CHAPTER 3

FRAMEWORK OF THE COMPUTER AIDED DIAGNOSIS SYSTEM

The framework of the CAD system that is developed in this research work is illustrated in Figure 3.1. The major processes involved in the CAD system are preprocessing, segmentation, ROI extraction, feature extraction, classification and performance analysis.

Figure 3.1 Framework of the CAD system
3.1 PREPROCESSING

The chest CT dataset is preprocessed to improve the quality of the CT slices and to make the dataset more suitable for further processing stages like segmentation and ROI extraction. Preprocessing the CT slice will enhance the radiological patterns that have been obscured by noise. The CT slices contain Gaussian and random noise (Hanson 1981). Removal of noise is done by using denoising techniques. The commonly used filters for denoising are mean filters, median filters, Laplacian filters, Weiner filters and Gaussian filters. In this research work the Gaussian filter is used for denoising as it retains the edges in the CT slice. The Gaussian filter has a response that is a bell shaped curve satisfying the Gaussian function. Filters generally smoothen the image and so the edges of the CT slices are enhanced by using edge detection techniques such as Canny edge detection (Canny 1986). Edges represent the meaningful discontinuities in the gray levels of an image (Gonzalez & Woods 2002). The Canny edge detector is easily affected by noise and so it is in general applied on a CT slice that has already been convolved with a Gaussian filter.

Other edge detection operators that are available are Roberts cross gradient operator (Roberts 1965), Prewitt operator (Prewitt & Mendelsohn, 1966), Sobel operator (Sobel 1970; Heath et al 1997) and the Laplacean operator. The edge detection operators are applied for enhancing the edges which in turn enhances the entire CT slice. Edge detection in this research work has been performed using the Canny edge detector and the Sobel operator.

The denoised and enhanced color CT slices are transformed into grayscale slices before any further processing is done. Preprocessing is an extremely important stage in the CAD system as the effectiveness of further
processes such as segmentation, ROI extraction and feature extraction, are largely dependent on the enhanced quality of the dataset used.

3.2 SEGMENTATION

Segmentation techniques are used to partition or subdivide an image into objects. In this research work the lung parenchyma is to be segmented from the chest CT slices. This results in the extraction of the left and the right lungs. The lungs are extracted so that computation time need not be wasted in processing regions in the CT slice other than the lung. The chest CT slice that was transformed from RGB to grayscale in the preprocessing step is thresholded. Thresholding transforms the grayscale slice into a binary slice. The histogram of the grayscale slice is first computed and the threshold is determined by analyzing the histogram. Thresholding separates the pixels in the image into two classes with intensity levels of 0 and 1. Otsu’s thresholding (Otsu 1979), optimal thresholding (Sonka et al 1998) and iterative thresholding (Ridler & Calvard 1978) are techniques that have been adopted in this research work. Morphological operators like open, close, dilate, erode etc. are applied to the thresholded CT slice to segment the lung parenchyma.

3.3 REGION OF INTEREST EXTRACTION

The diseased region in the CT slice is called the region of interest (ROI) that has to be extracted. Region growing algorithm and morphological operations are versatile techniques used for ROI extraction. But when the disease pattern has spread over the complete lung parenchyma, then region growing techniques will extract the entire lung region. This type of radiological pattern occurs in the case of CT slices affected with military TB, fibrosis, ground glass opacity and emphysema. Hence in the case of these diseases, region growing will not be suitable for ROI extraction. So the entire
lungs are divided into smaller ROI blocks of size 64 x 64, 32 x 32 or 16 x 16. As the block size of the ROI increases, the computations become faster as fewer ROIs have to be processed. It is inferred from literature that 32 x 32 and 16 x 16 are optimal ROI sizes. The features are extracted in the next stage from these extracted ROIs.

### 3.4 FEATURE EXTRACTION

The feature extraction process extracts the shape, texture and color features from the ROIs. However, as the CT slices have already been transformed to grayscale slices in the preprocessing step, they do not contain color information. Therefore only the shape and texture features are extracted from the ROIs. The extracted features are grouped to form a feature vector. In the literature, the texture features proposed by Haralick called the Haralick texture features (Haralick et al 1973) are extracted from the ROIs. In one of the research contributions for the classification of ILDs, the segmented lung parenchyma is divided into 32 x 32 sub blocks and GLH and QWF features are extracted from the blocks. In another research work for the classification of pulmonary TB, histogram statistical features like mean, variance, skewness, kurtosis and energy are extracted from the ROIs. In the third research work for the extraction of pleural effusion, shape and texture features like area, convex area, equivalent diameter, mean, eccentricity, solidity, standard deviation, perimeter, entropy and smoothness are extracted from the ROIs.

### 3.5 CLASSIFICATION

The classifier is trained with the feature vectors that have been extracted from the training dataset. The features are extracted from the query CT slice after preprocessing, segmentation and ROI extraction. The extracted features are given as input to the trained classifier for classification. These
Feature vectors are used by the classifier to classify the CT slice into the different disease classes. In this research work the SVM and ANN classifiers are used for classifying the query CT slices. Depending on the training received by the classifier, for the diagnosis of a specific type of disease, the features of the query slices are compared by the classifier with the corresponding features of the diseases that have already been diagnosed by the expert.

3.6 DIAGNOSIS

The query CT slices are initially diagnosed by a radiologist to determine the type of disease. The radiologist can use the classifier results to obtain a second opinion or for confirmation of the result. The diagnosis performed by the radiologist is recorded as the CT scan report. This report is the ground truth and is used for comparison with the classifier output, wherein the radiologist diagnosed results are compared with the results of the classifier for the query CT slices. The radiologist performs reasoning with both results and arrives at the final conclusion. This final conclusion is called the gold standard. After comparison with the gold standard the True Positive (TP), True Negative (TN), False Positive (FP) and False Negative (FN) values are derived.

3.7 PERFORMANCE ANALYSIS

The classifier results are compared against the radiologist's validations from which the performance of the system is evaluated. TP refers to CT slices that have been correctly classified as diseased by the CAD system and have also been diagnosed by the radiologist as diseased. TN refers to CT slices that have been classified by both the CAD system and the radiologist as normal. FN refers to CT slices that have been classified as normal by the CAD system but have been diagnosed as diseased by the
radiologist. FP refers to CT slices that have been classified as diseased by the CAD system but have been diagnosed as normal by the radiologist. These values are used to compute the performance metrics using Equations (3.1) to (3.11) (Fawcett 2006).

Specificity or True Negative Rate (TNR) \[ = \frac{TN}{TN + FP} \] (3.1)

Sensitivity or True Positive Rate (TPR) \[ = \frac{TP}{TP + FN} \] (3.2)

Accuracy \[ = \frac{TP + TN}{TP + FP + TN + FN} \] (3.3)

Precision or Positive Predictive Value (PPV) \[ = \frac{TP}{TP + FP} \] (3.4)

Negative Predictive Value (NPV) \[ = \frac{TN}{TN + FN} \] (3.5)

False Positive Rate (FPR) = 1 - Specificity \[ = \frac{FP}{TN + FP} \] (3.6)

False Negative Rate (FNR) = 1 - Sensitivity \[ = \frac{FN}{TP + FN} \] (3.7)

False Discovery Rate (FDR) = 1 - Precision \[ = \frac{FP}{TP + FP} \] (3.8)

Positive Likelihood Ratio (PLR) \[ = \frac{TPR}{FPR} \] (3.9)

Negative Likelihood Ratio (NLR) \[ = \frac{FNR}{TNR} \] (3.10)

Misclassification Rate (MR) \[ = \frac{FP + FN}{TP + TN + FP + FN} \] (3.11)
3.8 SIGNIFICANCE OF THE PERFORMANCE MEASURES ON THE CAD SYSTEM

The accuracy of a CAD system helps to discriminate between the presence and the absence of a disease. Sensitivity relates to the capability of the CAD system to detect the CT slices affected with the disease. Specificity is the ability of the CAD system to detect CT slices without the disease. Precision or the positive predictive value (PPV) is the proportion of the CT slices that are actually positive (TP) among a group of all CT slices that showed positive results. It is the ratio of correctly classified CT slices with the disease out of the group of all CT slices that have been classified by the CAD system as being diseased.

Negative Predictive value (NPV) is the proportion of the CT slices that are actually negative (TN) among a group of all the CT slices that were classified as negative by the system. False Positive Rate (FPR) is the proportion of all the CT slices that were wrongly classified as positive by the system (FP) out of the group that was negative (TN+FP). False Negative Rate (FNR) is the proportion of CT slices that are wrongly classified as negative (FN) by the CAD system out of a group that was positive (TP+FN). False discovery Rate (FDR) is the proportion of all the CT slices that were wrongly classified as positive by the system (FP) out of the group consisting of all CT slices classified as positive (TP+FP) by the system.

The Positive Likelihood Ratio (PLR) is a very useful measure that gives the probability of a positive test result in a CT slice with the disease (TP) compared to a positive result in a CT slice without the disease (FP). When the PLR is greater than 1 it indicates that the positive test result has occurred in CT slice with the disease compared to CT slices without the disease. A good diagnostic system has a PLR greater than 10. The Negative Likelihood Ratio (NLR) gives the probability that a negative test result occurs
in CT slices with the disease compared to the probability of a negative result occurring in a CT slice without the disease. The NLR should be lesser than 1, as it is less likely that a negative test result occurs in CT slices with the disease than in CT slices without the disease.

After these performance metrics have been computed, the ROC curves are plotted taking the TPF against the FPF. The AUC is a measure of verifying the system performance.