CHAPTER-V
DECISION SUPPORT SYSTEM FOR
CONGENITAL HEART SEPTUM DEFECT DIAGNOSIS
BASED ON CHEST X-RAY FEATURES
USING NEURAL NETWORKS

5.1 Introduction

One of the clinical tests performed to diagnose Congenital Heart Septum Defect is the Chest Radiography (X-Ray) through which the contour of size, position and shape of the heart can be viewed. In order to diagnose Congenital Heart Septum Defect, a physician analyzes the chest X-ray and extracts the features like heart size measurements [Bar36] and also determines whether there is any fluid around the lungs. But manual extraction of features and diagnosis is a difficult task for a physician, due to the reason that heart size will not be fixed in nature, instead it vary from person to person based on the characteristics like age, sex, height, weight etc., and also it is a time consuming process. Therefore, in the present study, an algorithm is developed to automatically analyze and to extract the features from Chest X-ray based on Digital Image Processing techniques. Also, a Decision Support System is developed to automatically classify the Congenital Heart Septum Defect Diagnosis based on chest X-ray features using Backpropagation Neural Network model. The Network is trained by using a Delta Learning Rule. The proposed algorithm and Decision Support System are implemented in MATLAB 7.3 with GUI features.

5.2 The Chest Radiography (Chest X-ray)

Imaging with X-rays involves exposing a part of the body to a small dose of ionizing radiation to produce pictures of the inside of the body. X-rays are the oldest and most frequently used form of medical imaging. A chest X-ray makes images of the heart, lungs, airways, blood vessels and the bones of the spine and chest. There exist different views of the chest radiography, which can be obtained by changing the relative orientation of the body and the direction of the X-ray beams. The most common views are *posteroanterior*, *anteroposterior* and *lateral*. In a posterioanterior (PA) view, the X-ray source is positioned so that X-rays enters through the posterior (back) aspect of the chest and exit out of the anterior (front) aspect where they are detected. To obtain this view, individuals stand facing a flat surface behind which is an x-ray detector. A radiation source is positioned behind the patient at a standard distance and X-ray beams are transmitted toward the patient. In anteroposterior(AP) views, the positions of the X-ray source and detector are reversed i.e., X-rays enter through the anterior aspect and exit through the posterior aspect of the chest. AP chest x-rays are harder to interpret than PA X-rays and are therefore generally reserved for some situations. Lateral views of the chest are obtained in a similar fashion as the posteroanterior views, except in the lateral view, the patient stands with both arms raised and the left side of the chest pressed against a flat surface. Among these views, posteroanterior (PA) is the frequently used view.

Chest radiographs are used to diagnose many conditions involving the chest walls, bones of the thorax and structures contained within the thoracic cavity including the lungs, heart and great vessels. For some conditions of the chest, radiography is good for screening. For example, the congestive heart failure is very commonly diagnosed by chest radiograph. The fig 5.1 show the normal heart of a chest X-ray where as the fig 5.2 shows the abnormal heart of a chest X-ray.

Fig 5.1: Chest X-ray Image of
Normal Heart

Fig 5.2: Chest X-ray Image of
Abnormal Heart

In order to diagnosis Congenital Heart Septum Defects based on Chest X-rays, a physician analyzes the Chest X-ray and extracts the two important features [MKK04]. The first feature is, verifying any fluid is there in the lung area which may be an indication of the abnormality of the heart. The second feature is size of the heart contour which determines an abnormality of a heart can be determined. The first feature can be easily obtained just by viewing the

image where as it is very difficult to get second feature i.e., heart size. In order to get the size of the heart, a physician manually draws the lines around the heart field of the Chest X-ray and then takes the various measurements including the Transverse diameter *T,* Long diameter *L,* Broad diameter *B,* Cardio Thoracic Ration *CTR,* Frontal Area of the Heart [Kab87]. To measure transverse diameter of the heart, a line was drawn horizontally between the clavicles and another line (perpendicular to the first) bisected the heart. Measurements are made from the midline (perpendicular line) to the points of greatest deviation of the heart to the right(r) & left (l), and the sum is taken as the Transverse diameter (T). The Transverse diameter of the chest is measured from the internal surfaces of ribs on the right and left side superior to the costal attachments of the diaphragm at the point where the width of the chest is greatest. The Long diameter (L) of the heart is measured from the junction of the right atrium and superior vena cava to the apex of the heart. The Broad diameter (B) of the heart represented a perpendicular to the long diameter of the heart extending from the right cardiophrenic angle to the left upper heart border. The above radiographic measurements are made to the nearest 0.05 cm.

In the fig 5.3 [Cri133], *A* represents the Transverse Diameter of the Upper Medias, *r* represents the greatest deviation of the heart to the right from the middle line, *l* represents the greatest deviation of the heart to the left from the middle line, *L* is the Longitudinal Diameter and *B* is the Broad Diameter of the

heart. The above radiographic measurements can be combined to calculate composite indices of heart size. The composite measurements are, the Transverse Diameter *T* which is calculated as (*r+l*), the Cardiothoracic Ratio *CTR* is the ratio of the transverse diameter of the heart to the transverse diameter of the chest and the Frontal Area *FA* of the heart, which is calculated from the formula *FA=* $^{\Pi}/4$ X *L* X B, where L represents the long diameter of the heart and *B* represents the broad diameter of the heart.
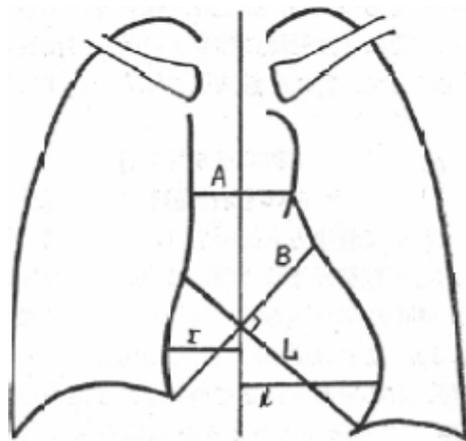

Fig 5.3: The contour of the Chest X- ray along with the heart

5.3 Digital Image Processing Techniques

5.3.1 Introduction

An image may be defined as a two dimensional function $f(x,y)$, where *x* and *y* are the spatial co-ordinates and the amplitude of *f* at any pair of co-ordinates *(x, y)* is called the intensities or gray levels of image at that point [RR06]. When *x, y* and the amplitude values of *f* are all finite discrete quantities,

the image is called as the *Digital Image*. i.e $f(x, y)$ must be nonzero and finite. Therefore,

$$0 < f(x) < \infty \qquad \text{... 5.1}$$

Generally, a Digital Image is represented in a matrix form by *M* rows and *N* columns. Therefore, a complete *M X N*, Digital Image is represented as

$$f(x) = \begin{pmatrix} f(0,0) & f(0,1) & \cdots & f(0,N-1) \\ f(1,0) & f(1,1) & \cdots & f(1,N-1) \\ \vdots & \vdots & & \vdots \\ f(M-1,0) & f(M-1,1) & \cdots & f(M-1,N-1) \end{pmatrix} \qquad \text{... 5.2}$$

The right side of the equation is called as Digital Image. Each element of this matrix array is called an *image element*, *picture element*, *pixel* or *pel*. A digital image can be processed based on these pixels only. There exists a relationship between the pixels in a digital image. The related pixels are called neighbors of pixels. A pixel *P* at co-ordinates *(x, y)* has four horizontal and vertical neighbors whose co-ordinates are given by

$$(x+1,y),(x-1,y),(x,y+1),(x,y-1) \qquad \text{... 5.3}$$

The set of pixels called, the 4-neighbors of *P*, is defined by $N_4(P)$. Each pixel is a unit distance from *(x, y)*. Some of the neighbors of p lie outside of the digital image if *(x, y)* is the border of the image. The four diagonal neighbors of *P* have the following neighbors.

$$(x+1,y+1),(x+1,y-1),(x-1,y+1),(x-1,y-1) \qquad \text{... 5.4}$$

These neighbors are denoted by $N_D(P)$. These neighbors along with the 4-neighbors are called the 8-neighbors of the *P*. Some neighborhood operations work with the value of the image pixels in the neighborhood and the corresponding values of a subimage that has the dimension as the neighborhood. The subimage is called a filter, mask, kernel, template or window. The values in a filter subimage are called coefficients rather than the pixels. The mask coefficients and the pixels of image under this mask are shown figures fig 5.4 and fig 5.5.

$f(x$-1, y-1)	$f(x$-1, $y)$	$f(x$-1, y+1)
$F(x, y$-1)	$F(x, y)$	$f(x, y$+1)
$f(x$+1, y-1)	$f(x$+1, $y)$	$f(x$+1, y+1)

$w(-1,-1)$	$w(-1,0)$	$w(-1,1)$
$w(0, -1)$	$w(0,0)$	$w(0,1)$
$w(1, -1)$	$w(1,0)$	$w(1,1)$

Fig 5.4: Pixels of image section under mask

Fig 5.5: Mask Coefficients showing coordinates

The operations that can be performed on digital images mainly depend on the relationships. The major operations performed on digital images are image enhancement, image restoration, compression, morphological processing, segmentation, etc,.

Some of the applications of digital image processing are nuclear medicine where the imaging is done based on gamma rays. Angiography is another application in an area called contrast enhancement radiography. This procedure

is used to obtain the images (called angiograms) of blood vessel. The ultraviolet application of Digital Image Processing varies from lithography, industrial inspection, microscopy, etc,. The dominant application of imaging in the microwave band is radar. The unique feature of radar is the ability to collect data over virtually any regions at any time regardless of weather condition. Some radar waves can penetrate clouds and certain conditions can also see through vegetation. In many cases radar is the only way to explore inaccessible regions of the earth's surface. The major application of imaging in the radio band is medicine and astronomy. In medicine radio waves are used in Magnetic Resonance Imaging.

5.3.2 Spatial Filtering

The spatial filtering of an image is used for smoothing images. That is for blurring and for noise reduction. Blurring is used in preprocessing steps, such as removal of small details from an image prior to object extraction and bridging of small gaps in lines or curves. Noise reduction can be accomplished by blurring with a *linear filter* and also by *non-linear filter.*

A *linear spatial filtering* of an image can be obtained by simply replacing the value of every pixel in an image by the average of the gray levels in the neighborhood defined by the filter mask. This type of filter is called as *averaging filter.* The general implementation for filtering an *M X N* image with

a weighted averaging filter of size *m x n* (m and n are odd) is given by the expression

$$g(x,y) = \frac{\sum_{s=-a}^{a}\sum_{t=-b}^{b} w(s,t)f(x+s,y+t)}{\sum_{s=-a}^{a}\sum_{t=-b}^{b} w(s,t)} \qquad \ldots 5.5$$

In the above equation *a* and *b* are integers that represents the co-ordinates of an image, *g(x,y)* represent the filtered image, *f(x+s, y+t)* represents the image to be filtered and the *w(s, t)* represents the filter mask. Using this process the sharp transition in gray levels of an image can be reduced. Because the random noise consists of sharp transition in gray levels, this filter gives an undesirable side effect that blur edges. Therefore, non- linear spatial filters are commonly used for noise reduction.

Order-Statistics Filters: Order Statistics Filters are non-linear spatial filters whose response is based on ordering (ranking) of the pixels contained in the image area compared by the filter and then replacing the value of the centre pixel with the value determined by the ranking result. One of the best Order Statistics filters is *Median Filter*. It replaces the value of the pixel by the median of the gray levels in the neighborhood of that pixel. Median filters are quite popular because for certain type of random noise. Median filters provide excellent noise reduction capability, with considerably less blurring than linear smoothing filters of similar size.

In order to perform Median Filtering at a point in an image, we first sort the values of the pixel and its neighbors to determine their median, and assign

123

this value to that pixel. For example, in 3x3 neighborhood the median is the 5th largest value in a 5x5 neighborhood. The median is the 13th largest value and so on. When several values in a neighborhood are the same, all equal values are grouped. For example, suppose that a 3x3 neighborhood has the values (10, 20, 20, 20, 15, 20, 20, 25, 100). These values are sorted as (10, 15, 20, 20, 20, 20, 20, 25, 100) which results in a median of 20. Thus the principle function of median filter is to force point with distinct gray levels to be more like their neighbors. The median ξ of a set of values is such that half the values in the set are less than or equal to ξ and half are greater than or equal to ξ.

5.3.3 Edge Detection and Linking

A problem of fundamental importance in image analysis is edge detection. Edges characterize object boundaries and therefore useful for segmentation, registration and identification of objects. A typical application of edge detection techniques are involved is an automatic object extraction.

Edges in an image are pixel locations with abrupt changes in gray levels. If we have a continuous image (i.e., assuming continuous values), we would say that the derivative of the image *f(x,y)* assumes a local maximum in the direction of the edge. Therefore, one of the edge detection techniques is to measure the gradient of *f* in a particular location. This is accomplished by using a *gradient operator*. Such operators, also called *masks*, provide finite-difference approximations of the orthogonal gradient vector f_x and f_y.

Gradient Operator

The gradient of an image $f(x, y)$ at location (x, y) is defined as the vector.

$$\nabla f = \begin{bmatrix} G_x \\ G_y \end{bmatrix} = \begin{bmatrix} \frac{\partial f}{\partial x} \\ \frac{\partial f}{\partial y} \end{bmatrix} \qquad ... 5.6$$

The gradient vector points in the direction of maximum rate of change of f at coordinates (x, y). In order to detect the edges, the magnitude of this vector is used. The magnitude of the vector ∇f is determined as

$$\nabla f = mag(\nabla f) = \left[G_x^2 + G_y^2 \right]^{1/2} \qquad ... 5.7$$

The quantity gives the maximum rate of increase of $f(x, y)$ per unit distance in the direction of ∇f.

Direction

The direction of the gradient vector is defined as

$$\alpha(x, y) = \tan^{-1} \left(\frac{G_y}{G_x} \right) \qquad ... 5.8$$

where $\alpha(x, y)$ represents the direction angle of the vector ∇f at (x, y). The angle is measured, with respect to x-axis. The direction of an edge at (x, y) is perpendicular to the direction of the gradient vector at that point.

Edge Detection Techniques

Robert's cross operator

The Roberts Cross operator performs a simple, quick to compute, 2-D spatial gradient measurement on an image. Pixel values at each point in the

output represent the estimated absolute magnitude of the spatial gradient of the input image at that point. The operator consists of a pair of 2×2 convolution kernels as shown in Figure 5.6. One kernel is simply the other rotated by 90°.

-1	0
0	1

0	-1
1	0

Fig 5.6: Robert's masks

These kernels are designed to respond maximally to edges running at 45° to the pixel grid, one kernel for each of the two perpendicular orientations. The kernels can be applied separately to the input image, to produce separate measurements of the gradient component in each orientation (call these G_x and G_y). These can then be combined together to find the absolute magnitude of the gradient at each point and the orientation of that gradient.

Sobel's operator

The operator consists of a pair of 3×3 convolution kernels as shown in fig 5.7. One kernel is simply the other rotated by 90°.

These kernels are designed to respond maximally to edges running vertically and horizontally relative to the pixel grid, one kernel for each of the two perpendicular orientations. The kernels can be applied separately to the input image, to produce separate measurements of the gradient component in

each orientation (call these G_x and G_y). These can then be combined together to find the absolute magnitude of the gradient at each point and the orientation of that gradient.

-1	-2	-1		-1	0	1
0	0	0		-2	0	2
1	2	1		-1	0	1

Fig 5.7: Sobel's masks

Prewitt's operator:

Prewitt operator is similar to the Sobel operator and is used for detecting vertical and horizontal edges in images. The Kernel used in the Prewitt's operator is

-1	-1	-1		-1	0	1
0	0	0		-1	0	1
1	1	1		-1	0	1

Fig 5.8: Prewitt's masks

The kernels can be applied separately to the input image, to produce separate measurements of the gradient component in each orientation (call these

Gx and *Gy*). These can then be combined together to find the absolute magnitude of the gradient at each point and the orientation of that gradient. The prewitt's masks are shown in figure 5.8.

Laplacian of Gaussian

The Laplacian is a 2-D isotropic measure of the 2nd spatial derivative of an image. The Laplacian of an image highlights regions of rapid intensity change and is therefore often used for edge detection. The Laplacian is often applied to an image that has first been smoothed with something approximating a Gaussian Smoothing filter in order to reduce its sensitivity to noise. The operator normally takes a single graylevel image as input and produces another graylevel image as output. The Laplacian *L(x,y)* of an image with pixel intensity values *I(x,y)* is given by:

$$\nabla^2 f = \frac{\partial^2 f}{\partial x^2} + \frac{\partial^2 f}{\partial y^2} \qquad \text{... 5.9}$$

Since the input image is represented as a set of discrete pixels, we have to find a discrete convolution kernel that can approximate the second derivatives in the definition of the Laplacian. The commonly used small kernels are shown in fig 5.9.

Because these kernels are approximating a second derivative measurement on the image, they are very sensitive to noise.

0	-1	0
-1	4	-1
0	-1	0

-1	-1	-1
-1	8	-1
-1	-1	-1

Fig 5.9: LoG's masks

Canny's Edge Detection

The Canny edge detection algorithm is known to many as the optimal edge detector. Canny's intentions were to enhance the many edge detectors already out at the time he started his work. He was very successful in achieving his goal and his ideas and methods can be found in his paper, *A Computational Approach to Edge Detection* [Can86]. In his paper, he followed a list of criteria to improve current methods of edge detection. The first and most obvious is low error rate. It is important that edges occurring in images should not be missed and that there be NO responses to non-edges. The second criterion is that the edge points be well localized. In other words, the distance between the edge pixels as found by the detector and the actual edge is to be at a minimum. A third criterion is to have only one response to a single edge. This was implemented because the first 2 were not substantial enough to completely eliminate the possibility of multiple responses to an edge. Based on these criteria, the canny edge detector first smoothes the image to eliminate noise and

then finds the image gradient to highlight regions with high spatial derivatives. The algorithm then tracks along these regions and suppresses any pixel that is not at the maximum (nonmaximum suppression).

Edge Linking

Since, the edge detection methodologies should yield pixels lying only on edges. In practice, this set of pixels seldom characterizes an edge completely because of noise breaks in the edge from non-uniform illumination and other effects that introduce spurious intensity discontinuities. Therefore, in order to link the discontinued edges the linking procedure is applied to assemble edge pixels into meaningful edge. There are several approaches to link edges. Among this one of the approaches is local processing. Using local processing, linking edge points is to analyze the characteristics of pixels in a small neighborhood (3x3) about every point (x, y) in an image that has been labeled an edge point by using canny edge detection algorithm. All points that are similar according to a, set predefined criteria are linked, forming an edge of pixels that share those criteria.

The two principle properties used for establishing similarity of edge pixels in this kind of analysis are (1) the strength of the response of the gradient operators used to produce the edge pixel and (2) the direction of the gradient vector. The first property is given by the value of ∇f, as defined in equation.

Thus an edge pixel with co-ordinates (x_0, y_0) in a predefined neighborhood of (x, y), is similar in magnitude to the pixel at (x, y) if

$$|\nabla f(x, y) - \nabla f(x_0, y_0)| \le E \qquad \text{... 5.10}$$

where, E is a nonnegative threshold. The direction (angle) of the gradient vector is given by $\alpha(x, y) = \tan^{-1}(Gy/Gx)$. An edge pixel at (x_0, y_0) in the predefined neighborhood of (x,y) has an angle similar to the pixel at (x,y) if

$$|\alpha(x, y) - \alpha(x_0, y_0)| < A \qquad \text{... 5.11}$$

where, A is a nonnegative angle threshold. The direction of the edge at (x, y) is perpendicular to the direction of the gradient vector at that point. A point in the predefined neighborhood of (x, y) is linked to the pixel at (x, y) if both magnitude and direction criteria are satisfied. This process is repeated at every location in the image. A record must be kept of linked points by assigning different gray levels to each set of linked edge points as the center of the neighborhood is moved from pixel to pixel.

5.4 Automatic Extraction of Chest X-ray features using Digital Image Processing Techniques

5.4.1 Introduction

In order to perform diagnosis of Congenital Heart Septum Defect based on Chest X-ray, it is required to extract the features at first. These features include determining whether there is any fluid around the lungs and measuring the heart size to determine the cardiac enlargement [SLCGJ01]. Determining

whether there is any fluid around the lungs is simple task which can be done by simply viewing any pixels are there with higher gray levels in the lungs area. But determining the heart size is not an easy task because it is not possible to directly measure the heart size instead it can be determined based on the different measurements including the Broad Diameter, Long Diameter, Transverse Diameter, Cardiothoracic Ratio and the Frontal Area of the Heart. Therefore in the present study, an algorithm is developed based on Digital Image Processing techniques to extract the Chest X-ray features automatically.

5.4.2 Material and Methods

Dataset Used

The data used for the present study are 2-D *posteroanterior (PA)* chest X-ray, which are obtained from the patients admitted in the various hospitals. In order to process the chest X-ray, the images are stored in JPG format.

Method

Since the obtained chest X-ray image may contain noise, this must be preprocessed in order to remove the noise from the image. In the developed algorithm, a median filter with a mask size of 11X11 is applied to the obtained Chest X-ray image to remove noise from the image and then the preprocessed image is used to extract the features. In order to extract the features, the developed algorithm initially extracts the heart field contour by applying the Canny Edge algorithm. There may be edge breaks in the extracted image due to

noise. Therefore in order to link the edges, the developed algorithm uses the local process edge linking method. Then processed image is used to extract the Chest X-ray features. The overall process of chest X-ray feature extraction algorithm is described in the following section.

5.4.3 Extraction of Chest X-ray features

5.4.3.1 Preprocessing

Digital images are prone to variety types of noise. Noise is the result of errors in the image acquisition process that result in pixel values that do not reflect the true intensities of the real scene. Noisy images makes difficult to clinically diagnosis. Therefore, the first step that occurs in the developed algorithm is preprocessing, which is a process of removing noise from the obtained Chest X-ray images. Using Digital Image Processing techniques, noise reduction can be accomplished by blurring with a linear filter and also by non-linear filtering. Blurring is used in preprocessing steps such as removal of small details from an image prior to large object extraction and bridging of small gaps in lines or curves. In the present study, a non liner filter called *Order-Statistics Filter* is used for removing noise.

Once the image is de-noised, then the next step that occurs in the developed algorithm is the extraction of the required features from the de-noised Chest X-ray image.

5.4.3.2 Extraction of Chest X-ray Features

In order to extract the required features from the de-noised image, the developed algorithm initially extracts the contour of the heart filed from the de-noised image by applying the Canny Edge algorithm. Due to noise in the image, the processed object may contain the breaks in the edges. Therefore, in order to get the completely closed boundary object, a local processing method is applied.

Now, the processed image can be used by the developed algorithm to take the heart size measurements [AAA07] as follows. Initially a mid point $I(rmid, cmid)$ is calculated in a segmented image. The rmid value is calculated as the middle value of the rows and the cmid is calculated as the middle value of the columns. To measure transverse diameter of the heart, based on midpoint a line is drawn horizontally between the clavicles, and a another line (perpendicular to the first) bisected the heart. To determine the greatest deviation of the heart to the right (r), a pixel $I(x_1, y_1)$ is determined from the midline to towards the right side which is having the y_1 values as the lowest value and then a line is drawn from midline $I(x_1, y_1)$. Now, the r value is determined by calculating the distance between the $I(x_1, y_1)$ to the bisected midline point using Euclidean distance method i.e $D=sqrt(x_2-x_1)^2+(y_2-y_1)^2$. Similarly to determine the greatest deviation of the heart to the left (l), a pixel $I(x_2, y_2)$ is determined from the midline to towards the left side which is having the y_2 values as the greatest value and then a line is drawn from midline to $I(x_2, y_2)$. Now the l value is

determined by calculating the distance between $I(x_2, y_2)$ to the bisected midline point using Euclidean distance method. Now the transverse diameter T is calculated as the sum of the l and r values. In order to determine L value, at first a pixel $I(x_3, y_3)$ is determined from the midpoint towards the left side of the image, whose y_3 value is the least value. Now a line is drawn from pixel $I(x_3, y_3)$ perpendicularly to the clavicles, which bisects the midline. The distance between the pixels $I(x_3, y_3)$ and the bisected pixel give the value of L. Similarly to determine B value, at first a pixel $I(x_4, y_4)$ is determined from the midpoint towards the right side of the image, whose y_4 value is the least value. Now a line is drawn from pixel $I(x_4, y_4)$ perpendicularly to the clavicles, which bisects the midline. The distance between the pixels $I(x_4, y_4)$ and bisected pixel gives the value of B. The Cardio Thoracic Ration of the heart is determined as the CTR=Transverse diameter/Chest diameter. The Frontal Area FA of the heart, which is calculated from the formula $FA= {}^{\Pi}/4 \times L \times B$, where L represents the long diameter of the heart and B represents the broad diameter of the heart. Therefore the features that are extracted from chest x-ray by applying the Digital Image Processing are as follows:

Features extracted from Chest X-ray

- Presence or absence of fluid around the lung area.
- r -- Greatest deviation of the heart to the right from the middle line
- l -- Greatest deviation of the heart to the left from the middle line

- *L*-- Longitudinal Diameter

- *B*-- Broad Diameter of the heart

- *T*-- Transverse Diameter

- *CTR*-- Cardiothoracic Ratio

- *CD*—Chest Diameter

- *FA*-- Frontal Area of the heart

Baseline Measurements of Heart Size

Baseline Measures	Mean
Direct Measures	
Transverse Diameter of Heart (T) cm	13.4
Broad Diameter of Heart (B) cm	13.4
Longitudinal Diameter of Heart (L) cm	13.9
Composite Measures	
Cardiothoracic ratio	0.43
Frontal Area of the Heart (cm^2)	147.1

Table 5.1: Baseline Measurements of Heart Size for age group of 21-80

The minimum and the maximum allowed values for the extracted features in terms of centimeters are: greatest deviation of the heart to the right from the middle line *(r)* 2.8-8.0 cm, greatest deviation of the heart to the left from the middle line *(l)* 10.0-23.0 cm, Transverse diameter 7.5-22.0 cm, Broad diameter 8.0-23.0 cm, Long diameter 10.0-23.0 cm and Chest diameter 21.0-43.0 cm. The table 5.1shows results of studies made on the baseline measurements of the

heart size along with the mean value for the age group of 21-80 years [DCTE85].

5.4.4 Experiments and Results

The developed Chest X-ray feature extraction algorithm is implemented in MATLAB 7.3[Lau05][SSD05]. Initially the implemented algorithm reads chest X-ray image in a jpg format and performs preprocessing. That is it removes the noise from the input image. The original chest X-ray image before and after preprocessing is shown in fig 5.10 and fig 5.11.

To extract Chest X-ray features, it applies the canny edge algorithm for the de-noised image. The result after applying the canny edge algorithm is shown in fig 5.12.
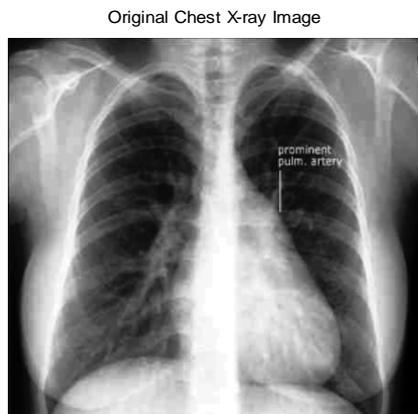
Fig 5.10: The Original Chest X-ray Image
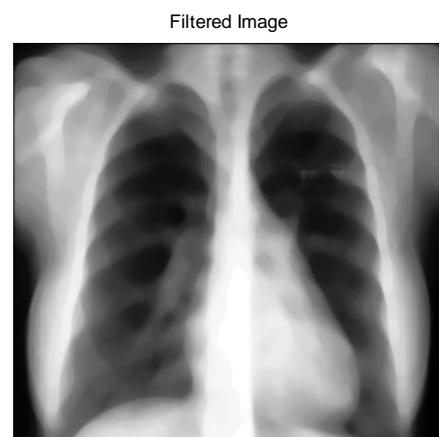
Fig 5.11: The Image after Noise Removal

The figure 5.12 shows that all the edges are not connected completely. Due to noise breaks in the edge from non-uniform illumination and other effects that introduce spurious intensity discontinuities, image may have breaks in the edges. Also the image has the edges, which are not necessary to extract the

Heart Contour. Therefore the developed algorithm, at first links the edge breaks based on the neighborhood operations and deletes the unnecessary edges by placing a constraint (the edges that have the large lengths are selected). The result of this operation is shown in fig 5.13. Once the contour of the heart field is extracted, then it can be used to measure the heart size. The image after applying the heart contour to the filtered image is shown in fig 5.14.
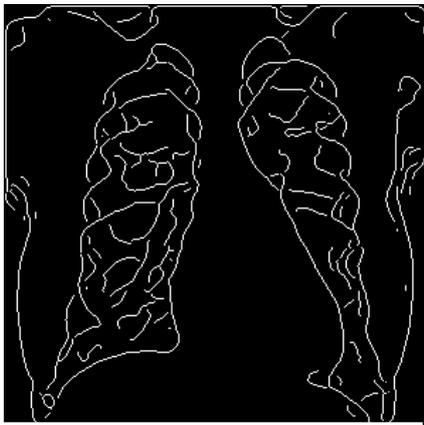
Image After Applying Canny Edge Algorithm

The Processed Image

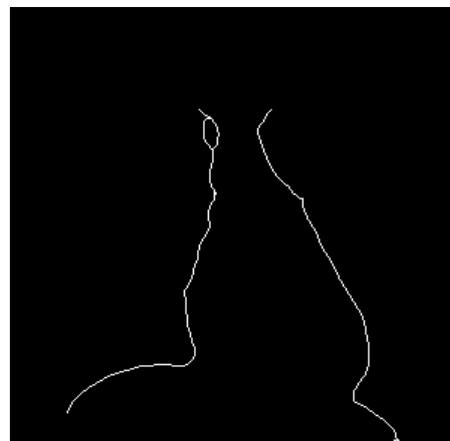*Fig 5.12: Canny Edge for a Filtered Image*

Fig 5.13: An Image representing the Heart Contour extracted by using the Developed Algorithm

Finally the implemented algorithm extracts the features of heart size measurements**.** Because the heart size includes both the direct and indirect measurements, direct measurements are extracted from the processed Chest X-ray image shown in figure 5.15 and the indirect measurements are derived from the direct measurements. The table 5.2 shows the direct and composite measurements that are taken by applying the developed algorithm.

Once the features are extracted, they can be used as input parameters along with the additional parameters age, gender, height, weight, B.P and heart beat to the Decision Support System.
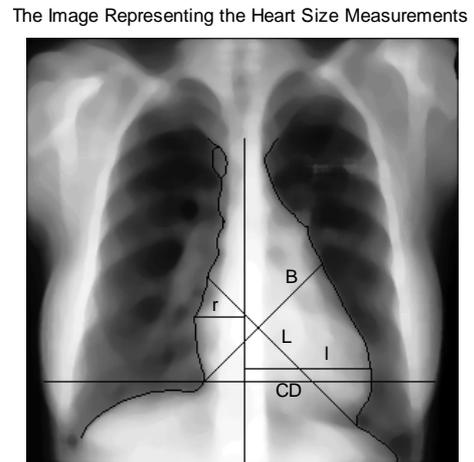

Fig 5.14: An Image after applying the extracted Heart Contour to filtered image

Fig 5.15: An Image representing the Heart Size Measurements by using developed algorithm

Baseline Measurements of Heart Size

Baseline Measures	size (cm)
Direct Measurements	
Transverse Diameter of Heart (T) cm	12.6
Broad Diameter of Heart (B) cm	11.313
Longitudinal Diameter of Heart (L) cm	14.007
Composite Measurements	
Cardiothoracic ratio	0.4214
Frontal Area of the Heart (cm^2)	124.45

Table 5.2: Features extracted from Chest X-ray by the developed algorithm

5.5 Decision Support System for Congenital Heart Septum Defect Diagnosis based on Chest X-ray using Neural Networks

5.5.1 Introduction

Though the features are extracted automatically from Chest X-ray by the developed algorithm, still it is difficult for a physician to diagnose Congenital Heart Septum Defect. Because the extracted feature values will not be same for all the patients instead they vary from person to person based on age, sex, weight, and height. This may cause the inaccuracy of the diagnosis and may increases the time delay of the diagnosis. Therefore in order to improve the diagnosis accuracy and to reduce the diagnosis time, it has become a demanding issue to develop an efficient and reliable medical Decision Support System [KAAE04]. Since Neural Networks [Luc96] have shown great potential to be applied in the development of medical Decision Support System for diagnosis of Heart Diseases, in the present study also, a Decision Support System is developed to perform the Congenital Heart Septum Defect Diagnosis classification based on the Chest X-ray features.

5.5.2 Materials and Methods

Parameters used

The parameters that are used to perform Congenital Heart Septum Diagnosis classification based on Chest X-ray are age, gender, weight, height, heart beat, blood pleasure and the features extracted from the chest X-ray by the developed algorithm. In the present study, to train and test the network, a total

number of 200 samples are used. Each sample is having a set of 14 input parameters and one output parameter. The parameter names, description and the allowed values for that are described in table 5.3.

#No	Attribute Name	Description	Allowed Values
1	Age	Patients Age	Continuous
2	Gender	Patients Gender	Binary
3	Height	Patients Height	Continuous
4	Weight	Patients Weight	Continuous
5	Systolic Blood Pleasure	Systolic Blood Pleasure (mmHg)	Continuous
6	Diastolic Blood Pleasure	Diastolic Blood Pleasure(mmHg)	Continuous
7	Heart Beat	Heart Rate of a patient (bpm)	Continuous
8	THR	Greatest deviation of the heart to the right r	Continuous
9	THL	Greatest deviation of the heart to the left l	Continuous
10	Transverse Diameter	Transverse Diameter T (cm)	Continuous
11	Broad Diameter	Broad Diameter B (cm)	Continuous
12	Longitudinal Diameter	Longitudinal Diameter L (cm)	Continuous
13	Cardio Thoracic ratio	Cardio Thoracic ratio CTR	Continuous
14	Frontal Area of the Heart	Frontal Area of the Heart FA (cm^2)	Continuous

Table 5.3: Parameter Names, Description and their Allowed Values of DSS for CHSD Diagnosis based on Chest X-ray features

Method

In the present study, in order to develop a Decision Support System for Congenital Heart Septum Defect Diagnosis based on Chest X-ray features, initially the Chest X-ray features are extracted by applying the developed Chest

X-ray feature extraction algorithm to the input images. Then, a Backpropgation Neural Network (discussed in section 2.2.7) is built by taking input parameters of the Congenital Heart Septum Defect data (Chest X-ray features along with the basic information). The network is trained using a supervised Delta Learning Rule. The dataset used to train the network is the Congenital Heart Septum Defect database, which are designed based on the extracted Chest X-ray features along with the basic information (Heart Rate, Systolic B.P etc) of a patient. The activation function used in this model is the sigmoid function. Once the network is trained, then it can be used to perform the diagnosis classification automatically for a new pattern. In order to make the Decision Support System user friendly, it is (the front-end) designed using MATLAB 7.3 with GUI features. The Decision Support system is developed not only for the diagnosis classification, but it can also be used to store and view the diagnosis result.

The architecture of a Decision Support System for Congenital Heart Septum Defect diagnosis based on Chest X-ray features is shown in fig 5.16. From the architecture it shows that, when the Chest X-ray image of a patient is given as input by the user, the developed Decision Support System automatically analyzes and extracts features, it does the diagnosis classification automatically and displays the result. The developed Decision Support System also stores the diagnosis result automatically, which can be used to view for future reference.
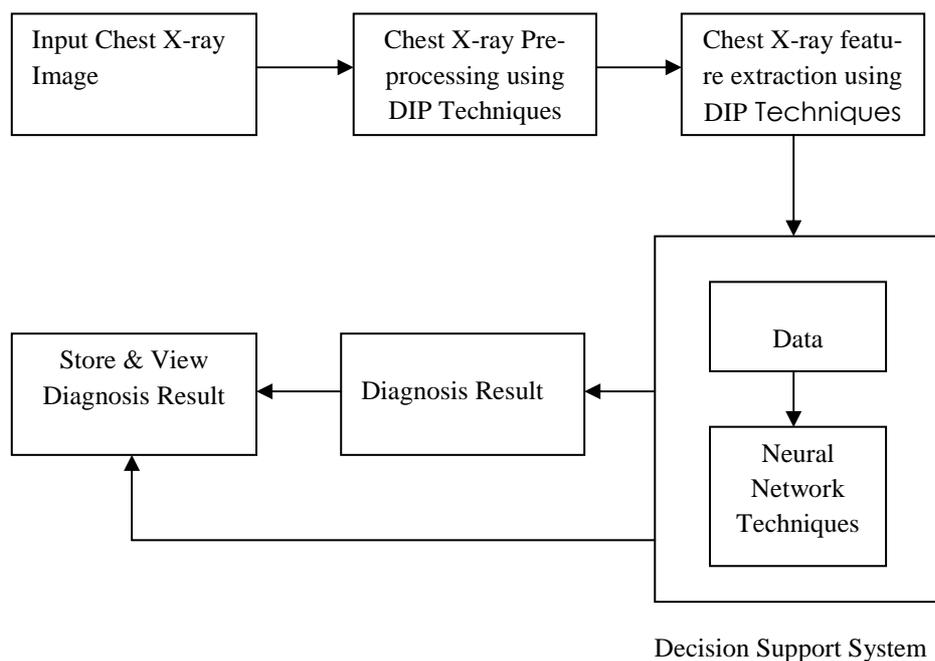
```
┌─────────────────┐      ┌──────────────────┐      ┌──────────────────┐
│ Input Chest X-ray│ ───▶ │ Chest X-ray Pre- │ ───▶ │ Chest X-ray featu-│
│ Image           │      │ processing using │      │ re extraction using│
│                 │      │ DIP Techniques   │      │ DIP Techniques   │
└─────────────────┘      └──────────────────┘      └──────────────────┘
```

Fig 5.16: Architecture of DSS for CHSD Diagnosis based on Chest X-ray features

5.5.3 Experiments and Results

Experiment:

The Decision Support System is designed and implemented using MATLAB 7.3 with GUI features by implementing the Backpropagation Neural Network Model. In order to implement Backpropagation Network Model, initially a Feed Forward Neural Network is built with 14 input nodes, 4 hidden nodes and one output node. The input parameters used in this system are the age, gender, B.P, weight, height, heart beat and the features extracted from the chest X-ray by using the developed algorithm and the output parameter indicates result of the diagnosis in terms of either normal or abnormal. Once the network is built then it can be trained by using a Delta Learning Rule. The

143

activation function used in this model is the sigmoid function. 200 samples are collected and used to train network. Among these samples 85% of the data are used for training and 15% of the data are used for testing. Once the network is trained then for a new case, the developed Decision Support System does the classification automatically. The Error performance (Mean Squared Error) of the training network is shown in fig 5.17. The least MSE value for the present experiment is 0.00012. Since the Neural Network solutions will not depends on algorithmic solution instead it depends on examples of the previous cases it gives more accurate results than the human diagnosis.
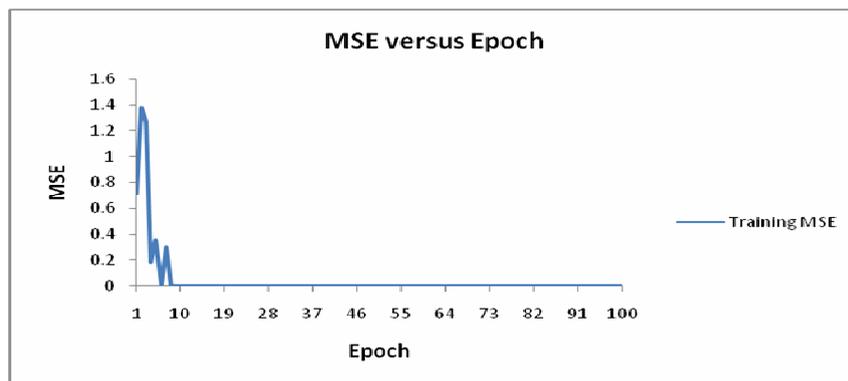
Fig 5.17: The Error Performance of a training network of DSS for CHSD Diagnosis based on Chest x-ray features

The developed Decision Support System performs five types of operations, which are represented in terms of NEW, ANALYSIS, DECISION, STORE and VIEW pushbuttons. Pushbutton NEW is used to clear the screen (for entering new patient information), the pushbutton ANALYSIS is used to automatically extract the Chest X-ray features based on the developed algorithm and to display the results. The pushbutton DECISION is used to perform

144

diagnosis classification automatically based on the selected parameters and to display the result, the pushbutton STORE is used to store the patient information along with the resultant value in terms of text format and the pushbutton VIEW is used to view the stored text file.

The developed Decision Support System can be used by a physician to automatically diagnose Congenital Heart Septum Defects based on Chest X-ray features by giving the patient's Chest X-ray image as input (in terms of patient number) along with the basic information heart rate, Systolic B.P, diastolic B.P etc of a patient. The developed system reduces the diagnosis time of a physician and also increases the accuracy of the diagnosis. The developed system is not only used for diagnosis, instead it can also be used to store and view the results of the diagnosis for future reference.

Result:

The developed Decision Support System can be tested by giving the Chest X-ray image as input (entering in terms of patient number) along with the basic information of a patient. Once this information is entered, then the ANALYSIS pushbutton can pressed to automatically analyze and to display the extracted Chest X-ray features. Once the features are extracted then the DECISION PUSHBUTTON button can be pressed to automatically display the diagnosis result. The results obtained through the developed system for an abnormal Chest X-ray of a patient is shown in fig 5.18.

Fig 5.18: Diagnosis result for original Chest X-ray image

To store the diagnosis result in a text format, the pushbutton STORE is pressed and to view the stored data text file, the pushbutton VIEW is pressed. The developed Decision Support System gave an accuracy of 93.33%, which is shown fig 5.19. The classification result of the experiment in terms of the confusion matrix is shown in table 5.4.
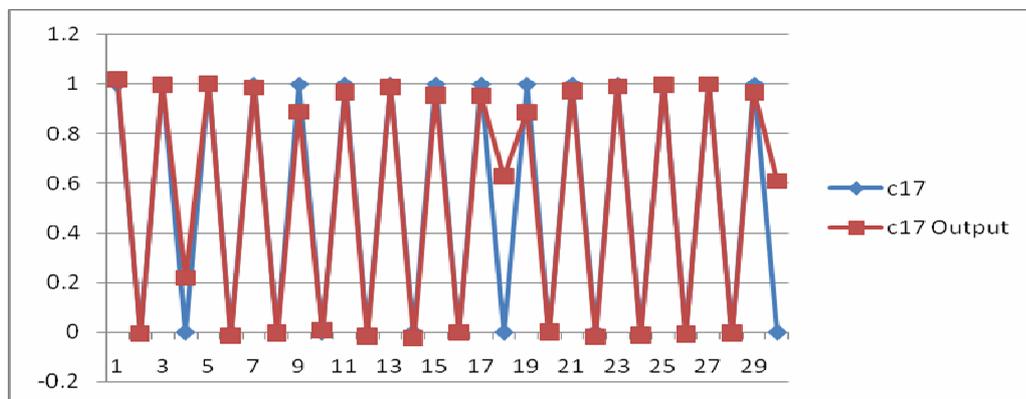

Fig 5.19: A chart representing the classification accuracy of the DSS
for CHSD Diagnosis based on Chest X-ray features

146

Output / Desired	0	1
0	13	0
1	2	15

Table 5.4: Confusion Matrix of DSS for CHSD Diagnosis based on Chest X-ray features classification

5.6 Conclusion

Congenital Heart Septum Defect Diagnosis based on Chest X-ray features is a difficult task for physicians due to the reason that the Chest X-ray images will not be similar for all person instead it varies from person to person. Therefore, the developed Decision Support Systems can be used by a physician to automatically extract Chest X-ray features and to perform the Congenital Heart Septum Defect Diagnosis classification automatically based on the extracted features. The developed Decision Support System decreases the diagnosis time and improves the accuracy of the diagnosis.