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Feature Extraction and Classification of Automatically Segmented Lung Lesion Using Improved Toboggan Algorithm

K. Bavya[1], Mr. P. Julian[2]

[1]M.E, Applied Electronics, Velammal Engineering College, Chennai, Tamil Nadu, India
[2]Assistant Professor, Velammal Engineering College, Chennai, Tamil Nadu, India

Abstract— The accurate detection of lung lesions from computed tomography (CT) scans is essential for clinical diagnosis. It provides valuable information for treatment of lung cancer. However, the process is exigent to achieve a fully automatic lesion detection. Here, a novel segmentation algorithm is proposed, it's an improved toboggan algorithm with a three-step framework, which includes automatic seed point selection, multi-constraints lesion extraction and the lesion refinement. Then, the features like local binary pattern (LBP), wavelet, contourlet, grey level co-occurence matrix (GLCM) are applied to each region of interest of the segmented lung lesion image to extract the texture features such as contrast, homogeneity, energy, entropy and statistical extraction like mean, variance, standard deviation, convolution of modulated and normal frequencies. Finally, support vector machine (SVM) and K-nearest neighbour (KNN) classifiers are applied to classify the abnormal region based on the performance of the extracted features and their performance is been compared. The accuracy of 97.8% is been obtained by using SVM classifier when compared to KNN classifier. This approach does not require any human interaction for lesion detection. Thus, the improved toboggan algorithm can achieve precise lung lesion segmentation in CT images. The features extracted also helps to classify the lesion region of lungs efficiently.

Keywords—computed tomography (CT), improved toboggan algorithm, local binary pattern(LBP), wavelet, contourlet, grey level co-occurrence matrix(GLCM), support vector machine(SVM), K-nearest neighbour(KNN).

I. INTRODUCTION

Lung cancer is the frequent cause for death in men and second most in women. In 2012, 1.8 million people got lung cancer and it resulted in 1.6 million deaths [1]. Early identification helps in survival benefit improvement. In United States about 17.4% diagnosed by means of lung cancer stay alive for about five years after diagnosis, while it's worse in developing world [1]. Profound analysis of radiographic images provides information about the microenvironment and need of intra-tumoral heterogeneity for personalized medicine [2]. Testing of huge numbers of image features extracted from computed tomography (CT) with high throughput provides information about spatial and temporal genetic heterogeneity by non-invasive way, which provides better results than invasive biopsy which helps in medical research, computer-aided diagnosis, radiotherapy and also evaluations of surgery results [5]. For this purpose, accurate segmentation of lung lesions is needy. One method for lung lesion segmentation is, radiologists describe the lesion physically. They may overrate the lesion volume to enclose the whole lesion. Different physical description is also varying. So, human interaction must be avoided. As a result, a highly proficient and automatic lung lesion segmentation approach is required. As shown in Fig 1, due to the diversity of lung lesions, segmentation accuracy is poor. So, to increase the segmentation accuracy the automatic segmentation using improved toboggan algorithm is used in the proposed work.

The segmented region of lung lesion does not produce an accurate boundary because of the similar pixel values between the lesion and adjacent tissues of the lesion [6]. So, the performance and efficiency is greatly dependent upon the feature vectors [7]. The feature vectors which are used in recent recovery and classification systems utilize the visual information of the image such as shape [8], texture [9], edges [10], color histograms [11], etc. Mostly, texture based image descriptors have been widely used in the field of pattern recognition to capture the fine details of the image [12]. The number of operations required to compute the features which contain information about image textural characteristics such as homogeneity, gray-tone linear dependencies contrast, number and nature of boundaries present is proportional to the number of resolution cells in the image and so these features are quickly computable [13]. Thus, in the

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proposed work the features like local binary pattern, wavelet, contourlet, gray level co-occurence matrix features are extracted and classified to obtain the efficient detection.

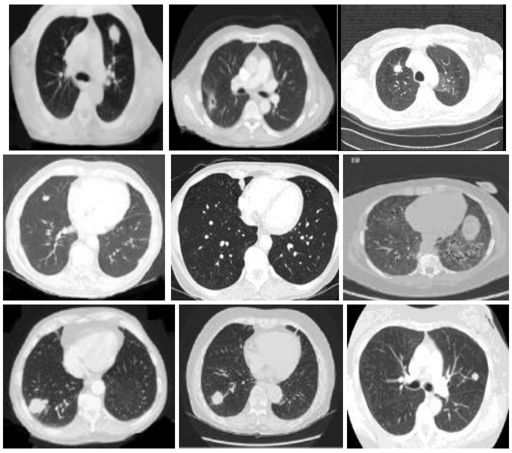

Fig.1: Different types of lung lesions

A. Related work

Based on the CT data of lung, many researchers have been done to relevant works on lesion segmentation, feature extraction and classification . D. M. Campos et al [3] proposed a supervised lung nodule segmentation which is based on shape, contrast, intensity to produce three preliminary segmentations and an artificial neural network to obtain an accurate segmentation. In [4], S. Diciotti et al proposed, an automated correction method based on a local shape analysis by making use of 3-D geodesic distance map representations. The advantage is, the nodule segmentation is done only for recognized vessel attachments. In [12], A novel image feature description based on the local wavelet pattern (LWP) was proposed to characterize the medical CT images for content-based CT image recovery. Successfully, the LWP is derived for each pixel of the CT image by utilizing the relationship of centre pixel with the local neighboring information. In [13] D. Wu et al proposed, a stratified statistical learning that detects the nodule texture, gray scale, shape and curvature which was built to provide a reasonable segmentation for the later classification. In [14] A. a Farag et al proposed, a general lung nodule shape model using implicit spaces where the shape model is fused with the image intensity statistical information. By this method the shape of nodule is analysed. But, the processing time is high. In [15], a novel pathological lung segmentation method was proposed where fuzzy connectedness algorithm was used to estimate the lung volume and texture features are used to identify the abnormal imaging patterns.

In order to perform the automatic lung lesion segmentation, it is necessary to develop an automatic and accurate method for the seed point selection. Using the algorithm of [16] the error caused by manual analysis was reduced and the segmentation accuracy was also improved. In [24], the problem of discrimination between a bright object against a dark background and vice-versa inherent in LBP and LTP has been solved. The clinical value of tumour heterogeneity is been measured and compare with traditional image features. They are applied to the trained SVM to provide more accuracy by classifying the extracted features [30]. But, it requires more samples. Accuracy of kNN classifier heavily depends on the choice of k. The problem of estimating 'k' for any test point becomes difficult due to several factors like the local distribution of training points around that test point, presence of outliers in the dataset, and, dimensionality of the feature space. so, A dynamic k estimation algorithm based on the neighbor density function of a test point and class variance as well as certainty factor information of the training points is proposed. Performance of the kNN algorithm with the proposed choice of k is evaluated and found improved [31]. But, it consumes more time.

All the above mentioned methods provide feasible ways for lung lesion detection, but they require pre-processing and also the number of human interactions was not clear. To provide fast, accurate and reliable lung lesion detection for clinical diagnosis feature extraction and classification has been to overcome all the above issues.

II. METHODS

The proposed method is a novel method helps to identify the lesion region of lung in CT image. The proposed method helps to achieve the automatic selection of the lesion seed point, which is one of the lesion segmentation problems. Fig. 2 represents the overview of the proposed method. The input is a slice of CT lung lesion image. The pre-processing is done by using the Otsu thresholding process to remove unwanted signals from CT lung lesion image. By using, the improved toboggan algorithm the seed points are selected initially and is applied to segment the lung lesion image automatically by region growing. Then, the lung lesion boundary is obtained by smoothening in lesion refining stage. From the segmented region of lung lesion the features like LBP, GLCM, wavelet, contourlet are been extracted to improve the accuracy. Then, the extracted features are been classified using the SVM and KNN classifiers

The figure.2 shown here provides the flow chart of the proposed work

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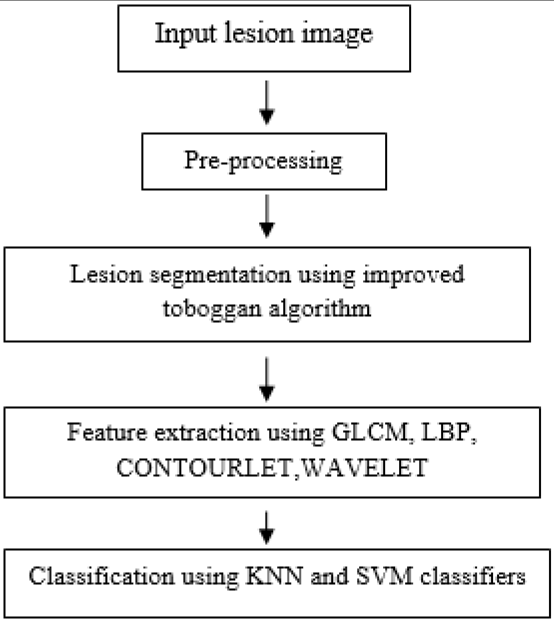

Fig.2: Block diagram of proposed segmentation algorithm

A. Pre-Processing

Pre-processing is done primarily. Otsu thresholding is used in pre-processing stage to remove the noise from the CT lung lesion image such that the segmentation process can be done precisely.

B. lesion segmentation using improved toboggan algorithm

Improved toboggan algorithm helps to overcome the over segmentation caused by the conventional toboggan approach by using a new back-off iteration for calculating the local minima pixels. Multi-scale Gaussian convolution is also used which provides image gradient changes in different directions. By using improved toboggan method, the highlighted blood vessels and noise in the gradient image are moved to the lower value of the lung field and the lesion remains with the higher value. Thus, the lesion could be improved in the label image for the automatic seed point selection.

In this method initially, the seed points for the segmentation process are selected by performing an back-off iteration. The small regions of seed point with the same minimum gradient value are marked by the same label. The toboggan gradient stack is used which helps to store the local minima pixels. Each new local minimum pixel obtained from the gradient magnitude of the image will be compared with the existing elements of the stack.

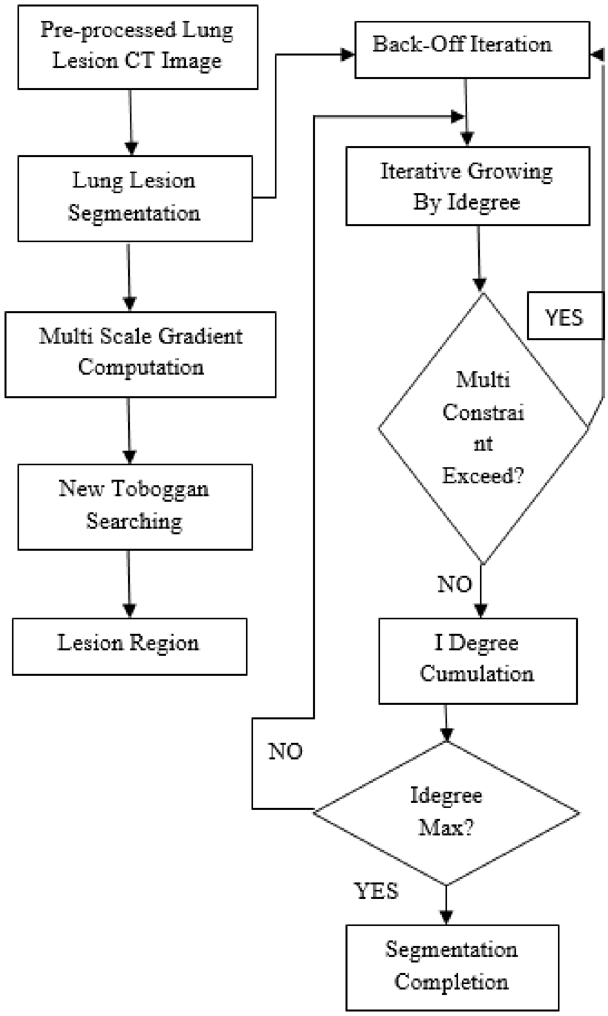

Fig.3: Lesion segmentation using improved toboggan algorithm

A value in the stack with the maximum similarity to the new local minimum would be marked as the original source pixel. Thus, the new minimum pixel value will be pushed into the stack and used to label the source pixel. By using distance constraint and growing degree constraint the iterative growing is done to select seed points. Thus, this approach successfully reduces the over segmentation [6]. The intensity of blood vessels which are close to the lung lesion are sometimes considered as part of the adjacent lesions and so lung lesion refining method is used to eliminate all incorrect vascularised regions and other tissues.

Lesion refining method provides more accurate lesion boundary detection by smoothening which improves the accuracy.

C. Feature Extraction

(i)Gray level co-occurrence matrix

A GLCM g[i,j] is defined by specifying displacement vector d=(dx,dy). GLCM Measures like, Entropy-Randomness of gray level distribution, Energy-uniformity

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of gray level in a Region of interest, Contrast-Measure of difference between gray levels of pixels and Homogeneity-Measure of similarity of texture of pixels. Assuming that the gray level appearing in each cell is quantized to Ng levels. Let lx = {1,2, ,Nx} be the horizontal spatial domain, ly = {1,2,. ,NY} be the vertical spatial domain, and G = {1,2, .*,Ng} be the set of Ng quantized gray levels. The set ly x lx is the set of declaration cells of the image ordered by their row-column designation. The image I can be represented as a function which assigns some gray level in G to pair of coordinates in ly x lx; I: ly x lx□G. These measures are arrays termed angular nearest-neighbour. To describe the Gray level spatial-dependence matrices the arrays must be highlighted by adjacent or nearest neighbour declaration cells. We consider a declaration cell with eight nearest-neighbour resolution.

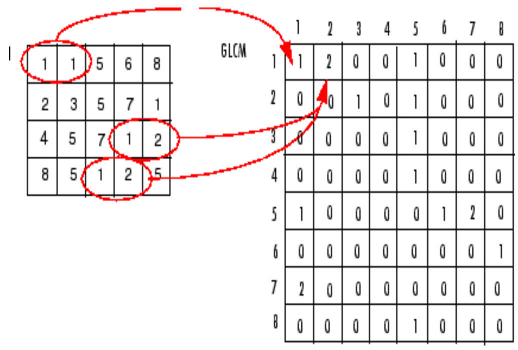

Fig.4: Processing of gray co-matrix to fill the values in the GLCM

It creates a gray-level co-occurrence matrix (GLCM) from image I. Gray co-matrix creates the GLCM by calculating how often a pixel value with gray-level value *i* occurs horizontally adjacent to a pixel value with the value *j*. Each element (*i*,*j*) in glcm specifies the number of times that the pixel with value *i* occurred horizontally adjacent to value *j*. If I is a binary image, which scales the image by two gray-levels. If I is an intensity of an image, gray co-matrix scales the image to eight gray-levels. Element (1,1) in the GLCM contains the value 1 because there is only one occurrence in the image where two, horizontally adjacent pixels have the values 1 and 1. Element (1,2) in the GLCM contains the value 2 because there are two occurrences in the image where two, horizontally adjacent pixels have the values 1 and 2. Gray co-matrix continue this processing to calculate all the values in the GLCM.

(ii) *Local Binary Pattern*

LBP is invariant to monotonic intensity changes of pixel values. Hence, it is robust to elucidation and contrast variations. LBP is the meticulous case of the Texture Spectrum model. It has been found to be a commanding feature for texture classification. It has further been determined that when LBP is combined with the Histogram of oriented gradients (HOG) descriptor, performance is improved considerably. The LBP feature vector, in its simplest form, is created in the following manner:

- Divide the examined window into cells.
- Each pixel in a cell is compared to the pixel at each of its 8 neighbours
- If the center pixel's value is greater than the neighbour's value, its represented by "0". Otherwise, represented as "1". This gives an 8-digit binary number.
- Then, the histogram is been computed over the cell.
- Then, normalize the histogram.
- This gives a feature vector for the entire image.

The LBP [38] code at *(x, y)* is calculated as follows:

$$LBP\ x, y = \sum_{B=0}^{B-1} S(Pb - Pc)\ 2^b\ ,$$

$$S(Z) = \begin{cases} 1, & z >= 0 \\ 0, & z < 0 \end{cases}$$

Where, *pc* is the pixel value at *(x, y)*, *pb* is the pixel value estimated pixel value using bilinear interpolation from neighbouring pixels in the *b*-th location on the circle of radius *R* around *pc* and *B* is the total number of neighbouring pixels. A 2*B*-bin histogram is been computed. In that some patterns occur more often than the others. The number of state transitions between 0 and 1 for them are at most two [24].those patterns are called uniform patterns and others are non uniform patterns. Each uniform pattern is given a bin and combining all non-uniform patterns into a single bin, the bin number is reduced. For example, if *B* = 8, it is reduced from 256 to 59.

(iii) *contourlet transform*

The contourlet transform is the one which is used to get smooth contours of images by using double filter bank structures. The contourlet transform provides fast execution based on a Laplacian pyramid breakdown followed by directional filterbanks. Here, it uses a double filter bank structure to get the smooth contours of images. In double filter bank, the Laplacian pyramid (LP) is used initially to capture the point discontinuities. If there is any point discontinuities then directional filter bank (DFB) is used to connect all those discontinuities into linear structures. The Laplacian pyramid (LP) breakdown

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produces only one band pass image that can avoid frequency scrambling and directional filter bank (DFB) allows only high frequency signals to pass through its directional sub bands. Thus, DFB with LP provides better multi scale decomposition and remove the low frequency. Therefore, image signals are passed through LP sub bands to get band pass signals and also pass signals through DFB to capture the directional information of the image. This double filter bank structure with the combination of LP and DFB is otherwise called as pyramid directional filter bank (PDFB)

(iv) Wavelet transform

Discrete wavelet transform generates useful subsets of frequency components (or) scales from region of interest. It is based on the fast fourier transformation. It creates high dimensional feature vector. So, dimensionality reduction is necessary and two methods are used for it. Feature selection and feature projection methods are used for dimensionality reduction. Wavelet transforms helps to represent the time-frequency illustration for continuous-time signals and so it is related to harmonic analysis. Discrete wavelet transforms uses discrete-time filter banks. These filter banks contains either finite impulse response (FIR) or infinite impulse response (IIR) filters. The continuous wavelet transform (CWT) are subjected to the uncertainty principle of Fourier analysis with respect to sampling theory [12].

In the region of interest, there are some occurrences in it, so it's difficult to assign concurrently an exact time and frequency response scale to that region of interest. The product of the uncertainties of time and frequency response of that region has a lower value. Thus, in the continuous wavelet transform scale of that region, such an occurrence marks an entire region in the time-scale plane, instead of just one point.

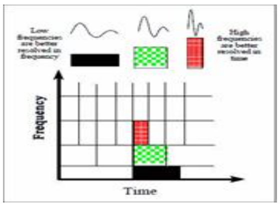

Fig.5: Wavelet Transform

Wavelets coefficients approximations aj and details dj through the discrete wavelet transform have a mean and variance that equals to, Mean is given by,

$$E(aj) = 2^{j/2(\mu 0)}$$

Variance is given by,

$$V(aj) = (\sum nh\text{^}2)\text{^}j\sigma 0\text{^}2$$

where μ0 and σ0 are the mean and the variance of the data, j is the scale of the wavelet transform, and h and g are scaling and wavelet filters, respectively.

Table.1: statistical measures by wavelet transform

FEATURES	NORMAL IMAGE	ABNORMAL IMAGE
MEAN	0.202	0.286
VARIANCE	0.342	2.348

D. Classification

(i) KNN classifier

KNN classifier is one of the most basic classifier of pattern recognition for classifying the features extracted. A feature extracted region is classified by a majority vote of its neighbours [31]. The classifiers by predicting nearest neighbour values classify the features extracted. The important issues involved in training this classifier are,

1. Validating 'K',
2. The type of distant metric used to classify

To make a prediction by using KNN classifier following steps is followed

1. Compute the distance of test samples with all training samples considered.
2. Find the k nearest vectors.
3. The number of selected nearest neighbour points should be much lesser than the original data points in a class
4. Arrange the distance measured in ascending order and choose the closest label.

In our proposed method, training phase and testing phase have been done with following stages:

Training phase:

1. Training images are placed in the folder.
2. Read the training sample
3. The KNN method is applied to extracted features which are taken as training samples and tuned for testing phase.

Testing phase:

1. Read the test images.
2. KNN is applied and the nearest neighbors are identified using the Euclidean distance function using the training data.
3. If the K neighbours have all the same labels its classification is stopped. Otherwise, compare distances between the K neighbours and construct the Euclidean distance matrix.

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4. Thus, KNN classification is done successfully and the output is displayed.

Euclidean distance, d = $\sqrt{\sum_{i=1}^{k}(x_i - y_i)^2}$

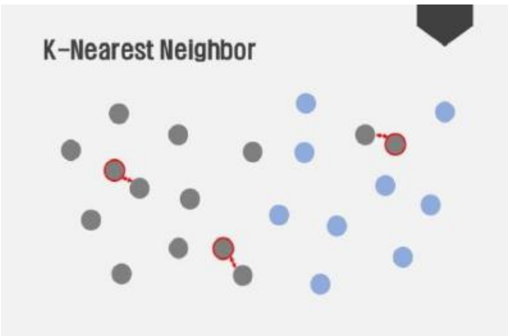


Fig.4: k-nearest neighbour searching

(ii) SVM classifier

Support vector machines are used to analyse the data for classification and regression analysis. It is done by supervised learning models[25]. SVM also performs non-linear classification efficiently. A support vector machine constructs a hyperplane which is used for classification..

The SVM classifier involves two stages. They are training and testing. The steps involved in it is as follows,

1. The trained samples are stored in a folder
2. The kernel function is defined based on trained feature vectors
3. It is used to measure the relative nearness of each test point to the data points
4. Thus, hyperplane is formed which helps to separate the normal and abnormal region
5. Thus, SVM classification is done successfully and its displayed using receiver operating curve

Fig.5 shows the SVM classifier with Hyperplane where H1 does not separate the classes, H2 does, but only with a small margin. H3 seperates them with the maximum margin.

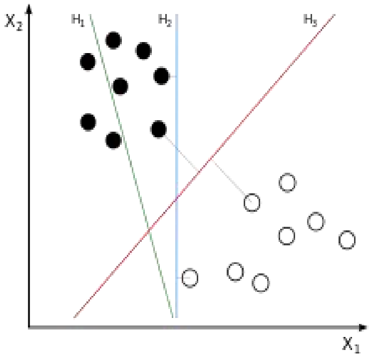


Fig.5: SVM Classifier with Hyperplane

III. RESULTS

A. Datasets

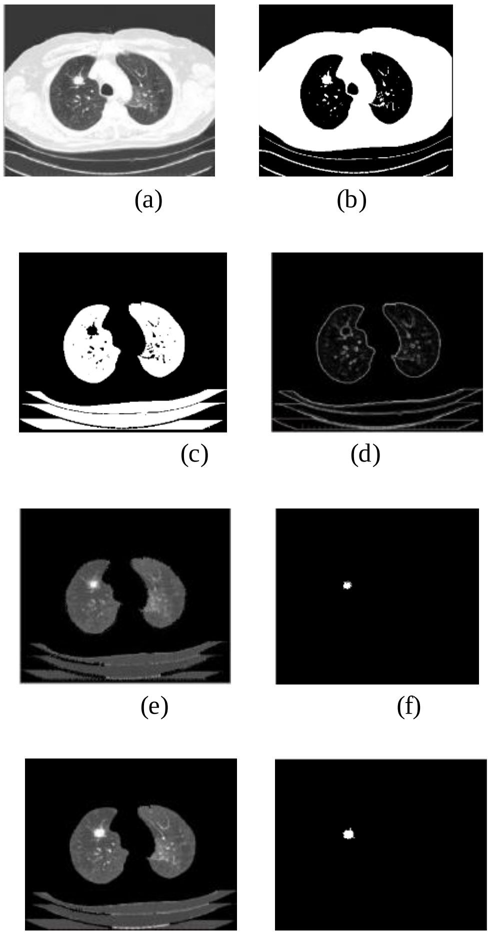
Publicly available and in-house acquired datasets are used to evaluate the performance of segmenting and classifying the lung lesion using CT image. The images have a slice thickness which ranges from 1.25 to 2.50 mm with a 0.70 mm × 0.70 mm resolution.

B. Human Interaction

In lung lesion automatic segmentation method using improved toboggan algorithm there is no human interaction for the initial seed point selection and also for further feature extraction and classification process.

C. Performance and Analysis of Proposed method

The output obtained for segmentation, feature extraction and classification of lesion is been shown here.



(a) (b)
(c) (d)
(e) (f)
(g) (h)

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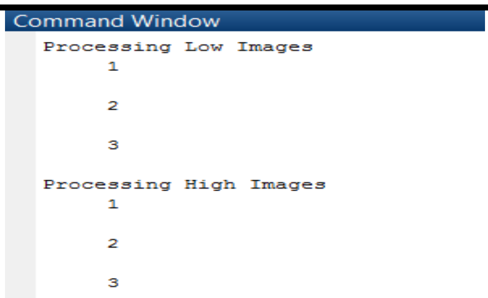
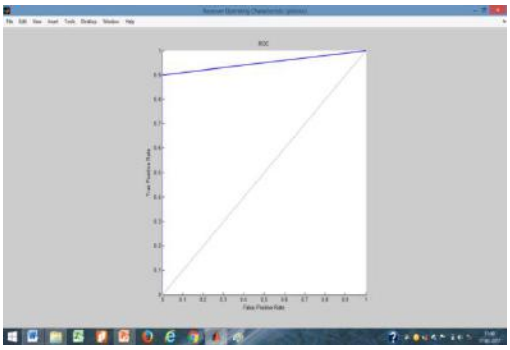
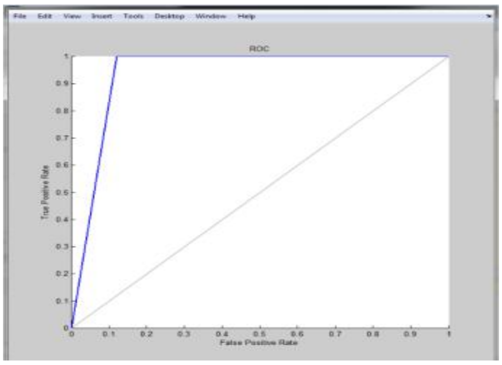


(i)



(j)



(k)

Fig .3: (a) input lung CT image, (b) Otsu threshold image, (c) noise removal image, (d) gradient image, (e) ROI based on original toboggan method, (f) output obtained based on original toboggan method, (g) ROI based on improved toboggan algorithm, (h) output obtained based on improved toboggan algorithm, (i) processing of feature extraction, (j) receiver operating curve for SVM classifier, (k) receiver operating curve for KNN classifier.

Table.2: Performance of Classifiers

S.NO	TYPE OF CLASSIFIER	ACCURACY
1	SVM	97.8%
2	KNN	82%

IV. DISCUSSION

The proposed method has an automatic lung lesion seed point(s) selection, lesion extraction lung lesion refinement stages followed by feature extraction and classification of lung lesion. In this method there is no human interaction. Feature extraction is done to the segmented image since a high degree of recognition is lacking for tissues connected to the adjacent lesion with similar intensity of pixels. Then, classification is done to classify the features extracted using SVM and KNN classifiers. Their performance has been compared. The limitation of our work is the sample size of patient population is less and also we could not include more image features in the training because of the limited training data. So, our future work will focus on increasing the size of our test samples and evaluate the performance

V. CONCLUSION

In this paper, an automatic, stable and quick-response automatic segmentation followed by feature extraction and classification has been tested for both public and clinical dataset. The initial seed points were first detected using an improved toboggan method for lesion segmentation. Then, the lesion features were extracted by using LBP, GLCM, wavelet, contourlet. Then, the classification is done finally using the SVM and KNN classifiers and their performance has been compared. The important component of this work is that it does not require human interactions for lesion seed point detection. Compared with the other segmentation methods this shows better accuracy and provides better results by classification.

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