A COMPUTER AIDED DIAGNOSIS SYSTEM FOR DETECTION OF LUNG CANCER NODULES USING EXTREME LEARNING MACHINE

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ABSTRACT

The Computer Aided Diagnosing (CAD) system is proposed in this paper for detection of lung cancer form the analysis of computed tomography (CT) images of chest. To produce a successful Computer Aided Diagnosis system, several problems has to be resolved. Segmentation is the first problem to be considered which helps in generation of candidate region for detecting cancer nodules. The second problem is identification of affected nodules from all the candidate nodules. Initially, the basic image processing techniques such as Bit-Plane Slicing, Erosion, Median Filter, Dilation, Outlining, Lung Border Extraction and Flood-Fill algorithms are applied to the CT scan image in order to detect the lung region. Then the segmentation algorithm is applied in order to detect the cancer nodules from the extracted lung image. In this paper, Fuzzy Possibilistic C Mean (FPCM) algorithm is used for segmentation because of its accuracy. After segmentation, rule based technique is applied to classify the cancer nodules. Finally, a set of diagnosis rules are generated from the extracted features. From these rules, the occurrences of cancer nodules are identified clearly. The learning is performed with the help of Extreme Learning Machine (ELM) because of its better classification. For experimentation of the proposed technique, the CT images are collected from reputed hospital. The proposed system can be able to detect the false positive nodules accurately.

Keywords - Computer Aided Diagnosis (CAD); Extreme Learning Machine (ELM); Nodule; Segmentation.

1. INTRODUCTION

The most familiar cancer that occurs usually for men and women is lung cancer. According to the report submitted by the American Cancer Society in 2003, lung cancer would report for about 13% of all cancer diagnoses and 28% for all cancer deaths. The survival rate for lung cancer analyzed in 5 years is just 15 %. If the disease is identified while it is still localized, this rate increases to 49%. However, only 15% of diagnosed lung cancers are at this early stage. The survival rate for the cancer patient can be increased by detecting the occurrence of cancer in earlier stages. Early detection can be attained in a population screening; the most common screenings for lung cancer make use of chest projection radiography, or low-radiation dose Computer Tomography (CT) scans [9]. It has been revealed in the Early Lung Cancer Action Project that low dose CT is more valuable than conventional chest X-ray for the detection of pulmonary nodules [16].

The difficulties for detecting lung nodules in radiographs are threefold:

- Nodule sizes will vary widely: Commonly a nodule diameter can take any value between a few millimeters up to several centimeters.
- Nodules exhibit a large variation in density – and hence visibility on a radiograph – (some nodules are only slightly denser than the surrounding lung tissue, while the densest ones are calcified).
- As nodules can appear anywhere in the lung field, they can be obscured by ribs, the mediastinum and structures beneath the diaphragm, resulting in a large variation of contrast to the background.

To overcome these problems, the author proposed a Computer Aided Diagnosing (CAD) [10] system for detection of lung nodules [8]. The lung cancer detection system is shown in figure 1. This paper initially apply the different image processing techniques such as Bit-Plane Slicing, Erosion, Median Filter, Dilation, Outlining, Lung Border Extraction and Flood-Fill algorithms for extraction of lung region. Then for segmentation Fuzzy Possibilistic C Mean (FPCM) algorithm is used and for learning and classification Extreme Learning Machine (ELM) is used.

2. RELATED WORK

Yamomoto et al., [1, 17] proposed image processing for computer-aided diagnosis of lung cancer by CT (LSCT). This paper presents the image processing method for computer-aided diagnosis of lung cancer by CT (LSCT). LSCT is the recently developed mobile-type CT scanner for the mass screening of lung cancer. In this novel LSCT system, one important difficulty is the increase of image information to about 30 slices per person from 1 X-ray film. To overcome these problems, the author tried to minimize the image information significantly to be displayed for the doctor, by image processing algorithms.

Yeny Yim et al., [2] stated about Hybrid lung segmentation in chest CT images [11] for computer-aided diagnosis. The author proposes an automatic segmentation technique for accurately identifying lung surfaces in chest CT images. The proposed technique consists of three steps. Initially, lungs and airways are extracted by an inverse seeded region growing and connected component labeling. Next, trachea and large airways are delineated from the lungs by three-dimensional region growing. Then, accurate lung region borders are acquired by subtracting the result of the second step from that of the first step. The proposed technique has been applied to 10 patient datasets with lung cancer or pulmonary embolism. Experimental results indicate that the segmentation method extracts lung surfaces automatically and accurately.

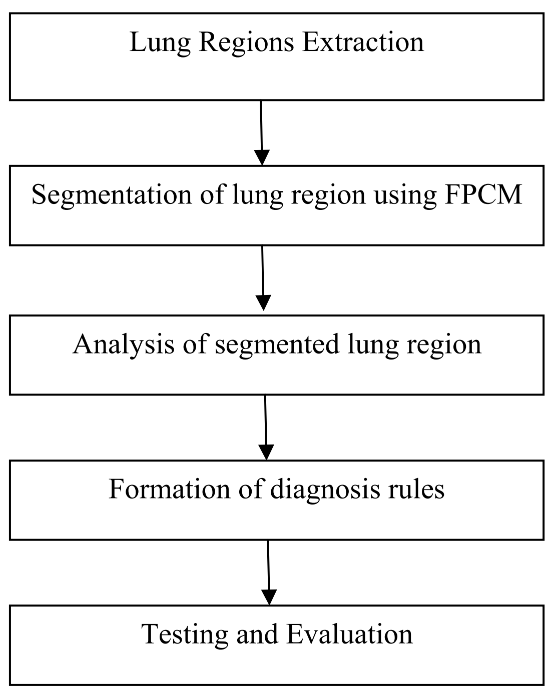

Figure 1. The Lung Cancer Detection System

Penedo et al., [3] put fourth Computer-aided diagnosis: a neural-network-based approach to lung nodule detection. In this paper, the authors have provided a computer-aided diagnosis system based on two-level artificial neural network (ANN) architecture. This technique was trained, tested, and evaluated in particular on the problem of detecting lung cancer nodules found on digitized chest radiographs. The initial ANN carries out the detection of suspicious regions in a low-resolution image. The input supplied to the second ANN is the curvature peaks computed for all pixels in every suspicious region. This is determined from the fact that small tumors possess and identifiable signature in curvature-peak feature space, where curvature is the local curvature of the image data when viewed as a relief map. The result of this network is thresholded at a selected level of significance to give a positive detection. Tests are carried out using 60 radiographs taken from a routine clinic with 90 real nodules and 288 simulated nodules. This paper employed free-response receiver operating characteristics method with the mean number of false positives (FP's) and the sensitivity as performance indexes to evaluate all the simulation results. The grouping of the two networks provide results of 89%-96% sensitivity and 5-7 FP's/image, depending on the size of the nodules [12].

Kanazawa et al., [4] described Computer aided diagnosis system for lung cancer based on helical CT images. In this paper, the author describes a computer assisted automatic diagnosis system for lung cancer that detects tumor candidates at an early stage from helical computerized topographic (CT) images. This mechanization of the process decreases the time complexity and increases the diagnosis confidence. The proposed algorithm consists of an analysis part and a diagnosis part. In the analysis part, this paper extracts the lung and pulmonary blood vessel regions and analyzes the features of these regions using image processing techniques. In the diagnosis part, this paper defines diagnosis rules based on these features, and detect tumor candidates using these rules. The author has applied the proposed algorithm to 450 patient's data for mass screening. The experimental results indicate that the proposed algorithm detected lung cancer candidates successfully.

Yamamoto et al., [5] explained Computer aided diagnosis system with functions to assist comparative reading for lung cancer based on helical CT image. The author have reported that a prototype computer-aided diagnosis (CAD) system [14] to automatically detect suspicious regions from chest CT images had been presented, and the CT screening system used was a TCT-900 super helix of the Toshiba Corporation. In this paper, the author proposes a new and automatic technique for an early diagnosis of lung cancer based on a CAD system in which all the CT images are read. In addition, the CAD system is equipped with functions to automatically detect suspicious regions from chest CT images, and to assist the comparative reading in retrospect. The min purpose of the CAD system are a slice matching algorithm for comparison of each slice image of the present and past CT scans, and an interface to display some features of the suspicious regions. The experimental results show that this CAD system can work effectively.

Cheran et al., [6] given Computer aided diagnosis for lung CT using artificial life models. This paper introduces a novel computer assisted detection method for lung cancer from CT images. The proposed technique is based on different algorithms like: 3D region growing, active contour and shape models, centre of maximal balls but it can be said that at the core of this approach are the biological models of ants also known as artificial life models. In the initial step of the algorithm the images are undergoing a 3D region growing for identifying the ribcage. Once the ribcage is recognized an active contour is used in order to build a confined area for the incoming ants that are deployed to make clean and accurate reconstruction of the bronchial and vascular tree. Then the branches of the recently reconstructed trees are checked to see whether they include nodules or not by using active shape models and to also to see if there are any nodules attached to the pleura of the lungs (centre of maximal balls). The next process is to eliminate the trees in order to offer a cleaner algorithm for localizing the nodules which is achieved by applying snakes and dot enhancement algorithms.

3. METHODOLOGY

3.1 Lung Region Extraction

The initial stage of the proposed Computer Aided Diagnosing (CAD) [7, 13] techniques is the extraction of lung region from the CT scan image. The basic image processing techniques are utilized for this purpose. The methods and steps involved in the extraction of lung region from CT image are shown in figure 2. The image processing techniques applied in the proposed technique are Bit-Plane Slicing, Erosion, Median Filter, Dilation, Outlining, Lung Border Extraction and Flood-Fill algorithms. Usually, the CT chest image not only contains the lung region, it also contains background, heart, liver and other organs areas.

The main aim of this lung region extraction process is to detect the lung region and regions of interest (ROIs) from the CT scan image. The first step in lung region extraction is application of bit plane slicing algorithm to the CT scan image. The different binary slices will be resulted from this algorithm. The best suitable slice with better accuracy and sharpness is chosen for the further enhancement of lung region. The next is application of

Erosion algorithm which enhances the sliced image by reducing the noise from the image. Then dilation and median filters are applied to the enhanced image for further improvement of the image from other distortion. Outlining algorithm is then applied to determine the outline of the regions from the obtained from noise reduced images. The lung region border is then obtained by applying the lung border extraction technique.

Finally, flood fill algorithm is applied to fill the obtained lung border with the lung region. After applying these algorithms, the lung region is extracted from the CT scan image. This obtained lung region is further used for segmentation in order to detect the cancer nodule.

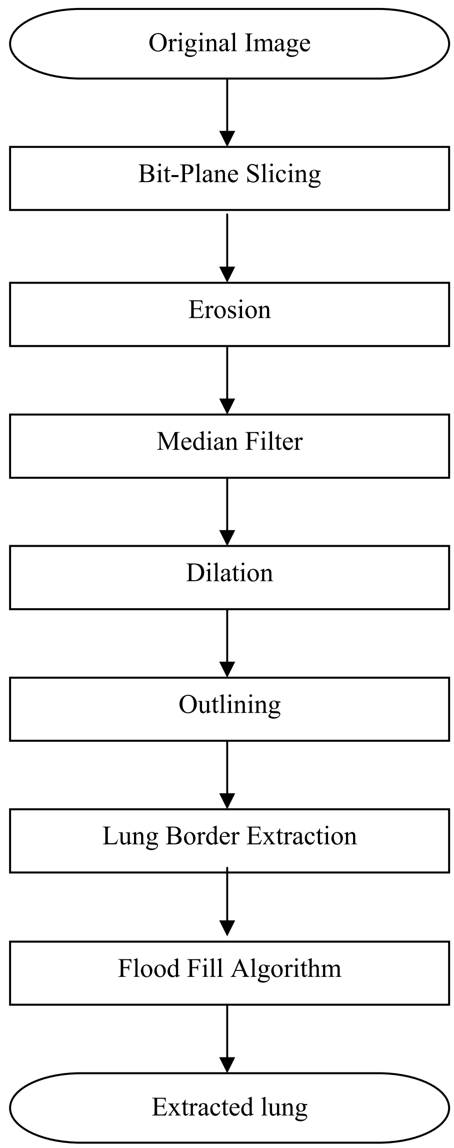

Figure 2. The proposed lung regions extraction method.

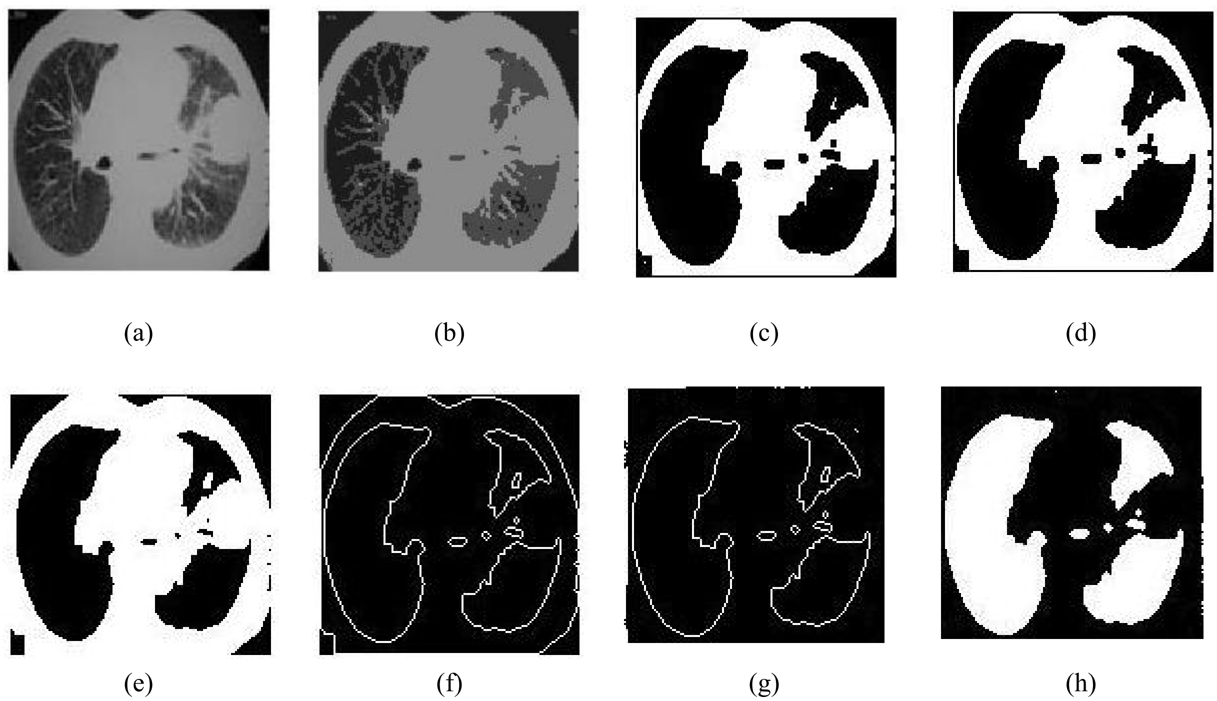

Figure 3. Lung regions extraction algorithm: a. original CT image, b. bit-plane-2, c. erosion, d. median filter, e. dilation, f. outlining, g. lung region borders, and h. extracted lung.

Figure 3 shows the application of different image processing techniques for the extraction of lung region from the CT scan image. The lung region obtained finally is shown in figure 3 (h).

3.2 Lung Regions Segmentation

After the lung region is detected, the next process is segmentation of lung region in order to find the cancer nodules. This step will identify the region of interest (ROIs) which helps in determining the cancer region. In this paper, Fuzzy Possibilistic C Mean (FPCM) is implemented for segmentation.

3.2.1 Fuzzy Possibilistic C Mean (FPCM)

FPCM is a clustering algorithm that combines the characteristics of both fuzzy and possibilistic c-means. Memberships and typicalities are important for the correct feature of data substructure in clustering problem. Thus, an objective function in the FPCM depending on both memberships and typicalities can be shown as:

$$J_{FPCM}(U,T,V) = \sum_{i=1}^{c}\sum_{j=1}^{n}(u_{ij}^{m} + t^{n})d?\,x_j, v_i)$$

with the following constraints:

$$\sum_{i=1}^{c}\mu_{ij} = 1, \forall j \in \{1, \ldots, n\}$$

$$\sum_{j=1}^{n}t_{ij} = 1, \forall i \in \{1, \ldots, c\}$$

A solution of the objective function can be obtained via an iterative process where the degrees of membership, typicality and the cluster centers are update via:

$$u_{ij} = [\sum_{k=1}^{c}(\frac{d?\,x_j, v_i}{d?\,x_j, v_k})^{2/(m-1)}]^{-1}, 1 \le i \le c, 1 \le j \le n$$

$$t_{ij} = [\sum_{k=1}^{n} (\frac{d?\, x_j, v_i}{d?\, x_j, v_k})^{2/(n-1)}]^{-1}, 1 \leq i \leq c, 1 \leq j \leq n$$

$$v_i = \frac{\sum_{k=1}^{n}(u_{ik}^m + t_{ik}^n)x_k}{\sum_{k=1}^{n}(u_{ik}^m + t_{ik}^n)}, 1 \leq i \leq c$$

FPCM produces memberships and possibilities simultaneously, along with the usual point prototypes or cluster centers for each cluster. FPCM is a hybridization of possibilistic c-means (PCM) and fuzzy c-means (FCM) that often avoids various problems. After the segmentation is performed to the lung region, the feature extraction and cancer diagnosis can be performed with the segmented image.

3.3 Features Extraction and Formulation of Diagnostic Rules

After the segmentation is performed on lung region, the features can be obtained from it and the diagnosis rule can be designed to exactly detect the cancer nodules in the lungs. This diagnosis rules can eliminate the false detection of cancer nodules resulted in segmentation and provides better diagnosis.

3.3.1 Feature Extraction

The features that are used in this paper in order to generate diagnosis rules are:

- Area of the candidate region
- The Maximum Drawable Circle (MDC) inside the candidate region
- Mean intensity value of the candidate region

i. Area of the candidate region

This feature can be used here in order to

- Eliminate isolated pixels.
- Eliminate very small candidate object.

With the help of this feature, the detected regions that do not have the chance to form cancer nodule are detected and can be eliminated. This helps in reducing the processing in further steps and also reduces the time taken by further steps.

ii. The Maximum Drawable Circle (MDC)

This feature is used to indicate the candidate regions with its maximum drawable circle (MDC). All the pixels inside the candidate region is considered as center point for drawing the circle. The obtained circle within the region is taken for consideration. Initially radius of the circle is chosen as one pixel and then the radius is incremented by one pixel every time until no circle can be drawn with that radius. Maximum drawable circle helps in the diagnostic procedure to remove more and more false positive cancerous candidates.

iii. Mean intensity value of the candidate region

In this feature, the mean intensity value for the candidate region is calculated which helps in rejecting the further regions which does not indicate cancer nodule. The mean intensity value indicates the average intensity value of all the pixels that belong to the same region and is calculated using the formula:

$$Mean(j) = \frac{\sum_{i=1}^{n} Intensity(i)}{n}$$

where j characterizes the region index and ranges from 1 to the total number of candidate regions in the whole image. Intensity (i) indicates the CT intensity value of pixel i, and i ranges from 1 to n, where n is the total number of pixels belonging to region j.

3.1.2 Formulation of Diagnostic Rules

After the necessary features are extracted, the following diagnosis rules can be applied to detect the occurrence of cancer nodule. There are three rules which are involved are as follows:
Rule 1: Initially the threshold value T1 is set for area of region. If the area of candidate region exceeds the threshold value, then it is eliminated for further consideration. This rule will helps in reducing the steps and time necessary for the upcoming steps.

Rule 2: In this rule maximum drawable circle (MDC) is considered. The threshold T2 is defined for value of maximum drawable circle (MDC). If the radius of the drawable circle for the candidate region is less than the threshold T2, then that is region is considered as non cancerous nodule and is eliminated for further consideration. Applying this rule has the effect of rejecting large number of vessels, which in general have a thin oblong, or line shape.

Rule 3: In this, the rage of value T3 and T4 are set as threshold for the mean intensity value of candidate region. Then the mean intensity values for the candidate regions are calculated. If the mean intensity value of candidate region goes below minimum threshold or goes beyond maximum threshold, then that region is assumed as non cancerous region.

By implementing all the above rules, the maximum of regions which does not considered as cancerous nodules are eliminated. The remaining candidate regions are considered as cancerous regions. This CAD system helps in neglecting all the false positive cancer regions and helps in detecting the cancer regions more accurately. These rules can be passed to the Extreme learning machine (ELM) in order to detect the cancer nodules for the supplied lung image.

3.4 Extreme Learning Machine

Extreme learning machine (ELM) meant for single hidden layer feed-forward neural Networks (SLFNs) [15] will randomly selected the input weights and analytically determines the output weights of SLFNs.

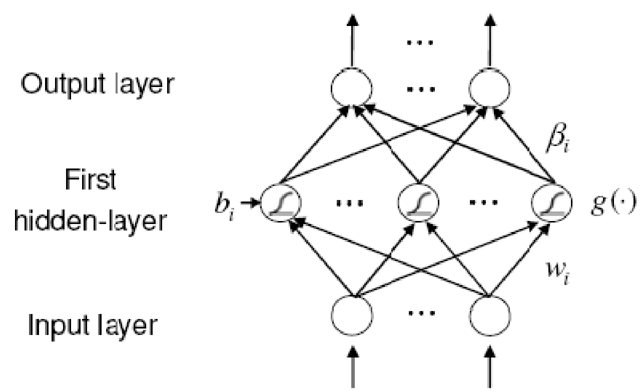

Figure 4. Structure of ELM network

This algorithm tends to afford the best generalization performance at extremely fast learning speed.
The structure of ELM network is shown in figure 4. ELM contains an input layer, hidden layer and an output layer.
The ELM has several interesting and significant features different from traditional popular learning algorithms for feed forward neural networks. These include the following:

- The learning speed of ELM is extremely fast. The learning step of ELM can be completed in seconds or less than seconds for many applications. In the past, it seems that there exists a virtual speed barrier which most (if not all) classic learning algorithms cannot break through and it is not unusual to take very long time to train a feed-forward network using classic learning algorithms even for simple applications.

- The ELM has better generalization performance than the gradient-based learning, such as, backpropagation in most cases. The traditional classic gradient-based learning algorithms and some other learning algorithms may face several issues like local minima, improper learning rate and over fitting, etc. For avoiding these issues, some methods such as weight decay and early stopping methods may need to be used often in these classical learning algorithms.

- The ELM likely to reach the solutions straightforward without such trivial issues. The ELM learning algorithm looks very simpler than most learning algorithms for feed-forward neural networks. Different from the traditional classic gradient-based learning algorithms which only work for differentiable activation functions, as easily observed the ELM learning algorithm could be used to train SLFNs with many non-differentiable activation functions.

3.4.1 Extreme Learning Machine Training Algorithm

If there are N samples (xi, ti), where xi = [xi1, xi2… xin] T ∈Rn and ti = [ti1, ti2, … , tim]T ∈Rn, then the standard SLFN with N hidden neurons and activation function g(x) is defended as:

$$\sum_{i=1}^{\tilde{N}} \beta_i \, g\big(w_i . x_j + b_i\big) = 0_j, j = 1, \dots\dots, N.,$$

where wi = [wi1, wi2, … , win]T is nothing but the weight vector that connects the ith hidden neuron and the input neurons, ßi = [ßi1, ßi2, … , ßim]T is the weight vector that connects the ith neuron and the output neurons, and bi is the threshold of the ith hidden neuron. The "." in wi . xj means the inner product of wi and xj. The SLFN aims to minimize the difference between oj and tj. This can be expressed mathematically as:

$$\sum_{i=1}^{\tilde{N}} \beta_i \, g\big(w_i . x_j + b_i\big) = t_j, j = 1, \dots\dots, N.,$$

or, more in a matrix format as H ß = T, where

$$H(a_1, \dots, a_{\tilde{N}}, b_i, \dots, b_{\tilde{N}}, x_1, \dots, x_N) = \begin{bmatrix} g(w_1, x_1 + b_1) & \cdots & g\big(w_g, x_g + b_g\big) \\ \vdots & \ddots & \vdots \\ g(w_1, x_1 + b_1) & \cdots & g\big(w_g, x_g + b_g\big) \end{bmatrix}_{N * \tilde{N}}$$

$$\beta = \begin{bmatrix} \beta_1^T \\ \vdots \\ \beta_{\tilde{N}}^T \end{bmatrix}_{\tilde{N} * m} \quad \text{and} \quad T = \begin{bmatrix} t_1^T \\ \vdots \\ t_{\tilde{N}}^T \end{bmatrix}_{N * m}$$

The matrix H is the hidden layer output matrix of the neural network. If the number of neurons in the hidden layer is equal to the number of samples, then H is square and invertible. Otherwise, the system of equations needs to be solved by numerical methods, concretely by solving

$$min_\beta \; ||H\beta - T||$$

The result that minimizes the norm of this least squares equation is

$$\hat{\beta} = H^{+}T$$

where H† is called Moore-Penrose generalized inverse. The most important properties of this solution are:

- Minimum training error.
- Smallest norm of weights and best generalization performance.
- The minimum norm least-square solution of Hβ = T is unique, and is

$$\hat{\beta} = H^{+}T$$

The ELM algorithm works as follows

Give a training set $N = \{(x_{1,}t_1)|x_1 \in R^n, t_1 \in R^m, 1 = 1 \dots \dots N\}$ activation function g(x) and hidden neuron $\widetilde{N}$, do the following

- Assigning random value to the input weight w_i and the bias $b_i, i = 1, \dots \dots \dots \widetilde{N}$
- Find the hidden layer output matrix H.
- Find the output weight β, using β̂=H⁺T, where β, H and T are defined in the same way they were defined in the SLFN specification above.

After the learning process is completed by providing several conditions, the proposed technique can be able to detect the cancer occurrence in the lung region automatically.

4. EXPERIMENTAL RESULTS

The experiments are conducted on the proposed computer-aided diagnosis systems with the help of lung images obtained from the reputed hospital. This experimentation data consists of 1000 lung images. Those 1000 lung images are passed to the proposed CAD system. The diagnosis rules are then generated from those images and these rules are passed to the Extreme Learning machine (ELM) for the learning process. After learning, a lung image is passed to the proposed CAD system. Then the proposed system will process through its processing steps and finally it will detect whether the supplied lung image is with cancer or not.

Lung Image	No. of Slices	No. of Cancerous Nodules	True Positive	False Positive
1-100	239	1	0	19
101-200	210	1	0	16
201-300	260	2	0	11
301-400	276	3	2	2
401-500	211	3(< 2 mm size)	2	10
501-600	287	0	0	4
601-700	245	5(< 2 mm size)	0	8
701-800	254	0	2	19
801-900	271	2	1	22
901-1000	221	4	3	11
Total	**2474**	**13**	**10**	**122**

Table 1. Results of applying the proposed CAD system to the dataset

Table 1 shows the results obtained by applying the proposed CAD system to the data images obtained from the reputed hospital. The number of slices obtained for the dataset is 2474 from which best suited slice is chosen for further proceedings. The number of cancerous nodule in the dataset is 13 and 8 nodules are less than 2mm size. The proposed technique detects 10 cancer nodules correctly. The false positive region detected by the proposed CAD system is 122. This result is better detection when compared to the conventional CAD system.

5. CONCLUSION

This paper presents the better Computer Aided Diagnosing (CAD) system for automatic detection of lung cancer. The initial process is lung region detection by applying basic image processing techniques such as Bit-Plane Slicing, Erosion, Median Filter, Dilation, Outlining, Lung Border Extraction and Flood-Fill algorithms to the CT scan images. After the lung region is detected, the segmentation is carried out with the help of Fuzzy Possibilistic C Mean (FPCM) clustering algorithm. With these, the features are extracted and the diagnosis rules are generated. These rules are then used for learning with the help of Extreme Learning Machine (ELM). The experimentation is performed with 1000 images obtained from the reputed hospital. The experimental result shows that the proposed CAD system can able to detect the false positive nodules correctly. Also the usage of Extreme Learning Machine will increase the accuracy of detecting the cancer nodules.

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