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Computer-aided diagnosis tool for the detection of cancerous nodules in X-ray images

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COMPUTER-AIDED DIAGNOSIS TOOL FOR THE DETECTION OF CANCEROUS NODULES IN X-RAY IMAGES

A Thesis
Submitted to the Graduate Faculty of the Louisiana State University and Agricultural and Mechanical College in partial fulfillment of the requirements for the degree of Master of Science in Electrical Engineering

in

The Department of Electrical and Computer Engineering

by
Pallavi Bomma
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Abstract

This thesis involves development of a computer-aided diagnosis (CAD) tool for the detection of cancerous nodules in X-ray images. Both cancerous and non-cancerous regions appear with little distinction on an X-ray image. For accurate detection of cancerous nodules, we need to differentiate the cancerous nodules from the non-cancerous. We developed an artificial neural network to differentiate them. Artificial neural networks (ANN) find a large application in the area of medical imaging. They work in a manner rather similar to the brain and have good decision making criteria when trained appropriately. We trained the neural network by the backpropagation algorithm and tested it with different images from a database of thoracic radiographs (chest X-rays) of dogs from the LSU Veterinary Medical Center.

If we give X-ray images directly as input to the ANN, it incurs substantial complexity and training time for the network to process the images. A pre-processing stage involving some image enhancement techniques helps to solve the problem to a certain extent. The CAD tool developed in this thesis works in two stages. We pre-process the digitized images (by contrast enhancement, thresholding, filtering, and blob analysis) obtained after scanning the X-rays and then separate the suspected nodule areas (SNA) from the image by a segmentation process. We then input enhanced SNAs to the backpropagation-trained ANN. When given these enhanced SNAs, the neural network recognition accuracy, compared to unprocessed images as inputs, improved from 70% to 83.33%.
Chapter 1: Introduction

Lung cancer is the leading cause of cancer death in the United States. Early detection and treatment of lung cancer is important in order to improve the five year survival rate of cancer patients [LLHF]. In a healthy person, cells in the lungs divide and reproduce at a controlled rate to repair worn-out or injured tissues and allow for normal growth. Lung cancer develops when cells inside the lungs multiply at an uncontrollable rate. These abnormal tissue masses are called tumors. Tumors are either non-cancerous (benign) or cancerous (malignant).

Medical imaging plays an important role in the early detection and treatment of cancer. It provides physicians with information essential for efficient and effective diagnosis of various diseases. Diagnosis of X-rays can be used as an initial step in nodule detection. The objective of the CAD system developed in this thesis is to help radiologists to improve their accuracy in cancer detection. We developed an Artificial Neural Network (ANN) to differentiate the cancerous nodules from other suspected nodule areas in the X-ray images. To improve the diagnosis accuracy of this ANN we introduced a pre-processing stage in the CAD system that involves various image enhancement techniques. Our main interest involved the detection of golf-ball tumor type of cancer. We can detect this type of cancer by the presence of round masses (tumors) in the X-ray image.

Six chapters follow this chapter. Chapters 2 and 3 provide background information about CAD and ANNs used in the area of medical imaging. Chapter 4 gives a description of the image database used in this thesis. Chapter 5 provides details on the
first stage of the CAD system involving various image enhancement techniques and their results. Chapter 6 provides details on the second stage of the CAD system – the ANN for cancerous nodule detection. Chapter 7 provides an overall summary and discusses the scope for future research in this area.
Chapter 2: Literature Review - CAD for Cancerous Nodule Detection

This chapter provides a detailed description of background information on lung cancer detection. The chapter starts with a description of different types of lung cancer and various diagnosis methods used. Then we move to a description of computer-aided diagnosis (CAD) and present a basic idea of the CAD system used in this thesis. Lastly, we discuss performance evaluation of CAD systems.

2.1 Types of Lung Cancer

There are two basic categories of lung cancer: small cell lung cancer and non-small cell lung cancer [OCM].

2.1.1 Small Cell Lung Cancer (SCLC)

Twenty out of every hundred lung cancers diagnosed are SCLC. Small cell lung cancer or oat cell cancer consists of small cancer cells that are mostly filled with the nucleus (the control center of cells). Small cell lung cancer often spreads quite early.

2.1.2 Non-Small Cell Lung Cancer (NSCLC)

There are three types of NSCLC lung cancer. They behave in similar ways and respond to treatment differently than SCLC.

Adenocarcinoma: Adenocarcinoma is the most common type of NSCLC and the most common form of lung cancer among women. The incidence of this type of lung cancer is increasing. Adenocarcinoma often appears toward the outer edges of the lungs in the mucous glands that line the airways. Like other forms of lung cancer, adenocarcinoma may spread to other parts of the body.
**Squamous Cell Carcinoma:** The most common lung cancer in men is squamous cell carcinoma. It usually appears in the larger breathing tubes. Like other NSCLCs, squamous carcinoma is a relatively slow-growing cancer.

**Large Cell Carcinoma:** Large cell carcinoma occurs less often and has larger cells than other NSCLCs. It usually first appears in the smaller breathing tubes and may spread quickly. Large cell carcinoma is diagnosed after other types of lung cancer are ruled out. Large cell carcinoma tends to grow quickly and spread (metastasize) at an earlier stage than other forms of non-small-cell lung cancer.

**2.2 Detection of Lung Cancer**

The prime method for cancer detection is through radiological imaging exams. There are many technologies used in the diagnosis of lung cancer like chest X-rays, CT scans, FDG-PET scans, bronchoscopy, fluorescent bronchoscopy, and sputum cytology. Some of the most commonly used technologies are X-ray, CT, MRI, and PET scans [LCD].

**2.2.1 X-Ray**

Chest X-ray diagnosis of lung cancer is one of the oldest and most effective ways of diagnosing asymptomatic cancers. X-rays are high energy radiation with waves shorter than those of visible light. Images obtained using low dose X-rays help diagnose disease, and high dose X-rays help to treat cancer. Although computer tomography (CT) is generally considered the most effective imaging modality for detection of pulmonary nodules, chest radiography remains the initial procedure, mainly because of its low cost, simplicity, and low radiation dose.
2.2.2 CT Scan

Computer tomography (CT), sometimes called a CAT scan, uses special X-ray equipment to obtain image data from different angles around the body, and then uses computer processing of the information to show a cross-section of body tissues and organs. CT imaging can show several types of tissue—lung, bone, soft tissue, and blood vessels—with great clarity. Using specialized equipment and expertise to create and interpret CT scans of the body, radiologists can more easily diagnose cancer problems. The image allows a physician to confirm the presence of a tumor and to measure its size, precise location, and the extent of the tumor's involvement with other nearby tissue. The CT scan can reveal some soft-tissue and other structures that cannot even be seen in conventional X-rays. Using the same dosage of radiation as that of an ordinary X-ray machine, a CT scan can increase the clarity by about 100 times for an entire slice of the body. The CT scan is often performed after a chest X-ray.

2.2.3 MRI Scans

Magnetic resonance imaging (MRI) is an advanced medical scanning technology used by physicians to obtain images of the internal structures of the body. MRI uses two safe and natural forces, a magnetic field and radio waves, to produce vivid images of internal body parts. Computer technology creates detailed images of the soft tissues, muscles, nerves, and bones in the human body. Radiologists interpret images to see if a medical condition is present. MRI provides doctors with a very high degree of accuracy to aid them in accurate diagnosis. MRI does not use any radiation, as compared to X-Ray and CT scanning techniques. The procedure is non-invasive without any known side effects.
2.2.4 PET Scans

The positron emission tomography (PET) scan creates computerized images of chemical changes that take place in tissue. The substance injected into the patient consists of a combination of a sugar and a small amount of radioactive material. The radioactive sugar can help in locating a tumor, because cancer cells take up or absorb sugar faster than other tissues in the body. A PET scanner detects the radiation. A computer translates this information into the images that a radiologist interprets. PET scans determine whether a breast mass is cancerous, but they are more accurate in detecting larger and more aggressive tumors than they are in locating tumors that are smaller than 8 mm and/or less aggressive. PET scans may be helpful in evaluating and staging recurrent cancers.

2.3 Diagnosis Procedure

2.3.1 Computer-Aided Diagnosis

Improving the ability to identify early-stage tumors is an important goal for physicians, because early detection of lung cancer is a key factor in producing successful treatments. Computer-aided diagnosis (CAD) involves the use of computers to bring suspicious areas on a medical image to a radiologist’s attention. CAD is a radiologist’s assistant for improving diagnostic accuracy [LLLF]. CAD for cancer detection in medical images starts with a digital image. The computer scans and marks suspicious looking areas in the image. Radiologists can then focus on those areas and decide if a biopsy or further evaluation is needed.
2.3.2 Block Diagram Representation

CAD systems for lung cancer detection typically follow a two stage approach [LLLH]. The first stage includes the initial processing of the image to detect a set of potential nodules. It not only removes the unwanted background information but also enhances the image. The second stage consists of classifying these suspicious regions into positive and negative regions. A positive region is a region that the radiologist feels should go to follow-up for additional information [BAF]. Various morphological features that can be taken into consideration while developing a CAD system include area, perimeter, size, shape, and moments [BAF]. These parameters show some variation between cancerous nodules and non-cancerous nodules.

Figure 2.1 shows a block diagram representation of the various stages involved in the diagnosis procedure used in this thesis. It basically consists of two stages: detecting the suspected nodule areas (SNAs), also known as the pre-scan process, and the subsequent analysis of these zones to confirm or refute the presence of nodules, i.e., differentiation of the cancerous nodules from the non-cancerous nodules. The procedure in the thesis follows Phase I closely, but uses an ANN for Phase II rather than separate operations for the separate blocks in Phase II.

2.4 Evaluation of CAD

The evaluation of a diagnosis system depends on statistical decision theory and gives estimates of the probabilities of decision outcomes of the various kinds of decision criteria (e.g., of true-positive fraction and false-positive fraction) used by the system [SP]. The following gives a brief description of some of the methods used by researchers for the evaluation of CAD systems.
Contrast Enhancement

Removal of Background Information

SNA Identification (by shape)

SNA Separation

Feature Extraction

Comparison

Feature Classification

Analysis of Results

Digital Chest Radiograph

Phase – I
Identification stage

Phase – II
Classification stage

Figure 2.1 – Block diagram representation of diagnosis procedure
2.4.1 Receiver Operation Characteristics

Relative (or receiver) operation characteristic (ROC) analysis is an analytical procedure for measuring the accuracy of a system. ROC curves show a relationship between the true-positive probability and the false-positive probability. The evaluation factor is the area under the curve $A_Z$ [SAEA]. (Figure 2.3 is an example.) ROC provides a desirable index of accuracy and the appropriate basis for an index of efficacy [SP]. It has the following three unique features.

1. The index of accuracy in ROC analysis is independent of the criterion adopted in the system for making a particular decision.

2. It supplies estimates of the probabilities of decision outcomes of various kinds for any criterion used by the system.

3. The ROC analysis supplies an index of the decision criterion, which reflects together the subjective probabilities and utilities that usually determine this criterion.

Researchers have used ROC analysis to compare the diagnostic performance of radiologists with and without the use of CAD.

2.4.2 Other Evaluation Methods for CAD

We can also evaluate the CAD system in terms of sensitivity, accuracy, and specificity [PCMC]. Sensitivity is the number of correctly classified SNAs out of the number of positive SNAs, specificity is the number of correctly diagnosed negative SNAs out of all negative SNAs, and accuracy is the number of correctly diagnosed SNAs out of the total number of SNAs [BAF].
Sensitivity = \frac{TP}{TP + FN},

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

Specificity = \frac{TN}{TN + FP},

where $TP$ denotes the number of true positives, $FP$ denotes the number of false positives, $FN$ denotes the number of false negatives, and $TN$ the number of true negatives.

2.4.3 Results of Various Evaluation Methods

CAD can improve the diagnostic accuracy for detection of cancer nodules. One explanation is that the program controlling the CAD system is consistently and comprehensively affected by all the data, but this may not always happen with the radiologists [MNWT]. The radiologists’ performance improved significantly with the support of a CAD system [MNWT, SAEA, AMEL]. This section gives the results of tests conducted by various radiologists on CAD systems to prove the above statement.

To experimentally demonstrate the advantage of using a CAD system, Shiraishi et al. [SAEA] selected a group of seventeen radiologists who were given a set of radiographs to detect cancerous nodules without and with the use of a CAD tool. They considered an ANN-based CAD system used for the detection of cancerous nodules in CT images. ROC analysis was applied to each radiologist’s observation individually. Table 2.1 gives $A_Z$ values for the seventeen radiologists for interpretation of the cancerous nodules without and with a CAD scheme [SAEA]. Figure 2.2 shows a graphical representation of the $A_Z$ values in Table 2.1.
Table 2.1 $A_Z$ values for a group of radiologists without and with CAD

<table>
<thead>
<tr>
<th>Radiologist</th>
<th>Without CAD scheme</th>
<th>With CAD scheme</th>
</tr>
</thead>
<tbody>
<tr>
<td>A</td>
<td>0.795</td>
<td>0.81</td>
</tr>
<tr>
<td>B</td>
<td>0.762</td>
<td>0.808</td>
</tr>
<tr>
<td>C</td>
<td>0.822</td>
<td>0.901</td>
</tr>
<tr>
<td>D</td>
<td>0.668</td>
<td>0.837</td>
</tr>
<tr>
<td>E</td>
<td>0.745</td>
<td>0.835</td>
</tr>
<tr>
<td>F</td>
<td>0.778</td>
<td>0.856</td>
</tr>
<tr>
<td>G</td>
<td>0.732</td>
<td>0.772</td>
</tr>
<tr>
<td>H</td>
<td>0.874</td>
<td>0.904</td>
</tr>
<tr>
<td>I</td>
<td>0.818</td>
<td>0.88</td>
</tr>
<tr>
<td>J</td>
<td>0.774</td>
<td>0.845</td>
</tr>
<tr>
<td>K</td>
<td>0.751</td>
<td>0.803</td>
</tr>
<tr>
<td>L</td>
<td>0.814</td>
<td>0.862</td>
</tr>
<tr>
<td>M</td>
<td>0.715</td>
<td>0.822</td>
</tr>
<tr>
<td>N</td>
<td>0.705</td>
<td>0.785</td>
</tr>
<tr>
<td>O</td>
<td>0.737</td>
<td>0.872</td>
</tr>
<tr>
<td>P</td>
<td>0.768</td>
<td>0.834</td>
</tr>
<tr>
<td>Q</td>
<td>0.702</td>
<td>0.781</td>
</tr>
<tr>
<td>Average= R</td>
<td>0.743</td>
<td>0.817</td>
</tr>
</tbody>
</table>

Figure 2.2 Graphical representation of $A_Z$ values shown in Table 2.1
For every radiologist in the study, the $A_Z$ value was higher using CAD than not using CAD. The ROC curves in Figure 2.3 show that ANNs improved the diagnostic accuracy of radiologists in differentiating benign from malignant pulmonary nodules [SAEA]. The ROC curves shown in Figure 2.3 represent the average $A_Z$ values from Table 2.1.

![ROC curves](image)

**Figure 2.3** - Average ROC curves for the radiologists in nodule detection without and with the use of CAD.

Matsuki *et al.* [MNWT] evaluated the effect of CAD systems on radiologists’ performance. The CAD system used here consisted of an ANN for the classification of nodules as cancerous nodules or non-cancerous. Out of the 99 malignant and 56 benign nodules identified by 12 radiologists, the CAD output affected the observers’ confidence in 59 cases. Twenty-five malignant and twenty-nine benign nodules showed beneficial effects in the confidence level and only five cases showed adverse effects in confidence level. Figures 2.4 and 2.5 show the number of cases affected either beneficially or
detrimentally by using CAD on non-cancerous and cancerous regions, respectively [MNWT]. The positive scale represents the number of cases benefiting from CAD (beneficial cases) and the negative scale shows the number of cases with a less accurate diagnosis after CAD (detrimental cases).

**Figure 2.4** Histogram showing the number of non-cancerous cases affected by CAD

**Figure 2.5** Histogram showing the number of cancerous cases affected by CAD
Abe et al. [AMEL] conducted large scale observer tests to examine how radiologists benefit from CAD. The tests involved the analysis of five different types of CAD schemes used for various purposes — detection of pulmonary nodules, temporal subtraction, detection of interstitial lung disease, differential diagnosis of interstitial lung disease, and distinction between benign and malignant pulmonary nodules. They analyzed the statistical significance of the difference between the areas under the ROC curves without and with CAD. In all of the tests, the diagnostic accuracy of the radiologists in total improved significantly when CAD was used.

All the tests conducted by Shiraishi et al., Matsuki et al., and Abe et al. provided additional evidence that CAD has the potential to improve the performance of radiologists in their decision making process in interpreting chest radiographs.

It is possible for both computers and humans to make diagnostic errors, but together they can improve the diagnostic performance. Researchers regarded CAD as a means for translation of the interpretation skills of experts. The potential of CAD will be most important in decision making in complex situations such as differential diagnosis, where the performance of a CAD system could exceed that of a human observer.
Chapter 3: Artificial Neural Networks - Background

This chapter provides a detailed description of the second stage (classification stage) of the CAD system presented in this thesis. The chapter starts with a brief description of the basic ANN architecture and then moves on to discuss the different modes of operation in neural networks. We then give a brief description of the main types of neural networks and their application in the medical imaging area.

3.1 Basic ANN Architecture

An artificial neural network is an information processing system that has certain performance characteristics in common with biological neural networks [FAU]. A neural network consists of a large number of simple processing elements called neurons.

![Diagram of a basic multilayer neural network]

Figure 3.1 – A basic multilayer neural network.
Each neuron connects to other neurons by means of directed communication links, each with an associated weight. The weights represent information used by the network to solve a problem. Figure 3.1 shows the basic design of a simple multilayer neural network with one hidden layer. In general, multilayer ANNs can have more than one hidden layer. There is no definite rule that defines the number of neurons in the hidden layers. The neurons in one layer are typically completely interconnected with the neurons in the next layer. Advantageous properties for using ANNs are their generalization and the capability for learning from training data, even when the rules are not known a priori [JVG].

3.2 Modes of Operation

There are two modes of operation in a neural network: training mode and operating mode. Once we complete the training of the network, we test it with sample data different from the training data.

- Training mode

Depending on the training algorithm used, we can classify the neural networks into three categories: fixed-weight networks, unsupervised networks, and supervised networks. There is no training required for fixed weight networks, and a training mode is supervised or unsupervised. In supervised training, the training data consists of many pairs of source/target training patterns. The network processes the source inputs and compares its resulting outputs against the target outputs, using the results to adjust its weights. In unsupervised or adaptive learning networks, the training set consists of input training patterns only. Weight updates in these networks often involve moving selected weight vectors closer to the input training vector.
• **Operating mode**

The main difference between training and operating mode is that weights change in training mode but not in the operating mode. We test the neural network in its operating mode.

• **Testing**

A testing set tests the performance of the neural network. The testing set is generally not part of the training set but a representation of the general types of inputs the ANN is expected to receive in practice. Apply each testing input to the ANN in operating mode and compare the resultant output to the target output. If the network performs well on the testing set, it can be expected to perform well on the general case. The round robin method (leave one out method) is a good example of training and testing procedure used to evaluate the performance of an ANN. In this method we train the ANN with all the cases except for one in the database. We apply this case for testing the ANN with the trained computer scheme.

### 3.3 Main Types of Neural Network

The main types of neural networks most commonly used for various applications are feedforward network, Hopfield network, and self-organizing map (SOM).

#### 3.3.1 Feedforward Backpropagation Network

The feedforward backpropagation network is a very popular model in neural networks [FAU]. It does not have feedback connections, but errors propagate backward from the output layer during training. Backpropagation is a gradient descent method to minimize the total squared error of the output computed by the neural network. Training a network by backpropagation involves three stages: the feed forward of the input
training pattern, the backward propagation of the associated error, and the adjustment of weights. The output errors determine measures of hidden layer output errors, which act as a basis for adjustment of connection weights. The process of adjusting the set of weights between the layers and recalculating the output continues until a stopping criterion is satisfied, such as the overall error falling below a given threshold. Once training is completed, we can use the network to find outputs for new inputs.

The dimensions of the input and output patterns determine the number of neurons in the input and the output layers, respectively. A general feedforward network has three fields of neurons: one for input neurons, one for hidden processing elements, and one for output neurons. There are connections from each neuron in each layer to all the neurons in the next layer. There is a set of weights for each layer of neurons beyond the input layer.

3.3.2 Hopfield Neural Network

The Hopfield network is a recurrent neural network [FAU]. This network has the property under certain conditions that its dynamics are guaranteed to converge. The inspiration for the Hopfield neural network was to store certain patterns in a manner rather similar to the brain. We can create a Hopfield network by supplying input data vectors, or pattern vectors (class patterns), corresponding to different categories. In a Hopfield network it is simple to set up the weights between nodes in order to attempt to set up a desired set of patterns as stable class patterns. The network classifies distorted patterns into these classes. When presented to a network, the distorted pattern associates with another pattern. If the network works properly, the associated pattern is one of the class patterns. Researchers sometimes call these networks as associative networks since
they associate a class pattern to each input pattern. In some cases (when the different class patterns are correlated), spurious minima can also appear. This means that some patterns are associated with patterns that are not among the class pattern vectors.

The Hopfield network has no special input or output neurons, but all are both input and output, and all connect to all others in both directions. After receiving the input simultaneously by all the neurons, they output to each other. This process continues until a stable state reaching, which represents the network output.

3.3.3 Self Organizing Map

A Self Organizing Map (SOM) is a neural network useful for finding groups or clusters within a dataset [FAU]. The big difference between using SOMs instead of feedforward networks for classification and clustering is that the SOM is unsupervised, so we do not need any target information when using them. The SOM automatically finds groups within the data. A SOM arranges the cluster units or neurons in a one- or two-dimensional array. The weight vector for a neuron represents a point in the input space. During the self-organization process, the cluster unit whose weight vector matches the input pattern most closely (typically the minimum of the squared Euclidean distance) is the winner. The winning unit and the neighboring units (in this SOM array) update their weights. These weight changes move the weight vectors closer to the source input vector to better enable the cluster unit to classify inputs similar to the source. Neurons that are close in the SOM represent similar inputs. This process continues until reaching a certain stopping condition.

Figure 3.2 gives an example of an SOM network with three inputs fully connected to nine output neurons arranged as a 3x3 array. SOMs can segment images using a multi-
spectral approach. The SOM geometry is in preference to multi-layer geometry due to a
decrease in the run time while providing a large number of meaningful classifications
[RGCE].

3.4 ANNs in Medical Imaging

Artificial neural networks have many applications in the field of medicine. Neural
networks play an important role in medical imaging for a variety of purposes. This
section describes a convolution neural network, Hopfield neural network and an SOM as
examples of applications of neural networks to CAD problems.

3.4.1 Convolution Neural Networks for Lung Nodule Detection

A convolution neural network (CNN) is a neural network based on a convolution
process. It is a simplified vision machine used for the detection of cancerous nodules.
[LLHFM, LLLHFM].

Figure 3.3 shows the architecture of a convolution neural network, with one
hidden layer, used for lung nodule detection [LLLH].
The input layer consists of $M^2$ neurons which correspond to an $M \times M$ pixel preprocessed image. The hidden layer comprises $n$ groups of $N \times N$ hidden processing elements where $N$ is equal to $M-k+1$. Each hidden neuron takes as input the values of a $k \times k$ neighborhood in the input image block [LLLH]. The $k \times k$ area is the receptive field. For neurons in the same feature map that are one neuron apart, their respective fields in the input layer are one pixel apart.

**Figure 3.3 – Convolution neural network with one output neuron.**
Each neuron in the group of the hidden layer map has the same set of $k^2$ weights and performs the same operation on corresponding parts of the input image. Hence, we can express the entire operation as a two-dimensional discrete convolution with the $k \times k$ convolution kernel.

### 3.4.2 Computerized Boundary Detection Using Hopfield Neural Network

An important step in most medical imaging analysis systems is to extract the boundary of an area in which we are interested [ZHU]. Manual tracking of the boundary becomes infeasible when dealing with large data sets. According to the active contour model proposed by Kass et al. [KWT], an active contour can detect a boundary by minimizing the energy function by using a modified Hopfield network. The potential energy function is a combination of internal energy, external energy, and the energy of the contour given by the following equation [ZHU]:

$$E_{\text{snake}} = \int_{\Omega} E(v) ds = \int_{\Omega} (E_{\text{int}}(v) + E_{\text{image}}(v) + E_{\text{ext}}(v)) ds,$$

where $v$ is the deformable active contour with parameters $s$ (spatial index) and $t$ (time index) defined over given open intervals $\Omega$ and $T$ respectively.

The network ensures convergence of the energy minimization process by strictly reducing the total energy at all iterations. The network consists from a single layer of neurons, with feedback connections from each neuron to every other neuron. The network maps all the estimated boundary points of the image to a two dimensional network consisting of a grid of neurons. We can define a class pattern as the case where we achieve stability with one neuron in each row in firing state. When the algorithm terminates upon reaching the stable state, one neuron in each row is ON (firing state). The positions of these neurons indicate the detected boundary location.
3.4.3 Segmentation of Images Using Artificial Neural Networks

Segmentation involves the separation of different regions in an image. Segmentation of tissues in medical images is necessary for addressing a wide range of clinical problems [RGCE]. Recent developments in image system designs have resulted in significant advances in the quality, stability, and speed of imaging procedures. Neural networks with both supervised and unsupervised learning methods segment images. A Kohonen SOM helps to segment images by a multi-spectral approach. Neurons close to each other in the SOM represent similar inputs. A typical measure of distance is the Euclidean metric. The input to each SOM neuron is a set of three images represented by an input vector. This input vector has three components corresponding to three-image input. These three images are a representation of the same image but with different weights. The SOM has a single layer (output) of neurons arranged in a two dimensional fashion. The SOM maps all pixels in the image from the input space to an output space. We can identify the output space by the output neuron whose connection weights closely match the given input vector, as measured in a Euclidean metric. The weights update and the SOM calculates the distance between the winning neuron and the updated neuron. This procedure continues until it converges to a final set of prototypical vectors.
Chapter 4: Input Data - X-ray Images

This chapter provides a detailed description of the X-ray image data presented as input to the CAD system in this thesis. The chapter starts with a brief introduction to various problems in detection of cancerous nodules in X-ray images and their description. We then discuss the database of X-ray images presented as input to the CAD system in this thesis.

Interpreting a chest radiograph is extremely challenging. Radiographs often contain at the same time large contrast variations and important low contrast details. Some nodules may be camouflaged by underlying anatomical structure or low quality of the images or variable decision criteria used by the radiologists.

4.1 True Positives and False Positives

The CAD tool developed in this thesis attempts to identify cancerous nodules in X-ray images. These identified nodules contain both true positives (TP) and false positives (FP). True positives are cancerous nodules correctly identified by the CAD system. FPs are non-cancerous regions that are detected as cancerous by the CAD system. Given below is a brief description of some common types of false positives that we encounter when detecting cancer nodules in chest X-rays.

4.1.1 Internal Organs

The appearance of internal organs in an X-ray image makes it more complicated for separation of the SNA regions. These internal organs overlap other image details in the X-rays thereby decreasing the relative contrast of nodule regions. The common
internal organs that we come across in a chest radiograph are lungs, heart, stomach, liver, etc. We use the size factor to distinguish them from nodules.

4.1.2 Rib Crossings

Rib crossings are the regions of intersection of ribs in the image. These show high contrast and are sometimes not much different from a cancerous nodule. These high contrast regions sometimes also appear due to the cross section of blood vessels and ribs in a two-dimensional view. The surrounding information plays an important role in differentiating these regions from others.

4.1.3 End-on Vessels

It is difficult to distinguish between subtle nodules and end-on vessels. The incident X-ray beam, parallel to the vessel, forms the shadow of an end-on vessel, and a small, round pattern characterizes its shape. These small round spots contain high contrast with a high degree of circularity. The size vs. contrast information helps us to distinguish them from real nodules. End-on vessels tend to have more contrast than nodules of the same size.

4.2 Description of X-ray Images

We designed the CAD tool in this thesis using a set of sample radiographs. We obtained radiographs from the School of Veterinary Medicine-small animal clinic at Louisiana State University. Neil Mauldin, Associate Professor of Veterinary Medicine, Oncology, and Radiation Oncology, and Maura Egan, a graduate assistant, selected the radiographs. Ryan DeVille, an undergraduate student in the Electrical and Computer Engineering department, scanned the radiographs on a five-megapixels resolution flatbed
scanner. The digitized images were 1268 X 2079 pixels. Each of these is an 8-bit gray scale image with gray scale values ranging from 0 to 255.

Figure 4.1 shows an X-ray image taken from the database with a few non-cancerous and cancerous regions marked.

Figure 4.1 An X-ray image of a German shepherd dog taken from the left side.
The database includes chest X-ray images of various dogs (German shepherd, Pekingese, Doberman etc.). The database contains a total of 57 images. These images include different views of dogs (left, right, and top). The number of tumors in each image ranges from 5 to 25. We used about 20 images from the database. The remaining images either have clearly evident tumors that can be easily identified without using CAD or continuous malignancy. The following chapter uses one of the images from the database as a running example to depict the effects of the employed sequence of image enhancements. The selected image is a digitized scan of a chest (left side view) radiograph of a German shepherd. The radiograph includes heart, lungs, stomach, ribs, vertebrae, and some tumors.
Chapter 5: Pre-processing Stage – Enhancing Nodules in Radiographs

This chapter provides a detailed description of the pre-processing stage of the CAD system presented in this thesis. The chapter starts with a brief introduction to image enhancement techniques and then moves on to discuss the methods used in our system for contrast enhancement, thresholding, noise filtering, and shape identification. Lastly, we discuss separation of the SNAs from the enhanced image.

5.1 Introduction

Image enhancement methods make images look better. Image enhancement is a solution to a computer imaging problem. Various image enhancement techniques emphasize and sharpen image features for display and analysis. The enhancement techniques in this work are a preprocessing step to ease the next processing stage, which identifies nodules. Enhancement methods operate in the spatial domain by manipulating the pixel data or in the frequency domain by modifying the spectral components. Some enhancement algorithms use both the spatial and frequency domains.

The enhancement techniques include point operations, where a particular equation modifies each pixel thereby not affecting the other pixel values, mask operations, where each pixel value changes according to the values of the pixel’s neighbors (using convolution masks), and global operations, where all the pixel values in the image (or sub-image) are taken into consideration. Spatial domain processing methods include all three types, but frequency domain operations, by nature of the frequency (and sequence) transforms, are global operations [GW].
Images typically have both large-scale and small-scale variation in intensity, representing features of varying sizes. An image contains information at varying frequencies, bounded at the low and high ends by the overall image dimensions and the pixel spacing, respectively. Histogram equalization improves the visibility of local (high-frequency) features only within limits imposed by the overall (low-frequency) variation in the image.

It is difficult with ordinary X-rays to differentiate between adjacent soft tissues/organs or to distinguish diseased tissue, such as a tumor, from the surrounding healthy tissue from which the cancer may have arisen. Image enhancement is necessary in order to differentiate the tissues, either increasing or decreasing the contrast of one tissue relative to another.

5.2 Contrast Enhancement by Histogram Equalization

We obtain the histogram of an image dividing the interval between minimum and maximum pixel value into equally spaced bins. Assign each pixel to the bin that surrounds its value. Next, we count the number of pixels corresponding to each bin. The image histogram is a plot of these frequency counts as a function of the bin locations. The shapes of histograms for the same image vary depending on the size of the intervals. Histograms are the basis for numerical spatial domain processing techniques [GW]. Histogram manipulation is an effective method for image enhancement.

Histogram equalization is one of the most important parts for any image processing. The basic principle of histogram equalization is that all the image intensities should be equally frequent. An image whose pixels tend to occupy the entire range of possible gray levels and, in addition, tend to be distributed uniformly will have an
appearance of high contrast and exhibit a large variety of gray tones. Peaks in the histogram represent frequent pixel intensities, and can often be related to nearly homogeneous regions. After histogram equalization, the peaks broaden, meaning that subtle intensity differences in a region become better resolved. Histogram equalization will not "flatten" a histogram. It redistributes intensity distributions. This means that any quantitative information in the pixel intensity is lost. We only maintain the ordering of pixel values, not their quantitative relationship. Because histogram equalization is a point process it does not introduce new intensities into the image. Existing values map to new values but the actual number of intensities in the resulting image will be equal or less than the original number of intensities.

Given below is an expression to calculate the new assigned value $k$ for each brightness level $j$ in the original image:

$$k = \sum_{i=0}^{j} \frac{N_i}{T} * I_{\text{max}} ,$$

where $N_i$ is the number of pixels with brightness values $i$, $I_{\text{max}}$ is the maximum pixel intensity value, and $T$ is the total number of pixels in the image.

Figure 5.1 shows an original input image and its histogram. The image is one of the database of images used in this study. Figure 5.2 shows the image after equalizing the histogram. Histogram equalization improved the relative contrast of the image.
Figure 5.1 Input image and its histogram.
Figure 5.2 Image after histogram equalization and its histogram.
5.3 Image Thresholding

Images at this point have improved contrast but there is too much irrelevant background information and clutter that needs to be removed. We can identify most of this background information by pixel values different from those of the nodules.

Image thresholding is a subclass of image segmentation as it divides an image into segments based on the value of pixels relative to a threshold value. The simplest of all thresholding techniques is to partition the image using a single global threshold [RI]. Segmentation is a process of scanning the image pixel by pixel and labeling each pixel as object or background depending on whether the gray level of that pixel is greater or less than the value of threshold. We obtain a binary image by marking pixels with values less than the threshold with zeros and the remaining pixels with ones.

The cancerous nodules in the X-ray image appear in low contrast. The non-nodule areas in the X-ray image are neither too bright nor too dark. We use a multi-level (two-level) thresholding to classify any point \((x,y)\) in the image \(f(x,y)\) as belonging to one object class if \(T_1 < f(x,y) \leq T_2\), to the other object if \(f(x,y) > T_2\), and to the background if \(f(x,y) \leq T_1\), where \(T_1\) and \(T_2\) are the two threshold values selected in case of two-level thresholding [GW]. Upon observing all the images in the database, the pixels within cancerous nodules were in the range 125 to 158. Hence we have the two threshold limits \(T_1 = 120\) and \(T_2 = 170\). We consider the pixels with values less than \(T_1\) and greater than \(T_2\) as background and set them to zero. The pixels whose values lie between \(T_1\) and \(T_2\) (foreground pixels) retain their pixel values. For easy processing of the image in further stages, we converted it into binary form by setting all the foreground pixel values equal to 255.
Figure 5.3 Image before and after multi-level thresholding.
Figure 5.4 Image before and after binarization.
The final image obtained is a binary image. This image still contains some unwanted information and needs to be further processed for its removal. Figure 5.3 shows the image before and after the first stage of thresholding (two level thresholding). Figure 5.4 shows the image before and after the second stage of thresholding (binary thresholding).

5.4 Median Filter

The image obtained after thresholding contains salt and pepper noise. This noise appears due to the presence of minute gray scale variations in the image. Median filtering is a common image enhancement technique for removing salt and pepper noise without significantly reducing the sharpness of the image [CHN].

A median filter reduces noise in an image, preserving useful details [GW]. Median filters are quite popular because they provide excellent noise-reduction capabilities, with considerably less blurring than linear smoothing filters of similar size. The median filter considers each pixel and its neighbors in the image to decide whether or not it is a representation of the surroundings. It replaces the pixel value with the median of the neighboring pixel values. We calculate the median by first sorting all the pixel values from the neighborhood into numerical order and then replace the pixel being considered with the middle pixel value [MF]. (If the neighborhood under consideration contains an even number of pixels, the average of the two middle pixel values is the median.) A median filter allows a great deal of high spatial frequency detail to pass while remaining very effective at removing noise on images thereby affecting less than half of the image pixels in a smoothing neighborhood.
Figure 5.5 Image before and after salt and pepper noise removal using a median filter.
The median filter has two main advantages.

1. The median is a more robust average than the mean and so a single very unrepresentative pixel in a neighborhood will not affect the median value significantly.

2. The median value is the value of one of the pixels in the neighborhood, so the median filter does not create new unrealistic pixel values when the filter straddles an edge. For this reason the median filter is much better at preserving sharp edges.

Figure 5.5 shows the image obtained after passing through the median filter.

5.5 Blob Analysis

Blobs (binary large objects) are areas of touching pixels within an image, in which all pixels have the same logical state. All the pixels in an image that belong to a blob are in foreground state [NILV]. In a binary image, pixels in the background have values equal to zero while every non-zero pixel is a part of a binary object. Blob analysis consists of a series of processing operations and analysis functions that produce information about blobs in an image. Blob analysis helps to detect and analyze any two-dimensional shape in an image.

Blob analysis eliminates blobs that are of no interest based on their spatial characteristics and keeps only the relevant blobs for further analysis. It is a powerful tool in object detection in applications involving a significant variance in the shape or orientation of the object [NILV].
Figure 5.6 Removing the blobs touching the boundary of the image.
Figure 5.7 Image after shape template matching
The binary image obtained after thresholding consists of interconnected SNA regions. By eroding the image most of the SNA regions separate. The first stage of blob analysis involves the elimination of foreground regions touching the boundary of the image. Most nodule areas lie in the center of the X-ray, hence this stage helps in eliminating other bright areas (like bones) appearing towards the boundaries of the image. The second stage involves the separation of round objects (SNAs) from the others by shape template matching. In this method we calculate the area of each blob and obtain a circle with radius \( r \) and the same area as that of the blob. This circle acts a template to locate the round objects. For each pixel \( p \) of the blob, we center a circle with radius \( r \) at \( p \) and calculate the following ratio value.

\[
\text{Ratio} = \frac{\text{Area of intersection of the circle and the blob}}{\text{Area of the circle/blob}}
\]

If at every point in a blob the ratio is less than 0.6, we eliminate the blob, i.e., we set all pixels in that blob to the background value (zero). Figures 5.6 and 5.7 show the threshold images after the first and second stages of blob analysis.

We use the final image obtained after various processing stages as a mask. This mask when projected onto the original input X-ray image using a basic watermarking technique results in the SNAs at a relatively high contrast. Figure 5.8 shows the resultant output image.
5.6 Summary

The following gives a brief summary of the entire procedure used to enhance the X-ray images. We increased the relative contrast in the image by histogram equalization. We then used a two level thresholding method to remove most of the unwanted background information. By filtering the image using a median filter, we get rid of most of the noise speckles obtained after thresholding. Blob analysis involves a sequence of steps for removal of unwanted foreground information. We use the final image obtained after blob analysis to project onto the original input X-ray image using a basic watermarking technique. The application of all these image enhancement techniques makes the problem of locating the SNA regions much simpler. A manual approach is used to separate the SNA from the final output image.

We use the SNA regions separated from this image as input to the next stage for further classification as cancerous or non-cancerous. Some of the SNA regions sent to the next stage contain un-enhanced image information. This happens because the enhancement procedures used in this stage do not enhance all the cancerous nodule regions.
Figure 5.8 The input image and the final output image.
Chapter 6: Classification of Suspected Nodule Areas Using Artificial Neural Networks

This chapter provides a detailed description of the classification stage of the CAD system presented in this thesis. The chapter starts with a brief description of the input images given to the neural network and then moves on to discuss the architecture, training, and testing of the neural network. Lastly, we discuss the output of the classification stage in the CAD system (neural network).

Various image processing techniques-such as those used in Chapter 5 (histogram equalization, thresholding, etc.) help in the process of SNA selection. The problem of detecting lung nodules requires a good classification of cancerous and non-cancerous regions. A large number of non-cancerous regions obtained with SNA selection include rib crossings, rib vessel crossings, and end-on vessels. We need to identify these regions and separate them. In this thesis we used artificial neural-networks (ANNs) to tackle this problem.

6.1 ANN Input

In the database of images, the size of the largest nodule was nearly 250 pixels in diameter and the smallest nodule observed was nearly 50 pixels in diameter (the actual physical size of the nodules ranged from 0.3 cm to 2 cm). We chose the optimum window size for the SNA selection to be 300 X 300 such that it contains some amount of surrounding information. This information helps in better classification of SNAs. The larger the image size the larger is the virtual memory required for the program that uses it. The processing time for the network also increases for larger images. So we
compressed the images to a smaller size (100 X 100) not only to decrease the processing time but also to increase the number of images in the training set due to the reduction of virtual memory requirement for each image. We obtained a set of thirty such SNAs from the previous image processing stage. These SNAs contained 14 cancerous and 16 non-cancerous regions. We also obtained a set of 30 unprocessed SNAs (same areas) from the initial X-ray image to compare the performance of the ANN on pre-processed and unprocessed SNAs. We transformed the two dimensional image data into a single dimensional array to simplify the task of presenting it as input to the neural network. We then created a master matrix in which each column contains the data of one input image and its corresponding target value.

6.2 Network Architecture

The network used for the classification of nodules in this thesis consists of an input layer, one hidden layer, and an output layer. The elements in one layer connect to the elements in the next layer by means of directed communication links, each with an associated weight. If $S$ is the number of processing elements in the destination layer and $R$ is the number of elements in the source layer, then the general form of a weight matrix ($W$) connecting these two layers can be written as [FAU] follows.

$$W = \begin{bmatrix}
W_{11} & W_{12} & \cdots & W_{1R} \\
W_{21} & W_{22} & \cdots & W_{2R} \\
W_{S1} & W_{S2} & \cdots & W_{SR}
\end{bmatrix}$$
The row indices on the elements of matrix $W$ indicate the destination neuron of the weight and the column indices indicate which source is the input for that weight. The total number of weight matrices in a network is equal to the sum of the number of hidden layers and the output layer. The ANN used in this thesis has one hidden layer and one output layer, so we have two weight matrices, the first one ($W_1$) connecting the input layer to the hidden layer and the second one ($W_2$) connecting the hidden layer to the output layer.

The total number of pixels in each SNA image is 10,000 (100 X 100). When we present the image as input to the ANN, it reads each pixel in the image by different input elements in the network, so the input layer consists of 10,000 elements. There is no rule that calculates the optimum number of elements in the hidden layer. The larger the number of elements in the hidden layer, the bigger will be the size of weight matrices which requires larger processing time and memory while training the network. If the number is too low, however, the network may not work to give the desired results. In this thesis, the network showed good results with five neurons in the hidden layer. The output of the ANN is a single value (in the range between 0 and 1) that decides whether the input given is a cancerous region or not, so we just have a single element in the output layer. Hence, the size of the weight matrix $W_1$ is $5 \times 10,000$, and the size of $W_2$ is $1 \times 5$.

We also added a bias factor to all the neurons in the network. This bias acts like a weight on a connection from a unit with a constant activation of 1.

Figure 6.1 shows the ANN architecture used in this thesis for classification of suspected nodule areas as cancerous or non-cancerous.
The communication links connect the input layer to the hidden layer and have weights associated with them.

One output processing element.

Hidden layer processing elements.

The communication links connect the input layer to the hidden layer and have weights associated with them.

Input layer.

Figure 6.1 Architecture of the artificial neural network used for the classification of SNA regions.
6.3 Training

Training of a neural network is necessary for it to perform the required task. In general the training procedure involves the following steps.

- Expose the network to pre-existing or source data.
- Evaluate the source data to calculate the output based on the current network state.
- Compare the generated output with known target values.
- Modify the state of the network to improve the performance.
- Repeat training until stopping criteria reached.

We used a log-sigmoid activation function to operate and train the network. The function used to perform this task must be a continuous, non-decreasing, differentiable function. The following figure shows a graphical representation of the log-sigmoid function [FAU].

![Log-Sigmoid Activation Function](image)

**Figure 6.2 Log-Sigmoid Activation Function**
We can represent the log-sigmoid function mathematically as $a = \text{logsig}(n)$, where $a$ is the output of the ANN and $n$ is the sum of the weighted inputs from the previous layer. In the above expression, $a \rightarrow 1$ as $n \rightarrow +\infty$ and $a \rightarrow 0$ as $n \rightarrow -\infty$. The ANN output is in the range between 0 and 1. In order to prevent the value of $n$ from moving to one extreme (towards $+\infty$ or $-\infty$) we preset the target values for the cancerous and non-cancerous regions as 0.1 and 0.9, respectively, instead of 0 and 1.

The main aim of the neural network is to identify if an input (enhanced) SNA region is cancerous or non-cancerous. We used the error backpropagation algorithm to train the network for this purpose. The following gives a brief description of the algorithm. The algorithm operates on one input-target pair $(s, t)$ at a time. The network has $L$ layers where $k = 1, 2, \ldots L$ denotes the layer and $f$ denotes the activation function of each neuron. Variable $a[k-1]_i$, denotes a value associated with the $i^{th}$ neuron in layer $k-1$.

1. Initialize the weights to small random values (these values can be both positive and negative).
2. Select an input-output pair $(s, t)$. Apply $s$ to the input layer. Let $a[0]_i = s_i$, for all $i$.
3. Propagate the signal forward through the network using
   
   $$a[k]_i = f(n_{\text{in}}[k]_i) = f(\sum w[k]_{ij} a[k-1]_j)$$
   
   for each $i$ and $k$ until the final outputs $a[L]_i$ have all been calculated. In the above equation $n_{\text{in}}[k]_i$ is the sum of weighted inputs to the $i^{th}$ neuron in layer $k$.
4. Compute the delta (error term) for the output layer,
   
   $$\delta[L]_i = f'(n_{\text{in}}[L]_i)(t_i - a[L]_i) ,$$
by comparing the actual outputs $a[L]_i$ with the target outputs $t_i$ for the input-output pair being considered.

5. Compute the deltas for the preceding layers by propagating the error backwards in the network:

$$\delta[k]_i = f' (n\_in[k]_i) \sum w[k]_{ji} \delta[k+1]_j,$$

for $k = L-1, \ldots, 2, 1$ until a delta has been calculated for every PE.

6. For a positive constant $\alpha$, use the change in weight value given by

$$\Delta w[k]_{ij} = \alpha \delta[k]_i a[k-1]_j$$

to update all connections according to $w[k]_{ij}^{\text{new}} = w[k]_{ij}^{\text{old}} + \Delta w[k]_{ij}$.

7. Repeat entire procedure from step 2 for the next training pair.

The network finishes one epoch when it completes the above procedure on all the input-target pairs. In the above algorithm, $\alpha$ is the training parameter. The error value for the network is the absolute value of the difference between the target and the output value calculated. The network continues to train until the maximum error value over all training input-target pairs falls below a certain threshold value or if the maximum number of epochs elapse. The neural network trains itself with each image from the master matrix until it satisfies the stopping condition. For the ANN developed in this thesis, we set the error threshold as 0.1 and the maximum number of epochs as 1000. Even when we increased the number of epochs (till 5000) the error value never reached the threshold value. The processing time is the time taken to train the ANN until it reaches a stopping criterion. The processing time for the ANN was very low (approximately one minute) for both (unprocessed and pre-processed) sets of SNA samples.
6.4 Testing

Before testing the network we present the SNAs used for training as input to the ANN. We first train the network with all processed SNAs and apply the trained inputs to the network to obtain the processed image outputs. We then train the network with unprocessed SNAs and apply the trained inputs to the network to obtain the unprocessed image outputs. Table 6.1 shows a few sample images, their input target values, and output results for both processed and unprocessed images in the training sets. These output values lie in a range between 0 to 1. We selected a threshold value of 0.5 to differentiate the output values of the cancerous and the non-cancerous regions. If the output value lies below 0.5, then it is said to be cancerous, and if the output value is greater than 0.5, then it is non-cancerous. We observed that the accuracy of the ANN (for both processed and unprocessed images) to be 100% (this value might change when dealing with very large number of images in the training set). This 100% detection accuracy indicates that the ANN is properly trained on the training set. This network is ready for testing to evaluate its performance. We set the training parameter $\alpha$ as 0.1 throughout the thesis, unless stated otherwise.

6.4.1 Testing Results

We used the round-robin technique (leave one out) for the training and testing of the neural network. In this method, we train the network with all the images except one, leaving that image for testing the network. This process repeats until the network tests all the images. We trained and tested the network with both the pre-processed and unprocessed SNA samples separately. Table 6.2 shows selected round-robin testing results
for corresponding processed and unprocessed SNAs (five cancerous and five non-cancerous SNAs).

Table 6.1 Table showing a few sample results of the ANN used in this thesis.

<table>
<thead>
<tr>
<th>Target (cancerous)</th>
<th>Processed image output</th>
<th>Unprocessed image output</th>
</tr>
</thead>
<tbody>
<tr>
<td>Target = 0.1</td>
<td>Processed image output = 0.21</td>
<td>Unprocessed image output = 0.32</td>
</tr>
<tr>
<td>Target = 0.1</td>
<td>Processed image output = 0.17</td>
<td>Unprocessed image output = 0.17</td>
</tr>
<tr>
<td>Target = 0.9</td>
<td>Processed image output = 0.76</td>
<td>Unprocessed image output = 0.7</td>
</tr>
<tr>
<td>Target = 0.9</td>
<td>Processed image output = 0.72</td>
<td>Unprocessed image output = 0.58</td>
</tr>
<tr>
<td>Target = 0.9</td>
<td>Processed image output = 0.69</td>
<td>Unprocessed image output = 0.69</td>
</tr>
</tbody>
</table>
In Table 6.2, rib crossings (non-cancerous SNAs) that appeared almost round gave output values close to 0.1 (cancerous SNAs) for both processed and unprocessed images. Some SNAs (example SNA-3 from Table 6.2) gave false results if they were unprocessed using the various image enhancement techniques. These accounted for the improvement in the accuracy values.
6.4.2 Accuracy

We evaluated the performance of the ANN in terms of its accuracy. Accuracy is the ratio of the number of SNAs recognized correctly to the total number of SNAs given as input to the neural network. The ANN when trained and tested with the unprocessed SNA samples gave an accuracy of 70%. With the processed SNA samples the accuracy of the ANN increased to 83.33%. We tested the network for various values of training rate $\alpha$, and any value of $\alpha > 0.005$ gave high accuracy values for the ANN. Table 6.3 lists the accuracy values for both the processed and unprocessed images at different values of $\alpha$ (training parameter). We set a value of $\alpha=0.1$ for training the network.

**Table 6.3** Table showing the variation of accuracy values with $\alpha$.

<table>
<thead>
<tr>
<th>Training Parameter $\alpha$</th>
<th>Accuracy values for unprocessed SNAs</th>
<th>Accuracy values for processed SNAs</th>
</tr>
</thead>
<tbody>
<tr>
<td>0.001</td>
<td>50.00%</td>
<td>50.00%</td>
</tr>
<tr>
<td>0.004</td>
<td>58.33%</td>
<td>60.00%</td>
</tr>
<tr>
<td>0.005</td>
<td>63.33%</td>
<td>81.67%</td>
</tr>
<tr>
<td>0.006</td>
<td>66.67%</td>
<td>83.33%</td>
</tr>
<tr>
<td>0.01</td>
<td>70.00%</td>
<td>83.33%</td>
</tr>
<tr>
<td>0.5</td>
<td>70.00%</td>
<td>83.33%</td>
</tr>
</tbody>
</table>
Chapter 7: Conclusion and Future Research

This chapter gives a brief summary of the CAD system developed in this thesis and the results obtained. At the end, we provide suggestions for future work.

7.1 Summary

We have designed a computer aided diagnosis (CAD) system to detect cancerous nodules in X-ray images. This CAD system comprises two stages: pre-processing stage and classification stage. The pre-processing stage consists of various image enhancement techniques (contrast enhancement, thresholding, noise removal and blob analysis) to improve the visibility of tumors in X-ray images. We separate the SNAs from the enhanced image and give them as input to the next stage. We used artificial neural networks in the classification stage. The ANN classifies the SNA as cancerous and non-cancerous regions. We used a round-robin technique for training and testing of the ANN. The detection accuracy depends on the correct classification of the SNAs. By including the pre-processing stage in the CAD system, we observed a significant improvement in the detection accuracy. The accuracy values increased from 70% to 83.33%.

7.2 Future Research

There is a scope for future work in this thesis to further improve the performance of the CAD system. We used a sequence of manual operations to separate the SNA regions from the processed X-ray image. Automation of this process would help to detect the cancerous nodules in the X-ray images faster. In this thesis, we presented a basic neural network model to classify the cancerous regions from the non-cancerous. We can further improve this network accuracy by training it on a larger data set.
Bibliography


[LCD] Lung Cancer Diagnosis -“http://www.iressa-us.com/content/patient/nsclc/diagnosis.asp”


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