CHAPTER 4
FUZZY RULE BASED CLASSIFIER APPROACH
FOR SCREENING OF CHRONIC OBSTRUCTIVE
PULMONARY DISEASE (COPD) FROM CHEST
CT SCANS WITH MEDIAN FILTERING

4.1 INTRODUCTION

COPD is a name that refers to two lung diseases, namely 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 it also can provide further detailed images of the parts of the body that cannot easily be seen on a normal chest radiograph. Many researchers have developed different techniques to improve the performance of the automatic screening process.

In the present research, the input image is first pre-processed. The lung region is segmented from that image, the cavity region in that lung region is segmented and some features extracted for training the classifier and the FRB classifier is used to identify the COPD affected lung. The pre-processing is done by using the adaptive median Filter (Magesh et al 2011) to avoid the noise in the input image and to increase the image quality. The lung segmentation is done by comparing the region growing technique and the 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 normal or affected. The classifier used in the proposed technique is the FRB classifier. The FRB Classifier is then trained using the parameters chosen from the sample lung CT scan images to identify the normal lung and the COPD affected lung.

4.2 INTRODUCTION ABOUT MEDIAN FILTER

Median filtering is a non-linear method used for the removal of impulsive noise. It is implemented on an image using a mask of odd length, the mask moves over the image and at each center pixel, the median value of the data within the window is taken as the output. When the filter window is centered at the beginning or at the end of the input image, some values must be assigned to empty the window positions. Thus the first and the last value carry-on appending strategy can be applied which means that the borders of the image can be filtered by duplicating the outmost values (Jiannan Shen 2012).

Median filter and its modifications belong to a wide class of filters based on the classification of the chosen sample collection. The 3-step error filtering process (Juraj & Jan 2003) includes,

1. Collection of N values of the measured variable.
2. Truncation of the maximal and minimal values.
3. Calculation of arithmetic average of the rest N-2 values.
Intuitive error filtering approach consists of two sequentially connected filters. The first one represents median filter, the second linear FIR filter is based on the principle of moving average with samples decimation. Median filter is often used in the case of rare impulse errors suppression superposed on useful signal. The filter is very often used in applications of video correction (Koschman & Abidi 2001). Low-pass filters are not applicable because of the blurring of the edges of the picture.

Median filtering is a kind of smoothing technique, as is Linear Gaussian filtering. All smoothing techniques are effective at removing noise in smooth patches or smooth regions of a signal, but adversely affects the edges. Preserving the edges is as important as reducing the noise in a signal. Edges are of critical importance to the visual appearance of the images. For small to moderate levels of (Gaussian) noise, the Median filter is demonstrably better than Gaussian blur at removing noise whilst preserving the edges for a given fixed window size. However, its performance is not much better than the Gaussian blur for high levels of noise, whereas, it is particularly effective for the speckle noise and salt and pepper noise (impulsive noise). Owing to the this, Median filtering is very widely used in Digital Image Processing (Arce 2004).

4.2.1 Advantages

- It’s simple to understand.
- The Median filter preserves the differences in brightness resulting in minimal blurring of regional boundaries.
- Preserves the positions of the boundaries in an image, making this method useful for visual examination and measurement.
- Median computer algorithm can be customized.
4.2.2 Common Applications

- Removal of speckle noise - Salt and Pepper.
- Enhancement of bright or dark features in an image.
- Stellar objects in deep-sky images removal.

4.3 FUZZY CLASSIFIER

In this section, a brief explanation of Fuzzy sets and Fuzzy Logic will be given for the purpose of providing a basic knowledge of some of the methods applied later in the research.

4.3.1 Fuzzy Sets

A collection of elements denoted by \{u\} forms the universe \(U\) where \(u\) is a generic element of \(U\). In Classical set theory, these elements may or may not belong to a particular crisp set. That is to say, an element must either belong or not belong to the set (Lee 1990). There is no possibility to partially belong to a set. In contrast, in Fuzzy set theory, elements do not need to belong to or not belong to binary but can belong by a certain degree to a particular fuzzy set. A fuzzy set \(F\) belonging to the universe \(U\) has a value \(x\) in the interval \([0, 1]\), that corresponds to the element \(u\).

The value \(x\) represents the degree of membership of which elements belong to \(F\). This is defined as \(\mu_F(u) = x\) where \(u\) is an element belonging to \(F\) and \(\mu_F(u)\) is the membership function of \(F\). In the case of \(\mu_F(u) = 0\) the element \(u\) does not belong to the set \(F\). If \(\mu_F(u) = 1\), \(u\) is considered to be fully part of \(F\) while if \(0 < \mu_F(u) < 1\), \(u\) is considered to be a fuzzy member of \(F\).
4.3.2 Fuzzy Set Operations

For this subsection, A and B are fuzzy sets with the corresponding membership functions $\mu_A(u)$ and $\mu_B(u)$ in the universe $U$. The following definitions are given in Zadeh (1965).

The union between two fuzzy sets (A and B) is described by the membership function $\mu_{A\cup B}(u)$ and is defined for all $u \in U$ given in Equation (4.1),

$$\mu_{A\cup B}(u) = \max(\mu_A(u), \mu_B(u)) \tag{4.1}$$

Intersection

The intersection between two fuzzy sets (A and B) is described by the membership function $\mu_{A\cap B}(u)$ and is defined for all $u \in U$ given in Equation (4.2),

$$\mu_{A\cap B}(u) = \min(\mu_A(u), \mu_B(u)) \tag{4.2}$$

4.3.3 Linguistic Variables

A linguistic variable is a variable that, instead of numerical values, consists of linguistic terms. The linguistic variable speed which may consist of the terms slow, medium and fast is considered. These linguistic terms can each be described using a Fuzzy set. As an example, slow speed of below 40 mph, medium of around 55 mph and fast to be above 70 mph is considered. The membership functions of these fuzzy sets can be seen in Figure 4.1.
Figure 4.1 The Membership Functions of the Fuzzy Sets Slow, Medium and Fast

Using linguistic variables in this way makes it possible to describe vague and ambiguous concepts in a way that is understandable by machines. This in turns means that calculations and a variety of operations can be performed on them.

4.4 OVERVIEW OF FUZZY RULE BASED CLASSIFIER

Fuzzy systems based on fuzzy if-then rules have been researched in various fields such as control, classification and modeling (Ishibuchi et al 2005). A fuzzy rule-based classifier is composed of a set of fuzzy if-then rules. Fuzzy if-then rules are generated from a set of given training patterns. The advantages of fuzzy classifiers are mainly two-folds, namely

(i) The classification behavior can be easily understood by human users. This can be done by carefully checking the fuzzy if-then rules in the fuzzy classifier because fuzzy if-then rules are inherently expressed in linguistic forms.
(ii) Non-linearity in classification exists. It is well known that it is difficult for non-fuzzy rule-based classifiers to perform non-linear classification because in most cases the classification boundaries are always parallel to the attribute axes.

(iii) The nonlinearity of fuzzy classification leads to high generalization ability of fuzzy rule-based classifiers while its classification behavior is linguistically understood.

A fuzzy rule-based classifier in the present research consists of a set of fuzzy if-then rules. The number of fuzzy if-then rules is determined by the dimensionality of the classification problem and the number of fuzzy partitions used for each attribute. A fuzzy if-then rules is generated by calculating the compatibility of the training patterns with its antecedent part for each class. The calculated compatibilities are summed up to finally determine the consequent class of the corresponding fuzzy if-then rule. An unseen pattern is classified by the fuzzy rule-based classifier. A set of generated fuzzy if-then rules using a fuzzy inference process.

In general, as the amount of information keeps growing due to the development of high-performance computers and high-capacity memories, it is difficult for any information system to efficiently and effectively process a huge amount of data at a time. This is because it takes an intractably long time to retrieve the whole data and it is not possible to handle the huge amount of data by just one information system. Also, it is possible that training patterns are generated over time and the designers of the information systems have to handle the dynamically available patterns in a manner of streaming process.

Classification belongs to the general area of pattern recognition and machine learning.
• Soft labeling: The standard assumption in pattern recognition is that the classes are mutually exclusive. This may not be the case, as the example in Figure 4.1 shows. A standard classifier will assign a single crisp label (rain). A fuzzy classifier can assign degrees of membership (soft labels) in all the four classes \{rain, clouds, wind, sunshine\}, accounting for the possibility of winds and cloudy weather throughout the day. A standard classifier can output posterior probabilities, and offer soft labelling too. However, a probability of, say, 0.2 for cloudy weather means that there is 20% chance that tomorrow will be cloudy. A probabilistic model would also assume that the four classes form a full group, i.e., snow, blizzards or thunderstorms must be subsumed by one of the existing four classes. Soft labelling is free from this assumption. A fuzzy classifier \(D\), producing soft labels can be perceived as a function approximator \(D: F \rightarrow [0,1]_c\), where \(F\) is the feature space where the object descriptions live, and \(c\) is the number of classes. While tuning such a function approximator outside the classification scenario would be very difficult, fuzzy classifiers may provide a solution that is both intuitive and useful.

• Interpretability: Automatic classification in most challenging applications such as medical diagnosis has been sidelined due to ethical, political or legal reasons, and mostly due to the black box philosophy underpinning classical pattern recognition. Fuzzy classifiers are often designed to be transparent. This means that the steps and logic statements leading to the class prediction are traceable and comprehensible.

• Limited data and available expertise: Examples include prediction and classification of rare diseases, oil depositions, terrorist activities and natural disasters. Fuzzy classifiers can be built using expert opinion, data or both.
4.4.1 Fuzzy If-Then Rule

In a pattern classification problem with $n$ dimensionality and $M$ classes, it is assumed that $m$ labeled patterns, $X_p = \{x_{p1}, x_{p2}, \ldots, x_{pn}\}$, $p = 1, 2, \ldots, m$, are given as training patterns. It is also assumed that without loss of generality, each attribute of $X_p$ is normalized to a unit interval $[0; 1]$. From the training patterns, fuzzy if-then rules of the following type are generated using Equation (4.3),

$$R_q: \text{If } x_1 \text{ is } A_{q1} \text{ and } x_n \text{ is } A_{qn} \text{ then class } C_q \text{ with } CF_{q}$$

where $R_q$ is the label of the $q$-th fuzzy if-then rule, $A_q = (A_{q1}; \ldots; A_{qn})$ represents a set of antecedent fuzzy sets, $C_q$ the consequent class, $CF_{q}$ is the confidence of the rule $R_q$, and $N$ is the total number of generated fuzzy if-then rules.

Triangular membership functions are used as antecedent fuzzy sets. Figure 4.1 shows triangular membership functions which divide the attribute axis into five fuzzy sets. Suppose an attribute axis is divided into $L$ fuzzy sets, the membership function of the $k$-th fuzzy set is defined as follows in Equation (4.4),

$$\mu_k(x) = \max \left\{ 1 - \frac{|x - x_k|}{v}, 0 \right\}, k = 1, \ldots, L$$

(4.4)

Where $x_k$ is defined in Equation (4.5),

$$x_k = \frac{k - 1}{L - 1}, k = 1, \ldots, L$$

(4.5)

And

$$v = \frac{1}{L - 1}$$

(4.6)
Let the compatibility of a training pattern $x_{p}$ be denoted with a fuzzy if-then rule $R_q$ as $\mu_{A_q}(x_p)$. The compatibility $\mu_{A_q}(x_p)$ is calculated as in Equation (4.7),

$$
\mu_{A_q}(x_p) = \prod_{i=1}^{n} A_{q_i}(x_{p_i}), q = 1, 2, \ldots, N \tag{4.7}
$$

Where $\mu_{A_q}(x_{p_i})$ is the compatibility of $x_{p_i}$ with the fuzzy set $A_{q_i}$ and $x_{p_i}$ is the i-th attribute value of $x_p$. Note that $\mu_{A_q}(x_{p_i})$ is calculated by Equation (4.4).

The number of fuzzy rules to be generated is $L^n$. That is, the number of rules increase exponentially for the division number and the dimensionality.

4.4.2 Generating Fuzzy If-Then Rules

A fuzzy classification system consists of a set of fuzzy if-then rules. The fuzzy if-then rules are generated from the training patterns $X_p$, $p = 1; 2; m$. The number of generated fuzzy if-then rules is determined by the number of fuzzy partitions for each axis. That is, the number of generated fuzzy if-then rules is the number of combinations of fuzzy sets that are used for attribute axes. Although different numbers of fuzzy partitions can be used for different the axes, the present research assumes that it is the same for all axes. In this case, the number of fuzzy if-then rules is calculated as $N = L^n$ where $n$ is the dimensionality of the pattern classification problem at hand. For the present research, all attributes are supposed to be divided in the same way (in the same fuzzy partition).
An illustrative example is shown in Figure. 4.3. Here, a two-dimensional pattern space is divided into $3^2 = 9$ fuzzy sub-spaces as each attribute is divided into three fuzzy sets. Each sub-space is labeled with a rule label ($R^1 \sim R^9$). For example, the antecedent part of Rule R6 has the fuzzy set $A_3$ for attribute $x_1$ and $A_2$ for attribute $x_2$. In this way, the total number of generated fuzzy if-then rules and the antecedent part of each fuzzy if-then rule are automatically determined after the number of fuzzy sets for each attribute is determined.

![Figure 4.2 Triangular Fuzzy Sets](image)

![Figure 4.3 Two-Dimensional Illustrative Example of Specifying the Antecedent Part of a Fuzzy if-then Rule (three fuzzy sets for both the two attributes)](image)
The consequent part of fuzzy if-then rules (i.e., \( C_q \) and \( CF_q \) in Equation (4.3)) is determined from the given training patterns once the antecedent part is specified. The consequent class \( C_q \) of the fuzzy if-then rule \( R_q \) is determined as follows,

\[
C_q = \arg\max_h \sum_{i=1}^{M} B^q_i
\]  
\((4.8)\)

Where,

\[
B^q_i = \sum_{x_p \in \text{Class } h} \mu_{A_q}(X_p)
\]  
\((4.9)\)

That is, the most matching class with the fuzzy if-then rule is selected considering the given training patterns. If there is no training pattern that is covered by the fuzzy if-then rules, the consequent class is set as empty. Also, in the case where multiple classes have the maximum value in (6), the consequent class is set as empty.

The confidence \( CF_q \) is determined as in Equation (4.10),

\[
CF_q = \frac{\beta C_q - \bar{\beta}}{\sum_{i=1}^{m} B^q_i}
\]  
\((4.10)\)

Where \( \bar{\beta} \) is expressed in Equation (4.11),

\[
\bar{\beta} = \frac{1}{M - 1} \sum_{h \neq C_q} B^q_h
\]  
\((4.11)\)

There are other formulations for determining the confidence.
4.4.3 Fuzzy Prototype-based Classifiers

There are fuzzy classifier models inspired by the idea of "fuzzifying" conventional classifiers. A typical representative of this group is the K-Nearest Neighbor classifier (K-NN). In the classical K-NN, the object $x$ is labeled as the majority of its $K$ nearest neighbors in a reference data set. The approximation of the posterior probabilities for the classes are crude, given by the proportion of neighbors out of $k$ voting for the respective class. Fuzzy K-NN uses the distances to the neighbors as well as their soft labels, if these are available.

The reference set for this classifier does not have to be selected from the existing data. A set of relevant objects (prototypes) with crisp or soft labels can be constructed. The class membership of $x$ is obtained by combining the similarities between $x$ and the prototypes. Fuzzy prototype-based classifiers can be related to popular classifier models including Parzen classifier, Learning Vector Quantization (LVQ) and RBF Neural Networks (Ludmila et al 1999).

Along with training from data, human expertise can be used. Experts can assign soft labels to prototypes, construct prototypes not present in the training data and specify meaningful types of combination of similarities. Providing this type of expertise is much more intuitive for the domain expert than the Training Fuzzy Rule Based classifiers. Experts may not be able to explicate the intuitive ways in which they reach a decision about class labels using the jargon of if-then rules and membership functions. On the other hand, in the training of fuzzy prototype-based classifiers the expert insight and intuition do not have to be taken to the fore, analysed and mimicked.
4.4.4 Fuzzy Combination Rules for Classifier Ensembles

In multiple classifier systems (classifier ensembles) the decisions of several classifiers are aggregated to produce a single (crisp or soft) class label. Given an object , let \( d_{ij}(x) \in [0, 1] \) be the degree of membership that classifier \( i \) suggests for class \( j \), \( i = 1, \ldots, L \) (number of classifiers), \( j = 1, \ldots, c \) (number of classes). Many conventional classifiers can produce soft labels, usually as estimates the posterior probabilities for the classes, conditioned on \( x \). The matrix \( \{d_{ij}(x)\} \) is called the decision profile for \( x \).

Fuzzy aggregation functions (aggregation rules) abound in fuzzy decision making. The overall support for class \( j \) is calculated using the decision profile entries for that class, which is the \( j \)th column of the matrix. Given an aggregation function \( A \), the soft ensemble output for class \( j \) is,

\[
de_{e,j}(x) = A(d_{1,j}(x), d_{2,j}(x), \ldots, d_{L,j}(x))
\]

Minimum, maximum and mean (order statistics in fuzzy disguise) are the most popular choices for \( A \). Instead any function \( A : [0, 1]^L \to [0, 1] \) can be used. For example, product or Ordered Weighted Averaging (OWA).

The aggregation can also be made by fuzzy integral, which combines the class support (evidence) with the competence of the classifiers in the ensemble.

4.5 Proposed Technique for Identification of Cavity

The block diagram of the proposed approach is shown in Figure 4.4. In this figure, samples of Lung CT scan images with COPD and without COPD are taken. The sample images are then preprocessed and sent
for segmentation. There segmenting the lung and cavity regions takes place. 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 whether the COPD is affected or not. After the preprocessing process, the lung and the cavity region needs to be segmented. After that, the chosen parameters are given to the classifier. Here, the Fuzzy Rule based classifier is used. The FRB classifier then identifies 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.

![Figure 4.4 Block Diagram of FRB Classifier for Screening of COPD with Median Filtering]
4.5.1 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 median filter is used as a 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 and noises such as white noise, salt and pepper noise are removed by using Median filter from the extracted lung image.

Median Filter

The median filter is a non-linear digital filtering technique, frequently used to remove the noise. Such noise reduction is a typical pre-processing step to improve edge detection on an image.

With median filtering, the value of an output pixel is determined by the median of the neighborhood pixels, rather than the mean. The median is much less sensitive to extreme values than the mean. The sliding median filter of a pre-defined window size \( W \times W \) (where \( W = 3 \)) centered \( i = (i_1, i_2) \) and defined spatially by the Equation (4.13) given below, the median, \( \mu \) of the pixels in \( \Omega_i^W \) is,

\[
\hat{u}(i) = \mu(i) = \text{median} \left\{ \frac{g(j)}{j \in \Omega_i^W} \right\}
\]

(4.13)

Thus, the output of the median filter is that \( \theta \) value which produces the least sum of absolute errors with all the pixels in the local
neighborhood defined by the mask. The output of the median filter at the spatial position \( i \) can also be given as in Equation (4.14),

\[
u(i) = \mu(i) = \arg \min_\theta \sum_{r \in q'} |g(r) - \theta|
\]  

(4.14)

### 4.5.2 Feature Extraction

After finding the regions, some features are extracted to diagnose the disease in the lung. To discover the disease in the lung, the extracted feature must be fed into the classifier, as the extracted features will give vital information about the region which is used to train the classifier. In the present research, an FRB classifier is used for feature extraction. The features that need to be extracted are the 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 the maximum repeated pixel in the lung region to find the total number of cavities in the lung region. As the normal lung would also have some cavities present in its region, to distinguish the normal lung image from the COPD affected lung, the total numbers of cavities present in the lung region should be found out and the result given to the FRB classifier. This classifier shows a more accurate value and it takes minimum time for an execution.

**Fuzzy Rule-Based Classifier (FRB)**

Various Data Mining techniques are there to deal with the classification problem. Amongst them, FRBCSs give an interpretable replica by means of linguistic labels in their rules.
Figure 4.5 Block Diagram of Fuzzy Rule Based Classifier

The block diagram given in Figure 4.5 gives overall approach of a simple fuzzy based classification. The main block of FRB consists of Fuzzifier, Inference, Defuzzifier and rules.

Consider $m$ labeled patterns $x_p = (x_{p1}, \ldots, x_{pn})$, $p = 1, 2, \ldots, m$ where $x_{pi}$ is the $i$th attribute value ($i = 1, 2, \ldots, n$). A set of linguistic values and their membership functions are there to describe each and every attribute. Fuzzy rules of the following form defined in Equation (4.15) is used,

Rule $R_j$:

If $x_1$ is $A_{j1}$ and $\ldots$ and $x_n$ is $A_{jn}$ then Class = $C_j$ with $RW_j$,                     \hspace{1cm} (4.15)

where $R_j$ is the label of the jth rule, $x = (x_1, \ldots, x_n)$ is an n-dimensional pattern vector, $A_{ji}$ is an antecedent fuzzy set on behalf of a linguistic term, $C_j$ is a class label, and $RW_j$ is the rule weight. Specially, the present research, the rule weight is computed using the Penalized Certainty Factor defined in Equation (4.16) (Ishibuchi & Yamamoto 2005) as,

$$PCF_j = \frac{\sum_{x_p \in Class_j} \mu_{A_j}(x_p) - \sum_{x_p \notin Class_j} \mu_{A_j}(x_p)}{\sum_{p=1}^{m} \mu_{A_j}(x_p)} \hspace{1cm} (4.16)$$
Let $x_p = (x_{p1}, \ldots, x_{pn})$ be a new pattern, L denote the number of rules in the rule base and M the number of classes of the problem. The steps of the FRM are then as follows,

- **Matching degree:** is the strength of activation of the if-part for all the rules in the rule base with the pattern $x_p$. A conjunction operator (t-norm) is functional to carry out this computation.

  \[ \mu_{A_j}(x_p) = T(\mu_{A_{j1}}(x_{p1}), \ldots, \mu_{A_{jn}}(x_{pn})), \quad j = 1, \ldots, L. \quad (4.17) \]

- **Association degree:** To compute the association degree of the pattern $x_p$ with the M classes according to each rule in the rule base. When using rules in the form this association degree only refers to the consequent class of the rule (i.e. $k = \text{Class}(R_j)$).

  \[ b_j^{k} = h(\mu_{A_j}(x_p),RW_j^{k}), \quad k = 1, \ldots, M, \quad j = 1, \ldots, l. \quad (4.18) \]

- **Pattern classification soundness degree for all classes:** An aggregation function is used that combines the positive degrees of association calculated in the previous step.

  \[ Y_k = f(b_j^{k}, j = 1, \ldots, L \text{ and } b_j^{k} > 0), \quad k = 1, \ldots, M. \quad (4.19) \]

- **Classification:** A decision function $F$ is applied over the soundness degree of the system for the pattern classification of all the classes. This function will determine the class label $l$ corresponding to the maximum value.

  \[ F(Y_1, \ldots Y_M) = \arg \max(Y_k). \quad k = 1, \ldots, M \quad (4.20) \]
The maximum repeated pixel intensity in the cavity regions of a lung is then found out. To discover the maximum repeated pixel, the intensities of all the pixels in each cavity of a lung has to be found out by implementing histogram and thereafter all the pixels of every cavity need to be compared with each other. After discovering the maximum repeated pixel in the cavities of a lung, the result has to be given to the classifier. Similarly, the maximum repeated pixel is found in the whole lung region and the result gives to the classifier. By comparing all the features, the classifier detects whether the lung is affected by COPD or not.

4.5.3 Training and Testing Using FRB Classifier

To train the classifier, some of the data features are taken to identify the normal lung region and COPD affected lung. The classifier will then find whether the given CT scan image is normal or abnormal. The data features which have been chosen for training the FRB classifier are the number of cavities in the lung region, the maximum area of cavity in the lung region, the minimum area of cavity in the lung region, the total number of pixels in each cavity, the maximum repeated pixel in the cavity regions together and the maximum repeated pixel in the lung region. After computing all the data features, the values have to be given to the classifier. For instance, after choosing three normal CT scan images and three abnormal CT scan images, all the six data features need to be calculated separately. After calculating all the six data features for every chosen CT scan images, the result has to be given to the FRB classifier. Using those results, the classifier is trained to identify the normal and abnormal lung from the given CT scan image.

After the FRB classifier is trained, a new CT scan image is given to find whether it has COPD or not. Afterwards, the six data features such as the 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 given to the FRB classifier. The classifier then compares the values of all the six data features with the stored values of the normal and abnormal CT scan images, as all the six data features of the five normal CT scan images and five abnormal CT scan images have been stored during training. After comparison, the FRB classifier will identify whether the given CT scan image comes under the normal or abnormal category.

4.6 RESULTS AND DISCUSSION

The Figure 4.6 shows the normal and abnormal lung images taken as input image for segmentation and further classification.

![Normal Image](image1.png) ![Abnormal Image](image2.png)

(a) Normal Image (b) Abnormal Image

**Figure 4.6 Sample Images of Normal and Abnormal Lungs Images**

The input images are initially filtered using the 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 4.7.
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 4.8 shows a sample image of segmented lungs with COPD and without COPD.

After the lung is segmented from the present sample images, the cavities have to be segmented from the lung region. Using the cavities in the lung region, it is identified whether a lung is COPD affected or not.
Figure 4.9 Sample Image of Lungs After Segmenting the Cavities

The Figure 4.9 shows a sample one CT Scan image of the COPD affected lung after segmentation of the cavities.

4.7 PERFORMANCE ANALYSIS USING EVALUATION METRICS

The evaluation of the COPD identification of the images is carried out using the following metrics which is defined in the Equations (3.14, 3.15 and 3.16),

<table>
<thead>
<tr>
<th>Techniques</th>
<th>TP</th>
<th>TN</th>
<th>FP</th>
<th>FN</th>
<th>Sensitivity (%)</th>
<th>Specificity (%)</th>
<th>Accuracy (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>SVM Technique</td>
<td>19</td>
<td>18</td>
<td>7</td>
<td>6</td>
<td>76</td>
<td>72</td>
<td>74</td>
</tr>
<tr>
<td>Proposed FRB Technique</td>
<td>22</td>
<td>23</td>
<td>2</td>
<td>3</td>
<td>88</td>
<td>92</td>
<td>90</td>
</tr>
</tbody>
</table>

Table 4.1 shows the comparison of sensitivity, specificity and accuracy between the proposed and the existing technique for 50 input images. The tabular column shows that the proposed technique gives better performance than the existing technique.
Figure 4.10  Comparative Evaluation Metrics Analysis of Existing SVM and FRB Techniques

Figure 4.10 shows the accuracy comparison between proposed technique and the existing technique for 50 input images. The plotted graph shows that the proposed FRB technique is better than the performance of SVM technique.

4.8  SUMMARY

This chapter clearly discusses about the proposed algorithm for finding the COPD disease in lungs. The process and other general information about the proposed techniques like median filtering and fuzzy rule based classifier have been thoroughly explained in this chapter. The performance evaluation of the proposed approach has also been discussed. The performance of this proposed approach is compared with the existing SVM techniques with certain parameters like sensitivity and accuracy values. It is observed from the experimental results that the proposed technique provides the better results.