An Optimized ANFIS Classifier Approach for Screening of COPD from Chest CT Scans with Adaptive Median Filtering

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Abstract— **In medical image processing, Chronic Obstructive Pulmonary Disease 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. If COPD is detected earlier, the formation of lung cancer is prevented. CT scan may afford additional information and also it can provide further detailed images of parts of the body that cannot easily be seen on a normal chest radiograph. Many researchers have been developed different techniques to improve the performance of automatic screening process. This paper involves in improves the accuracy over the existing technique using the adaptive region growing property and ANFIS classifier. Initially, pre-processing is carried out for the input image using median filtering technique to make the image fit for further processing and to remove the noises. The contours of the image will be obtaining using region growing technique. The ANFIS classifier is optimized to speed up the process and to produce optimized result.. The classification will be carried out by the features which have been taken from the segmented image. The proposed technique is implemented in MATLAB and the performance is compared with the existing technique. From the experimental result it can be said that the proposed method achieved more accuracy as compared with existing techniques.**

Keywords—**Chronic obstructive pulmonary disease, ANFIS classifier, Adaptive Median filtering, Local Gabor XOR Pattern (LGXP)**

I. INTRODUCTION

Chronic Obstructive Pulmonary Disease (COPD) is a major and increasing global health issues, which is predicted to become the third commonest cause of death and the fifth commonest cause of disability in the world by 2020 [1]. While there have been major advances in the understanding and management of asthma, COPD has been relatively neglected and there are no current therapies that reduce the inevitable progression of this disease. However, because of the enormous burden of disease and escalating healthcare costs, there is now renewed interest in the underlying cellular and molecular mechanisms [2] and a search for new therapies [3], resulting in a re-evaluation of the disease [4]. Despite its enormous global importance, there has been relatively little research into COPD and it is the most underfunded disease in relation to the global burden of disease [5].

COPD is under-diagnosed not only in its early stages, but even when lung function is severely impaired. This is perhaps surprising, since simple and inexpensive spirometers that are suitable in clinical practice are now available, and lung function is a powerful predictor of all cause mortality, regardless of smoking status. No other disease that is responsible for comparable morbidity, mortality and cost is neglected by healthcare providers as much as COPD. It may well be that the true burden of the disease is not fully appreciated, and the message that COPD is both preventable and treatable has yet to be fully understood by most healthcare providers. The hope is that highlighting these facts will help to raise the profile of COPD and begin to change long-held attitudes.

More recently, lung computed tomography (CT) scanning has been used to quantify emphysema in life and has been related to both lung morphology and function [4].

This paper is developed to effectively classify the abnormal and normal CT scan lung images. In this paper, the input image is given for preprocessing there adaptive median Filter is used to reduce the noise in the input image and to

increase the image quality; then lung region is segmented from that image by comparing the region growing technique and the Local Gabor XOR pattern (LGXP) based region growing technique, after that cavity region is segmented from

the classification. The ANFIS classifier is optimized here which uses the parameters chosen from the sample chest CT scan images to identify the normal lung and tuberculosis affected lung. Finally experimental results are given that compares the existing and proposed results here using Sensitivity,Specificity and Accuracy and proves proposed works efficiency.

II. RELATED WORKS

Medical images are often corrupted by noise arising in image acquisition process. Accurate diagnosis of the disease requires that medical images be sharp, clear and free of noise. Thus, image denoising is one of the fundamental tasks required by medical image analysis. There exist several denoising techniques for medical images like Median, Wavelet, Wiener, Average and Independent Component Analysis (ICA) filters. The ICA is a statistical and computational technique for revealing hidden factors that underlie sets of random variables, measurements, or signals. In this work, ICA has been used to separate out noise from the image to provide important diagnostic information to the physician and its usefulness is demonstrated by comparing its performance with other noise filtering methods. The performance of the ICA and other denoising techniques is evaluated using the metrics like Peak Signal-to-Noise Ratio (PSNR), Mean Absolute Error (MAE) and Mean Structural Similarity Index (MSSIM) [6]. The ICA based noise filtering technique gives 25.8245 dB of PSNR, 0.7312 of MAE and 0.9120 of SSIM. The experimental results and the performance comparisons show that ICA proves to be the effective method in eliminating noise from the medical image.

Extreme Learning Machine (ELM) meant for Single Hidden Layer Feed-Forward Neural Networks (SLFNs). This algorithm tends to afford the best generalization performance at extremely fast learning speed. 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 ELM 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. The classifier trains the classifier to identify the normal and abnormal lung from the given CT scan image. After the ELM classifier is trained, give a new CT scan image to find whether it has COPD or not [7].

A hybrid Neural-Digital Computer-Aided Diagnosis (N.CADx) system is proposed for early detection and classification of cancerous lung nodules of size 3-15 mm.

the lung region 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., next different features are extracted and finally given for Digital image processing techniques are used for noise reduction, image enhancement, and "suspect" search and localization. The neural classification concerns feature extraction and diagnosis of a particular pattern-class aimed at high degree of "true positive fraction" detection and low "false positive fraction". Applying fuzzy linguistic concepts, [8] have developed a multi-label output encoding procedure, for purposes of neural training and for interpretation of the activity distributions in the output neurons. Over five output neurons, that were used in the nodule diagnosis problem, the activity distribution is interpreted by the centroid as the normalized disease index-NDI, or as a nodule detection probability-NDP value associated with a confidence level factor. The proposed N.CADx system has great potential in many medical applications.

COPD is usually related to cardiovascular risk and sudden death. An effective tool for the diagnosis of exacerbations in COPD patients is the Heart Rate Variability (HRV) analysis of polysomnograms, corresponding to patients who must be monitored in a clinical center. As an alternative, [9] present an ambulatory electrocardiography technique to control the COPD patients at home, by studying patients's ECGs (Electrocardiogram) in distinct periods of time, to extract possible differences in two situations: 1) previous to the exacerbation and 2) during acute episodes. Results indicate that the spectral parameters experiment important differences when they are measured in an exacerbation episode, compared to the values obtained in the ECG recordings obtained one or two months before.

III. PROPOSED WORK

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 [4]. 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 ANFIS is optimized and taken as a classification technique.

A. 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 adaptive median filter is used as pre-processing technique. The image is passed through the median filter to lower the noise and to get a better image. The input image is a normal

RGB image. The RGB image is converted into grey scale image because the RGB format will not support for further process. Then the grey scale image contains noises such as white noise, salt and pepper noise etc. This can be removed by using adaptive Median filter from the extracted lung image.

Adaptive Median Filter

The standard median filter performs well as long as the spatial noise density of the salt and pepper noise is not large. The filter performance degrades when the spatial noise variance of the salt and pepper noise increases chen and Whu (1998). Further with larger image and as the size of the kernel increases, the details and the edges becomes obscured (Maragos and Schafer 1987). The standard median filter does not take into account the variation of image characteristics from one point to another. The behavior of adaptive filter changes based on statistical characteristic of the image inside the filter region defined by the mxn rectangular window S_{xy} [10]. The adaptive median filter differs from other adaptive filter as the size of the rectangular window S_{xy} is made to vary depending on

Z_{min}= Minimum gray level value in S_{xy}

Z_{max}= Maximum gray level value in S_{xy}

Z_{med}= Median of gray level in S_{xy}

Z_{xy}= Gray levels at coordinate (x,y)

S_{max} = Maximum allowed size of S_{xy} [11].

The adaptive median filtering algorithm works in two levels, denoted by LEVEL1 and LEVEL2. The application of AMF provides three major purposes: to denoise images corrupted by salt and pepper (impulse) noise; to provide smoothing of non- impulsive noise, and also to reduce distortion caused by excessive thinning or thickening of object boundaries. The values Z_{min} and Z_{max} are considered statistically by the algorithm to be 'impulse like' noise components, even if these are not the lowest and highest possible pixel values in the image.

The purpose of LEVEL1 is to determine if the median filter output Z_{med} is impulse output or not. If LEVEL1 does find an impulse output then that would cause it to branch to LEVEL2. Here, the algorithm then increases the size of the window and repeats LEVEL1 and continues until it finds a median value that is not an impulse or the maximum window size is reached, the algorithm returns the value of Z_{xy}.

Every time the algorithm outputs a value, the window S_{xy} is moved to the next location in the image. The algorithm is then reinitialized and applied to the pixels in the new location. The median value can be updated iteratively using only the new pixels, thus reducing computational overhead.

B. 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 2. 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 Figure2.
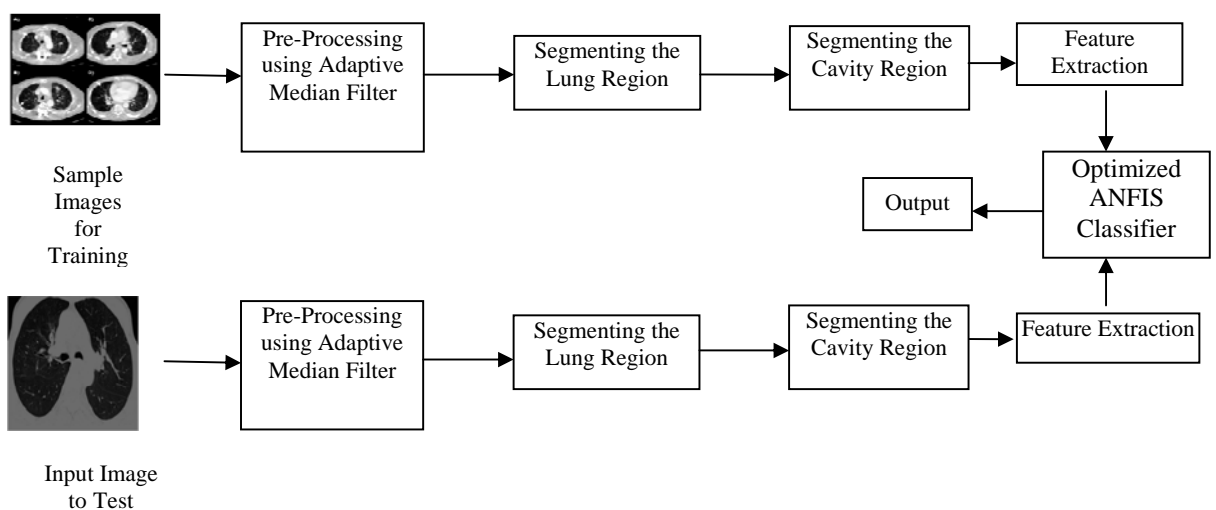

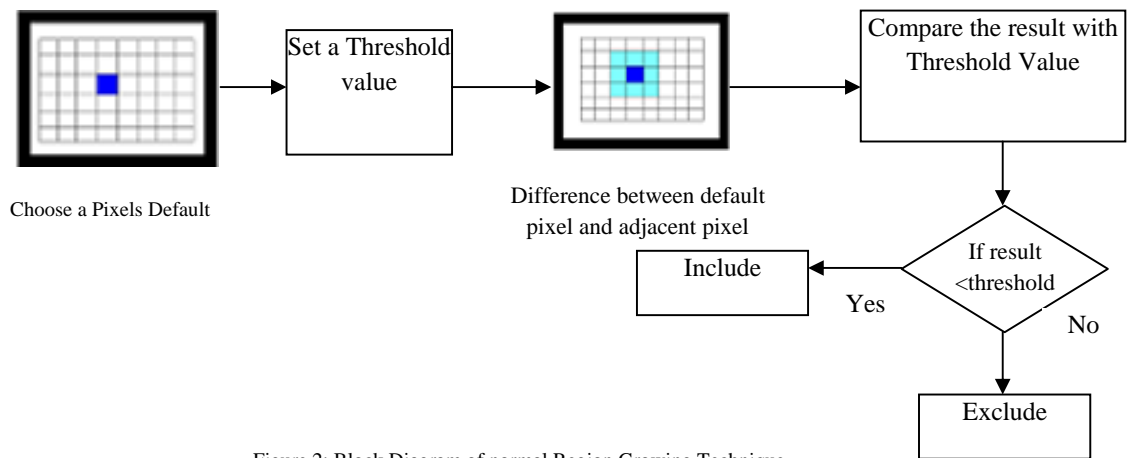Figure 1: Block Diagram of Proposed Technique

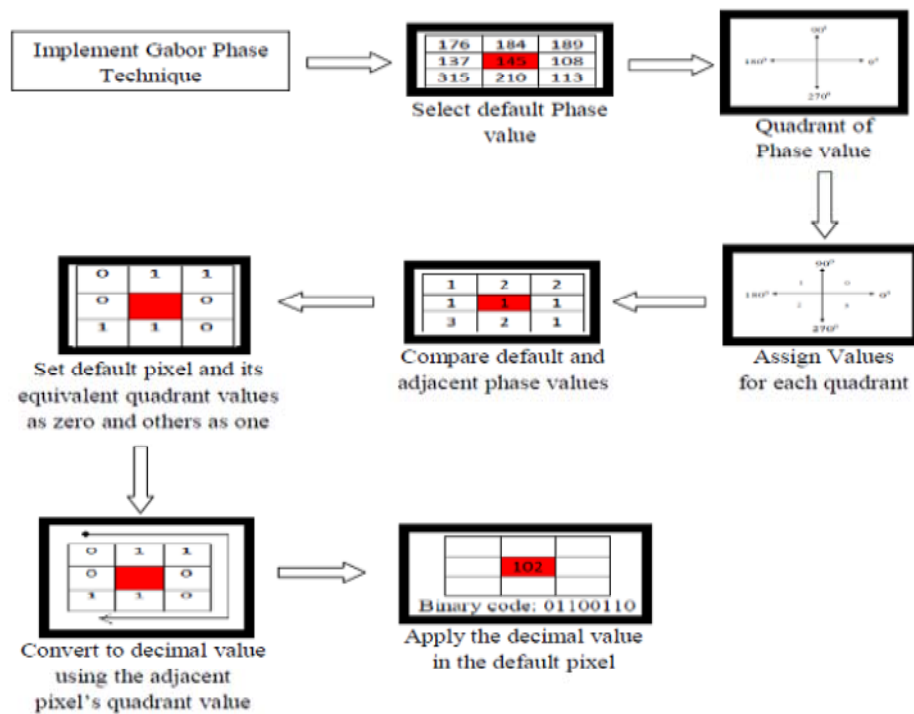Figure 2: Block Diagram of normal Region Growing Technique

Figure 3: Block diagram of LGXP Technique

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. The LGXP technique is used to find the texture image.

In LGXP technique, apply the Gabor Phase Technique on every pixel in the chest CT scan image. The Gabor Phase Technique will exchange all the pixel values to phase values (0 to 360). Later than 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 two and for the fourth quadrant the value is three. After choosing default phase value of a pixel and make sure under which quadrant this phase value comes and assign respective quadrant value to that pixel. After conveying respective quadrant value to the default pixel, check the adjacent pixel's phase values and assign the respective quadrant values to those adjacent pixels. After that convert the adjacent pixel's value as zero which

have the same quadrant value of the default pixel. If the above condition is not satisfied, 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. Similarly 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.

Later than applying the LGXP technique to all the pixels, the region growing technique is applied 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 or not. 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 independently, 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.

C. Local Gabor XOR Pattern (LGXP)

The fundamental idea of technique [17] is to effortlessness the sensitivity of Gabor phase to the differing positions; whether two phases replicate 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.

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

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

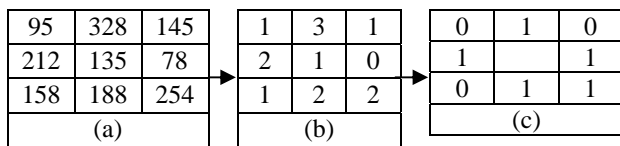| 0	1	0
1		1
0	1	1
(c)		

Figure 4: Example of LGXP method where the phase is quantized into 4 ranges

The Figure 4 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 ultimately the result of the binary labels are concatenated together as a local pattern of the central pixel. In the Figure.3, (a) is the matrix with initial phase of the pixels after relating the Gabor filter and (b) is the result after quantization and (c) is the consequence after XOR comparison with the center quantized value. From the obtained matrix, can construe 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:

$$LGXP_{\mu v}(P_c)$$
$$= [LGXP_{\mu v}^N, LGXP_{\mu v}^{N-1}, \ldots \ldots \ldots \ldots . LGXP_{\mu v}^1]_{binary}$$
$$= \left[\sum_{i=1}^{N} 2^{i-1} . LGXP_{\mu v}^i \right]_{decimal}$$

Where, P_c denotes the central pixel in the Gabor phase map with scale v and orientation μ , N is the size of the neighborhood and $LGXP_{\mu v}^i$ (i = 1,2, … …, N) denotes the pattern calculated between P_c and its neighbor P_i, which is computated as follows:

$$LGXP_{\mu v}^i$$
$$= q\left(\Phi_{\mu v}(P_c) \right) \otimes q\left(\Phi_{\mu v}(P_i) \right), \qquad\qquad i$$
$$= 1,2, \ldots . . N$$

Where $\Phi_{\mu v}$ denotes the phase, $\otimes$ 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.

$$a \otimes b = \begin{cases} 0, & if \ a = b \\ 1, & else \end{cases}$$
$$q\left(\emptyset_{\mu v}(.) \right) = i, \qquad if \frac{360^* i}{e} \leq \Phi_{\mu v}(.)$$
$$< \frac{360^*(i+1)}{e}, \qquad i$$
$$= 0,1, \ldots \ldots \ldots \ldots . b - 1$$

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

$$H = [H_{\mu_O v_0 1}, \ldots, H_{\mu_O v_0 m;, \ldots}; H_{\mu_{O-1} v_{s-1} 1;, \ldots}, H_{\mu_{O-1} v_{s-1} m}]$$

Where $H_{\mu v}$ (i = 1,2, … . , m) denotes the histogram of the ith sub block of the LGXP map with scale v and orientation.

D. Cavity Segmentation

After the lung segmentation, identify the cavities in the lung. The cavities present in the lung region are an essential thing to identify the COPD affected lung. To identify the cavity in the lung, set an adaptive thresholding that separates the foreground from the background with nonuniform illumination. After that, compare the threshold with all the pixels. While comparing the pixels to the threshold value, if the pixel value is greater than the threshold value then it would be the cavity region and if the pixel value is less than the threshold value then it would be the lung region. The Figure.6 shows the block diagram for segmenting the cavity region from the lung region.
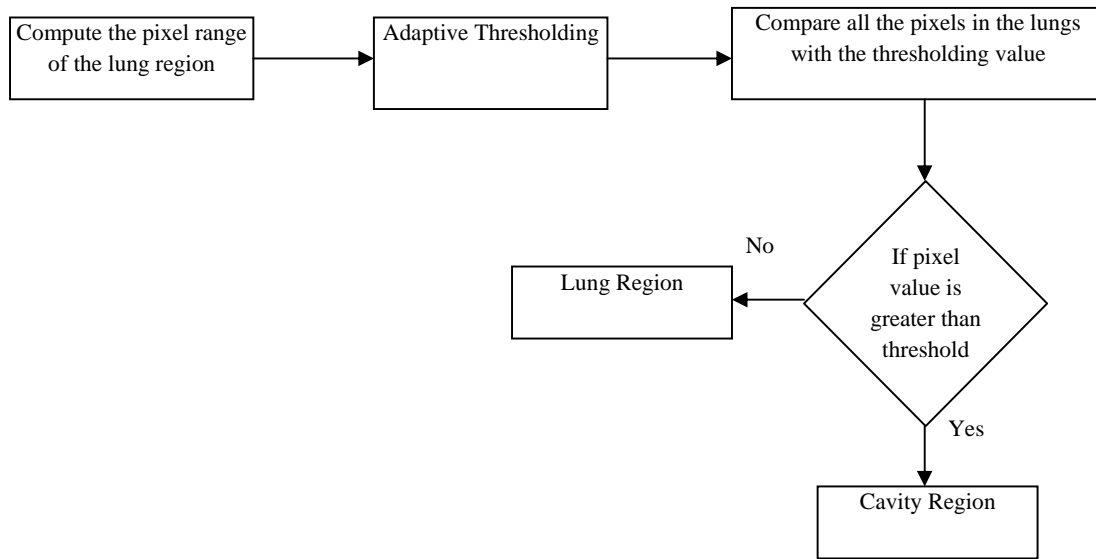
Figure 5: Block diagram of Cavity Segmentation

E. 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 Optimized ANFIS 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 ANFIS classifier. This classifier shows more accurate value and it took minimum time for an execution.

IV. OPTIMIZED ANFIS CLASSIFICATION

The ANFIS is a fuzzy Sugeno model put in the structure of adaptive systems to make easy learning and adaptation [12]. Such structure makes the ANFIS modeling more efficient and less reliant on expert knowledge. To present the ANFIS structural design, two fuzzy if–then rules based on a first order Sugeno model are measured

Rule 1: If (x is A1) and (y is B1) then ($f1 = p1x + q1y + r1$).

Rule 2: If (x is A2) and (y is B2) then ($f2 = p2x + q2y + r2$),

where x and y are the inputs, Ai and Bi are the fuzzy sets, fi are the outputs within the fuzzy region precise by the fuzzy rule, pi; qi and ri are the design parameters that are determined throughout the training process. The ANFIS

architecture to put into practice these two rules is shown in Fig. 6, in which a circle indicates a fixed node, while a square indicates an adaptive node.

In the first layer, all the nodes are adaptive nodes. The outputs of layer 1 are the fuzzy membership grade of the inputs, which are given by the following equation

$$O_i^1 = \mu_{Ai}(x), \qquad i = 1,2,$$
$$O_i^1 = \mu_{Bi-2}(y), \qquad i = 3,4,$$

where $\mu_{Ai}(x)$, $\mu_{Bi-2}(y)$ can adopt any fuzzy membership function. For example, if the bell shaped membership function is employed, $\mu_{Ai}(x)$ is given by the below equation

$$\mu_{Ai}(x) = \frac{1}{1 + \{\left(\frac{x - c_i}{a_i}\right)^2\}^{b_i}}$$

where a_i, b_i and c_i are the parameters of the membership function, governing the bell-shaped functions, as a result.
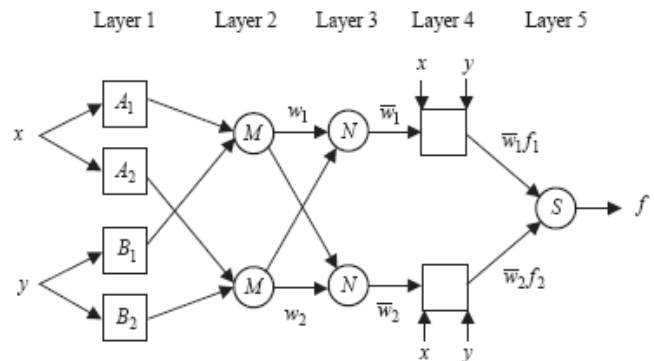

Figure 6: ANFIS architecture

In the second layer, the nodes are fixed nodes. They are labeled with M, indicating that they carry out as a simple multiplier. The outputs of this layer can be corresponding to as which the called as firing strengths of the rules are given in below equation.

$$O_i^2 = w_i = \mu_{Ai}(x)\mu_{Bi}(y),$$
$$i = 1,2,$$

In the third layer, the nodes are also fixed nodes. They are labeled with N, indicating that they play a normalization role to the firing strengths from the preceding layer.

The outputs of this layer can be represented as in below equation

$$O_i^3 = \overline{w}_i = \frac{w_i}{w_1 + w_2}, \quad i$$
$$= 1,2,$$

which are the so-called normalized ring strengths.

In the fourth layer, the nodes are adaptive nodes. The output of each node in this layer is simply the product of the normalized firing strength and a first-order polynomial. Thus, the outputs of this layer are given by below equation.

$$O_i^4 = \overline{w}_i f_i = \overline{w}_i(p_i x + q_i y + r_i), \quad i$$
$$= 1,2$$

In the fifth layer, there is only one single fixed node labeled with S. This node performs the summation of all incoming signals. Hence, the overall output of the model is given here

$$O_i^5 = \sum_{i=1}^{2} \overline{w}_i f_i = \frac{(\sum_{i=1}^{2} w_i f_i)}{w_1 + w_2}, \quad i$$
$$= 1,2$$

It can be experiential that there are two adaptive layers in this ANFIS structural design, that is the first layer and the fourth layer. In the first layer, there are three changeable parameters $\{a_i, b_i, c_i\}$ which are connected to the input membership functions. These parameters are the so-called premise parameters. In the fourth layer, there are also three modifiable parameters $\{p_i, q_i, r_i\}$, pertaining to the first order polynomial. These parameters are so-called consequent parameters [12].

This technique is optimized by combination of the gradient descent algorithm and a least squares algorithm is one of the methods proposed by Jang, for an effective search for the optimal parameters and to further speed up the learning process.

A. Learning algorithm of ANFIS

In this model, the gradient descent and nonnegative least square algorithms have been used for the parameter learning in training process.

The task of the learning algorithm for this architecture is to alter all the modifiable parameters, namely $a_i, b_i, c_i\}$ and $\{p_i, q_i, r_i\}$, to make the ANFIS output match the training data. When the premise parameters a_i, b_i and c_i of the membership function are fixed, the output of the ANFIS model can be defined as in below equation

$$f$$
$$= \frac{w_1}{w_1 + w_2} f_1$$
$$+ \frac{w_2}{w_1 + w_2} f_2$$

Substituting above Eq then it yields

$$f$$
$$= \overline{w}_1 f_1 + \overline{w}_2 f_2$$

By substituting the fuzzy if–then rules, it becomes

$$f = \overline{w}_1(p_1 x + q_1 y + r_1)$$
$$+ \overline{w}_2(p_2 x + q_2 y$$
$$+ r_2)$$

After rearrangement, the output can be expressed as in below equation

$$f = (\overline{w}_1 x)p_1 + (\overline{w}_1 y)q_1 + (\overline{w}_1)r_1 + (\overline{w}_2 x)p_2 + (\overline{w}_2 y)q_2$$
$$+ (\overline{w}_2)r_2$$

which is a linear combination of the variable resultant parameters p1; q1; r1; p2; q2 and r2. The least squares method can be used to classify the optimal values of these parameters easily. 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.

### B. Training And Testing Using Optimized ANFIS 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 Optimized ANFIS 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 Optimized ANFIS classifier. Using those results train the classifier to identify the normal and abnormal lung from the given CT scan image. After the Optimized ANFIS 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 Optimized ANFIS classifier. The Optimized ANFIS 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 Optimized ANFIS classifier will identify whether the given CT scan image comes under normal category or abnormal category.

V. RESULTS AND DISCUSSION

The experiment is conducted in MATLAB. The figure 7 shows the normal and abnormal lung images.
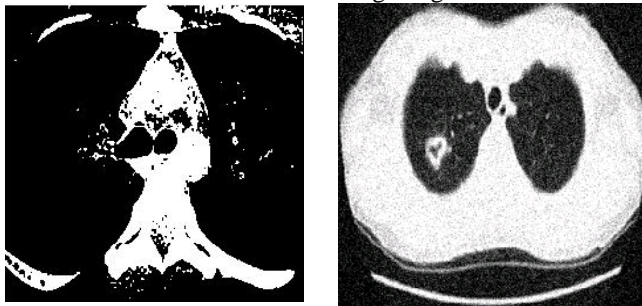
(a)Normal Image with Noise   (b) Abnormal Image with Noise

Figure.7 Sample images of normal and abnormal lungs images

The sample images are taken and the images are filtered using median filter. The filtering technique is used to remove the various noises that are present in the sample image and it improves the quality of the images as shown in the figure 8.
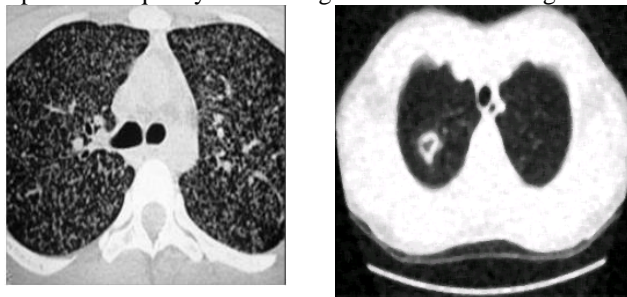
(a)Normal Image after filtering process   (b) Abnormal Image after filtering process

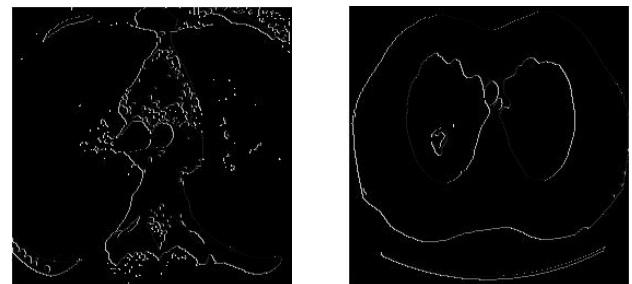Figure 8: Sample image of Lungs after Filtering process

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.9 shows a sample image of segmented lungs with COPD and without COPD.
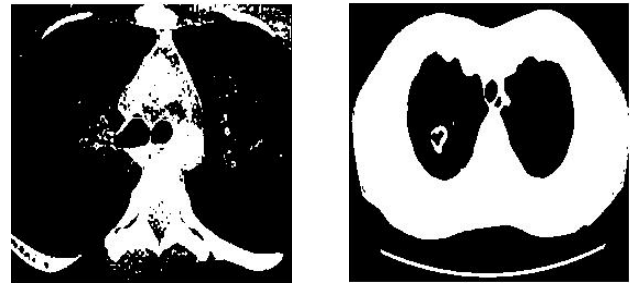
(a)Normal Image after segmentation process   (b) Abnormal Image after segmentation process

Figure 9: Sample image of Lungs 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 10 shows a sample image of segmented cavities and segmented cavities with CT scan image for the COPD affected lung.

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

Figure 10: Sample image of Lungs after segmenting the cavities

VI. PERFORMANCE ANALYSIS USING EVALUATION METRICS

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

$$\text{Sensitivity} = \frac{TN}{FP + TN}$$

$$\text{Accuracy} = \frac{TN + TP}{TN + TP + FN + FP}$$

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.

Specificity is the proportion of true negatives that are correctly identified by a diagnostic test. It shows how ood the test is at rejecting 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: 1 COMPARATIVE ANALYSIS OF EXISTING TECHNIQUE WITH PROPOSED TECHNIQUE

Techniques	TP	FN	FP	TN	Sensitivity (%)	Specificity (%)	Accuracy (%)
SVM	19	6	7	18	76	72	74
ELM	20	5	5	20	80	80	80
FRB	22	3	2	23	88	92	90
Optimized ANFIS	24	1	1	24	96	96	96

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.
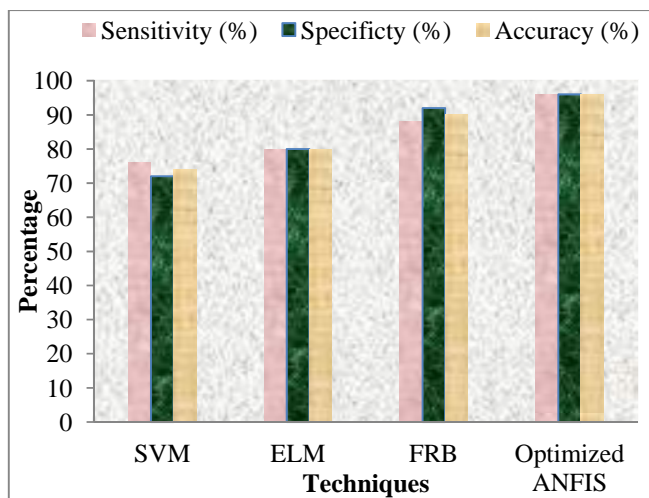

Figure 11: Comparison Graph for Sensitivity,Specificity and Accuracy for existing and proposed techniques

The figure 11 shows the Accuracy, Specificity and Sensitivity comparison between proposed technique and the existing technique. The graph shows that the proposed technique gives better Accuracy, Specificity and Sensitivity than the existing technique.

VII.CONCLUSION

An optimized technique is proposed for the detection of COPD in the lungs using CT scan images here. This technique initially preprocesses using adaptive median filter.

Then lungs and cavity are segmented from which features are extracted for classification. An optimized ANFIS technique is used here for classification of abnormal and normal lungs. This technique is optimized by combination of the gradient descent algorithm and a least squares algorithm is one of the methods proposed by Jang, for an effective search for the optimal parameters and to further speed up the learning process. The experiment is conducted for 50 CT scan lung images and performance of this approach is compared with existing SVM, ELM and previously proposed FRB technique. Obtained results shows best performance for proposed Optimized ANFIS than FRB, ELM and SVM technique.

In future this work can be extended towards 2D to 3D processing which becomes necessity at present. And large CT Scan Image Database can be implemented for training the system to get maximum result. Then from detected abnormality various lung diseases can also be detected by proper training and with efficient feature extraction. Classification techniques for different lung diseases can be added with technique by modifying or hybrid classification technique.

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