A New Strategy to Detect Lung Cancer on CT Images

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Abstract - *Lung cancer has a very low level of healing, with effective detection, the survival of lung cancer can be highly appreciated. In the early stages, lung cancer detection plays an important role in human health. Computed tomography (CT) images, which provide an electronic density of tissues, are widely applied in radiotherapy planning. Based on CT technology, the proposed system consists of a few steps like photo acquisition, preprocessing, feature extraction and categorization. At the preprocessing stage, RGB images are converted to grayscale images, used for reducing the Gabor filter, the Adaptive thresholding method transforms CT scan images into binary images, and the REGIONPROPS function is used for the right body, from the binary image to the region. Feature extraction platforms, such as contrast, correlation, energy, home genetics, are characterized by a static method called Gray Level Co-occurrence Matrix (GLCM). In the final stage, features integrated with Support vector machines (SVM) and Back Propagation Neural Network (BPNN) are used to detect lung cancer from CT images. The performance of the proposed approach shows the accuracy of 96.32% accuracy in SVM and 83.07% accuracy in BPNN.*

Key Words: lung cancer detection; image processing; adaptive threshold; GLCM; BPNN; SVM

1. INTRODUCTION

WHO has reported (WHO 2018), cancer, accounting for 8.8 million deaths, a leading cause of global death. Compared with other cancers, such as breast cancer, brain cancer and prostate cancer, lung cancer, which is responsible for 1.76 million deaths, the highest mortality rates.

The main reason for non-accidental death is cancer. Lung cancer is one of the most serious human problems in the world. The death rate of lung disease is the death of all other types of cancer worldwide in men and women. Studying cancer at early stages is very difficult. Many PC-aided systems are designed to detect lung cancer at its premature stage. Image enhancement and classification can be a great work, especially when performing the medical field. During this paper, various strategies for detecting lung cancer disorders have been discussed and whether it is modest or deadly. Computer tomography (CT) may be more effective than X-rays for lung cancer detection and detection.

2. LITERATURE REVIEW

There are many existing strategies for diagnosing lung cancer, such as computed tomography (CT), chest radiography (X-rays), magnetic resonance imaging (MRI scan) and sputum Cyrillic [1] [2]. B. Sahiner et.al., [3] There are two stages in the paper-printing process. In the first phase, the sound and film artificial can be removed using the median filter. In the second stage, the decay structure material is applied thrice; But each time the structure decreases the size of one of the components. The unexpected ribcage part has been removed from the results obtained. This preprocessing also maintains a tumour, reducing segmentation problems on. [4] The lung area classifies extinction methods in two categories, rule-based and pixel-classified sections. [5] City creates an image processing algorithm for the detection of lung cancer in images, and initially, the rate of lung cancer survival rates increased by 14% to 49%. [6] Used in the sense that the algorithm for image segmentation, in this study, features were extracted by GLCM, and classified by BPNN. [7] To reduce false positive rates, Computed Tomography (CT) images represent an automated computer-aided detection (CAD) system to detect a large lung sample from surrounding Chest radiographs. Artificial intelligent algorithms are considered as powerful tools for background and categorization [8], such as BPNN and SVM, these models are generally applied to analysis due to fast learning advantages, self-adaptations, and strong tolerance of errors. These features make it possible that models based on artificial intelligent algorithms can meet the image processing technology, perform better in cancer detection [9].

On this paper, we have proposed two models based on SVM and BPNN, respectively, using it with the features used to identify lung cancer from city images. In addition, the strength of these two models has been compared to lung cancer detection.

3. METHODOLOGY

Focus on the method to obtain a more accurate result. In the proposed method, it is increasing in contrast to the input image via the pre-processing method. The first one is done by converting the input image to a grayscale image. The images have been corrected with the Gabor filter to enhance image contrast. Frequency and adaptation presentations of Gabor filters are similar to human visual systems, and they have been considered strongly for constructive representation and discrimination [1].

In image processing, the division is a more important part, ideally enhanced images in this section are divided into two or more sub-segments, which will be easy to represent images for more elements of the element. Partitioning objects can be used for recognition, speed, or binding boundaries between binary systems. Image splitting target is related to clusters of pixels, individual surfaces, objects, or natural elements of the object in relevant image areas. We mainly follow a method like a threshold. Feature extraction, the process of comparing a pixel is to offer this paper. The first phase of the collection of City images (normal and unusual) from database found at IMBA Home (Via-LCAP public access) begins. [1]

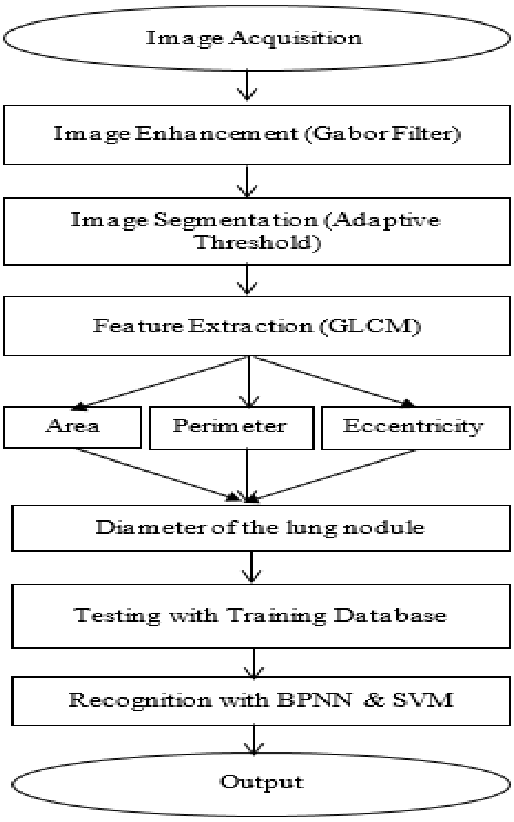

Figure 1: Methodology

3.1 Image Acquisition

An image is artificial which limits visual perception, which usually has an object with a real object or a person's appearance. The first step of pre-processing consists of the human lung image to create a visible representation of some organs and tissues. There are many medical images capturing methods such as tactile imaging, magnetic resonance imaging (MRI), computed tomography (CT), positron emission tomography (PET), etc. Single-photon emission math tomography (Spect), etc. the images collected from ELCAP public lung image database which is released December 20, 2003. The whole-lung dataset consists of 50 CT scans obtained in a single breath hold with a 1.25 mm slice thickness. DICOM (Digital Imaging and Communication in Medicine) has become a standard for medical imaging.
The acquired image is in raw form. A lot of noise in the acquired image is observed. To improve contrast, transparency, background sound separation, it needs to be pre-processed. Therefore, different techniques like enhancement, the required form is developed from images.

3.2 Image Enhancement

The image begins with image enhancement in the pre-processing phase. The goal of image enhancement is to provide better input for information about the information contained in the image or to the modernization of knowledge or other automated image processing techniques for the human audience. Image enhancement strategies can be divided into two broad categories: Spatial Domain Method and Frequency Domain Process [10].

1) Spatial domain techniques- which operate directly on pixels.
2) Frequency domain techniques- which operate on the Fourier transform of an image.

Different image enhancement strategies can be identified as the Spatial Domain Method and Frequency Domain Process. This includes polishing and light removal, laziness etc. There are many ways to improve the image, but the Gabor filter is considered suitable for both CT and MRI images. In the image enhancement stage, we have used the following Gabor filter strategies.

Gabor filter: Gabor filter is a linear filter which is defined by a coherent function multiply by a Gaussian function replicating the reflection. Due to the quality of the convoluted property, the transit of the Fourier transit of Gabor filters is impulse transcript to the Pharmacological function and Fourier transformation of the Fourier transformation of Gaussian Function [11]. It basically analyzes whether there is a concrete frequency content in the concrete directions of the local region of the area of analysis or analysis. A set of Gabor filters with different frequencies and adaptations may be helpful for an element of effective features from an image. Isolated domain, given by 2D Gabor filter,

$$Gc[i,j] = Be^{\wedge}((i^{\wedge}2+j^{\wedge}2)/(2\mu^{\wedge}2))\cos(2\pi f(i\cos\beta+j\sin\beta))...(1)$$
$$Gc[i,j] = Ce^{\wedge}((i^{\wedge}2+j^{\wedge}2)/(2\mu^{\wedge}2))\sin(2\pi f(i\cos\beta+j\sin\beta))...(2)$$

Where B and C determine the normalization reason. 2-D Gabor filters are rich in image processing, especially texture analysis and category features. F defines the fitted frequency for the texture. By varying β, we can look for a specific texture based texture. By varying μ, we support the basis of the region or size of the image being analyzed.

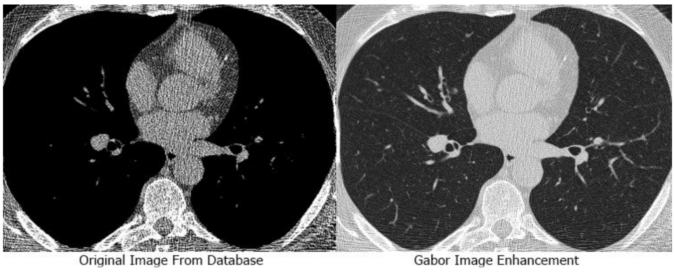

Figure 2: Original Image to Gabor Image

3.4 Image Segmentation:

Image segmentation helps make the presentation of such an image more meaningful and easier to analyze. Image segmentation objects and borders are allocated. This is the process of determining the label of pixels per image, such as labelled pixels sharing specific visual properties [12]. Image splitting result is a set of segments that covers a set of contours that are fully taken from the entire image or image. Each pixel in a region's image is significantly different from some of the featured or notable properties, such as color, intensity, or texture, related to similar features. [13] In this study, we have used the adaptive threshold image segmentation method:

Adaptive threshold: Adaptive Thresholding usually takes a grayscale or color image as input and, in a simple implementation, represents a binary image segmentation output. For each pixel of the image, a threshold has been calculated. If the pixel value is below the threshold, it is set to the background value, otherwise, it estimates the forum value. In adaptive thresholding, different threshold values for different local areas are used.

There are two main ways to find threshold: (i) Chow and Kaneko [14] methods and (ii) Local thresholding. The idea behind both methods is that the smaller image can have almost identical illuminations in the region, thus making it more suitable for thresholding. Chow and Kaneko segment an image into a row overlapping subcontinent and find out the best threshold for each sub-continent by investigating its histogram. The results of threshold submissions are separated for every single pixel. The error of this method is computational and is therefore not suitable for real-time applications.

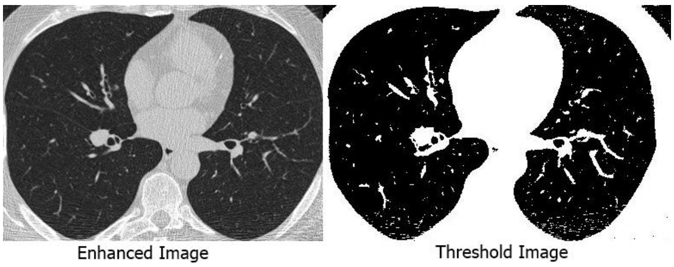

Figure 3: Gabor to threshold

3.5 Body Region extraction

In this study, the body area of a lung city image was found using MATLAB's Image Processing Toolbox's REGIONPROPS function. The binary image of the adaptive threshold was considered as input on REGIONPROPS, and a decreasing set of features was selected to describe the binary image. The selected features were 'Area', 'Boundingbox' and 'Field Image'. The 'area' was a scalar, indicating the total number of pixels in each part of the image. The lower edge of the 'Boundingbox' volume has the coordinate and the minimum area rectangle in the area with length and width. The 'FilledImage' binary image filling the logical matrix which was the same size in the same region. After counting three properties, the indicator related to the area related to the greater area was obtained, then the minimum encoding rectangles can be taken to crop the noise-free image and the area of the body used as a template to extract the fill image.

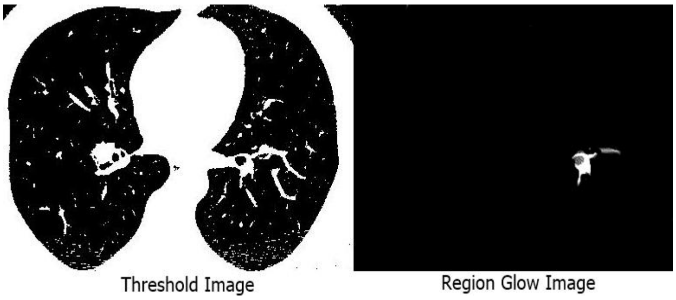

Figure 4: Threshold to Region Glow

4. Feature Extraction

For extracting feature using the Gray-level co-occurrence Matrix (GLCM) to represent a set of features to reduces the misclassification of the glaucoma image. GLCM describes how many coordinates of pixel brightness values in an image illustration. GLCM represents the combined frequency of all pairs of gray levels i and j divided by a distance in the direction of nodules. GLCM Characteristics of basic character areas, perimeter, and Eccentricity this scale is measured in [15]. The GLCM, proposed by Haralick [20], was utilized as the main tool for image texture analysis in this study. A binary representation of the shape object expanded. Size features refer to the geometric properties of an object, and the external boundary is used to calculate these characteristics. The area, perimeter, and circularity are big features that we count in our method. Extra shape features can provide powerful information for the category of images. The properties of shape vary for different types of a tumour. Size is calculated by using the image region attached to the image. Boundary pixel circumference and area are counted. The measurement is calculated using the area and the circumference. The formulas used to calculate size features are given in table 1.

E_d (i,j) is the boundary pixels of the region.
$E_d(i,j)$ = 1, if connectivity of b(i,j) == 2; 0, else
b(i,j) = 1, f(i,j) ≥ T_h or 0, f(i,j) < T_h

$T_h = \frac{1}{2}$ [max f(i,j) – min f(i,j)]

Table -1: GLCM Calculating Table

Sl. No	Shape Feature	Formula
1.	Perimeter (P)	$\sum_{i,j=0}^{M,N} E_d\,(i,j)$
2.	Area (A)	$\sum_{i,j=0}^{M,N} b(i,j)$
3.	Eccentricity (E)	$\frac{4\pi A}{p^2}$

5. CLASSIFICATION

5.1 Back Propagation Neural Network

BPNN is one of the most widely used artificial nerve networks (ANN), it has been widely applied in many cases (21). Three layers of level BPNN detection models including an input level I, a hidden layer H, and an output level O (Fig. 5) are used for training. Each layer consists of various neurons and layers interconnected by the set of related weights. Neurons have received input from input from primary input or interconnection neuron and output. In the process of learning BPNN, the error compression technique was used to adjust interconnected weight to obtain the desired output for given input.

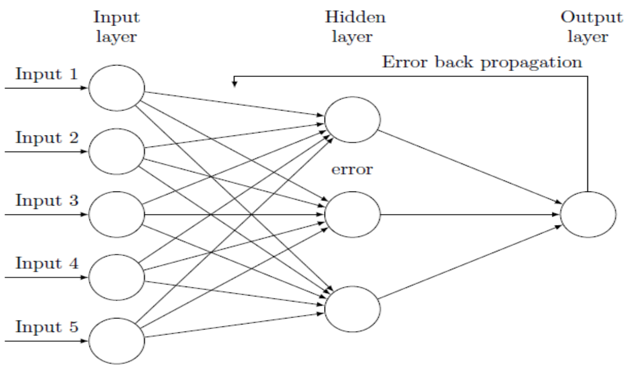

Figure 5: BPNN process

To compute the output from each unit, input connected to a unit was multiplied by its corresponding weight, the results were summed, a bias was added to the summed value, then an activation function was applied to it. Therefore, the output O_j was defined as:

$$O_j = f\left(\sum_i w_{ij} O_i + \theta_i\right) \quad \text{.....................(3)}$$

where $f()$ was activation function, w_{ij} was the weight of the connection from unit i in the previous layer to unit j, O_i was the output of unit i from the previous layer; and θ_j was the bias of the unit.

The error was propagated backward to update the weights and biases. For a unit j in the output layer, the error Err_j was defined as:

$$Err_j = O_j(1 - O_j)(T_j - O_j) \quad \text{....................(4)}$$

Where w_{ik} was the actual output of unit j, and T_j was the known target value of the given training tuples. The error of a hidden layer unit j was defined as

$$Err_j = O_j(1 - O_j)\sum_k Err_k w_{jk} \quad \text{................(5)}$$

Where w_{jk} was the weight of the connection from unit j to a unit k in the next layer, and Err_k was the error of unit k. Weights and Biases were updated by the following equations:

$$w_{ij} = w_{ij} + (l) Err_i O_i \quad \text{.........................(6)}$$

$$\theta_i = \theta_i + (l) Err_i \quad \text{..............................(7)}$$

where l was the learning rate, a constant typically had a value between 0.0 and 1.0.

On this paper, the hidden layers and the output layer were activation functions, hypoglycemic tangent, sigmoid transfer function and linear transfer functions. Train function increases gradient and the proportion of educated educators ('traingdx') Gradient descendants.

5.2 Support Vector Machine (SVM)

Support vectors are a learning model that is supervised by the relevant learning algorithm, which can analyze and analyze patterns for analysis. Basic SVM input takes a set of data and for every given input, predicts that the two classes form the input, it creates a non-probable binary linear classification. SVM uses a kernel function that maps the given information to a different location. Separation can be made with very complex boundaries. Various types of kernel functions, including perennials, rbf, quadrangle, multi-layer perceptron (mlp). Each kernel creates its own parameter γ, σ, and so on. Figure 6 shows the highest margin hyper plane. The main hyper-plane algorithm is a way to create non-linear classification using the most margin hyper-plan kernel techniques.

6. RESULT AND DISCUSSION

To test the proposed technique, CT images are obtained from the IMBA Home (Via-LCAP public access) image database consortium (LIDC) dataset, which offers the opportunity to do research. This test information consists of 2740 lung images. The figure of this 2740 lungs are passed on to the proposed system. Then the rules of determination are generated from those images and these rules are sent to classification for the teaching process. After learning, the lungs picture is passed on to the proposed system. Then the proposed procedure will be processed through its processing steps and finally it will detect whether lung cancer is cancerous or not. Table 2 listed the performance of BPNN and SVM models on the prediction set. It could be seen that BPNN model has a better performance than SVM model on identification lung cancer from CT images. BPNN model, the Accuracy was 96.32%, the Error rate was just 3.68%, the Sensitivity was 96.71%, and the Specificity was 96.09%. While for SVM model, the Accuracy was 83.07%, the Error rate was 16.93%, the Sensitivity was 65.64%, the Specificity was 92.36%, it suggested that BPNN was more suitable and effective for lung cancer detection from CT images.

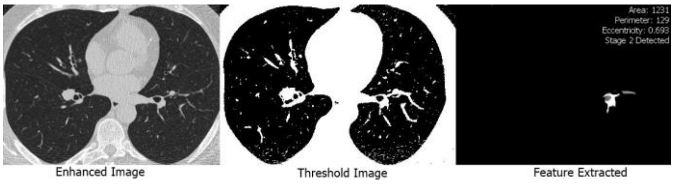

Figure 6: Detected image

Table:2 **Performance of BPNN and SVM**

Classifier	Accuracy	Error rate	Sensitivity	Specificity
BPNN	96.32%	3.68%	96.71%	96.71%
SVM	83.07 %	16.93 %	65.64 %	92.36 %

7. CONCLUSION

In this study, it was shown that lung cancer can be detected in early stage of city images using image processing technology and artificial intelligent algorithms. In our proposed system, first, the City images were extended to remove sounds using the Gobo Filter. Second, the predefined images are converted into binary images by following the thresholding method. Thirdly, physical areas are expelled from binary images (in contrast, correlation, energy and unity) using GLCM in body areas. Finally, BPNN and SVM, together with features, are used to establish lung cancer detection models. The results showed that the BPL model and SVM model estimates were respectively 96.32% and 83.07% for lung cancer detection at Forecast Set (2740 Figures), it has been decided that the SVM-based model is a promising tool for recognition of lung cancer at the initial stage, above The theory proves validation. In the future, we will apply deeper nerve network tactics to lung cancer detection problems and look for new systems for pulmonary needle detection.

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