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An Adaptive Fuzzy Rule based Approach with Laplacian Gaussian Filtering for Screening of Chest CT Scans

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Abstract

Chronic Obstructive Pulmonary Disease (COPD) is a name that refers to two lung diseases; they are chronic bronchitis and emphysema. The name COPD is used since both diseases are characterized by impediment to airflow that interferes with normal breathing and the two frequently co-exist with each other. Many researchers have developed different techniques to improve the performance of automatic screening process. In this paper, first the input image is pre-processed; the lung region is segmented from that image, segmented the cavity region in that lung region, extracted some features for training the classifier and used the FRB classifier to identify the COPD affected lung. The pre-processing is done by using the gaussian filter and the lung segmentation is done by comparing the region growing technique and the Local Gabor XOR pattern (LGXP) based region growing technique. The cavity segmentation is done by evaluating the pixel range in the segmented lung region and setting a threshold value from that evaluated pixels and comparing every pixel with that threshold value. After the lung and cavity segmentation, some parameters are chosen to train the classifier to identify whether an x-ray image is a normal or affected. The classifier used in proposed technique is FRB classifier. The FRB Classifier is then trained using the parameters chosen from the sample chest CT scan images to identify the normal lung and tuberculosis affected lung.

Keywords: Chronic Obstructive Pulmonary Disease (COPD), Fuzzy Rule Based Classifier (FRB), Local Gabor XOR pattern (LGXP), Medical Imaging, Region Growing Technique.

1. Introduction

Medical imaging has developed into one of the most important fields within scientific imaging due to the rapid and continuing progress in computerized medical image visualization and advances in analysis methods and computer-aided diagnosis. Several research applications are selected to illustrate the advances in image analysis algorithms and visualization. Recent results, including previously unpublished data, are presented to illustrate the challenges and ongoing developments. A multitude of diagnostic medical imaging modalities are used to probe the human body. Interpretation of the resulting images requires sophisticated image processing methods that enhance visual interpretation, and image analysis methods that provide automated or semi-automated tissue detection, measurement and characterization [1,2]. In general, multiple transformations will be needed in order to extract the data of interest from an image, and a hierarchy in the processing steps will be evident, e.g. enhancement will precede restoration, which will precede analysis, feature extraction and classification. Often these are performed sequentially, but more sophisticated tasks will require feedback of parameters back to preceding steps so that the processing includes a number of iterative loops [6,7].

COPD occurrence is generally higher than recognized by health authorities [3, 4]. Few population-based occurrence surveys have been carried out, and prevalence estimates have repeatedly relied on expert opinion or self-reported

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doctor diagnosis, a disreputably unpredictable source of information for COPD [8]. For example, in the USA National Health and Nutrition Examination Survey III, 70% of those with airflow obstruction had never received the diagnosis of COPD [5]. The burden of COPD can be assessed in a number of ways such as mortality, morbidity, prevalence, disability-adjusted life years, cost and quality of life. A number of authors have reviewed this topic in detail elsewhere [9, 20, 19].

In this paper, first the input image is pre-processed; the lung region is segmented from that image, segmented the cavity region in that lung region, extracted some features for training the classifier and used the Fuzzy Rule Based (FRB) classifier to identify the tuberculosis affected lung. The pre-processing is done by using the Laplace Gaussian Filter to avoid the noise in the input image and to increase the image quality. The cavity segmentation is done by evaluating the pixel range in the segmented lung region and setting a threshold value from that evaluated pixels and comparing every pixel with that threshold value. After the lung and cavity segmentation, some parameters are chosen to train the classifier to identify whether an x-ray image is a normal or tuberculosis affected. The classifier used in proposed technique is Fuzzy Rule Based (FRB) classifier. The Fuzzy Rule Based (FRB) classifier is then trained using the parameters chosen from the sample chest CT scan images to identify the normal lung and tuberculosis affected lung.

2. Related Work

The computer-aided diagnosis (CAD) system is used for early detection of tuberculosis in lungs by analyzing chest 3D computed tomography (CT) images. The underlying idea of developing a CAD system is not to delegate the diagnosis to a mechanism, but quite than a machine algorithm acts as a support to the radiologist and points out locations of suspicious objects, so that the overall sensitivity is raised.CAD systems meet four main objectives, which are improving the quality and accuracy of diagnosis, increasing therapy success by early detection of cancer, avoiding unnecessary biopsies and reducing radiologist interpretation time [11].

V.M. Katoch [12] explained that the diagnosis of tuberculosis is mostly based on clinical features, demonstration of acid fast bacilli (AFB) and isolation of Mycobacterium tuberculosis from the clinical specimens. These techniques have limits of speed, warmth and specificity. Several rapid techniques for detection of early growth have been described for last two decades which can help in obtaining the culture and sensitivity reports early. Important among such methods are BACTEC, mycobacterial growth indicator tuber (MGIT), and Septi-chek, MB / BacT systems. This growth can be recognized by rapid methods based on lipid analysis and specific gene probes, PCR-RFLP methods and ribosomal RNA sequencing. Advance improvement in knowledge about genetic structure of tubercle bacillus helps to develop gene probes and gene amplification methods for detection of tubercle bacillus, from culture or directly in clinical specimens and molecular detection of drug resistance. The gene probes can help in rapid identification of isolates, gene amplification methods developed for diagnosis of tuberculosis are obviously highly sensitive especially in culture negative specimens from different paucibacillary forms of disease. The molecular methods drug resistant mutants for drugs like rifampicin can be detected with reasonable certainty within hours.

In recent years great advances have been made in Computer Aided Diagnosis (CAD) systems for detecting disease from Computed Tomography scans, mainly due to the advances made in the scanning machines which allow a greater amount and quality of information to be extracted during a single breath of the patient. The use of textural analysis and pattern recognition techniques for regression or classification is most suited to the evaluation of global conditions (e.g. Ground glass, Emphysema) rather than local (small nodules), which won't be concerned with in this report. This recent progress in CAD in Chest Radiology has been discussed in Giger M.L. (2001) [13], where it has been noted that the amount of 3-D image data from thoracic CT scans greatly increases the number of images that much be reviewed by the radiologist and therefore a search aid may be a great benefit.

Uchiyama et al. [14] said that the selected regions in 315 HRCT images from 105 patients, relating to six different patterns, i.e., ground-glass opacities, reticular and linear opacities, nodular opacities, honeycombing, emphysematous change, and consolidation, labeled by 3 radiologists. The lungs were first segmented, using standard technique, then divided into many contiguous regions of interest (ROIs) with a 32x32 matrix and classified using artificial neural networks. The accuracy varied from 88 to 100%, with specificity in detecting a normal ROI of 88.1%.

Sluimer et al. [15, 20] presented a CAD system to automatically distinguish normal from abnormal tissue in HRCT chest scans of 116 patients, producing 657 ROIs labeled as containing normal or abnormal tissue. The circular ROIs with an 80-pixel diameter were extracted from the peripheral lung region in slices at the height of the aortic arch, with each ROI required to contain at least 75% abnormal tissue. An accuracy of 86.2% as obtained, comparable to those of a radiologist when evaluating only the ROIs, i.e. without seeing the whole scan.

N. Lee et al [16] explained that the digital CT is a technique used for recording images in computer code as an alternative of on x-ray film. The images are displayed on a computer monitor can be enhanced or lightened or darkened before they are printed on film. Images can also be manipulated; the radiologist can magnify or zoom in on an area. This screening will generate large number of CT images to be determined by a small number of radiologists resulting in misdiagnosis due to human errors caused by visual fatigue. The sensitivity of human eye decreases with increasing number of images. Hence, it may be helpful for a radiologist, if a computer-aided system is used for detection of tumours in CT images. Computer-aided detection (CAD) involves the use of computers to bring suspicious areas on a CT to the radiologist's attention. It is used after the radiologist has done the initial review of the CT. There are several image processing methods proposed for extract of tumours from CT image for better view of area and shape of tumour.

3. Proposed Technique for the Identification of Cavity

The block diagram of the proposed approach is shown in figure 1. In this figure some sample chest CT scan images are taken with COPD and without COPD. The sample images are then preprocessed and then send for segmentation process. There segmenting the lung and cavity regions. After the lung and cavity regions are segmented from the sample images, some parameters are chosen to train the classifier. First the preprocessing is done to find weather the COPD is affected or not. After the preprocessing process, need to segment the lung and the cavity region. After that the chosen parameters are given to the classifier, here the FRB classifier is used. The FRB classifier then identify whether the input chest CT scan image is affected by COPD or not by comparing the parameters from the sample images and from the input image.

3.1. Pre-processing

The input image is subjected to the pre-processing steps to make the image suitable for further process. The pre-process is used to load the input image to the MATLAB environment and it will remove the noise present in the input image. Here the Laplacian Gaussian filter is used as pre-processing technique. The image is passed through the Laplacian Gaussian filter to lower the noise and to get a better image. The Laplacian Gaussian filter will also increase the image quality and the corner of the images.

3.2. Laplacian Gaussian Filter

The Laplacian is a 2-D isotropic quantity measure of the 2nd spatial derivative of an image. The Laplacian of an image highlights the regions of rapid intensity change and therefore often used for edge detection. The Laplacian is frequently applied to an image that has been smoothed first with something approximating a Gaussian smoothing filter in order to reduce its sensitivity to noise, and hence the two variants will be described together. The operator normally takes a single gray level image as input and produces another graylevel image as output.

The Laplacian of an image with pixel intensity values is given by:

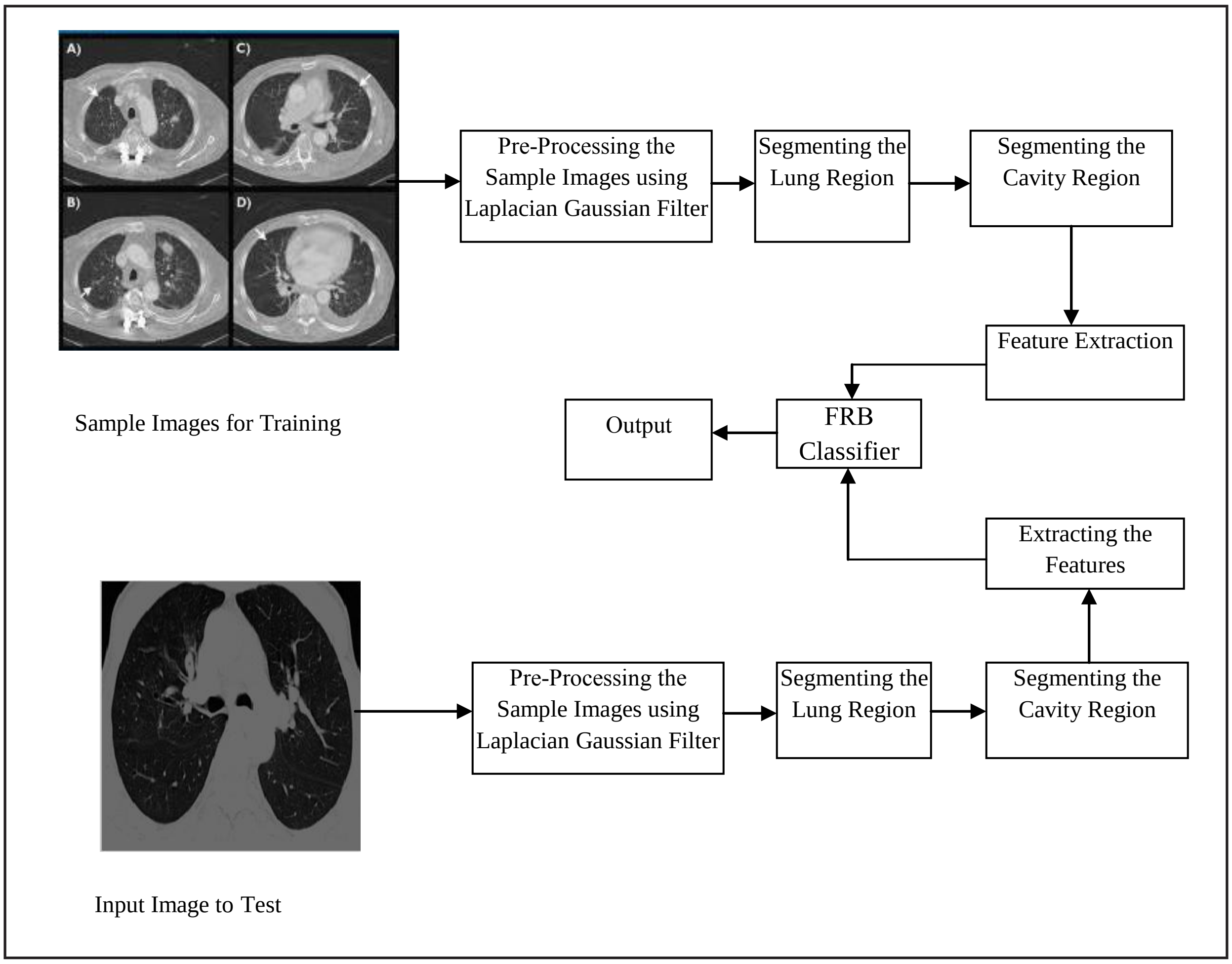
Since the input image is denoted as a set of discrete pixels, have to find a discrete convolution kernel that can estimated the second derivatives in the definition of the Laplacian. Two commonly used small kernels are shown in Figure 2.

Figure 3.6. Two Commonly Used Discrete Approximations to the Laplacian Filter

0	-1	0
-1	4	-1
0	-1	0

-1	-1	-1
-1	8	-1
-1	-1	-1

Figure 1. Block Diagram for Proposed Technique



Because these kernels are approximating a second derivative measurement on the image, they are very sensitive to noise. To counter this, the image is often Gaussian smoothed before applying the Laplacian filter. This pre-processing step reduces the high frequency noise components prior to the differentiation step.

3.3. Lung Segmentation

Lung segmentation is a process of segmenting the lungs from the chest CT scan image. The normal process of region growing technique for segmenting the lungs is shown in the figure 3.7. First choose a pixel from the chest CT scan image as default. Then need to set a threshold value for comparison to find the pixel intensity for the lung area in the chest CT scan. The default pixel which chosen is compared with the adjacent pixel values. If the difference between the default pixel and the adjacent pixel is greater than the threshold value, have to exclude that adjacent pixel. If the difference between the default pixel and the adjacent pixel is less than the threshold value, have to include that adjacent pixel for region growing. Compare all the pixels except the left pixels with its adjacent pixels by keeping one pixel as default. The process of normal region growing technique is shown in the Figure3.

In this paper, comparing the normal region growing technique with the Local Gabor XOR Pattern (LGXP) based region growing technique to segment the lungs from the chest CT scan image Shufu Xie et al (2010). The LGXP technique is used to find the texture image.

The LGXP based region growing technique is as follows. In LGXP technique, apply the Gabor Phase Technique on every pixel in the chest CT scan image. The Gabor Phase Technique will convert all the pixel values to phase values (0 to 360). After converting all the pixel values to phase values, find these phase values comes under which quadrant. Each quadrant has certain values. For the first quadrant the value is zero and for the second quadrant the value is one and for the third quadrant the value is

Figure 3.7. Block Diagram of Normal Region Growing Technique

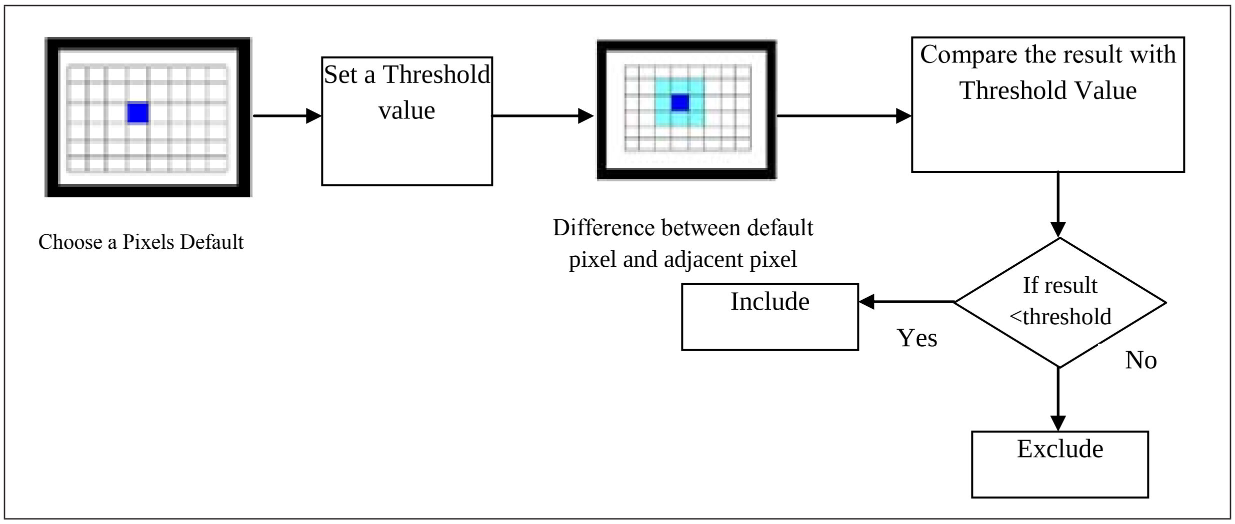
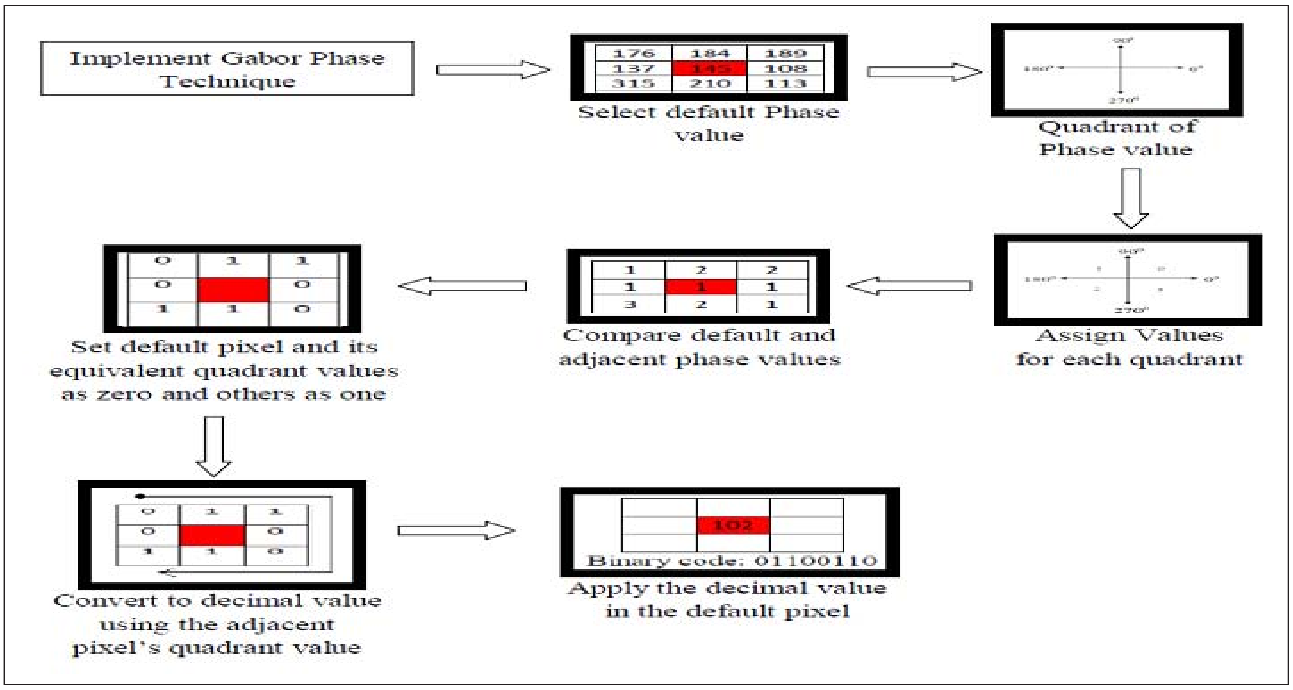


Figure 3.8. Block Diagram of LGXP Technique



two and for the fourth quadrant the value is three. After that choose a default phase value of a pixel and check under which quadrant this phase value comes and assign respective quadrant value to that pixel. After assigning respective quadrant value to the default pixel, check the adjacent pixel's phase values and assign the respective quadrant values to those adjacent pixels. Then convert the adjacent pixel's value as zero which has the same quadrant value of the default pixel. If the adjacent pixels value does not have the same quadrant value of the default pixel, convert the adjacent pixel's value as one. Now the pixel values would be like binary values as zeros and ones. After converting the pixel values as binary format, make that binary format as decimal value and apply that decimal value to the default pixel. The process of taking the binary value is shown in the figure. Likewise apply this LGXP process for all the pixels in the chest CT scan by keeping one pixel as default. The sample process of LGXP technique is shown in the Figure.3.8.

After applying the LGXP technique in all the pixels, then implement the region growing technique for segmenting the lungs using the phase value of the pixels from the

LGXP process. Then compare the normal region growing technique and LGXP based region growing technique. By comparing both the techniques check whether the same pixel as default. During this process, if the difference between the adjacent pixel and the default pixel got the value as less than the threshold value on both the techniques separately, include that adjacent pixel for region growing or else need to exclude that adjacent pixel. But the adjacent pixel and the default pixel which have chosen to compare should be same on both the techniques.

3.4. Local Gabor XOR Pattern (LGXP)

The fundamental idea of technique is to ease the sensitivity of Gabor phase to the differing positions, whether two phases reflect same local feature must be determined in a "looser" way. Specifically, if two phases belongs to the same interval (for instance: 00, 900), they are believed to have similar local features or else they reflect different local features. In this section, the LGXP descriptor is presented.

Figure 3.9. Example of LGXP Method Where the Phase is Quantized Into 4 Ranges

95	328	145
212	135	78
158	188	254
(a)		

1	3	1
2	1	0
1	2	2
(b)		

0	1	0
1		1
0	1	1
(c)		

The Figure 3.9 shows an instance for the LGXP encoding method where the phase is quantized into 4 ranges. In LGXP technique, phases are first quantized into disparate ranges and the LGXP operator is applied to the quantized pixels of the central pixel and each of its neighboring pixels and eventually the result of the binary labels are concatenated together as a local pattern of the central pixel. In the Figure.3.9, (a) is the matrix with initial phase of the pixels after applying the Gabor filter and (b) is the result after quantization and (c) is the result after XOR comparison with the center quantized value. From the matrix which we got after XOR comparison, we can deduce the binary value obtained is 01011101 and its equivalent decimal value is 93. The pattern of LGXP in binary and decimal form is as follows:

Where, denotes the central pixel in the Gabor phase map with scale v and orientation, N is the size of the neighborhood and denotes the pattern calculated between and its neighbor , which is computated as follows:

Where denotes the phase, denotes the LXP operator, which is based on XOR operator, q denotes the quantization operator which calculates the quantized code of the phase according to the number of phase ranges.

Where, e denotes the number of phase ranges. With the pattern explained above, one pattern map is computed for each Gabor kernel. Thereafter, each pattern map is split into m non overlapping sub blocks and the histograms of all the sub blocks of scales and the orientations are concatenated to form the proposed LGXP descriptor of the input face image

Where denotes the histogram of the sub block of the LGXP map with scale v and orientation.

3.5. Feature Extraction

After finding the regions, extract some features to diagnose the disease in the lung. To discover the disease in the lung, have to feed the extracted feature into the classifier, because the extracted features will give vital information about the region which is used to train the classifier. In this paper an FRB classifier is used for feature extraction. The features need to extract are number of cavities in the lung region, minimum area of cavity region, maximum area of cavity region, total number of pixels in each cavity, maximum repeated pixel intensity in the cavity region and maximum repeated pixel in the lung region to find the total number of cavities in the lung region. Because the normal lung would also have some cavities present in its region. So to distinguish the normal lung image and the COPD affected lung should find the total numbers of cavities present in the lung region and give the result to the FRB classifier. This classifier shows more accurate value and it took minimum time for an execution.

3.6. Fuzzy Rule-Based Classifier (FRB)

Lot of techniques is there in the Data Mining to deal with the classification problem. Amongst them, FRBCSs give an interpretable replica by means of linguistic labels in their rules.

Consider *m* labeled patterns), *p* = 1, 2, . . . ,*m* where is the *i*th attribute value (*i* = 1, 2, . . . , *n*). A set of linguistic values and their membership functions are there to describing each and every attribute. Use fuzzy rules of the following form:

Rule: If is and . . . and is then Class = with

where is the label of the *j*th rule, is an *n*-dimensional pattern vector, is an antecedent fuzzy set on behalf of a linguistic term, is a class label, and is the rule weight. Specially, in this paper the rule weight is computed using the Penalized Certainty Factor defined in [38] as:

Let be a new pattern, *L* denotes the number of rules in the rule base and *M* the number of classes of the problem; then, the steps of the FRM are as follows:

1. Matching degree, is the strength of activation of the if-part for all rules in the rule base with the pattern . A conjunction operator (t-norm) is functional in order to carry out this computation.
2. Association degree. To compute the association degree of the pattern with the M classes according to each rule in the rule base. When using rules in the form shown in (1) this association degree only refers to the consequent class of the rule (i.e. k = Class()).
3. Pattern classification soundness degree for all classes. We use an aggregation function that combines the positive degrees of association calculated in the previous step.
4. Classification. Apply a decision function F over the soundness degree of the system for the pattern classification for all classes. This function will determine the class label l corresponding to the maximum value.

Then find the maximum repeated pixel intensity in the cavity regions of a lung. To discover the maximum repeated pixel, first have to find the intensities of all the pixels in each cavity of a lung by implementing histogram and thereafter need to compare all the pixels of every cavity with each other. After discovering the maximum repeated pixel in the cavities of a lung, have to give the result to the classifier. Similarly, find the maximum repeated pixel in the whole lung region and give the result to the classifier. The classifier detect the lung is affected by COPD or not by comparing all the features.

4. Training and Testing Using FRB Classifier

Some of the data features are to be taken to identify the normal lung region and COPD affected lung by this the classifier is trained. The data features will then train the classifier and the classifier will find whether the given CT scan image is normal or abnormal. The data features which have chosen for training the FRB classifier are number of cavities in the lung region, maximum area of cavity in the lung region, minimum area of cavity in the lung region, total number of pixels in each cavity, maximum repeated pixel in the cavity regions together and maximum repeated pixel in the lung region. After computing all the data features, have to give the values to the classifier. For instance, choosing three normal CT scan images and three abnormal CT scan images, need to calculate all the six data features separately for all the CT scan images had chosen. After calculating all the six data features for every chosen CT scan images, have to give the result to the FRB classifier. Using those results train the classifier to identify the normal and abnormal lung from the given CT scan image. After the FRB classifier is trained, give a new CT scan image to find whether it has COPD or not. Afterwards, the six data features such as number of cavities in the lung region, maximum area of the cavity region, minimum area of the cavity region, total number of pixels in each cavity, maximum frequent pixel in the cavity region and maximum repeated pixel in the lung region are calculated for the new CT scan image. The computed values of all the six data features are then give to the FRB classifier. The FRB classifier is then comparing the values of all the six data features with the stored values of normal and abnormal CT scan images. Because during training have stored all the six data features of the five normal CT scan images and five abnormal CT scan images. After comparison, the FRB classifier will identify whether the given CT scan image comes under normal category or abnormal category.

5. Results and Discussion

The experiment is conducted in MATLAB. The figure 4.5 shows the normal and abnormal lung images.

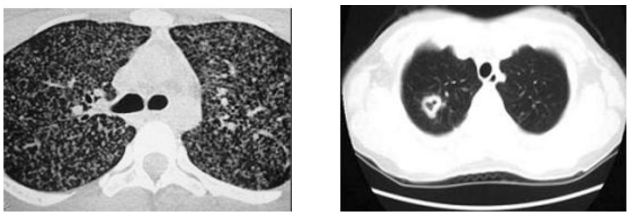
The sample images are taken and the images are filtered using gaussian filter. The filtering technique is used to remove the various noises that are present in the sample

Table 4.1. Comparative Analysis of Existing Technique with Proposed Technique

Techniques	*TP*	*TN*	*FP*	*FN*	*Sensitivity*	*Accuracy*
SVM Technique	3	9	1	1	0.9	0.857
ELM Technique	2	7	1	0	0.75	0.897
Proposed FRB Technique	1	5	1	0	0.55	0.919

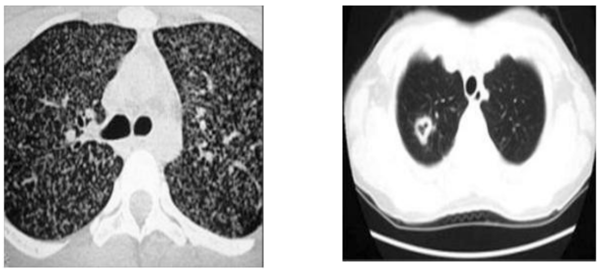
image and it improves the quality of the images as shown in the figure 4.6.

Figure 4.5. Sample Images of Normal and Abnormal Lungs Images



(a)Normal Image (b) Abnormal Image

Figure 4.6. Sample Image of Lungs After Filtering Process



(a) Normal Image after filtering process (b) Abnormal Image after filtering process

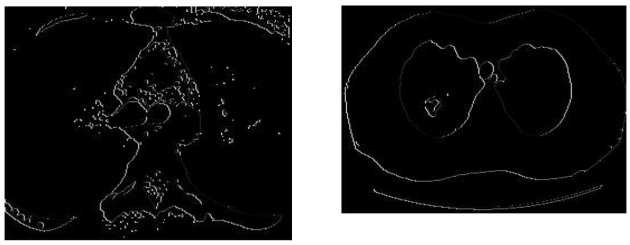
The filtered image is given to the process of lung segmentation. The lung segmentation process only segments the lung region from the sample CT scan images. The Figure 4.7 shows a sample image of segmented lungs with COPD and without COPD.

Figure 4.7. Sample Image of Lungs After Segmentation Process

(a) Normal Image after segmentation process (b) Abnormal Image after segmentation process

After the lung is segmented from the present sample images, have to segment the cavities from the lung region. Using the cavities in the lung region identify whether a lung is COPD affected or not. The Figure 4.8 shows a sample image of segmented cavities and segmented cavities with CT scan image for the COPD affected lung.

Figure 4.8. Sample image of Lungs After Segmenting the Cavities



(a)Normal Image after segmenting cavities (b) Abnormal Image after segmenting cavities

5.1. Performance Analysis Using Evaluation Metrics

The evaluation of the COPD identification of the images is carried out using the following metrics,

Where,

True Positive TP, True Negative TN, False Negative FN, False Positive FP

Sensitivity is the proportion of true positives that are correctly identified by a diagnostic test. It shows how good the test is at detecting a disease.

Accuracy is the proportion of true results, either true positive or true negative, in a population. It measures the degree of veracity of a diagnostic test on a condition.

Table 1shows the accuracy comparison between proposed technique and the existing technique. The tabular column shows that the proposed technique gives better performance than the existing technique.

6. Conclusion

In this paper, proposed an efficient technique for the detection of COPD in the lungs using CT scan Images. The proposed technique contains pre-processing, lung segmentation, cavity segmentation, feature extraction, training and testing using FRB classifier. The FRB classifier is efficient and simple in nature. The performance of the proposed technique and the existing technique is analyzed using evaluation metrics. To evaluate these metrics, should need some terms like True Positive, True Negative, False Positive and False Negative. After evaluating these metrics it shows that the performance of proposed technique is better when compared to the existing technique in terms of accuracy. The result shows that the accuracy of proposed technique higher than existing techniques.

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