CHAPTER 5

CAD SYSTEM FOR DETECTION OF BRONCHIECTASIS
FROM CHEST CT IMAGES

The proposed model was tailored for detection of bronchiectasis from CT images of chest. A set of CT images of the chest with known diagnosis was collected and these images were first denoised using Wiener filter. The lung tissue was then segmented from the denoised images using optimal thresholding from which the PBRs were extracted by applying pixel based segmentation. For each PBR a GLCM was constructed. From the GLCM texture features were extracted and these features were used to construct feature vectors. These feature vectors represent those features that discriminate the PBRs from the healthy regions of the lung. A PNN was constructed and trained using this set of feature vectors. The images together with the PBRs and the corresponding feature vector and diagnosis were stored in an image database. The mean feature vector of the PBRs in each image known to be affected by bronchiectasis was determined. The mean of the feature vectors of all the PBRs known to be affected by bronchiectasis was also computed. Rule for diagnosis was based on the distance between the mean feature vector of each image and the mean of the feature vectors of all the PBRs affected by bronchiectasis. Similarly, rule for determining the severity of the disease was generated based on the extent of dilation of the bronchial region. The rules were then validated by a human expert. The validated rules were stored in the KB.
When a physician gives a CT image as input to the CAD system, the Inference and Forecasting Subsystem first transforms the image into a set of feature vectors, one for each PBR in the image. It then performs the diagnosis using two techniques. The first technique uses the trained PNN for diagnosis. The second technique uses the similarity between the feature vectors of the image and the mean of the feature vectors of the PBRs in the image database calculated using Mahalanobis distance. The final diagnosis and the severity of the disease are determined by correlating the diagnosis determined by both the techniques in consultation with the Knowledge Base. Thus the CAD system developed gives a “second opinion” to the physician indicating whether the image is diseased with Bronchiectasis or not and the severity of the disease, in case the image is diseased. The system also retrieves similar cases from the database.

5.1 CAD SYSTEM FOR DETECTION OF BRONCHIECTASIS FROM CHEST CT IMAGES USING PNN

The framework tailored in accordance with the proposed model for a CAD system used to detect Bronchiectasis from CT images of chest is shown in Figure 5.1. The major components of the CAD system are Image Denoising Subsystem, Segmentation Subsystem, Feature Extraction Subsystem, Training Subsystem, Image Database, Rule Generation Subsystem, Rule Validation Subsystem, Knowledge Base and Inference-cum-Forecasting Subsystem. Each subsystem is discussed in the following subsections.
Figure 5.1  Framework of CAD System for Detection of Bronchiectasis from Chest CT Images
5.1.1 Image Denoising Subsystem

The input to this subsystem is a JPEG image of chest CT scan of size 512x512 pixels. Hanson (1981) has mentioned that the ultimate source of noise in CT image is the random noise, Gaussian noise is also present in CT images.

Input:

Chest CT

Process:

Step 1: A piecewise Wiener filter defined by equation (5.1) was applied on the image for eliminating Gaussian white noise present in the CT chest image.

\[ b(n_1, n_2) = \mu + \left( \frac{\sigma^2 - \nu^2}{\sigma^2} \right) (a(n_1, n_2) - \mu) \]  \hspace{1cm} (5.1)

where \( \nu^2 \) is the noise variance, \( \mu \) and \( \sigma^2 \) are the estimates of the local mean and variance around each pixel given by equations (5.2) and (5.3) respectively.

\[ \mu = \frac{1}{Nm} \sum_{n_1 \in \eta} a(n_1, n_2) \]  \hspace{1cm} (5.2)

\[ \sigma^2 = \frac{1}{Nm} \sum_{n_1 \in \eta} a^2(n_1, n_2) - \mu^2 \]  \hspace{1cm} (5.3)

where \( \eta \) is the N-by-M local neighborhood of each pixel in the chest CT image A.
Step 2: The denoised CT chest image B obtained as the output of Weiner filter was deconvolved with Point Spread Function (PSF) using Wiener filter algorithm to get the deblurred image. This eliminates blurring that is equivalent to convolving the true chest CT image with a PSF and possible additive noise.

**Output:**

Denoised chest CT

5.1.2 **Segmentation Subsystem**

Segmentation was done on the denoised CT images to delineate the ROIs and other anatomical structures based on the technique proposed by Garnavi et al (2005). The fat tissues and bones were first removed from the denoised chest CT image and the ROIs were then extracted from the resulting lung region.

5.1.2.1 **Lung Tissue Extraction**

To segment the lung region from the surrounding bones, fat and background the following steps were adapted.

- **Step 1:** Image thresholding
- **Step 2:** Background removal
- **Step 3:** Hole filling
- **Step 4:** Lung region extraction

These steps are discussed in the following subsections.
5.1.2.1.1 Thresholding

A thoracic CT contains two main groups of pixels:

i. High-intensity pixels located in the body (body pixels)

ii. Low-intensity pixels that are in the lung and the surrounding air (non-body pixels)

Optimal thresholding proposed by Hu et al (2001) was applied on the denoised CT image to separate lung tissue with low-density from high-density parts.

Input:

Denoised chest CT

Process:

Step 1: The initial threshold level, T is chosen to be the global threshold value determined by Otsu’s (1979) method.

Step 2: Image is segmented using T, which produces two groups of pixels G₁, consisting of all pixels with intensity values greater than or equal to T and G₂, consisting of pixels with value less than T.

Step 3: The average intensity values μ₁ and μ₂ for the pixels in the regions G₁ and G₂ were computed.

Step 4: New threshold value was computed using equation (5.4).

\[ T = \frac{1}{2} (\mu_1 + \mu_2) \quad (5.4) \]

Step 5: Steps 2 to 4 were repeated until the difference in T in successive iterations was less than or equal to 0.5.
Step 6: When convergence was reached, the image was thresholded at value $T_c$, the threshold value at convergence. Every pixel with intensity higher than $T_c$ was set to 0 to indicate body pixels and the others pixels were set to 1 to indicate non-body pixels.

Output:

Binary image

5.1.2.1.2 Background Removal

Background pixels are identified as non-body pixels connected to the borders of the image. Thus, every connected region of non-body pixel that is connected to the border was considered as background and discarded. These non-lung pixels were removed using morphological operations.

Input:

Binary Image

Process:

Step 1: The thresholded image obtained from the previous stage was taken as the mask image.

Step 2: A marker image was created with zero everywhere except along the border, where it equals the mask image.

Step 3: Elements of the marker image connected to the outside, according to the connectivity definition were determined.

Step 4: Elements of the marker image that are not connected to the outside were set to the lowest possible value. This suppresses structures that are lighter than their surroundings and that are connected to the
image border, thereby separating the lung region from the thoracic wall and mediastinum.

**Output:**

Binary image without the background

### 5.1.2.1.3 Filling the Holes

Noises caused by imaging operation, patterns caused by diffuse lung disease and airways such as the trachea or the bronchi makes some empty cavities within the lung parenchyma. These holes within the lung tissue caused by noise or airways were removed.

**Input:**

Binary image without the background

**Process:**

The holes were removed by filling the white pixels that are not connected to the border with 0.

**Output:**

Binary image containing the two lungs without any holes

### 5.1.2.1.4 Lung Region Extraction

Finally the left and right lungs were identified and the lung tissue was extracted by replacing the black pixels in the binary image with the original intensity values in the corresponding pixel positions of the denoised image.
Input:

Binary image containing the two lungs without any holes

Process:

Each black pixel was replaced by the grayscale value in the corresponding pixel position in the original image.

Output:

Grayscale image containing the two lungs

5.1.2.2 ROI Extraction

The main goal of this step is to determine the ROIs in lung image. The ROIs for our system are the PBRs.

Input:

Grayscale image containing the two lungs

Process:

Step 1: Intensity values of the segmented image were adjusted to increase the contrast.

Step 2: Pixel based segmentation was used to extract the PBRs from the entire lung region.

Step 3: The PBRs were labeled.

Step 4: The regions other than these PBRs were removed by morphological operations.
Output:

ROIs

5.1.3 Feature Extraction Subsystem

The radiological features of bronchiectasis (Rudrapatna et al 2006) are signet ring sign, tram-tracks, string of beads, circles filled with air or air and fluid, tubular and branching opacities, bronchi visible within 1 cm of the pleura. Majority of the medical images are generally in the gray level with few modalities containing color images. These images of different categories can be distinguished using their texture characteristics.

Input:

ROI

Process:

Step 1: GLCM was created for each PBR. The GLCM is based on the estimation of the second-order joint conditional probability density functions, \( p(i,j,d,\theta) \). GLCM is defined as a matrix of relative frequencies, \( p(i,j) \) with which two neighboring pixels separated by distance, \( d \) at a specified angle, \( \theta \) occur on the image, one with gray level, \( i \) and the other with gray level, \( j \). Such GLCMs depend on the angular relationship between neighboring pixels as well as on the distance between them. Once the GLCMs are calculated along each direction, several texture descriptors are calculated to capture the texture properties and differentiate among regions with different textures.

Step 2: The following fifteen features of the ROI were considered for quantitative analysis:
i. Area: It is a scalar value that gives the actual number of pixels in each ROI and hence the extent of dilation of the bronchial region.

ii. Convex Area: It is a scalar value that gives the number of pixels in Convex Image of the ROI which is a binary image with all pixels within the hull (the smallest convex polygon that can contain the region) filled in.

iii. Equiv Diameter: It is the diameter of a circle with the same area as the ROI.

\[
\text{Equivdiameter} = \sqrt{\frac{4 \times \text{Area}}{\pi}} \tag{5.5}
\]

iv. Eccentricity: It is the eccentricity of the ellipse that has the same second-moments as the extracted ROI. The eccentricity is the ratio of the distance between the foci of the ellipse and its major axis length. The value is between 0 and 1.

v. Solidity: It is the proportion of the pixels in the convex hull that are also in the ROI.

\[
\text{Solidity} = \frac{\text{Area}}{\text{Convex Area}} \tag{5.6}
\]

vi. Energy: It is the sum of squared elements in the GLCM of each ROI (Howarth and Ruger 2004). Energy is also known as uniformity and angular second moment. Value ranges between 0 and 1.

\[
\text{Energy} = \sum_{i,j} p^2(i,j) \tag{5.7}
\]
vii. Contrast: It is the measure of the intensity contrast between a pixel and its neighbor over the whole ROI (Howarth and Ruger 2004). Contrast is also known as variance and inertia. Value ranges between 0 and \((\text{size (GLCM, 1)} - 1)^2\)

\[
\text{Contrast} = \sum_{i=1}^{N_x} \sum_{j=1}^{N_y} (i-j)^2 p(i,j) 
\]

(5.8)

viii. Correlation: It is the measure of how a pixel is correlated to its neighbor over the ROI (Howarth and Ruger 2004). Value ranges between -1 and 1.

\[
\text{Correlation} = \frac{\sum_{i=1}^{N_x} \sum_{j=1}^{N_y} ij p(i,j) - \mu_x \mu_{row}}{\sigma_x \sigma_{row}} 
\]

(5.9)

ix. Homogeneity: It is the measure of closeness of the distribution of elements in the GLCM to the GLCM diagonal of each ROI (Howarth and Ruger 2004). Value ranges between 0 and 1.

\[
\text{Homogeneity} = \sum_{i,j} \frac{p(i,j)}{1+|i-j|} 
\]

(5.10)

x. Mean: It is the measure of average intensity of the ROI.

\[
m = \sum_{z \in z} z p(z) 
\]

(5.11)

xi. Standard Deviation: It is the measure of average contrast of each ROI.

\[
\sigma = \sqrt{\sum_{z \in z} (z - m)^2 p(z)} 
\]

(5.12)

xii. Smoothness: It is the measure of relative smoothness of intensity in the ROI. Value ranges between 0 and 1.
Smoothness = $1 - \frac{1}{1 + \sigma^2}$  \hspace{1cm} (5.13)

xiii. Third Moment: It is the measure of the skewness of the histogram of the intensity levels of the ROI. It is 0 for symmetric histogram, positive for histogram skewed to the right and negative for histogram skewed to left.

$$\text{Third moment} = \sum_{i=0}^{L-1} (z_i - m)^3 p(z_i)$$  \hspace{1cm} (5.14)

xiv. Uniformity: It is the measure of the uniformity of the intensity levels in each ROI (Gonzalez and Wood 2002). It is maximum when all gray levels are equal and decreases from there.

$$\text{Uniformity} = \sum_{i=0}^{L-1} p_i(z_i)$$  \hspace{1cm} (5.15)

xv. Entropy: It is the measure of the randomness of intensity in each ROI.

$$\text{Entropy} = -\sum_{i=0}^{L-1} p(z_i) \log_2 p(z_i)$$  \hspace{1cm} (5.16)

where $z_i$ is a random variable specifying the intensity, $p(z)$ is the histogram of intensity levels of the region and $L$ is the possible intensity levels.

Features defined from (i) to (v) were extracted directly from the image and features defined from (vi) to (xv) were extracted from the GLCM of the image.

Output:

Feature vector
5.1.4 Image Database

The images were stored in the image database along with the identifier for each ROI, the corresponding feature vector and diagnosis. The image database was created in oracle 10g and organized as two relations: IMAGES (Imageid, Image) and FEATURES (Imageid, Rooi, Area, ConvexArea, EquivDiameter, Eccentricity, Solidity, Energy, Contrast, Correlation, Homogeneity, Mean, StandardDeviation, Smoothness, ThirdMoment, Uniformity, Entropy, Diagnosis). The image was stored in BLOB format. The data type for ImageID is VARCHAR2(15), ROIID is NUMBER(4), diagnosis is NUMBER(1) and for the remaining attributes NUMBER(13,8). The primary key of IMAGES is Imageid and that of FEATURES is {Imageid, Rooi}.

5.1.5 Probabilistic Neural Network

PNN is a radial basis network. In this work it is used to classify the diseased and non diseased regions. The PNN is implemented as a three layer network (Rutkowski 2004). The architecture of PNN is shown in Figure 5.2. X1 to X15 are the feature vectors given as input for training and F1 and F2 are the output of the system, that is, diseased and not diseased respectively.
The PNN consists of 15 input units comprising the input layer, 572 pattern units comprising the hidden layer and 2 category units comprising the output layer. The 15 input units correspond to the 15 features discussed in section 5.1.3, the 572 pattern units correspond to the 572 feature vectors with known diagnosis and the 2 category units correspond to the 2 classes, diseased and not diseased. Each input unit is connected to each of the pattern units and each pattern unit is, in turn, connected to one and only one of the 2 category units. The links from the input units to the pattern units represent modifiable weights. The PNN was created with the described architecture and trained to determine the optimal weights.

Figure 5.2 Probabilistic Neural Network
Input:

Feature vectors, \(x_k\) (\(k = 1, 2, \ldots, 572\))
Target vector, \(T\)

Process:

Step 1: The feature vector \(x_k\) of the training set was normalized to have unit length by dividing it by its magnitude.

Step 2: The \(k^{th}\) normalized training feature vector was placed on the input units.

Step 3: The weights linking the \(l^{th}\) input unit and the \(k^{th}\) pattern unit were set such that: \(w_{lk} = x_{lk}, \ l=1,2,\ldots,15\)

Step 4: A single connection was made from the \(k^{th}\) pattern unit to the category unit corresponding to the known class of that feature vector

Output:

Optimized weight vector, \(W\)

5.1.6 Rule Generation Subsystem

The rules were generated based on the following parameters:

i. The feature vector \(y_i\) of the \(l^{th}\) PBR in the image

ii. The mean vector \(m_\alpha\) of the sample population diseased with bronchiectasis

iii. The distance \(d(y_i, m_\alpha)\) between \(y_i\) and \(m_\alpha\)

iv. The area \(Area(y)\), that is, the total number of pixels in all the PBRs in the image
Input:

Feature vectors, $x_k$ (k = 1, 2, ..., 572)
Target vector, T

Process:

Step 1: The mean feature vector of each of the images was determined.

Step 2: The Mahalanobis distance from the mean feature vector of each bronchiectasis affected image to the mean of the feature vectors of PBRs affected by bronchiectasis, stored in the database was calculated.

Step 3: The mean of the distances calculated in step 2 was determined to be 15.

Step 4: The mean value determined in step 3 was taken as the threshold. Based on this threshold the rule generated for diagnosis is

If $\text{mean}(d(y,m_x)) < \text{threshold}$, then
category = bronchiectasis
Else
category = not diseased

Step 5: Based on the guidance of the radiologists, the rule generated to determine the severity of the disease is

If $\text{Area}(y) \leq t_f$, then
severity = 1 (low)
Else if $t_f < \text{Area}(y) \leq t_h$, then
severity = 2 (medium)
Else
severity = 3 (high)
The values for the thresholds, $t_l$ and $t_u$, were estimated as 25 and 50 by experimentation and validated in consultation with a radiologist.

**Output:**

Rules for diagnosis and severity determination

### 5.1.7 Rule Validation Subsystem

The system was tested with a set of images. The same set of test images were also given to a radiologist for manual diagnosis. The result of manual diagnosis was found to match with the diagnosis produced by our CAD system. The rules generated by the rule generation subsystem were thus validated by the radiologist.

### 5.1.8 Knowledge Base

The feature vectors of the PBRs with the corresponding diagnosis were stored in the KB. They serve as facts in the KB. In addition, the validated rules obtained from the rule validation subsystem were stored in the Knowledge Base. These facts and rules will be used in the decision making process.

### 5.1.9 Inference and Forecasting Subsystem

When a chest CT image is given to the Inference and Forecasting Subsystem it is first processed to transform the image into a set of feature vectors, one for each PBR. The feature vectors are then applied to the trained PNN and the diagnosis is performed based on the classification result of the PNN and the rules stored in the KB based on analysis of similarity measure.
5.1.9.1 Preprocessing Subsystem

The CT chest image is first preprocessed to be made suitable for classification. The image is preprocessed as discussed in sections 5.1.1 through 5.1.3.

5.1.9.2 Classification Subsystem

The CT chest image is classified using two techniques, PNN and Similarity Based Classification in correspondence with KB. It involves deciding whether the CT image given by a physician user is diseased by Bronchiectasis or not diseased and the severity of the disease.

5.1.9.2.1 Similarity Based Classification

In this technique the image is classified based on the mean of the distance between feature vector of each affected region in query image and the mean of the vectors of the PBRs labeled as bronchiectasis affected in database. The distance is determined by applying Mahalanobis distance calculated using equation (5.17).

\[ d(y, m_x) = (y - m_x)^T C_x^{-1} (y - m_x) \]  

(5.17)

where \( y \) is the feature vector of the PBR in the query image, \( C_x \) and \( m_x \) are the covariance matrix and the mean of the vector population defined by equations (5.18) and (5.19) respectively.

\[ m_x = \frac{1}{K} \sum_{k=1}^{K} x_k \]  

(5.18)

\[ C_x = \frac{1}{K - 1} \sum_{k=1}^{K} (x_k - m_x)(x_k - m_x)^T \]  

(5.19)

where \( K = MN \) and image is of size \( M \times N \).
Input:

Feature vector

Process:

Step 1: The distance $d(y_i, m_x)$ was computed for each PBR $y_i$.

Step 2: The mean distance, $m$ between the feature vectors of the PBRs in the query image and the mean feature vector of the PBRs in the image database was computed.

Step 3: With this value of similarity measure, the inference is made by applying the rules stored in the KB.

   a. If $m$ is less than threshold, the image is classified as diseased with bronchiectasis, else it is not diseased.

   b. If the image is classified as affected by bronchiectasis, the area $a_i$ of the PBRs is computed.

   c. If $a_i$ is less than or equal to $t_1$, the image is classified to be diseased with low severity, if $a_i$ is above $t_1$ but less than or equal to $t_2$, it is classified to be diseased with medium severity, else it is classified to be diseased with high severity.

Output:

Diagnosis, severity level.

5.1.9.2.2 Probabilistic Neural Network Classification

The diagnosis of image is also performed using PNN. When the feature vector of the query image is given as input to the trained PNN it produces 1 for condition diseased with bronchiectasis and a 0 for not affected by Bronchiectasis.
**Input Layer:**
**Input:**

15 features

**Process:**

Computes distances from the input vector to the training feature vectors.

**Output:**

A vector whose elements indicate how close the input is to a training input

**Hidden Layer:**
**Input:**

Output of input layer

**Process:**

Sums the contributions for each class of inputs to find the closeness of a pattern unit to the input vector.

**Output:**

A vector of probabilities

**Output Layer:**
**Input:**

Output of hidden layer
**Process:**

Selects the maximum probability

**Output:**

1 for condition diseased with bronchiectasis and a 0 for not affected by bronchiectasis.

PNN has been used for training due to the following reasons: the training process is fast, it is a parallel structure, it is guaranteed to converge to an optimal classifier as the size of the representative training set increases and training samples can be added or removed without extensive retraining.

### 5.2 EXPERIMENTAL RESULTS

The image database used by this system consists of 1500 CT images of the chest that includes 168 CT images affected by bronchiectasis, 159 normal CT images and the remaining CT images affected by other lung disorders. 572 PBRs were extracted from the 168 bronchiectasis affected CT images. The system was tested with 100 CT images of the chest.

Four distinct cases were found based on the diagnosis of disease and severity conditions. They are listed as follows:

i. Image affected by bronchiectasis with low severity

ii. Image affected by bronchiectasis with medium severity

iii. Image affected by bronchiectasis with high severity

iv. Image not affected by bronchiectasis

The results obtained for an image affected by bronchiectasis with low severity is shown in Figure 5.3 and Table 5.1. Figure 5.3 (a) shows the
input image, (b) the denoised image, (c) the lung tissue and (d) the ROI. Table 5.1 shows the diagnosis by similarity based classification, radiologist and PNN.

![Image](image.png)

(a) Original Image  
(b) Denoised Image

(c) Segmented Image  
(d) Extracted ROI

**Figure 5.3** Results Obtained for an Image Affected by Bronchiectasis with Low Severity

<table>
<thead>
<tr>
<th>No of Regions Detected</th>
<th>Mean Distance</th>
<th>Severity Value</th>
<th>Diagnosis by radiologist</th>
<th>PNN</th>
</tr>
</thead>
<tbody>
<tr>
<td>2</td>
<td>7.9708</td>
<td>1</td>
<td>Low Severity</td>
<td>Diseased</td>
</tr>
</tbody>
</table>
The results obtained for an image affected by bronchiectasis with medium severity is shown in Figure 5.4 and Table 5.2. Figure 5.4 (a) shows the input image, (b) the denoised image, (c) the lung tissue and (d) the ROI. Table 5.2 shows the diagnosis by similarity based classification, radiologist and PNN.

Figure 5.4 Results Obtained for an Image Affected by Bronchiectasis with Medium Severity

Table 5.2 Results Obtained for an Image Affected by Bronchiectasis with Medium Severity

<table>
<thead>
<tr>
<th>No of Regions Detected</th>
<th>Mean Distance</th>
<th>Severity Value</th>
<th>Diagnosis by Radiologist</th>
<th>PNN</th>
</tr>
</thead>
<tbody>
<tr>
<td>4</td>
<td>3.6651</td>
<td>2</td>
<td>Medium Severity</td>
<td>Diseased</td>
</tr>
</tbody>
</table>
The results obtained for an image affected by bronchiectasis with high severity is shown in Figure 5.5 and Table 5.3. Figure 5.5 (a) shows the input image, (b) the denoised image, (c) the lung tissue and (d) the ROI. Table 5.3 shows the diagnosis by similarity based classification, radiologist and PNN.

![Images](image1.png)  ![Images](image2.png)

(a) Original Image  (b) Denoised Image

![Images](image3.png)  ![Images](image4.png)

(c) Segmented Image  (d) Extracted ROI

Figure 5.5  Results Obtained for an Image Affected by Bronchiectasis with High Severity

Table 5.3  Results Obtained for an Image Affected by Bronchiectasis with High Severity

<table>
<thead>
<tr>
<th>No of Regions Detected</th>
<th>Mean Distance</th>
<th>Severity Value</th>
<th>Diagnosis by Radiologist</th>
<th>PNN</th>
</tr>
</thead>
<tbody>
<tr>
<td>11</td>
<td>6.6672</td>
<td>3</td>
<td>High Severity</td>
<td>Diseased</td>
</tr>
</tbody>
</table>
The results obtained for an image which is not affected by bronchiectasis is shown in Figure 5.6. Figure 5.6 (a) shows the input image, (b) the denoised image, (c) the lung tissue and no ROIs are extracted. Table 5.4 shows the diagnosis by similarity based classification, radiologist and PNN.

(a) Original Image

(b) Denoised Image

(c) Segmented Image

Figure 5.6 Results Obtained for an Image Not Affected by Bronchiectasis

Table 5.4 Results Obtained for an Image Not Affected by Bronchiectasis

<table>
<thead>
<tr>
<th>No of Regions Detected</th>
<th>Diagnosis by Radiologist</th>
<th>Similarity Based Classification</th>
<th>PNN</th>
</tr>
</thead>
<tbody>
<tr>
<td>11</td>
<td>Not diseased</td>
<td>Not diseased</td>
<td>Not diseased</td>
</tr>
</tbody>
</table>

The values achieved for the various performance measures are given in Table 5.5.
Table 5.5 Performance Measures

<table>
<thead>
<tr>
<th>Performance Measures</th>
<th>Similarity Based Classification</th>
<th>Probabilistic Neural Network</th>
</tr>
</thead>
<tbody>
<tr>
<td>Specificity</td>
<td>99.54%</td>
<td>99.54%</td>
</tr>
<tr>
<td>Accuracy</td>
<td>96.49%</td>
<td>98.19%</td>
</tr>
<tr>
<td>Precision</td>
<td>98.83%</td>
<td>99%</td>
</tr>
<tr>
<td>Recall</td>
<td>89.44%</td>
<td>95.30%</td>
</tr>
</tbody>
</table>

In this work a CAD system has been developed using CBIR for Bronchiectasis. The diagnosis has been done using Mahalanobis similarity measure and PNN. After diagnosis the query image with the correct diagnosis is added to the database to increase the size of the training set, thereby improving the performance of the system. The performance measure of the system for each technique has been evaluated under the guidance of an experienced radiologist and compared. The specificity of the system is same for both Mahalanobis similarity measure and PNN and is 99.54%. The accuracy of the system with Mahalanobis similarity measure is 96.49% and that of PNN is 98.19%. Precision of 99% has been achieved with PNN and it is 98.83% for Mahalanobis similarity measure. The recall value with PNN is 95.30% and that of Mahalanobis similarity measure 89.44%. It has been found that the system shows higher efficiency with PNN to classify the images as diseased or not. The system developed efficiently detects the images diseased by bronchiectasis and classifies according to the severity conditions. The system is able to differentiate bronchiectasis from other diseases and hence performs efficiently even when tested with images having other lung disorders. It was found that segmentation of lung parenchyma would be a challenging task in the presence of peripherally placed PBRs. This was not an issue in case of CT images affected by bronchiectasis. Hence the next work aimed at solving the problem of handling segmentation in images with peripherally placed PBRs.