CHAPTER 2

LITERATURE REVIEW

This chapter presents a review of the literature on CAD systems for lung diseases and addresses some of the most relevant techniques, algorithms and methods for preprocessing, segmentation, region of interest (ROI) extraction, feature extraction and classification of chest abnormalities. The major algorithms and techniques used in this research work are also discussed. Finally the novelty of the research work proposed in this thesis is presented.

2.1 ROLE OF PREPROCESSING AND SEGMENTATION TECHNIQUES IN CAD

The chest CT slice dataset is initially preprocessed to enhance the slice and make it suitable before subsequent image processing stages such as segmentation and ROI extraction. Segmentation follows the preprocessing step and involves the processing of chest CT slices wherein only the lung regions called the lung parenchyma are partitioned from the remaining portions of the CT slice. The segmentation technique used is disease specific and also depends on the type of medical image under consideration.

Elizabeth et al (2012a) in their work have developed a CAD system for the detection of lung cancer, with an automated technique for the segmentation of lung parenchyma from chest CT images. The chest CT image was initially denoised using a piecewise Wiener filter and deconvolved with a
point spread function (PSF) to obtain a deblurred image. The image was then enhanced using a Laplacean operator to extract the edges and segmented by optimal thresholding. The background and airways were eliminated by morphological filling operation. Morphological erosion and dilation operations were used to separate the left and the right lungs and Canny edge operator was used to detect the edges. The pathology bearing regions (PBRs) in the lung images were determined using pixel based segmentation. The PBRs were labeled and the regions other than the PBRs were removed by morphological operations. A GLCM and histogram were then computed for each PBR. Fifteen shape and texture features were extracted from the GLCMs and histograms of the PBR. The extracted features and the PBRs were stored in the image database. A PNN was used to classify the diseased and non-diseased regions. The CAD system had been tested using 20 chest CT images with peripherally placed PBR, 80 images with internally placed PBR and 100 normal lung images. Precision of 96.07%, specificity of 96% and accuracy of 97% were achieved by the system. This system was effective in cases of peripheral PBRs that were of moderate size but failed when a major portion of the lung was affected on the periphery.

Darmanayagam et al (2013) in their work have developed a CAD system to detect bronchiectasis, TB and pneumonia using a novel segmentation approach to segment lung parenchyma from the chest CT images with severe pathology attached to the borders. The chest CT image was denoised using an adaptive Wiener Filter and the edges of the image were extracted using Laplacean filters. The lung parenchyma was extracted from the rest of the chest CT images by iterative thresholding and morphological fill and close operations were used to remove the background, airways and the non-lung components. The shape features extracted from the segmented lung were the input to the trained feed forward BPNN. The output of the NN consisted of two classes: completely segmented lung and
incompletely segmented lung. If the lung was completely segmented then further processing was not needed. But if the lung was incompletely segmented then morphological dilation, erosion and translation operations were carried out to reconstruct the lung borders and obtain the two lungs.

The ROIs were next extracted from the lung regions and shape and texture features were extracted. The GLCM was created for each ROI and features were extracted from it and stored in the image database. Then a BPNN was trained with the features that were stored in the image database. A knowledge-base (KB) was constructed using the dataset that was used for training and the outputs produced by the NN. Finally an inference subsystem was used to generate the diagnostic results based on the correlation between the classification results provided by the NN and the inference provided by the KB. The image database consisted of 400 ROIs that were extracted from 50 chest CT images consisting of 20 bronchiectasis CT images, 20 TB CT images and 10 pneumonia affected CT images. The training image dataset consisted of 183 CT images of which 150 were correctly segmented and 33 were incompletely segmented. An accuracy of 97.37%, specificity of 97.71% and precision of 95.74% were obtained by the system. The drawback of the system was that along with the lung parenchyma, additional regions were also segmented.

Korfiatis et al (2011) in their work have proposed an automated vessel tree segmentation technique for lung parenchyma affected by reticular patterns. The dataset consisted of 15 Multidetector CT (MDCT) scans corresponding to three normal patients and 12 patients diagnosed with Interstitial Lung Diseases (ILDs) from the Department of Radiology at the University Hospital of Patras, Greece. The ILDs manifested ground glass and reticular patterns. The algorithm consisted of two-stages. In the first stage 3D histogram thresholding lung fields (LF) segmentation was combined with an
edge highlighting wavelet preprocessing step. When ILD patterns were present especially at the borders, these thresholding algorithms were unable to segment the LFs accurately. A 3D multi-scale vessel enhancement filter based on the eigen-value analysis of the Hessian matrix was used to capture the characteristics of the vessel tree. Then an Expectation Maximization (EM) segmentation algorithm was applied to the output of the filter to determine the voxels with high responses providing the vessel tree volume candidate. In the second stage 52 GLCM features were extracted and Stepwise Discriminant Analysis (SDA) was used to reduce the dimensions of the features that were applied to a SVM classifier to differentiate between vessel tree segments and reticular patterns. The SVM assigned a label as vessel or ILD to each tree voxel. The segmentation accuracy was evaluated by computing the area overlap (AO), True Positive Fraction (TPF) and False Positive Fraction (FPF). For the proposed system: AO was 0.931, TPF was 0.935 and FPF was 0.074. The response of the system to different image noise levels and the effectiveness of the segmentation algorithm for different levels of disease severities has to be addressed as a future work.

Liming et al (2011) in their work proposed an algorithm to automatically segment the lung parenchyma and tumor area from chest CT scan. The algorithm was based on two binarization operations. The optimal threshold was initially computed and used to produce a binary image of the lung. The trunk boundary was obtained by using the boundary tracking method and all pixels outside the boundary were set to zero. Optimal thresholding was again applied to the resultant image. The contour of each region in the lung was determined using boundary tracking method. The area of each contour was computed and the smaller areas were removed. The contours with the two largest areas were the left and right lungs. The pixels inside the contour were made white and those outside the contours were made black to form a mask image. The resultant mask image was mapped with the
original image resulting in the extracted lung parenchyma. Mathematical morphological operations such as dilation, erosion, open and close were used to segment the tumour regions. The dataset consisted of CT images of dimensions 512 x 512 corresponding to 26 patients. The accuracy rate of the algorithm was 95.2%.

Bliton et al (2011) in their work have proposed an automatic method to segment the lungs from a CT scan by using a 3D surface modelling. Fifteen chest CT slices of size 512 x 512 were used. Initially thresholding and region growing techniques were used to identify the lung borders. ACM was used to determine the visceral pleura and a B-spline curve was used to determine the parietal pleura. The region between the parietal and visceral pleura is the pleural space. The entire pleural space was modelled using a 3D surface. The mean and the standard deviations of the pleural effusion region were determined for an average of 20 slices. Each slice was divided into 5 x 5 blocks and the mean and the standard deviation values were determined. Two consecutive slices were considered and the next slice was sampled at the same location where the pleural effusion was located on the previous slice. The mean and standard deviations were computed for the 5 x 5 square on the new slice to determine the location where only half of the values as calculated for the previous slice were obtained. In case a square satisfying the constraint was detected then, the slice was scanned by the algorithm to identify the pixels with pleural effusion. The intensity of a pixel was determined from the 5 x 5 region surrounding it. As the scanning progressed in case a fixed number of pixels were scanned, without any pixel having an intensity equivalent to a pixel with pleural effusion, then the scanning was stopped. Morphological operations were used to extract the effusion region. The edges of the effusion region were sampled and were used to generate a benzier surface that was used to reduce the noise near the edges. The false positive rate ranged between 3.7% to 19% and the correlation
between automatic and manual estimate of the lung volume improved from 0.59 to 0.81. The limitation of this system was that this technique only worked on pleural effusions having a specific shape and not on all images.

Mesanovic et al (2012) in their work have proposed a method of lung segmentation that can be used for quantification of lung disease and to automatically determine the disease progression in a patient. The dataset used in this work was from the Picture Archiving and Communication System (PACS) (Choplin 1992). Fifteen patients with pleural effusion were selected and 1584 slices at an average of 106 slices per patient were considered. A pair of images called the baseline image and the follow-up image was selected from the CT scans of the same patient taken over a period of time and the healthy area in the lung parenchyma was determined in both the images. The segmented area of the healthy parenchyma in the baseline image was extracted by applying B-spline registration and transformation. The healthy region in the follow-up image was extracted using region growing. The areas obtained from both the segmentation processes were then compared to determine if there was a progression in the disease, regression in the disease or if there was a state of stagnation. The same set of images were annotated by the radiologist and the disease progression was categorized into four classes such as severe progression, moderate decrease progression, mild progression and minor change in disease. The average Pearson's correlation value computed between the proposed method and human observers was 0.9805 indicating significant correlation. The images obtained using this algorithm and the results obtained by manual segmentation were compared and there were minor variations with visual observations.

Thus it can be concluded from the literature that no gold standard method exists, that can be used for lung segmentation from CT slices.
2.2 \textbf{TECHNIQUES FOR REGION OF INTEREST EXTRACTION IN CAD SYSTEMS}

The ROIs are to be extracted from the segmented lungs. The techniques used for ROI extraction vary depending on the type of radiological pattern that has to be extracted. This section explains the common ROI extraction techniques that have been used in literature.

Shen et al (2010) in their work have proposed a hybrid knowledge-based Bayesian classification approach for the automatic detection of TB cavities from chest X-rays (CXRs). The CXR images were collected from hospitals in Alberta, Canada. They were initially converted to greyscale images and the upper lung zones (ULZ) were then extracted using a 400 x 200 mask. The resultant sub-image was histogram equalized and gaussian smoothed to enhance the contrast and to reduce the noise. The enhanced sub-images were fed to the mean shift segmentation block which was used to automate the initial contour placement. This technique clustered the neighboring pixels having similar characteristics and selected the initial contour. The clustering process was controlled by applying adaptive thresholding which produced a binary image, to which the directional GVF model combined with Dirichlet boundary conditions was applied to delineate the candidate TB cavities. Two feature descriptors describing the region boundaries and circularity of the region were computed. The Gradient Inverse Coefficient of Variation (GICOV) was the first descriptor that was used to describe the region boundaries and circularity was the second descriptor that was extracted, as the shape of a TB cavity is circular in a CXR. The GICOV threshold and the circularity threshold were computed for individual lung fields to accommodate varied lung conditions in order to distinguish a true cavity from all the other cavities that had been previously delineated.
The extracted cavities were next classified as TB cavities and non-TB cavities using a Bayesian classifier, based on the features that had been extracted. In the upper half of the ULZs the cavities are hidden by the clavicles and so they were not detected. Hence a mask was used to extract the upper half of the ULZs. The GICOV thresholds that had already been computed were recalculated with respect to the pixels in this region. A higher circularity threshold was used, as the cavities now were hidden by the clavicles and so did not appear circular. The newly detected cavities were again classified using the Bayesian classifier. The CXR dataset consisted of three sets: 20 in the cavity set belonging to patients who were diagnosed with TB, 19 in the non-cavity set from patients who were diagnosed with TB but did not exhibit cavities and 110 in the normal set from patients who were not diagnosed with TB and who did not exhibit cavities in the CXRs. The effectiveness of the cavity detection system was verified for the hybrid approach that used both GICOV and circularity descriptors. A true positive rate (TPR) of 82.35% was achieved by the system. An area to be addressed is that some of the cavities are missed by this algorithm as automatic initialization fails to place the initial contours inside the cavities.

Xu & Cheng (2011) in their work have proposed a TB cavity detection system for the automated detection of cavities from chest radiographs. Initially without applying any preprocessing techniques, the original 512 x 512 CXR image was applied to a 2D Gaussian-model-based Template Matching (GTM) module, for automated candidate detection. Then based on the knowledge of the dimensions of the largest and smallest cavity, a set of artificial templates of various object sizes and angles were generated, using 2D circular Gaussian ring distribution. The artificial templates were used for matching the cavities of different sizes and wall thicknesses that were present on the CXR. Normalized Cross Correlation (NCC) was used as the similarity measure between the template and the template-sized sub-image.
at that position. The NCC of the set of templates was then thresholded so that the candidate cavities could be located by GTM. Hessian-matrix based Image Enhancement (HIE) technique was used for preserving the strong edges related to the cavity and for noise suppression. An improved Fluid Vector Flow (IFVF) technique which is an edge-based snake model, was applied to the results of the HIE technique for fast and accurate extraction of the TB cavities. Circularity features were extracted from the cavities. Then the cavities were classified using Circularity Thresholding. The CXR images were taken from the Japanese Society of Radiological Technology (JSRT) database and a CXR image database from the University of Alberta Hospital, Canada. The images were grouped into 3 sets: 20 images for the cavity set, 20 images for the non-cavity set and 20 images for the normal set. A TPR of 67.9% and false positive rate (FPR) of 32.1% was achieved. The detection rate can be further improved if this technique is combined with automatic lung field segmentation techniques.

Yao et al (2009) in their work proposed an automated method to identify the areas of pleural effusion and measure their severity without considering the radiologist’s manual input. The thin chest CT scans were denoised using an anisotropic diffusion filter. The lung regions were segmented using region growing and morphological methods. 3D region growing and mathematical morphological operations were used for segmenting the lung parenchyma. The trachea was first removed. Then seed points were positioned on either sides of the trachea to indicate that they were two points located within the lungs. The 3D region growing process was initiated from the position of the seed points to segment the lungs. Morphological operations were used to close gaps and fill holes. The visceral and the parietal layers of the pleura were extracted by first forming a layer at the bottom of the lung and at the inner rib cage, then a bernstein polynomial was fitted to each of the layers. Finally an ACM was used to fit and refine
both the layers. The end points of the visceral and parietal layers were joined together and the ratio of pleural effusion volume and total lung volume was calculated using a scanline algorithm. This method was tested on the CT scans of 15 patients. The regression analysis between the radiologist's observations and the computer evaluation was carried out and the Pearson correlation coefficient was computed to be 0.956. The limitations of the scheme was that the segmentation was conducted on each 2D slice separately and not on the entire CT stack.

Tolouee et al (2011) in their work have proposed a novel approach for automatic classification of lung tissue of patients affected with ILDs. Initially the noise in the HRCT image was reduced by using a smoothing low pass filter. The image was thresholded by Otsu’s method (Otsu 1979) and repetitive dilations were applied to remove the background pixels. The lung borders were reconstructed using Canny edge operator and the image was then divided into sub-blocks for feature extraction. Two sets of overcomplete wavelet filters namely Discrete Wavelet Frames (DWF) and Rotated Wavelet Frames (RWF) were used to extract the texture features. The ROIs were convoluted with the filters in the filter bank and features were calculated from the intensity distribution in the resulting set of filtered images. The energy measure of the wavelet coefficients was obtained for both DWF and RWF.

A sequence of the energy features were extracted from the ROI. These features were normalized before classification using Fuzzy k-NN (FKNN) classifier. The images were classified as normal, honeycombing, ground glass and reticular. The dataset consisted of 339 HRCT slices taken from 17 HRCT scans of patients and from each scan about 20 slices were chosen. The images were collected from Noor and Athari Imaging Centers at Iran. The results for the classification of honeycombing images against all other images had an accuracy of 97.16%, sensitivity of 98.66% and
specificity of 96.66%. The classification of ground glass images against all the other images resulted in an accuracy of 95%, sensitivity of 86.66% and specificity of 97.11% and the classification of reticular images against all the other images had an accuracy of 93.16%, sensitivity of 84.66% and specificity of 94.67% respectively. It was observed that the RWF features were better than the DWF features. As the scale levels increased the dimensionality of the features increased resulting in high computational complexity. 3 D analysis can be considered and the system can be trained for different anatomical locations of the lung.

Chen et al (2014) in their work have proposed a CAD system for the detection of lung nodules. The lung CT images are initially binarized using thresholding techniques. Next the lung parenchyma is segmented using simple image processing operations. The trachea and bronchi are then removed using region growing methods. The lung edges are repaired using the rolling ball method, morphological edge repairing method and fast marching boundary methods. The ROIs are next extracted using thresholding method. The shape feature, roundness is next determined for the extracted ROIs. These features are used to determine if the extracted ROIs are nodules or non nodule regions. This system has not been tested using a classifier.

Yao et al (2013) proposed an automated technique to evaluate the volume of pleural effusion on chest CT scans. 103 slices of size 512 x 512, from 89 patients affected by pleural effusion were considered. Anisotropic diffusion filter was used to preprocess the image. Otsu’s thresholding was used to identify the lung borders. A 3D region growing method was used to segment the lungs. Morphological operations were used to fill holes and close gaps. The visceral pleura was then detected by using an active contour model. To detect the parietal pleura a B-spline curve was fitted to the rib cage to which a bernstein polynomial was fitted. An active contour model was used
to refine the results. The space between the parietal and visceral pleura is the region affected by pleural effusion. This method could not be used to measure loculated effusions. Ninety one CT slices from 77 patients were used to validate the results. The volume of the pleural effusion was estimated in case of manual and automated segmentation and the correlation between them was 0.97. The average error observed during intra observer comparison was 11% and the dice coefficient values were close to 0.7. The performance is not on par with manual segmentation methods and does not work well with loculated effusions.

2.3 FEATURE EXTRACTION SCHEMES FOR CAD SYSTEMS

The CT slices are transformed from RGB to greyscale during preprocessing and hence the ROIs that were extracted after segmentation do not contain color information. Therefore only shape and texture features are extracted from the ROIs. The different techniques that are used to extract the features and form the feature vectors are discussed in this section.

Peng et al (2010) in their work have proposed the Uniformity Estimation Method (UEM) to extract texture features that are rotation invariant in multiple directions to detect pathological changes in chest CT images. The lung CT image was first enhanced using gamma correction and thresholding was applied using Otsu’s method (Otsu 1979) to obtain a binary image. Morphological operations were then applied to the binary image to remove the vessels. Region growing techniques were used to obtain the lung regions. The lung was then divided into 30 x 30 sub-regions and the sub-regions covering more than 70% of the lung were considered for feature extraction. Pathologically changed sub-regions, exhibited changes in the local structure and intensity compared to the normal regions. In order to discriminate between pathologically changed regions and normal regions, the
uniformity information of brightness and structure were determined in multiple directions from the image.

The texture features were next extracted in multiple directions from the sub-regions using the Extension of rotation invariant Local Binary Pattern (ELBP). This technique was applied to a circular neighborhood and interpolation was done to compute the gray value of the neighboring pixels which did not fall exactly in the pixel position. But ELBP failed to describe the structural information of the pixel. So to describe the local structure around a central point, gradient orientation of the point was first applied. The Gradient Orientation Difference (GOD) between two central points was calculated, to determine the similarity between their local structures. A conditional probability density function was generated and texture features like entropy, gradient orientation uniformity emphasis, gradient orientation difference emphasis, high gray level emphasis and low gray level emphasis were computed for classification. Finally SVM classifier was used for the classification of the sub-regions. About 1757 images of 45 patients from Inha University Hospital were used. The dataset included 433 normal images, 339 images with centrilobular emphysema, 492 images with panlobular emphysema, 151 images with bronchiolitis and 342 images with honeycombing. Sensitivity of 97.8%, specificity of 99.8% and accuracy of 98.8% were achieved by the system. But the performance of the system depends on the direction of the feature extraction.

Depeursinge et al (2012b) in their work have proposed a near-affine-invariant set of texture features based on wavelet transform to discriminate between healthy and diseased HRCT lung images. The HRCT dataset used consisted of 85 patients with ILD images taken from a publicly available database (Depeursinge et al 2012a). The images were of the size 512 x 512 from which 1448 hand drawn ROIs were annotated by two
radiologists. The ROIs were sub-divided into 32 x 32 blocks and atleast 75% of the pixels in the block should be in the annotated region. A total of 17848 blocks were evaluated. Healthy tissue was annotated from the normal portions of the diseased lungs. Semiautomatic segmentation based on region growing and mathematical morphological operations were used to obtain the lung regions. The seed point for the region growing process was defined by the user and each 26-connected neighbor was added to the region. This image contained holes, which were filled using closing morphological operations.

Each resultant image after the holes were filled, were divided into overlapping blocks of size 32 x 32. For each block the GLH was applied with 22 bins and the number of air pixels in each block was also computed, resulting in a single 23-dimensional feature vector. The QWF coefficients were computed for each block which were then concatenated with the GLH feature vector. Each feature was then normalized by mapping between 0 and 1. The normalized features were applied to a OAA SVM classifier to differentiate between five classes of lung tissue types namely normal, emphysema, GGO, fibrosis and micro nodules. The SVM classifier performed block wise classification. The classification accuracy of healthy tissue patterns was 88.45%, with precision and specificity of 67.28% and 94.31% respectively. Emphysema tissue patterns had a classification accuracy of 96% with precision and specificity of 78.72% and 97.87%. GGO tissue patterns had a classification accuracy of 88.38% with precision and specificity of 71.36% and 90.55%. Fibrosis tissue patterns had a classification accuracy of 90.5% with precision and specificity of 82.73% and 93.97% respectively. Micro nodules tissue patterns had a classification accuracy of 90.51% with precision and specificity of 81.56% and 93.78% respectively. The GLH characterizes the composition of the tissue density and QWF characterizes the composition of the tissue structure. 3-D region growing technique includes
the trachea as a lung region and it has to be manually removed. The parameters of QWF can be tuned to improve the results.

Yao et al (2011) in their work have proposed a texture based detection and classification method for detecting pulmonary lesions in patients infected with H1N1 using computer assisted texture analysis and SVMs. Initially the trachea was eliminated from the lung CT image and then based on its position two seed points were placed in the right and left lungs. The seeds were then expanded to segment the entire area of the lungs by using a 3D region growing algorithm. A histogram based thresholding technique was used to refine the segmentation and a rolling ball algorithm was then used to smoothen the lung boundary. The segmented lung image was then divided into sub-blocks of 16 x 16 pixels. Twenty five texture features were extracted from each sub-block based on histogram statistics, co-occurrence matrix and run-length matrix.

A multidimensional feature vector was formed from the extracted texture features. The feature vector obtained in the H1N1 patients was compared with the feature vectors from patients with normal lungs, fibrosis, parainfluenza and bacterial pneumonia. The training process consisted of three stages: manual labeling of ROIs by radiologists; secondly dividing the image into texture blocks of size 16 x 16 pixels and computing the texture features and finally applying the set of feature vectors and texture blocks to the SVM classifier to classify the types of disease. SVM was used for both training and testing. Two classifiers were trained, of which one classifier was used to differentiate between normal tissues and ground glass opacity (GGO) in H1N1 and the second classifier was used to differentiate between GGO in H1N1 and fibrosis. In the testing phase, the SVM classifier was applied to the manually segmented regions of the lung CT and regions of opacity in HINI were differentiated from abnormal features exhibited by lung fibrosis. The
The dataset consisted of 40 chest CT images consisting of 4 H1N1 images, 20 fibrosis images, 10 normal images and 7 images of chest infections other than H1N1. The areas under the ROC curve was 99.9% for training data and 99.3% for testing data when the classifier differentiated between H1N1 and Normal images. Limited number of samples (4 H1N1 images) have been used in this study and hence the results have to be verified for an expanded dataset. The potential of this technique in diagnosing disease and quantifying the severity is yet to be assessed.

Chang et al (2012) have proposed in their work a cost effective feature selection technique and a hierarchical OAA SVM to improve the time and accuracy of a CAD system. The CAD system was used to differentiate the disease patterns of DILDs. The classification process consisted of the feature extraction process and class labelling process using classifiers. Reducing the number of features computed, in turn reduces the time taken for feature computation. So classification was first carried out using the simple and inexpensive features and then using complex and expensive features. The SVM classifier was designed for binary classification and so cannot be directly applied for multiclass problems. Hence the OAA method was used in this work. The HRCT dataset consisted of 14 healthy cases, 16 emphysema cases, 35 patients with cryptogenic organizing pneumonia, 36 patients with interstitial pneumonia (IP), four patients with pneumonia and one patient with acute IP. One ROI was selected per image and each ROI was represented by a 24-dimensional feature vector comprising of 13 textural features and 11 shape features. Based on the extracted features the ROIs were classified as consolidation, emphysema, GGO, reticular opacities and normal lung with accuracies of 99.67%, 97.89%, 94.04%, 92.42% and 92.97% respectively. The overall accuracy of the proposed method was 92.63%. Though the system has shown promising results, the time for the quantification of the
entire HRCT requires more than an hour which is a major limitation to implementing the system in the clinical field.

Jaeger et al (2014) in their work have proposed an automated approach for the detection of TB in CXRs that can be used on portable X-ray scanners. Three sets of CXRs were considered, of which the first two sets were used as training and testing sets for the classifier and the third CXR set was used for training the lung model. The first CXR set was from the Montgomery County (MC) dataset, the second CXR set from Shenzhen Hospital, China while the third CXR set was from the JSRT. The lung field masks for the JSRT dataset was provided by van Ginneken et al (2006). The lung in the input CXR was first segmented using the graph cut optimization method along with the lung model. The lung model that was used represented the average lung shape of the training mask from the JSRT dataset. The similarity between the input CXR and the training CXRs was computed using the Bhattacharyya coefficient and the graph cut approach was used to model the lung field.

Two feature sets were extracted from the lung fields. Object detection inspired features constituted the first feature set consisting of intensity, gradient magnitude and shape descriptor histograms. The histogram bins were the features extracted from the histograms and these features were all grouped together to form the feature vector. Content based image retrieval (CBIR) based image features was the second feature set consisting of the Tamura texture descriptors, color and edge direction descriptor, fuzzy color and texture histogram, Hu moments, color layout descriptor, edge histogram descriptor, primitive length, edge frequency, autocorrelation and elliptical shape features. The feature vectors of both the feature sets were applied to a SVM classifier to classify the data into normal and abnormal CXR classes. The segmentation performance was 90.1%. The area under the curve (AUC)
was 86.9%, accuracy was 78.35% and sensitivity was 95% for the MC dataset. The AUC was 88% and accuracy was 82% for the Shenzhen Hospital dataset that was slightly higher than the MC dataset. There are very few existing systems reported in literature with which the results of this study can be compared.

Bhuvaneswari et al (2014) in their work have proposed an automatic classification scheme for lung diseases using chest CT images that is based on a novel feature extraction technique. Gabor filter and Walsh Hadamard transform have been combined using the median absolute deviation technique. The CAD system consisted of three stages. Initially the images are preprocessed by denoising using a median filter. The images are then converted into grayscale. The image is divided into 16x16 blocks and features are extracted by the novel fusion based feature extraction technique. Next feature selection is carried out by applying genetic algorithm to select the top ranked features. Finally classifiers like decision tree, K nearest neighbor (KNN), Multi layer perceptron Neural Networks (MLP-NN) are employed to perform classification of the lung diseases. A total of 400 datasets for the diseases bronchitis, emphysema, pleural effusion and normal lung were used for training and testing. The PNN classifier achieved a classification accuracy of above 90%. This work can include more feature extraction and feature selection techniques.

Keshani et al (2013) in their work have proposed an intelligent system for the detection, segmentation and recognition of lung nodules. Lung CT images were transformed into binary images by applying adaptive fuzzy thresholding. Masking techniques were used to remove corners and bone regions from the lungs and to isolate the nodules that were originally non-isolated. The ACM was then applied to accurately segment the lung. From the segmented lung 2D and 3D features were extracted. Using the extracted
features, SVM classifiers were used to label the regions as nodule and non-nodule areas. As some of the contours of the nodules got deformed in the SVM classification process, active contour modeling was used to model the thin edges. The connectivity of a nodule was determined to identify a solitary nodule. So the original lung image was grouped into four classes namely lung wall (LW), parenchyma (PA), bronchioles (BR) and nodules (ND). It was concluded that if the class ND was attached to the class PA then the class was a solitary nodule else it was a BR connected nodule or a LW connected nodule. Four groups of datasets were used in this work. Group 1 was called as Clinical-1 and consisted of four CT datasets containing thirteen nodules that were approved by medical experts. In the second group called Clinical-2 there were four CT datasets with six nodules. The third group of data provided by ANODE09 website (van Ginneken et al 2010b) contained five CT datasets that included 39 nodules. The fourth group was from Early Lung Cancer Action Program (ELCAP) and contained 50 CT datasets and 397 nodules. The overall detection rate was 89% and the segmentation accuracy was 98.1%. The algorithm failed when the diseased region was located at the periphery of the lung.

2.4 ROLE OF CLASSIFIERS IN CAD SYSTEMS

The feature vectors that are extracted from the ROI characterize it and the quality of the feature vector is dependent on its ability to be distinctive among different classes. This implies that within a class, the features should be similar. The function of a classifier is to partition the feature vectors present in a feature space into distinct classes based on their similarity. In this section a brief insight is provided into a few of the classifiers that have been commonly used in CAD systems.

Ma et al (2014) in their work have proposed a new method that is robust to classifiers and features, to fuse the classifiers in a weighted-sum
form. Common CT Imaging Signs of Lung Diseases (CISL) is used in the diagnosis of lung diseases. A multiple classifier fusion method was proposed to recognize the CISLs that was based on the confusion matrix of the classifiers and the classification confidence values of the classifiers. To obtain the confusion matrix of each classifier, four sets of features were extracted from each CISL. The extracted features were Histograms of Oriented Gradients (HOG), wavelet transform based features, LBP and the CT value Histogram (CVH). These features were used to compute the confusion matrix for each classifier. The confusion matrix and the confidence values of each classifier were fused to form the weights of the classifier's confidence values. The classifiers were then fused in a weighted-sum form. Five types of classifiers namely SVM, BPNN, Naive Bayes, k-NN and Decision Tree were combined for CISL recognition. The fused classifier was tested on lung CT images and the classification results outperformed the results due to single classifiers. The accuracy rate of the fused classifier was 76.79%. It was observed that the accuracy rates of a combined classifier were generally higher than that of single classifiers. Also, higher the number of the classifiers used, better the performance. Some unsatisfactory results are because the classification confidences of classifiers are not uniform.

Bagci et al (2012b) in their work have proposed a computer assisted detection system for detecting and quantifying the tree-in-bud (TIB) opacities in lung CT images. The dataset of 60 lung CT images consisted of 39 parainfluenza CTs and 21 normal lung CT images of size 512 x 512. The CT images of the parainfluenza patients included TIB opacities, ground glass opacities (GGO), nodules and consolidations. The lungs were initially segmented using fuzzy connectedness (FC) image segmentation algorithm in which one seed is assigned by the user either in the right or left lung based on the location of minimum intensity valued voxels in the body region. The TIB pattern has a complex shape, high intensity variations with nearby voxels and
boundaries with high curvatures. A ball-scale or b-scale filtering method was used to retain voxels with small b-scale values as the candidate TIB patterns and to discard voxels with high b-scale values.

Local shape features, GLCM features, local gradient shape statistics and steerable features were the different types of shape and textural features extracted from the selected b-scale patterns to characterize the TIB patterns. These extracted features were applied to a SVM classifier. The entire dataset was divided into training and testing sets with 30 images in each set. In the training step a radiologist manually labelled the TIB regions in the images. Each lung was divided into three regions and a severity score ranging from one to five was assigned to each region. This manually assigned score during training was compared with the computer scores that were obtained during testing. The texture features were extracted from the training images and applied to the SVM classifier for training. The local shape and texture features were extracted from the testing images and applied to the trained SVM classifier. The proposed CAD system achieved an overall accuracy of 90.96%. A multiclass classifier with specifically tuned detection filters for each abnormality class can be designed as an extension to detect different types of abnormalities using the same system. The feasibility of combining the imaging patterns of different lung diseases and their clinical information into a CAD system can also be considered.

Lee et al (2009) in their work have analyzed the performance of several machine classifiers that were used to differentiate obstructive lung diseases in HRCT images. The dataset consisted of 67 normal lung images, 70 images of bronchiolitis obliterans, 65 images of centrilobular emphysema and 63 images of panlobular emphysema from the Department of Radiology, Asan Medical Centre, Korea. One ROI was sampled from each lung. Initially automatic lung segmentation was performed. The blood vessels and the chest
wall were removed by thresholding all regions in the image with densities corresponding to -400 to -1024 Hounsfield Units (HU). After segmenting the lung, different sizes of ROIs were considered and texture analysis was performed. For each CT image, radiologists labelled three sizes of ROIs: 16 x 16, 32 x 32 and 64 x 64 corresponding to the three diseases or normal lung. Four descriptors were used in this work and each ROI was represented using a 13 dimensional feature vector. Naïve Bayesian, Bayesian, ANN and SVM classifiers were compared experimentally based on the training time, testing time, accuracy, sensitivity and specificity. A five-fold cross-validation scheme was used to verify the cross-validity of the input data. The SVM classifier outperformed all the other classifiers as it was reasonably fast in training and its sensitivity and specificity were small. The overall accuracy of the SVM classifier was 64.1% for 16 x 16 ROI, 75.7% for the 32 x 32 ROI and 83.1% for the 64 x 64 ROI which indicated that as the ROI size increased the overall accuracy also showed improvement.

Korfiatis et al (2010) in their work have proposed a CAD scheme for identifying and quantifying IP patterns in MDCT datasets. The dataset of 14 MDCT scans belonging to four normal patients and ten patients, who exhibited GGO and reticular patterns, was obtained from the Department of Radiology at the University Hospital of Patras, Greece. A two stage 3D LF segmentation technique was used in the preprocessing step. In the first stage a 3D histogram thresholding algorithm was combined with an edge-highlighting wavelet preprocessing step. In the second stage, a supervised texture classification refinement stage using a SVM classifier was used for cases of undersegmentation.

The vessel tree structure was segmented next by applying a 3D multiscale filter to enhance the vessels. Then the EM algorithm was used to threshold the voxels. The vessel tree regions were removed from the LFs to
obtain the lung parenchyma (LP). The GLCM was calculated in thirteen directions for each image from each of which 13 GLCM-based features were extracted. The dimensions of the feature vectors formed were reduced using SDA and then normalized. The reduced feature vectors were applied to the k-NN classifier which was used to label each voxel of the LP as normal, ground glass or reticular. The classifier dataset was divided into ten subsamples of which nine were used as the training data and one as the testing data. The training dataset applied to the classifier consisted of 150 reticular, 100 GGO and 100 normal cubic volumes of interest (VOIs). The performance of the CAD system in identifying the GGO and reticular patterns were evaluated using volume overlap (VO), TPF and FPF. The VO of GGO was 0.734±0.057 and reticular was 0.815±0.037. The TPF of GGO was 0.638±0.055 and reticular was 0.942±0.023. The FPF of GGO was 0.361±0.027 and reticular was 0.147±0.032.

Elizabeth et al (2012b) in their work have proposed a CAD system for selecting a significant slice from a set of slices of a CT scan to analyze the nodules that correspond to lung cancer. A set of chest CT images, each consisting of multiple slices were selected. Each slice was initially thresholded using Otsu’s algorithm which was adapted for operation on Digital Imaging and Communications in Medicine (DICOM) images. Canny operator was used to detect the edges of the binary image. Morphological and connectivity operations were carried out on the edge detected image to obtain the thresholded lung. A greedy snake algorithm was then applied to reconstruct the lung borders and get the segmented lung parenchyma. The tumour regions were extracted by using a region growing approach and all regions that were non-candidate nodules were removed using a morphological erosion filter. The regions that were not present at the same location in the previous and next slice were pruned and regions that were not pruned constituted the ROIs. The shape and texture features of the ROIs were
extracted to form the feature vectors. The feature vectors were used to train a Radial Basis Function Neural Network (RBFNN). ROIs that were greater than 9 pixels and existed in at least three consecutive slices were considered as nodules. The slice containing the ROIs with the largest area was selected as the significant slice. The accuracy, recall, specificity and precision of the system were 94.44%, 92.31%, 94.92% and 80% respectively.

Desir et al (2012) in their work have proposed an automatic image classification system to discriminate between normal and pathological Fibered Confocal Fluorescence Microscopy (FCFM) images of the lung. The FCFM dataset used in this work consisted of 93 images of smokers and 133 images of non-smokers. Four feature vectors were computed from the datasets. The first feature vector had 120 features consisting of 103 contrast features, one shape and sixteen Haralick texture features (Haralick et al 1973). The 103 contrast features extracted were five global histogram statistics features, eighty local histogram statistics features, one density feature, sixteen local densities features and one sum of image gradient feature. The second feature vector had 140 features which were extracted based on the Haralick parameters that were computed from the GLCM. The third feature vector had 54 features based on the LBP operator. The fourth feature vector consisted of 128 features based on the Scale Invariant Feature Transform (SIFT) algorithm. These feature vectors were then fed as input to a SVM. The results of the SVM indicate that the LBP operator provided maximum discrimination between the normal and diseased FCFM images. The LBP features were applied to a SVM classifier with Recursive Feature Elimination (SVM-RFE) which provided a rank for each of the LBP features. The binary patterns that represented the edges had better discriminative properties and those representing flat areas could be discarded. The best classification rates of 90% and 95% were obtained for non-smoker and
smoker groups without RFE. The classification rates were 84.75% and 94.17% for the non-smoker and smoker groups with SVM-RFE.

2.5 PARTICLE SWARM OPTIMIZATION

PSO is a stochastic optimization technique introduced by Kennedy & Eberhart (1995) that is inspired by the social behavior of bird flocking, fish schooling and general swarming behavior. Similar to other evolutionary computation algorithms, such as genetic algorithms (GAs), PSO is a population-based search method that exploits the concept of social sharing of information. Here an individual or particle’s social behavior is influenced by the behavior of the swarm. This means that each individual (called particle) of a given population (called swarm) can benefit from the previous experiences of all other individuals in the same population. The social behavior is modeled as a multi dimensional space that is collision free in which each particle (i.e., candidate solution) will adjust its flying velocity and position according to its own flying experience as well as those of the other companion particles in the swarm.

Sutar & Janwe (2011) in their work have proposed a segmentation technique for MRI using a C-means clustering algorithm in which the neighbourhood attraction is optimized using PSO. An MRI based brain tumour classification scheme was developed. The segmentation scheme was based on the individual pixel intensities, neighboring pixel intensities and on the spatial location of the pixels. The drawback of the Fuzzy C-Means (FCM) clustering algorithm is that it is affected by noise and so not suitable for medical images. During the clustering process, every pixel will try to attract the neighboring pixel towards its own cluster. This attraction depends on the pixel intensities $\lambda$ and the spatial location of the pixels $\xi$ which was optimized using the PSO where the most fitted particle represented the optimum values of $\lambda$ and $\xi$. In the first trial MRI with Gaussian noise was used as the sample
for segmentation and yielded optimized values of 0.9438 and 0.8801 for λ and ξ. In the second trial, MRI without noise was used and the optimized values of λ and ξ were 0.9392 and 0.9812 respectively.

### 2.6 Texton Co-Occurrence Matrix for Natural Images

Liu & Yang (2008) in their work had proposed the usage of texton co-occurrence matrix (TCM) for image retrieval. The TCM discriminates color, shape and texture features better than GLCM and CCG. The natural images from the image database were first converted into greyscale images and then transformed into texton images. The concept of texton was proposed in 1981 by Julesz (Julesz 1981; Leung & Malik 2001) who defined textons as “the putative units of pre-attentive human texture perception”. Textons are defined as a set of blobs or emergent patterns that share a common property all over the image. Image features are closely related to the textons. If the textons are small and have large tonal differences between neighboring textons then the image will have a fine texture. If the textons consist of several pixels then the image will have a coarse texture. There are many types of textons in images.

In a 2 x 2 block if three or four of the pixel values were identical, then those pixels formed a texton. Hence in a 2 x 2 block of pixels, five types of textons were identified. By applying five 2 x 2 grids (corresponding to the five types of textons) to the image, all the texton components in the image were identified. The final texton image was created by superimposing all the texton components that had been identified by the grids while the remaining pixels were replaced by zeros. Next a GLCM was computed for the greyscale texton image to convert it into the TCM. Energy, contrast, entropy and homogeneity features were extracted from the GLCM to form the feature vectors which were used for image retrieval. A total of about 80 images were
taken from the VisTex database. Eight image categories are selected and each category consisted of 10 images of size 512 x 512. The second database considered was the Corel database from which 2000 images were selected. The performance of the TCM was better than that of GLCM and CCG. Average precision for the first database was 59.81% and the second database was 61.95%.

2.7 LOCAL GABOR XOR PATTERN TECHNIQUE

Xie et al (2010) in their work have proposed the LGXP technique that encodes the Gabor phase by using the Local XOR Pattern (LXP) operator for face recognition. Here the facial image was first convolved with the Gabor kernel. This produced a Gabor magnitude image and a Gabor phase image. Gabor phase embodies more discriminating power than Gabor magnitude hence the Gabor phase image was alone considered. The Gabor phases in the Gabor phase image were then quantized into four different ranges by thresholding the 3 x 3 neighborhood of each pixel with the phase range that had been defined. The LXP operator was applied to the quantized phases of the center pixel and each of its 3 x 3 neighbors. A binary label was assigned to every pixel. The resulting binary labels were concatenated together as the local patterns of the center pixel. One pattern map was calculated for each gabor kernel. Each pattern map was then divided into ‘m’ non-overlapping sub-blocks. The histograms of all the sub-blocks were computed for all scales and orientations. The computed histograms were then concatenated to form the LGXP descriptor of the input face image. This technique had been evaluated on the FERET and Face Recognition Grand Challenge databases and the face recognition rates were 100% and 90.7% respectively.
2.8 RESEARCH DIRECTION

Comparing with the existing works discussed in literature, this research work is different in the following aspects:

The first research work is an approach to classify ILDs from chest CT slices using a SVM classifier. Here PSO is used to optimize the order $\gamma$ and the number of decomposition levels $N$ of the QWF. The number of decomposition levels and the order of the QWF together determine the number of wavelet coefficients that are extracted. Hence PSO has been used in this work to select the best subset of optimal discriminative features from the set of features derived from the QWF after applying (Gaussian Mixture Model) GMM with EM algorithm. The effectiveness of the wavelet coefficients in improving the classification accuracy is enhanced in this work by optimizing $\gamma$ and $N$ for the classification task using PSO. The PSO is also used in this work to detect the best subset of optimal discriminative features from the set of features derived for the wavelet transforms by applying GMM and EM algorithm and to select the best values of cost $C$ and kernel parameter $\sigma$ of the SVM classifier, as these parameters influence the effectiveness of the classifier. Reducing the number of features in turn reduces the time taken to compute the feature vector as stated by Chang et al (2012).

The second research work focuses on a CAD system that is developed for the detection of types of pulmonary TB namely Cavitary and Miliary TB from chest CT slices. Here the texton is used to identify the regions in the slice that have common properties of texture. The texton has good discriminative properties over shape and texture and this property of the texton that was initially applied only to natural images (Liu & Yang 2008) is used in this work to extract the texture features from chest CT slices. Gabor filters are invariant to illumination, rotation, scale and translation, while providing good response to noise and distortion. The LGXP histogram
descriptor formed by concatenating several histograms, instead of using only one histogram, is more robust to phase variations. The quantized code remains invariant even if there is any significant change in the phase, as long as the change in phase lies within a quadrant. Due to these advantages, the texton image and the LGXP descriptor are combined and used for the classification of TB. Conversion of an image to a texton image results in reduction in the data to be analyzed. This automatically reduces the computation time for feature extraction.

The third research contribution is the development of a CAD system for the detection and classification of pneumothorax, pleural effusion, normal and CT slices affected by other diseases. The segmentation and ROI extraction schemes that are developed use basic arithmetic and morphological operations. When the lung regions are segmented the pneumothorax region is also present along with the segmented lung. Algorithms to compute the extent to which the lung has been affected by the disorder that will indicate the severity of the disorder is also a part of this work.