Lung Cancer Detection using Modified Gabor Filter, Gradient Operators And Morphological Segmentation Tool

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Abstract— Lung Cancer is a disease of irregular cells multiplying and growing into a tumour. It's hard to believe, but lung cancer is the primary cause of cancer deaths among both women and men. Every year more people die of lung cancer than of colon, prostate and Breast cancers. Some important facts of lung cancer are Excluding Skin cancer, lung cancer is the second most common cancer in both women and men. Statistics from Indian Council of Medical Research (ICMR) recommend that lung cancer is fast turning into a plague in India. It is a high mortality cancer due to poor access to affordable health care and diagnosis at late stage. At the time of diagnosis only 15 percent of the cases of lung cancer are curable. Due to the nature of the disease patients with lung cancer present themselves for diagnosis at a much later stage than other cancers. Globally lung cancer accounts for 8.4% percent of all cancers in women and 14.5% in men. For lung cancer Smoking is the single largest contributor. Other causes are exposure to carcinogenic toxins like radon, asbestos, radiation and air pollutants. Exposure to women to smoke from the burning of charcoal for cooking is also a cause of lung cancer. About 20 percent we can reduce the risk of lung cancer by doing physical activities and exercise is known to improve lung function. In recent times, image processing measures are frequently used in a number of medical areas for enlargement of the image in preceding recognition and managing periods, where the instant aspect is really important to determine the abnormality problems in objective figures, mainly in a variety of malignancy tumours such as lung cancer, breast cancer etc.

Keywords— Lung Cancer, Modified Gabor filter, Gradient operators, Morphological segmentation tool.

I. INTRODUCTION

In initial stages it is vital to find the lung tumour with minimum time delay and give an improved solution to reduce the lung cancer. Detection of lung cancer consists of three stages like Image enhancement, feature extraction and Image segmentation. Research work aiming Image precision and superiority is the interior aspects of this research, picture superiority, growth as well as dimensions are depending on the development phase where small pre processing methods are used based on Modified Gabor filter (MGF) [1] within Gaussian policies for Image enhancement.

For extracting required features gradient operators are used. For segmentation stage Morphological segmentation tool used which consists of number of conceptual stages.

Several researchers worked on Image processing techniques for identification of lung cancer. For Image enhancement earlier researchers used kalman filters, Hessian Based filters but these methods have drawbacks like poor and non uniform response for images of varying sizes and varying contrast [2, 3]. Some of the researchers used interpolation methods which is complex and time taking [4].Other methods for enhancement are by using Discrete Cosine Transform (DCT), Fast Fourier Transform (FFT) , Auto Enhancement Algorithm (AEA)[5,6] ,Discrete Wavelet Transform(DWT)[7] all these methods are time consuming and less accurate. To overcome these drawbacks a modified Gabor filter is used for Image Enhancement. For feature extraction earlier researchers employed methods like Binarization [8], Gray level Co-occurrence matrix (GLCM)[9] and Masking approach[10]. Depending on these methods, conclusion is prepared whether the lung has nodule or not but these methods have drawbacks like visibility of the geometric and intensity based statistical features are not clear and physical measurements i.e. shape measurements are not clearly visible that will decide the appearance of the object.

To overcome these drawbacks gradient operators are used for feature extraction which consist of modulated Intensity gradient and Texture gradient. Segmentation algorithms like watershed algorithm, Thresholding approach are having many drawbacks like [11, 12]

- Local structures of images such as boundaries and flat areas are appeared differently

- Image segmentation is a low level procedure in image analysis. So, segmentation algorithms partition images using low level concepts of images such as texture, pixel colour, pixel intensity.

- Another drawback is the lack of exact criteria for evaluating segmentation algorithms.

To overcome above drawbacks texture watershed segmentation method is used for segmentation.

In this research work X-ray lung images and CT scan lung images are collected from various hospitals and they are analyzed by using Image processing techniques. This new method gives promising results compare to other methods. Hence, the proposed method can be applied to detect the cancer in early stage and it is helpful to medical practitioners, medical equipments manufacturing industries.

II. PROPOSED METHOD

A new method is proposed for the identification of lung cancer which involves MGF, gradient operators and Morphological segmentation tool and this proposed method gives promising results compared to other methods. The block diagram of proposed method is shown in figure 1.
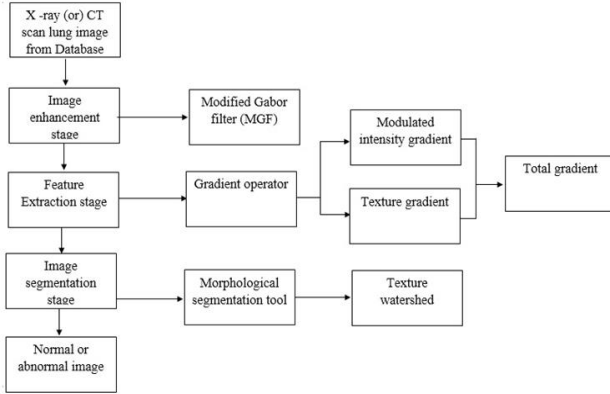

Fig1. Proposed method of Lung Cancer Detection System.

III. IMPLEMENTATION

3.1. Enhancement of Image using MGF

The Gabor filter [1] is applied to 2D X-ray lung images for the analysis and they related directly to Gabor wavelets. Image enhancement is the initial and important stage in lung cancer detection; it takes X-ray lung image as the input from the database. In Gabor filter the number of rotations and dilations are present and these are time taking .This results in blurred image which is not appropriate for next stages in image processing. To overcome this drawback a MGF approach has been implemented. The modifications are as follows.

- At the initial stage spatial aspect ratio is not considered, this leads to reduction of distortion of image at the beginning.
- The spatial aspect ratio is considered at the kernel size directly.
- This helps to get clear images and significant change in Peak Signal to Noise ratio values.
- The above steps provide improved overall response [13].

Mathematical model of MGF [13] is as follows:

$$f(p,q:\sigma,\theta,\psi,\lambda) = \exp\left[-\frac{1}{2}\left(\frac{c_1^2+d_1^2}{\sigma^2}\right)\left(\cos\left(2\pi\frac{c_1}{\lambda}\right)+\psi\right)+j\left(\sin\left(2\pi\frac{d_1}{\lambda}\right)+\psi\right)\right]$$

Where

$$c_1 = 2\frac{c\cos(\theta)+d\sin(\theta)}{n-1}$$ and

$$d_1 = 2\frac{-c\sin(\theta)+d\cos(\theta)}{n-1}$$

Where n – size of the kernel

$$M(c,d) = I(c,d) * f(p,q,\sigma,\psi,\theta,\lambda)$$

Where $M(c,d) -$ Modified Gabor Filter image

Algorithm for MGF

- Read the image from database for lung cancer detection

- Using bilinear transformation method decimates the image by 2
- Find nXn Gabor filter kernel for the defined parameters
- Apply MGF to the image for the theta in steps of 45^0
- For different values of theta add all the magnitude of the images.
- Interpolation is done to the sum image by a factor 2 using bilinear transformation

3.2. Feature extraction using Gradient operators

The output of Enhancement is given to the feature extraction. Here features of the lungs will be extracted by using gradient operators.

3.2.1. Modulated intensity gradient based segmentation

Modulated intensity gradient method involves convolving image with the gradient operators. High value of gradient magnitude is the points with sudden change in the intensity of two areas and these are called edge pixels. To form closed boundaries these points linked together. For this segmentation method operators like Laplace, Sobel and canny operators are used. In Digital image processing edge detection is very useful. Out of numerous methods, in this research work canny operator is used instead of sobel operator because Sobel operator is easy, but it is not accurate in noisy environment but canny operator or canny edge detector has many advantages such as smoothing effect to eliminate the noise there in the images, through non-maximal suppression improves the signal to noise ratio. The only disadvantage is canny operator is time taking because use of complex algorithms.

3.2.2. Texture based segmentation

The term texture is difficult to define, but it represents aspects of surface pattern such as colour, regularity, coarseness and directionality. Texture is a phenomenon that is widespread, hard to define and easy to recognise. Features of the texture can be used for segmentation. Addition of Modulated intensity and Texture gradient gives the total gradient and it gives the information related to the texture and intensity gradient by considering all perceptual edges in the image. For feature extraction Multidimensional dual tree Complex Wavelet transform (CWT) [14] is used and it is based on a computationally competent, independent Filter Bank (FB). By using complex Perfect Reconstruction (PR) FB acting as a Hilbert transformer splits each output of the FB into its negative and positive frequency decompositions but this method has basic constraint. This method can be derived straight from any real two channel high pass FB $i_0(n)$ or low pass FB with filters $i_1(n)$

$$i_p(n) = j^n i_0(n) \quad and \quad i_n(n) = j^n i_1(n)$$

Where $i_p(n) \ and \ i_n(n)$ are the positive and negative frequency components and this leads to the rotation in the Z plane by 90^0
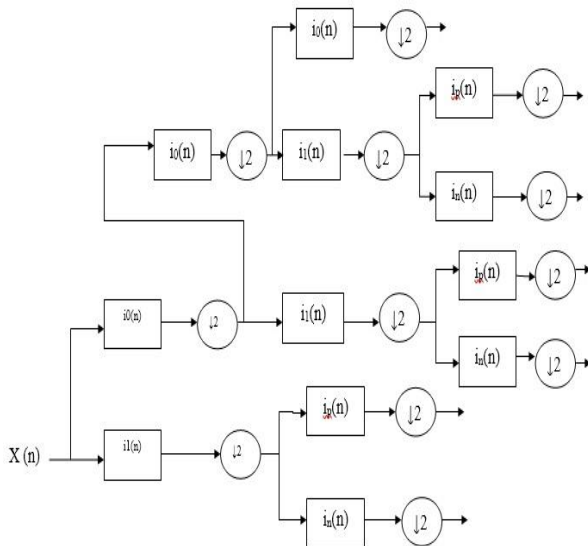

Fig (2): Basic FB Structure with positive and negative filters.

The basic FB structure as shown in figure 2, in this structure if high pass FB and low pass FB satisfy the PR conditions then a positive and negative filter components also satisfies the PR conditions, and then the FB will separate the positive and negative frequency components of a signal which are analytic. Here the input data rate of the sub band signals is equal to the total data rate. This FB structure has a basic limitation in the overall frequency of each channel.

Using Z transform, the wavelet coefficients are considered in the first stage
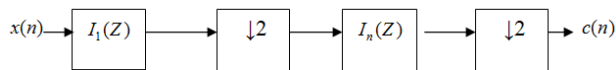
By using the nobel operators, the wavelet coefficients are equal to
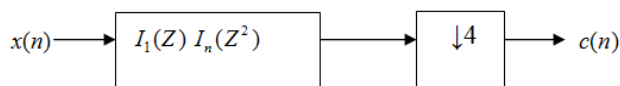
Therefore the total frequency response is obtained as shown below

$$I_{tot}(z) = I_1(Z) \, I_n(Z^2)$$

In Fourier domain the frequency response is given by

$$I_{tot}(e^{j\omega}) = I_1(e^{j\omega}) I_n(e^{j2\omega})$$

To overcome the limitation Hilbert transform is applied to the image then the wavelet transform is applied to original data and Hilbert transformed data and these two are combined to obtain CWT. Here at all scales single Hilbert transform is applied to the coefficients; therefore it cannot be applied for all scales at a time. To overcome this dual tree implementation is implemented in 1998. Kingsbury introduced Dual tree CWT and it is applied to the wavelet transform and it consist of two real DWTs, gives the real part and imaginary part of the transform. The dual tree CWT is very easy to apply because there is no data flow between the two real DWTs

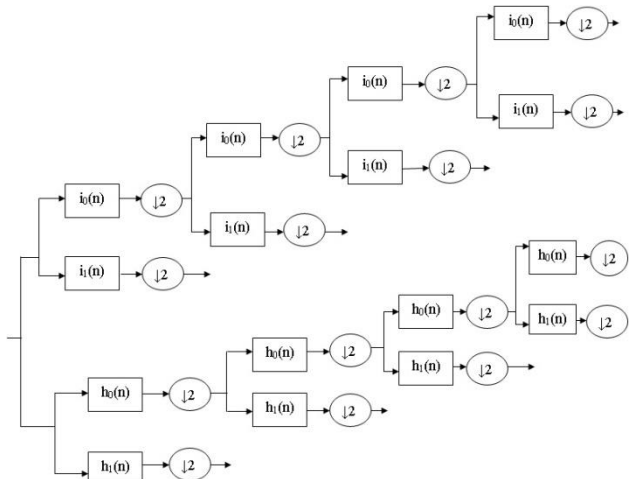The real part of the transform and Imaginary part of the transform are shown in figures 3 and 4.

Fig 3: Real part of the transform used to implement CWT
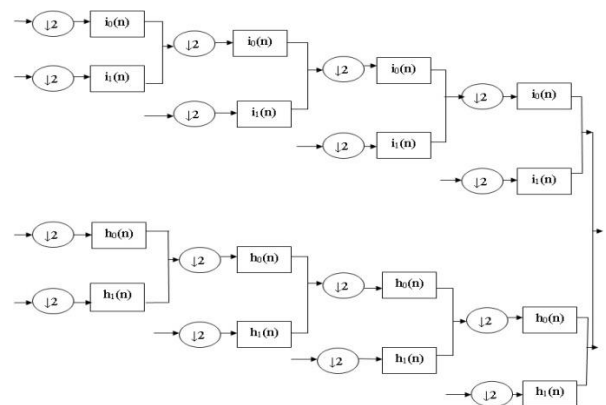

Fig 4: Imaginary part of the transform used to implement CWT

Let $h_0(n), h_1(n)$ denote the low pass or high pass filters for the lower FB and let $i_0(n), i_1(n)$ denote the low pass or high pass filters for the upper FB. Here the filters are considered so that the complex wavelet $\psi(t) = \psi_i(t) + j\psi_h(t)$ is analytic .where $\psi_h(t)$ denote the real wavelet in the transform. For the design of CWT no complex arithmetic operations are necessary anyhow the filters are real themselves as shown in figure3 and the inverse operation is shown in figure 4. Final image is obtained by adding the two real signals and average is taken. The using the figure 3 and figure 4 alone original signal x(n) can be recovered.

Let us consider the two real DWTs defined by the square matrices M_i and M_h

$$M = \begin{bmatrix} M_i \\ M_h \end{bmatrix}$$

Here the real signal is represented by p, then $Z_i = M_i p$ denotes the real part and $Z_h = M_h p$ denotes the imaginary part. Final output is obtained by adding real and imaginary part with complex coefficient and is given by $Z_i + jZ_h$

An inverse of M is

$$M^{-1} = \frac{1}{2}\left[M_i^{-1}\ M_h^{-1}\right],$$

And verify

$$M^{-1}.M = \frac{1}{2}\left[M_i^{-1}\ M_h^{-1}\right].\begin{bmatrix}M_i \\ M_h\end{bmatrix} = \frac{1}{2}[I + I] = I$$

Forward transform (M) and inverse transform (M^{-1}) is given by

$$M = \frac{1}{\sqrt{2}}\begin{bmatrix}M_i \\ M_h\end{bmatrix}\ and\ M^{-1} = \frac{1}{\sqrt{2}}\left[M_i^{-1}.\ M_h^{-1}\right]$$

(1)

If the two real DWTs are orthogonal, then the transpose of M_i is inverse $M_i^t.M_t = I$ and transpose of M^h is inverse $M_t.M = I$. The real and imaginary parts are given by equation (1).The complex coefficients can be calculated by using the formula

$$M_c = \frac{1}{2}\begin{bmatrix}I & jI \\ I & -jI\end{bmatrix}.\begin{bmatrix}M_i \\ M_h\end{bmatrix}$$

(2)

$$M_c^{-1} = \frac{1}{2}\left[M_i^{-1}.M_h^{-1}\right].\begin{bmatrix}I & I \\ -jI & jI\end{bmatrix}$$

(3)

The complex sum and difference matrix in (2) is unitary

$$\frac{1}{\sqrt{2}}\begin{bmatrix}I & jI \\ I & -jI\end{bmatrix}.\frac{1}{\sqrt{2}}\begin{bmatrix}I & I \\ -jI & jI\end{bmatrix} = I$$

Here dual tree CWT satisfies $M_c^*.M_c = I,$ where $*$ denotes conjugate transpose if the two DWTs are orthogonal. If

$$\begin{bmatrix}a \\ b\end{bmatrix} = M_c.p$$

When the input signal p is complex, then $a \neq b^*$ in this case a and b need to be calculated and when p is real, then $a = b^*$ in this case a need to be calculated. When the dual tree CWT is given as input to the real signal, the output will be real and imaginary, they are stored as shown in (1) .when it is applied to complex signal the output will be complex, and it is represented by (2). Here parseval's theorem is used by dual tree CWT and in (1) $\frac{1}{\sqrt{2}}$ factor is included.

$$\sum_{j,n}\left(\left|d_i(j,n)\right|^2 + \left|d_h(j,n)\right|^2\right) = \sum_n |x(n)|^2$$

Algorithm for feature extraction using Gradient operators
- Finding the Dual tree CWT.
- Finding the real and imaginary part i.e. complex magnitude
- Applying median filtering.
- Next applying the Morphological erosion for reconstruction purpose.
- Using the interpolation function find the texture gradient.
- By using the Gaussian gradient estimation function, find the modulation intensity gradient.
- Add the texture gradient image and modulation intensity gradient image to get the total gradient image.

IV. IMAGE SEGMENTATION USING MORPHOLOGICAL SEGMENTATION TOOL (I.E. TEXTURE WATERSHED)

The output of feature extraction is given to the segmentation. In this stage the objects are separated from the background, as well as from each other. Initially watershed algorithm was implemented to find the water level and water basis from the satellite images. Segmentation means process of partitioning a binary image or gray scale image into multiple segments i.e. set of pixels. In image processing one of the difficult and important parameter is segmentation of non trivial images and it plays important role in automated analysis procedures. The watershed transform [15] also called as texture watershed is a morphological segmentation tool; it is applied to the gray scale image the boundary corresponds to peaks, while the regions correspond to local troughs in the gradient.

Let us consider a scalar function $v(m,n)$ with $(m,n) \in Q^2$ representing an image I. For this image Morphological gradient is calculated and is given by

$$\delta_{Ev} = (v \oplus E) - (v - E)$$

Where $(v \oplus E)$ - Elementary dilation of v

$(v - E)$ - Elementary erosion of v

E - structuring element

The Morphological based laplacian is defined by

$$\Delta_{Ev} = (v \oplus E) - 2v + (v - E)$$

It allows us to differentiate influence areas of maxima as well as minima. The condition for minima is areas with $\Delta_{Ev} > 0$ while for maxima areas with $\Delta_{Ev} < 0$. For designing the Morphological based filters consider

$$\Delta_{Ev} = 0$$ it allows us to understand and analyse locations of the edges and represent an important properties of the Morphological filters. If the pixel is located within the influence area of a maximum apply erosion to the image similarly if the pixels located within the influence area of minima apply dilation to the image.

Consider M i.e. minimum is set of pixels p of ε associated with the catchment basin $G(s)$. Here water drop falls at p and finally reaches M. When the catchment basin is applied to the image the output is related to the influence areas of its minima and the watershed will be represented by the lines that separate catchment basins. For calculating watershed there are several algorithms are there, here watershed is based on immersion analogy process. Consider $t_{\min}$ is the smallest value taken by v and $t_{\max}$ is the largest value taken by v. Let threshold be defined by $T_t = \{ p \in \varepsilon, v(p) \le t \}$ at level t. Next recursion is defined with t i.e. gray level starting from $t_{\min}$ ending at $t_{\max}$.

Let be the union of set of basins be X_t defined at level t and related component at level $t+1$. These two levels having the threshold set T_{t+1} we will get either an extension of a basin in X_t or a new minimum. By finding $\min_t$ and by considering the union of all minima at level t, watershed is defined using immersion process

$$X_{t_{\min}} = T_{t_{\min}}$$

$$\forall t \in [t_{\min}, t_{\max} - 1], X_{t+1} = \min_{t+1} \cup IW_{T_{t+1}}(X_t)$$

$$IW_{T_{t+1}} = \bigcup_{j=1}^{k} jW_{T_{t+1}}(X_{t_i})$$

With

Where k - minima of image I and $jW_{T_{t+1}}(X_{t_i})$ is defined by

$$jW_\varepsilon(Y_j) = \{ W \in \varepsilon, \forall k \ne j, d_\varepsilon(W, Y_j) \le d_\varepsilon(W, Y_k)$$

At the end of the method the watershed transform of I i.e. image is the complement of $X_{t_{\max}}$ in ε.

Algorithm for Image segmentation using Texture watershed Algorithm

- Image reconstruction using normal image (i.e. Binary image or Gray scale image).
- Find Maxima of the image (first perform the erosion and dilation next find the maxima and superimposing with original image).
- Using Distance transformation formula find the distance between the lines (i.e. minima to minima or maxima to maxima).
- To apply watershed first find maxima and minima. Usually maxima is used for watershed
- Finally the segmented image is superimposing with the original image.

V. ANALYSIS OF RESULTS

5.1. Enhancement of Image using MGF

The enhancement details are shown in Figure 5. Here the X-ray and CT scan lung image are collected from various Hospitals and maintained a data base. An X-ray lung image (normal and abnormal image) is selected form the database.

The output of this stage is considered as the input to the next stage. Figure 5(a) represents the normal X-ray lung image and Figure 5(b) represents the enhanced lung image using MGF. Figure 5(c) shows the abnormal lung image and Figure 5(d) shows the enhanced lung image for abnormal image.
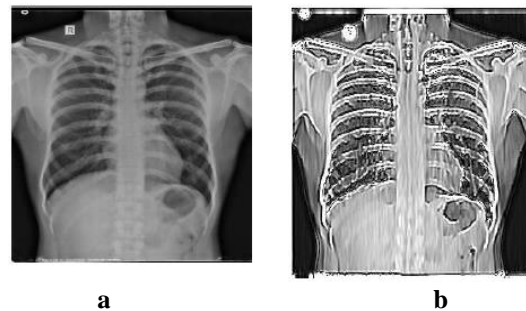

a   **b**
Fig.5. Enhancement of image using MGF a) normal lung X-ray image b) Enhanced image by MGF for normal X-ray lung image
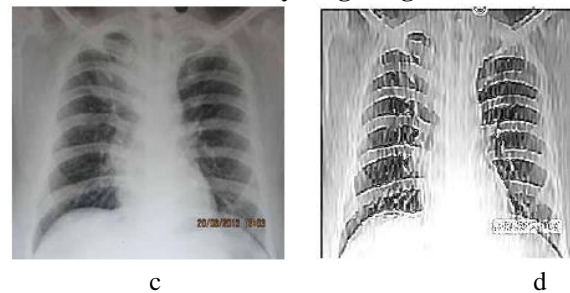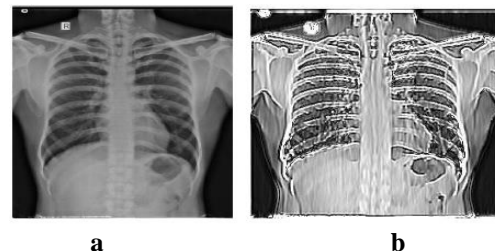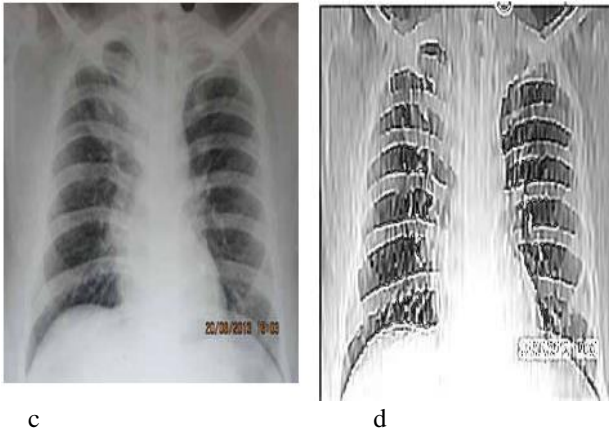

c   **d**
Fig.5. Image enhancement using MGF c) abnormal X-ray lung image d) enhanced image by MGF for abnormal X-ray lung image

5.2 Feature extraction using Gradient operators

This phase takes enhanced normal or abnormal X-ray lung image generated by enhancement stage. Here the features are extracted by using texture gradient and modulated intensity gradient. Total gradient is obtained by adding these two gradients. Figure 6(a) shows the enhanced X-ray lung image under normal condition. Figure 6(b) and 6(c) indicates the modulated intensity gradient image and texture gradient image for Figure 6(a). Figure 6(d) indicates the total gradient image for figure 6(a). Figure 7(a) shows the enhanced X-ray lung image under abnormal condition. Figure 7(b) and 7(c) indicates the modulated intensity gradient image and texture gradient image for Figure 7(a). Figure 7(d) indicates the total gradient image for figure 7(a).

a   **b**
Fig.5. Enhancement of image using MGF a) normal lung X-ray image b) Enhanced image by MGF for normal X-ray lung image
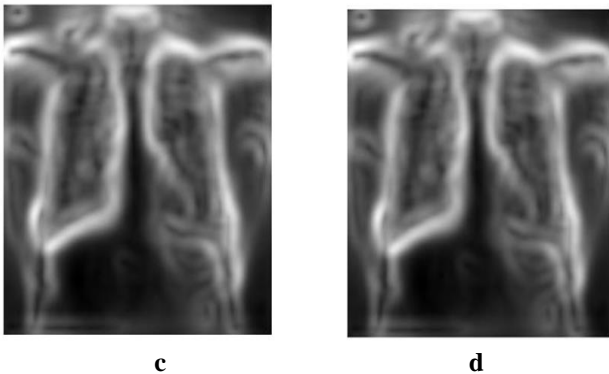
c   d

Fig.5.Image enhancement using MGF c) abnormal X-ray lung image d) enhanced image by MGF for abnormal X-ray lung image
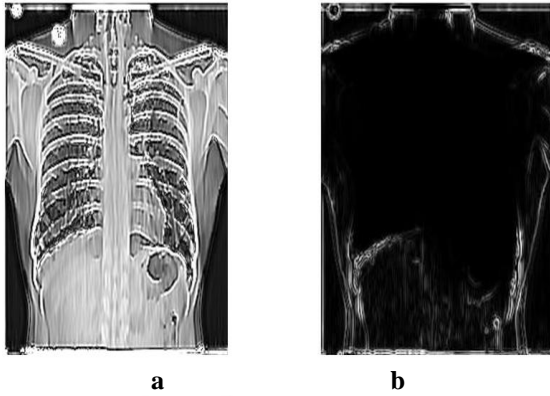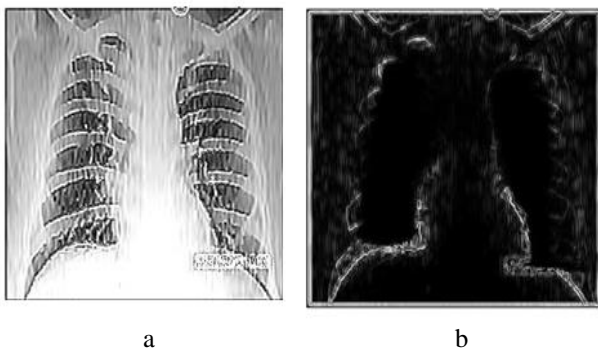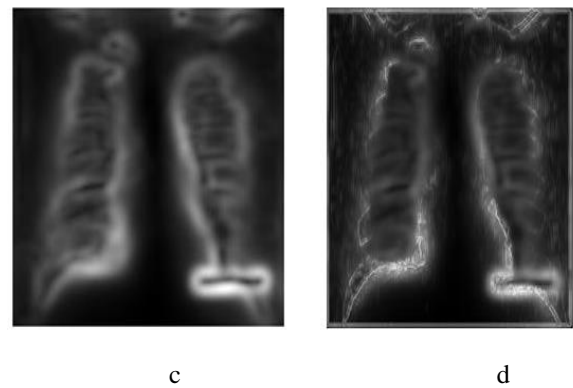

a   b

c   d

Fig.6.Feature extraction using gradient operators for normal X-ray lung image a) Enhanced lung image by MGF b) Modulated intensity gradient image c) Texture gradient image d) Total gradient image.


a   b

c   d

Fig.7.Feature extraction using gradient operators for abnormal X-ray lung image a) Enhanced lung image by MGF b) Modulated gradient image c) Texture gradient image d) Total gradient image.

5.3. Image Segmentation using Morphological segmentation tool

In this stage the objects i.e. nodules are separated from the background, as well as from each other. This stage takes output of the feature extraction i.e. total gradient image. Image segmentation stage compares the total gradient image and the original image, calculates the maxima, minima and colour difference between the two images. Figure 8(a) indicates the total gradient image for normal lung X-ray image Figure 8(b) shows the segmented image using texture watershed for normal lung X-ray image. Figure 8(c) indicates the total gradient image for abnormal lung image Figure 8(d) shows the segmented image using texture watershed for abnormal lung image.
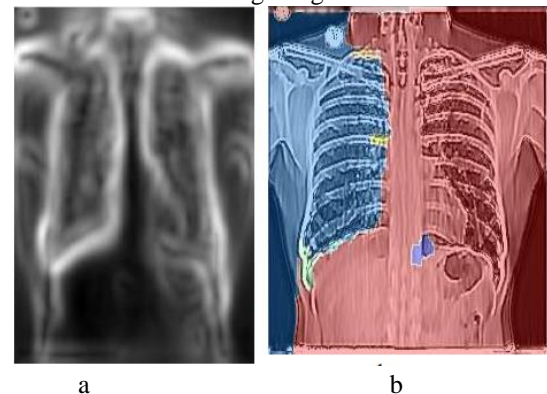
a   b
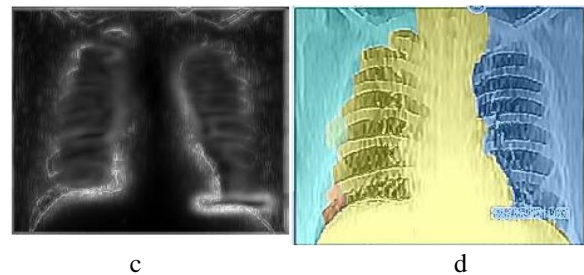
c   d

Fig.8. segmentation using gradient operators for normal X-ray lung image a) Total gradient image b) segmented image. Image segmentation using gradient operators for abnormal lung X-ray image c) Total gradient image d) segmented image.

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In the next stage segmented image is converted binary image and count the number of black pixels, number of white pixels in normal and abnormal lung image and apply back propagation neural networks to find the presence of Cancer cells in the lungs.

VI. CONCLUSION

By using the MGF, gradient operators and morphological segmentation tool an efficient lung cancer detection system is developed. The modifications in Gabor filter (MGF) include the consideration of spatial aspect ratio at the kernel size directly instead of at the initial stage. This modification results in reduction of distortion of the image at the beginning and helps to obtain clear images at the initial stage. Applying dual tree CWT on the gradient operators for extracting features it has many advantages like smoothing effect to remove noise present in the images through non-maximal suppression and improves the PSNR. Here real part and imaginary parts of the image are added to get the total gradient image. For the image segmentation watershed transform is used i.e. texture watershed, in this stage maxima is calculated (i.e. lowest deepest point) to apply watershed. Finally the segmented image is superimposing with the original image, depending on the segmented image the presence of lung cancer is identified. For analysis a normal X-ray lung image and abnormal lung image is selected from the database and results are found to be fruitful. The presence of the cancer cells is decided by the next stage by using neural networks. Hence, this proposed method of lung cancer detection using MGF, gradient operators and morphological segmentation tool helps in early detection of cancerous cells present in lungs.

Note: The same process is applied for CT scan lung images and the results are shown below

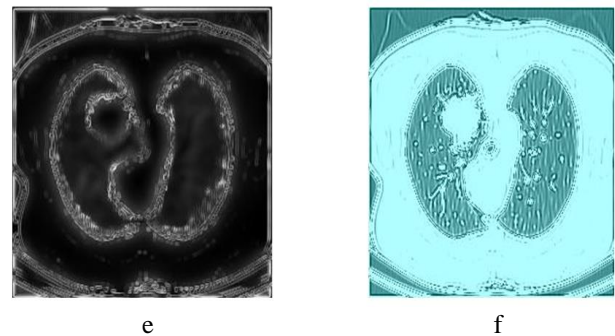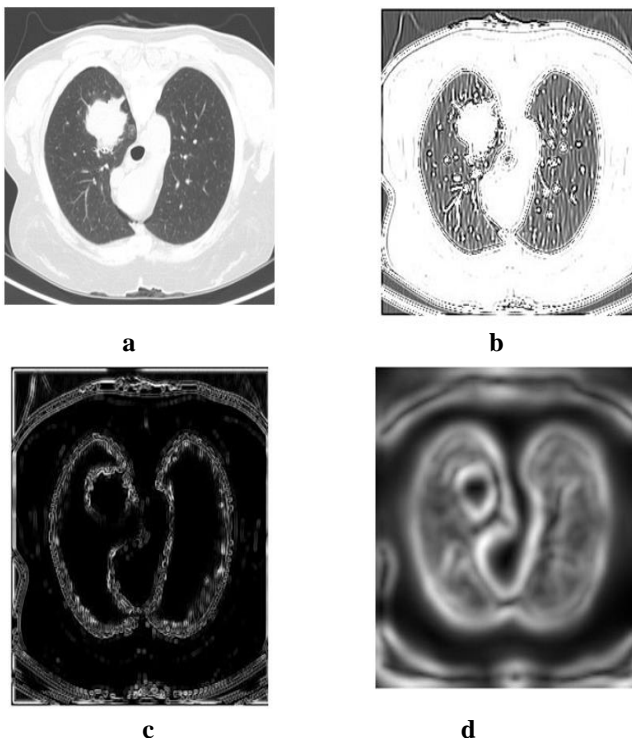a

b

c

d

e

f

Fig.9. a) input CT scan lung image b) Enhanced CT scan image using MGF c) Modulated intensity gradient CT scan image d) texture gradient CT scan image e) Total gradient CT scan image f) Segmented CT scan image.

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