}{(TP + FN)} \quad (4.7)$$

Table 5: Performance Measures and comparative study

Performance Measures	Amjed S. Al-Fahoum [82]	Kaijun Zhou[90]	Proposed Method
Specificity	84%	84%	96%
Accuracy	80%	82%	94%
Sensitivity	76%	80%	92%

The comparative study of performance metrics performed among the 2 existing methods [82, 90] and the proposed is demonstrated in table 5. The performance of the classifier model is determined with the help of ROC curve. ROC curve is a plot of the true positive rate versus the false positive rate (a),(b) and (c) for respectively.

Area under the curve for existing methods were found out to be 0.858 and 0.867, which indicates the false positive rate is high compared to proposed method. Since the areaunder the curve is 0.971 there is a balance between the detection rate and the false positive rate and thereby the number of false positives is reduced. After comparing the performances and ROC curves of both approaches, proposed method gives better results with respect to all three metrics.

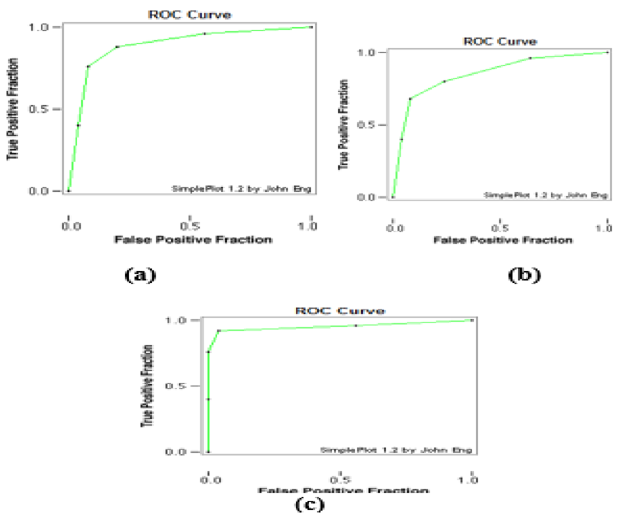
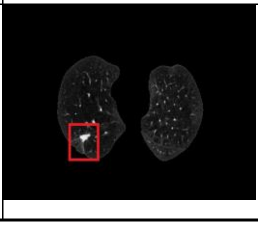
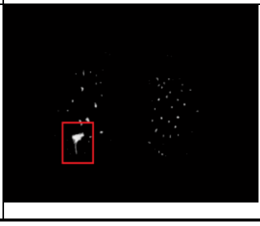


Figure 12: Comparative study among Amjed S. Al-Fahoum , Kaijun Zhou and proposed method

Table 6: Steps involved in extraction of lung nodules

Input image	Segmentation of Lung Regions	Extraction of CC in lung regions	Segmentation of Lung cancer
			

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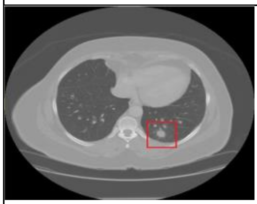
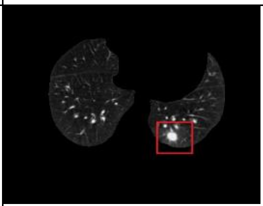
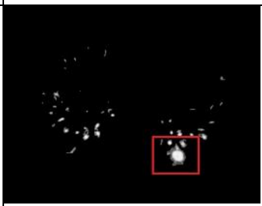
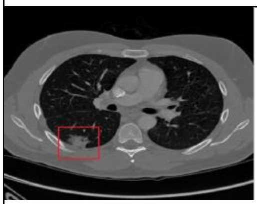
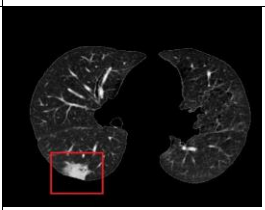
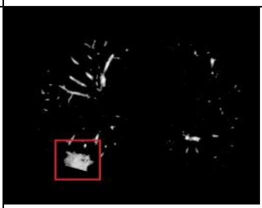
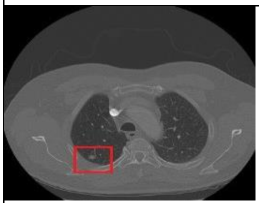
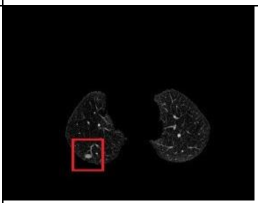
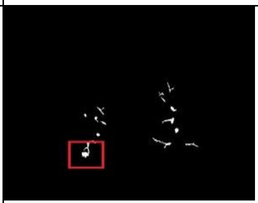
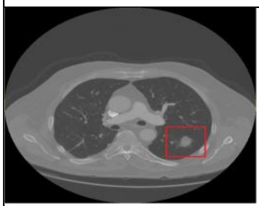
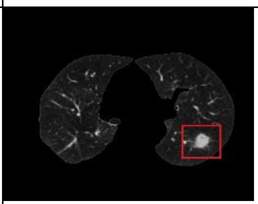
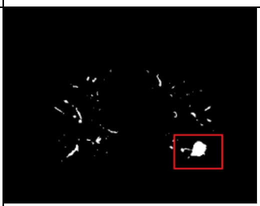
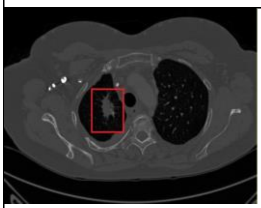
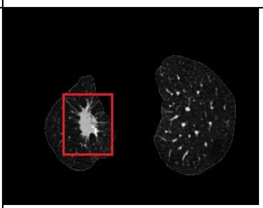
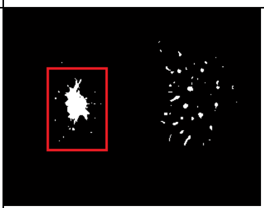
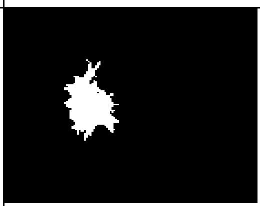
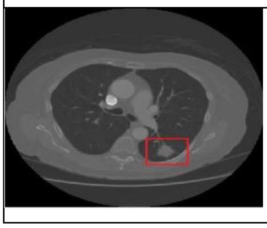
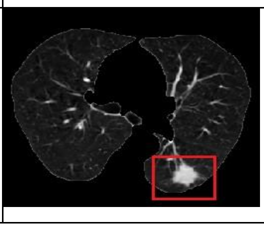
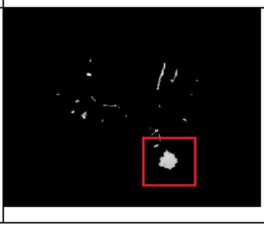
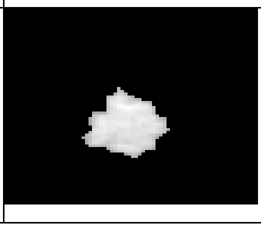
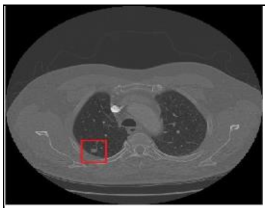
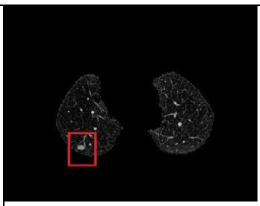
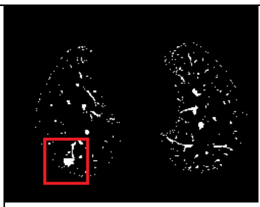
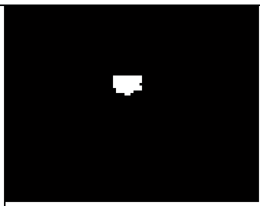
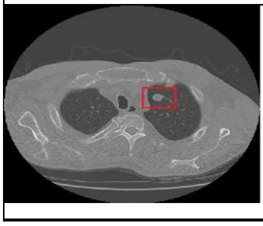
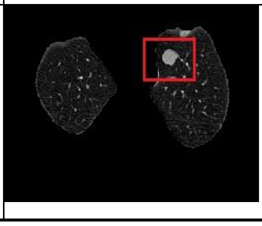
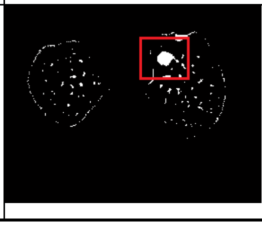
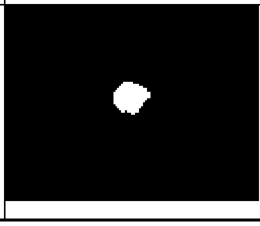
Input image	Segmentation of Lung Regions	Extraction of CC in lung regions	Segmentation of Lung cancer
			
			
			
			
			
			

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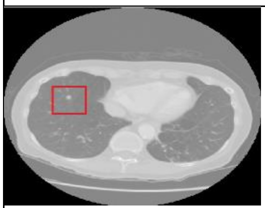
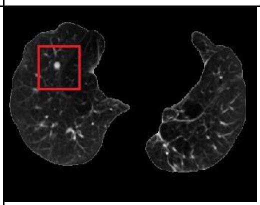
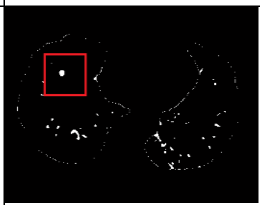
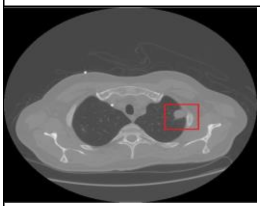
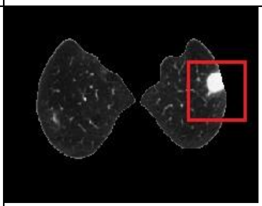
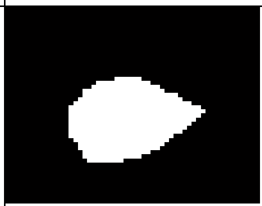
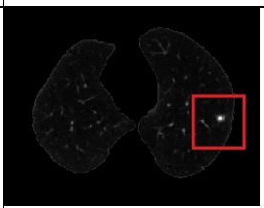
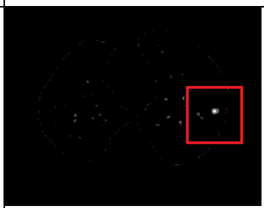
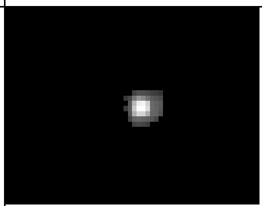
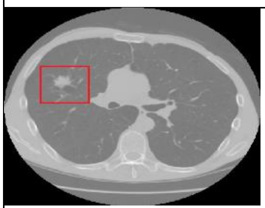
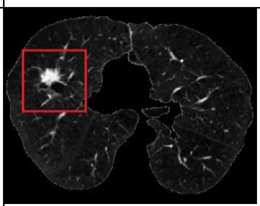
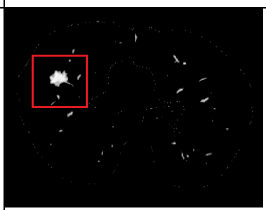
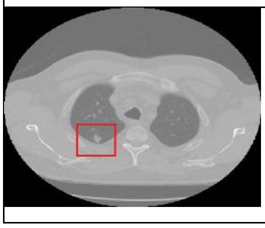
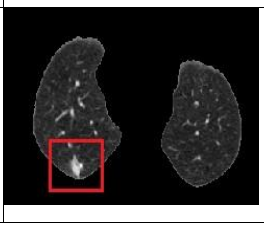
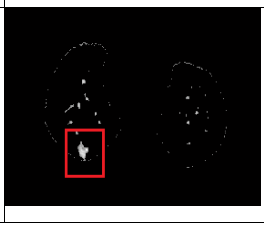
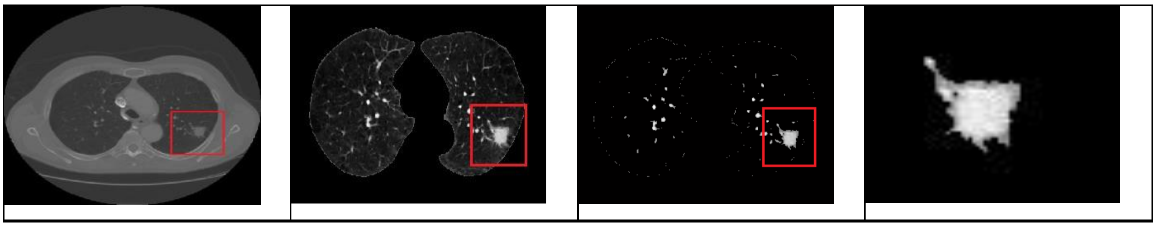
Input image	Segmentation of Lung Regions	Extraction of CC in lung regions	Segmentation of Lung cancer
			
			
			
			
			



Conclusion

The proposed method detects isolated, juxta-pleural, juxta-vascular and pleural-tail nodules using morphological operators, boundary estimation techniques with Solidity, Equiv-Diameter, Skewness, Extent, Contrast, Minoraxislength, Energy, Circularity, Majoraxislength, Variance, Correlation, Kurtosis, Mean, Standard Deviation, Eccentricity, Mean Intensity and Surface Analysis features. The proposed method gives an accuracy of 94%, Sensitivity of 92% and Specificity of 96% with area under curve of 0.971 in Receiver Operating Curve (ROC) graph, which is better than the existing system.

References

1. Amjed S Al-Fahoum, Eslam B Jaber, and Mohammed A Al-Jarrah. Automated detection of lung cancer using statistical and morphological image processing techniques. Journal of Biomedical Graphics and Computing, 4(2):33, 2014.
2. Kaijun Zhou and Guirong Weng. The method of detecting pulmonary nodules by snake model. In Control, Automation and Information Sciences (ICCAIS), 2015 International Conference on, pages 174–178. IEEE, 2015.
3. Binsheng Zhao, David Yankelevitz, Anthony Reeves, and Claudia Henschke. Two-dimensional multi-criterion segmentation of pulmonary nodules on helical ct images. Medical Physics, 26(6):889–895, 1999.
4. Jane P Ko, Henry Rusinek, Erika L Jacobs, James S Babb, Margrit Betke, Georgeann McGuinness, and David P Naidich. Small pulmonary nodules: volume measurement at chest ct—phantom study 1. Radiology, 228(3):864–870, 2003.
5. Toshiaki Okumura, Tomoko Miwa, J-I Kako, Shinji Yamamoto, R Matsumoto, Yukio Tateno, Takeshi Iinuma, and Toru Matsumoto. Automatic detection of lung cancers in chest ct images by variable n-quoit filter. In Pattern Recognition, 1998. Proceedings. Fourteenth International Conference on, volume 2, pages 1671–1673. IEEE, 1998.
6. Rafael Wiemker and André Zwartkruis. Optimal thresholding for 3d segmentation of pulmonary nodules in high resolution ct. In International Congress Series, volume 1230, pages 653–658. Elsevier, 2001.
7. Colin C McCulloch, Robert A Kaucic, Paulo RS Mendonça, Deborah J Walter, and Ricardo S Avila. Model-based detection of lung nodules in computed tomography exams 1: thoracic computer-aided diagnosis. Academic Radiology, 11(3):258–266, 2004.
8. JB Jeeva et al. A computer aided diagnosis for detection and classification of lung nodules. In Intelligent Systems and Control (ISCO), 2015 IEEE 9th International Conference on, pages 1–5. IEEE, 2015.
9. Hiram Madero Orozco, Osslan Osiris Vergara Villegas, Vianey Guadalupe Cruz Sánchez, Humberto de Jesús Ochoa Domínguez, and Manuel de Jesús Nandayapa Alfaro. Automated system for lung nodules classification based on wavelet feature descriptor and support vector machine. Biomedical engineering online, 14(1):9, 2015.
10. Sruthi Ignatious and Robin Joseph. Computer aided lung cancer detection system. In Communication Technologies (GCCT), 2015 Global Conference on, pages 555–558. IEEE, 2015.
11. Amal A Farag, Hossam E Abd El Munim, James H Graham, and Aly A Farag. A novel approach for lung nodules segmentation in chest ct using level sets. IEEE Transactions on Image Processing, 22(12):5202–5213, 2013.