CHAPTER 6

A NOVEL NEURO FUZZY LOGIC BASED CLASSIFIER FOR DIAGNOSING APPENDICITIS

Clinical repositories containing large amounts of biological, clinical, and administrative data are increasingly becoming available as health care systems integrate patient information for research and utilization objectives. Data mining techniques can be used to discover useful patterns by exploring and analyzing clinical repositories. It is feasible to incorporate data mining techniques into the classification process to discover useful patterns for classification rules from training samples. This chapter thus assesses the role of the data mining techniques namely Fuzzy Logic based classifier and a Back propagation based Neural Networks in the diagnosis of severity of appendicitis in patients presenting with right iliac fossa (RIF) pain. It is based on the statistics already collected about the presence of appendicitis from patients data set of around 2230 data sets collected from BHEL Hospital, Tiruchirappalli. The conclusion is that Neuro fuzzy logic based classifiers can be used an effective tool for accurately diagnosing the severity of appendicitis.

6.1 Fuzzy Logic

Fuzzy Logic provides a simple way to arrive at a definite conclusion based upon vague, ambiguous, imprecise, noisy, or missing input information. It is a form of mathematical logic in which truth can assume a continuum of values between 0 and 1. Fuzzy logic is designed for situations where information is inexact and traditional digital on/off decisions are not possible.
Fuzzy Logic is a problem-solving control system methodology that lends itself to implementation in systems ranging from simple, small, embedded micro-controllers to large, networked, multi-channel PC or workstation-based data acquisition and control systems. It can be implemented in hardware, software, or a combination of both. Fuzzy Logic provides a simple way to arrive at a definite conclusion based upon vague, ambiguous, imprecise, noisy, or missing input information. Fuzzy Logic’s approach to control problems mimics how a person would make decisions, only much faster. Fuzzy Logic was conceived as a better method for sorting and handling data but has proven to be an excellent choice for many control system applications since it mimics human control logic [79-84].

We use Fuzzy Logic rule based classifier for mining patient data set of people suffering with Appendicitis. Initially feature selection is done to reduce the number of features used in classification while maintaining acceptable classification accuracy. Less discriminatory features are eliminated, leaving a subset of the original features which retains sufficient information to discriminate well among classes. The two data mining tasks performed by our Neuro fuzzy logic based classifier are classification and prediction. Classification maps data into predefined groups or classes. It is often referred to as supervised learning, because the classes are determined before examining the data. Prediction is used for predicting a future state based on the past and current state.

The advantages of using fuzzy logic for clinical data set are it is inherently robust since it does not require precise, noise-free inputs and can be programmed to fail safely if a feedback sensor quits or is destroyed. The output control is a smooth control function despite a wide range of input variations. It can control nonlinear systems that would be difficult or impossible to model mathematically [85-88].
6.2 Methodology

This chapter reports on an analysis of a database of patients operated for appendicitis. The purpose of this study was to assess the role of a Neuro fuzzy logic rule based classifier in the diagnosis of severity of appendicitis in patients presenting with right iliac fossa (RIF) pain. The input parameters of the Neuro fuzzy classifier are the pain site, pain nature, nausea, previous surgery, RIF tenderness, rebound tenderness, guarding, rigidity, temperature, white blood cell count, neutrophil count and the output parameters are different classes of appendicitis namely mild (inflammation only), moderate (inflammation, faceolith and turgid) and severe (gangrenous and perforated) appendicitis. The methodology used was a Fuzzy logic rule based classifier and Back propagation Neural network for diagnosing appendicitis. It is based on the statistics already collected about the presence of appendicitis from patients data set of around 2230 records collected from BHEL Hospital, Tiruchirappalli, India.

6.3 Alvarado scoring system for Appendicitis

Alvarado scoring system depends on the presence and absence of certain variables and which provides an accurate guide to whether or not the patient has the appendicitis. Table 6.1 summarizes the symptoms and their corresponding score in an Alvarado scoring system.
Table 6.1 Alvarado scoring system for diagnosing Appendicitis

<table>
<thead>
<tr>
<th>Symptoms</th>
<th>Score</th>
</tr>
</thead>
<tbody>
<tr>
<td>Migratory right iliac fossa pain</td>
<td>1</td>
</tr>
<tr>
<td>Nausea / Vomiting</td>
<td>1</td>
</tr>
<tr>
<td>Anorexia</td>
<td>1</td>
</tr>
</tbody>
</table>

**Signs**

<table>
<thead>
<tr>
<th>Sign</th>
<th>Score</th>
</tr>
</thead>
<tbody>
<tr>
<td>Tenderness in right iliac fossa</td>
<td>2</td>
</tr>
<tr>
<td>Rebound tenderness in right iliac fossa</td>
<td>1</td>
</tr>
<tr>
<td>Elevated temperature</td>
<td>1</td>
</tr>
</tbody>
</table>

**Laboratory findings**

<table>
<thead>
<tr>
<th>Test</th>
<th>Score</th>
</tr>
</thead>
<tbody>
<tr>
<td>Leucocytosis</td>
<td>2</td>
</tr>
<tr>
<td>Shift to the left of neutrophils</td>
<td>1</td>
</tr>
</tbody>
</table>

| Total | 10 |

Aggregate score 7-10 (emergency surgery group): These patients were prepared and all underwent emergency appendicectomy.

Aggregate score 5-6 (observation group): These patients were admitted and kept under observation for 24 hours with frequent re-evaluation of the clinical data and reapplication of the score. Condition of some patients improved shown by a decrease in score and therefore they were discharged with the instructions that they should come back if symptoms persist or increase in intensity.

Aggregate score 1-4 (discharge home group): These patients, after giving initial symptomatic treatment, were discharged and sent home with the instructions, to come back if symptoms persist or condition become worse.
6.4 Proposed Scoring system for diagnosing the severity of appendicitis using Neuro Fuzzy Logic based classifier

Based on the statistics collected about the presence of appendicitis from a patient’s data set from BHEL Hospital, Tiruchirappalli, we propose a scoring system for Back Propagation Neural Network and Fuzzy Logic based classifier as shown in Table-6.2.

<table>
<thead>
<tr>
<th>Symptoms</th>
<th>Score</th>
</tr>
</thead>
<tbody>
<tr>
<td>Right iliac Fossa pain</td>
<td>2</td>
</tr>
<tr>
<td>Tenderness in Right Iliac Fossa</td>
<td>2</td>
</tr>
<tr>
<td>Mpt. Tenderness</td>
<td>2</td>
</tr>
<tr>
<td>Shift of Pain</td>
<td>1</td>
</tr>
<tr>
<td>Foetor</td>
<td>1</td>
</tr>
<tr>
<td>Nausea / Vomiting</td>
<td>1</td>
</tr>
<tr>
<td>Anorexia</td>
<td>1</td>
</tr>
</tbody>
</table>

**Signs**

<table>
<thead>
<tr>
<th>Signs</th>
<th>Score</th>
</tr>
</thead>
<tbody>
<tr>
<td>Rebound tenderness in Right Iliac Fossa</td>
<td>1</td>
</tr>
<tr>
<td>Elevated temperature</td>
<td>1</td>
</tr>
<tr>
<td>Guarding</td>
<td>1</td>
</tr>
<tr>
<td>Rigidity</td>
<td>1</td>
</tr>
<tr>
<td>Rovsing sign Test</td>
<td>1</td>
</tr>
</tbody>
</table>

**Laboratory findings**

<table>
<thead>
<tr>
<th>Laboratory findings</th>
<th>Score</th>
</tr>
</thead>
<tbody>
<tr>
<td>Leucocytosis - 4000-8000</td>
<td>1</td>
</tr>
<tr>
<td>Count - 8000-11000</td>
<td>2</td>
</tr>
<tr>
<td>- &gt; 11000</td>
<td>3</td>
</tr>
<tr>
<td>Shift to the left of neutrophils -60-60</td>
<td>1</td>
</tr>
<tr>
<td>60-70</td>
<td>2</td>
</tr>
<tr>
<td>&gt; 70</td>
<td>3</td>
</tr>
</tbody>
</table>

**Maximum Score** 21
Aggregate score 15-21 (Gangrenous Appendicitis): If the aggregate Score is between 15-21 then the appendicitis is Gangrenous or Severe Appendicitis.

Aggregate score 8-14 (Moderate Appendicitis): If the aggregate Score is between 8-14 then the appendicitis is Moderate Appendicitis.

Aggregate score 1-7 (Mild Appendicitis): If the aggregate Score is between 1-7 then the appendicitis is Mild Appendicitis.

6.5 Construction and Working of Fuzzy Inference System

Fuzzy inference system consists of a fuzzification interface, a rule base, a database, a decision-making unit, and finally a defuzzification interface. The function of each block in a Fuzzy inference system shown in Figure 6.1 is as follows:

- a database which defines the membership functions of the fuzzy sets used in the fuzzy rules;
- a decision-making unit which performs the inference operations on the rules;
- a fuzzification interface which transforms the crisp inputs into degrees of match with linguistic values; and
- a defuzzification interface which transforms the fuzzy results of the inference into a crisp output.

The working of FIS is as follows. The crisp input is converted to fuzzy by using fuzzification method. After fuzzification the rule base is formed. The rule base and the database are jointly referred to as the knowledge base. Defuzzification is used to convert fuzzy value to the real world value which is the output [89-95].

6.6 Mamdani’s Fuzzy Inference Method

1. Determining a set of fuzzy rules.

2. Fuzzifying the inputs using the input membership functions.

3. Combining the fuzzified inputs according to the fuzzy rules to establish rule strength.

4. Finding the consequence of the rule by combining the rule strength and the output membership function.

5. Combining the consequences to get an output distribution.

6. Defuzzifying the output distribution if a crisp output class is needed.

6.6.1 Creating Fuzzy Rules

Fuzzy rules are a collection of linguistic statements that describe how the FIS should make a decision regarding classifying an input or controlling an output. Fuzzy rules are always written in the following form:

if (input 1 is membership function 1) and/or (input 2 is membership function 2)

and/or . . . then (output n is output membership function).
For example: if Leucocytosis count is high and Neutrophil count is high then appendicitis is severe appendicitis.

This process of taking an input such as Leucocytosis count and processing it through a membership function to determine high count value is called fuzzification. Also, AND/OR in the fuzzy rule should be defined. This is called fuzzy combination.

6.6.2 Fuzzification

Fuzzification is the process where the crisp quantities are converted to fuzzy. The purpose of fuzzification is to map the inputs from a set of features of the patients suffering with appendicitis to values from 0 to 1 using a set of input membership functions. These input membership functions, can represent fuzzy concepts such as high or low, present or absent, etc. The membership functions for the variables leucocytosis, neutrophil and appendicitis are shown in figure-6.2, figure-6.3 and figure-6.4 respectively.
Figure 6.2 Input membership function for the variable Leucocytosis

\[
L_{\text{low}}(x) = \begin{cases} 
0 & x < 3000 \\
\frac{(x-3000)}{1000} & 3000 < x < 4000 \\
1 & 4000 < x < 8000 \\
\frac{(9000-x)}{1000} & 8000 < x < 9000 
\end{cases}
\]

\[
L_{\text{med}}(x) = \begin{cases} 
0 & x < 7000 \\
\frac{(x-7000)}{1000} & 7000 < x < 8000 \\
1 & 8000 < x < 10000 \\
\frac{(11000-x)}{1000} & 10000 < x < 11000 
\end{cases}
\]

\[
L_{\text{high}}(x) = \begin{cases} 
0 & x < 9500 \\
\frac{(x-9500)}{1500} & 9500 < x < 11000 \\
1 & x > 11000 
\end{cases}
\]
Figure 6.3 Input membership function for the variable Neutrophil

\[ N_{\text{low}}(x) = \begin{cases} 
0 & x < 25 \\
(x-25)/15 & 25 < x < 40 \\
1 & 40 < x < 60 \\
(65-x)/5 & 60 < x < 65 
\end{cases} \]

\[ N_{\text{med}}(x) = \begin{cases} 
0 & x < 50 \\
(x-50)/10 & 50 < x < 60 \\
1 & 60 < x < 70 \\
(80-x)/10 & 70 < x < 80 
\end{cases} \]

\[ N_{\text{high}}(x) = \begin{cases} 
0 & x < 65 \\
(x-65)/5 & 65 < x < 70 \\
1 & x > 70 
\end{cases} \]
Figure 6.4 Output membership function for the variable Appendicitis

\[ A_{\text{mild}}(x) = \begin{cases} 1 & x < 6 \\ (x-6) & 6 < x < 7 \\ 0 & x > 7 \end{cases} \]

\[ A_{\text{mod}}(x) = \begin{cases} 0 & x < 7 \\ (x-7)/2 & 7 < x < 9 \\ 1 & 9 < x < 13 \\ (14-x) & 13 < x < 14 \end{cases} \]

\[ A_{\text{gang}}(x) = \begin{cases} 0 & x < 13 \\ (x-13)/2 & 13 < x < 15 \\ 1 & x > 15 \end{cases} \]
6.6.3 Consequence

The consequence of a fuzzy rule is computed using two steps:

1. Computing the rule strength by combining the fuzzified inputs using the fuzzy combination process.
2. Clipping the output membership function at the rule strength.

6.6.4 Combining Outputs into an Output Distribution

The outputs of all of the fuzzy rules must now be combined to obtain one fuzzy output distribution. This is usually done by using the fuzzy OR.

6.6.5 Defuzzification of Output Distribution

Defuzzification means the fuzzy to crisp conversion. The fuzzy results generated cannot be used as such to the applications, hence it is necessary to convert the fuzzy quantities into crisp quantities for further processing. This can be achieved by using defuzzification process. The defuzzification has the capability to reduce a fuzzy to a crisp single-valued quantity. Defuzzification can also be called as rounding off method. The Mean of maximum techniques is used for defuzzification. This technique takes the output distribution and finds its mean of maxima to come up with one crisp number.
6.7 Designing a Fuzzy Logic Rule based Classifier for appendicitis clinical dataset

The Steps followed in designing a simple fuzzy logic rule based classifier are:

1. Here we are try to predict the presence and severity of appendicitis among the patients in a hospital.

2. To determine the input and output relationships and choose a minimum number of variables for input to the Fuzzy Logic engine. Here the input parameters are the pain site, pain nature, nausea, previous surgery, RIF tenderness, Mpt tenderness rebound tenderness, guarding, rigidity, Temperature, White blood cell count and Neutrophil count and output parameters are different classes of appendicitis namely mild(Inflammation only), moderate(Inflammation, FACEolith and Turgid), and severe(Gangrenous and Perforated) appendicitis. The system inputs and outputs are shown in Figure-6.5

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**Figure 6.5 - System Inputs and Outputs**

- Right iliac Fossa Pain
- Tenderness in RIF
- Mpt Tenderness
- Nausea
- Guarding & Rigidity
  - Rovsing sign Test
- Leucocytosis count
- Neutrophils

**Appendicitis Diagnosis System Using Fuzzy Logic & Neural Networks based classifier**

- Mild Appendicitis
- Inflammation and Turgid Appendicitis
- Gangrenous Appendicitis
3. Using the rule-based structure of Fuzzy Logic, break the control problem down into a series of IF X AND Y THEN Z rules that define the desired system output response for given system input conditions. Typical examples of the fuzzy rules framed are given in Table-6.3. The number and complexity of rules depends on the number of input parameters that are to be processed and the number fuzzy variables associated with each parameter.

4. Create Fuzzy Logic membership functions that define the meaning (values) of Input/output terms used in the rules.

5. Create the necessary pre and post-processing Fuzzy Logic routines if implementing in Software, otherwise program the rules into the Fuzzy Logic Hardware engine.

6. Test the system, evaluate the results, tune the rules and membership functions, and retest until satisfactory results are obtained.

**Table 6.3 Sample Fuzzy rules framed for diagnosing the severity of appendicitis**

| If Pain Site and Pain Shift and RIF Tenderness and Nausea and Temperature and Leucocytosis Count and Neutrophils Then Appendicitis |
|---|---|---|---|---|---|---|
| RIF Present Present Present High High High Severe Appendicitis |
| RIF Absent Present Absent Normal Low Low Mild Appendicitis |
| RIF Present Absent Absent Mild Medium Medium Moderate Appendicitis |
| Elsewhere Present Present Present High High High Severe Appendicitis |
| RIF Present Absent Absent Normal High Medium Mild Appendicitis |
| RIF Absent Present Absent Normal High Medium Moderate Appendicitis |
For example, the rules can be interpreted as follows

**Rule 1:** if Pain site = RIF and Pain shift = present and RIF Tenderness = Present and Nausea = Present and Temperature = High and Leucocytosis count = High and Neutrophil = High, then Appendicitis = Severe Appendicitis, i.e., if the patient’s pain site is right iliac fossa and pain shift is present and tenderness in right iliac fossa is present and Nausea is present and Temperature is High and Leucocytosis count is high and Neutrophil count is high, then appendicitis risk is Severe Appendicitis.

**Rule 2:** if Pain site = RIF and Pain shift =Absent and RIF Tenderness = Present and Nausea = Absent and Temperature = Normal and Leucocytosis count = Low and Neutrophil = Low, then Appendicitis = Mild Appendicitis, i.e., if the patient’s pain site is right iliac fossa and pain shift is absent and tenderness in right iliac fossa is present and Nausea is absent and Temperature is Normal and Leucocytosis count is low and Neutrophil count is low, then appendicitis risk is Mild Appendicitis.

**Rule 3:** if Pain site = RIF and Pain shift = Present and RIF Tenderness = Absent and Nausea = Absent and Temperature = Mild and Leucocytosis count = Medium and Neutrophil = Medium, then Appendicitis = Moderate Appendicitis, i.e., if the patient’s pain site is right iliac fossa and pain shift is present and tenderness in right iliac fossa is absent and Nausea is absent and Temperature is mild and Leucocytosis count is medium and Neutrophil count is medium, then appendicitis risk is Moderate Appendicitis.
**Rule 4:** if Pain site = Elsewhere and Pain shift = present and RIF Tenderness = Present and Nausea = Present and Temperature = High and Leucocytosis count = High and Neutrophil = High, then Appendicitis = Severe Appendicitis, i.e., if the patient’s pain site is elsewhere and pain shift is present and tenderness in right iliac fossa is present and Nausea is present and Temperature is High and Leucocytosis count is high and Neutrophil count is high, then appendicitis risk is Severe Appendicitis.

**Rule 5:** if Pain site = RIF and Pain shift = Present and RIF Tenderness = Absent and Nausea = Absent and Temperature = Normal and Leucocytosis count = High and Neutrophil = Medium, then Appendicitis = Mild Appendicitis, i.e., if the patient’s pain site is right iliac fossa and pain shift is present and tenderness in right iliac fossa is absent and Nausea is absent and Temperature is Normal and Leucocytosis count is high and Neutrophil count is medium, then appendicitis risk is Mild Appendicitis.

**Rule 6:** if Pain site = RIF and Pain shift = Absent and RIF Tenderness = Present and Nausea = Absent and Temperature = Normal and Leucocytosis count = High and Neutrophil = Medium, then Appendicitis = Moderate Appendicitis, i.e., if the patient’s pain site is right iliac fossa and pain shift is present and tenderness in right iliac fossa is present and Nausea is absent and Temperature is normal and Leucocytosis count is high and Neutrophil count is medium, then appendicitis risk is Moderate Appendicitis.

Fuzzification of the used factors are made by aid of the follows functions. These formulas can be determined by aid both of the expert-doctor and literature.
The Table-6.4 gives the confusion matrix representation of the results obtained by Fuzzy logic rule based classifier.

### Table 6.4 Confusion Matrix representation of the results Obtained by Fuzzy logic rule based classifier

<table>
<thead>
<tr>
<th>Correct class</th>
<th>Classified as</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Mild appendicitis</td>
</tr>
<tr>
<td>Mild appendicitis</td>
<td>178</td>
</tr>
<tr>
<td>Moderate appendicitis</td>
<td>43</td>
</tr>
<tr>
<td>Gangrenous appendicitis</td>
<td>0</td>
</tr>
</tbody>
</table>
Figure 6.6 Experimental results for high values of WBC and Neutrophil count

The symptoms and laboratory findings of the patients were presented to the fuzzy logic based expert system. For a patient presenting with right iliac fossa pain, presence of RIF tenderness, pain shift, foetor, guarding, rigidity, rebound tenderness and WBC, Neutrophil count values of 13700 and 107 respectively, the system predicted gangrenous appendicitis as shown in figure 6.6.

The Fuzzy logic based expert system predicted gangrenous appendicitis score of 17 for high values of WBC and Neutrophil count.
Figure 6.7 Experimental results for low values of WBC and Neutrophil count

The symptoms and laboratory findings of the patients were presented to the fuzzy logic based expert system. For a patient presenting with right iliac fossa pain, absence of RIF tenderness, pain shift, foetor, guarding, rigidity, fever and WBC, Neutrophil count values of 4590 and 39 respectively, the system predicted mild appendicitis as shown in figure 6.7.

The Fuzzy logic based expert system predicted mild appendicitis score of 6 for low values of WBC and Neutrophil count.
6.8 Back Propagation Neural Network (BPN)

BPN is a multilayer feed forward net trained by back propagation. The training of a network by BPN involves three stages, the feed forward of input training patterns, calculation and back propagation of the associated error and adjustment of weights [96-102]. Even if training is slow, a trained net can produce its output very rapidly. Numerous variation of BPN has been developed to improve the speed of the training process.

Figure 6.8 Architecture of BPN

During feed forward, each input unit (X_i) receives an input signal and broadcast this signal to each of the hidden units O_1…O_p. Each hidden unit then computes its activation and sends its signal O_j to each output unit. Each output unit computes its activation (O_k) to form the response of the net for the given input pattern.

During training each output unit compares its computed activation O_j with its target value T_j to determine the associated error for that pattern with that unit. Based on this error, the factor
is computed. Bias is used to distribute the error at output unit $O_k$ back to all units in the previous layer. It is also used to update weights between the output and the hidden layer. In a similar manner, the factor $Err_j$ is computed for each hidden unit $O_j$. It is not necessary to propagate the error back to the input layer, but $Err_j$ is used to update the weights between the hidden layer and the input layer.

After all of the $Err$ factors have been determined, the weights for all layers are adjusted simultaneously. The adjustment to the weight $W_{jk}$ (from the hidden unit $O_j$ to output unit $O_k$) is based on the factor $Err_k$ and the activation of the hidden unit $O_j$. The adjustment to the weight $W_{ij}$ (from input unit $X_i$ to hidden $O_j$) is based on the factor $Err_j$ and the activation $X_i$ at the input unit.

Since the usual motivation for applying a BPN is to achieve a balance between correct responses to training pattern and good responses for new input patterns (i.e. balance between memorization and generalization), it is not necessarily advantageous to continue training until the total squared error actually reaches a minimum. Hecht-Nielsen suggests using two sets of data in training, a set of training and a set of training-testing patterns. As long as the error for the training-testing pattern decreases, training continues. When error begins to increases, the net is starting to memorize the training patterns too specifically (and staring to lose its ability to generalize). At this point, training is terminated [103-108].

**6.9 Back Propagation Neural Network Algorithm**

Back propagation is a supervised learning technique used for training artificial neural networks. The Steps in a BPN are
1. Present a training sample to the neural network.

2. Compare the network’s output to the desired output from that sample. Calculate the error in each output neuron.

3. For each neuron, calculate what the output should have been, and a scaling factor, how much lower or higher the output must be adjusted to match the desired output. This is the local error.

4. Adjust the weights of each neuron to lower the local error.

5. Assign "blame" for the local error to neurons at the previous level, giving greater responsibility to neurons connected by stronger weights.

6. Repeat the steps above on the neurons at the previous level, using each one’s “blame” as its error.

**Back Propagation Network Algorithm**

**Input:**
- \(D\), a dataset consisting of the training tuples and their associated target values;
- \(I\), the learning rate;
- Network, multilayer feed-forward network.

**Output:**
- A trained neural network.

**Method:**
- Initialize all weights and biases in network;
- While terminating condition is not satisfied {
  - for each training tuple \(X\) in \(D\) {
    - //Propagate the inputs forward:
      - for each hidden or output layer unit \(j\) {
        \[ I_j = \sum_i W_{ij} O_i + O_j \; ; \]
        - //compute the net input of unit \(j\) with respect to the previous layer, \(i\)
          \[ O_j = \frac{1}{1+e^{-I_j}} \; ; \]
        - //compute the output of each unit \(j\)
        - //Back propagate the errors:
          - for each unit \(j\) in the output layer
            \[ Err_j = O_j (1-O_j) (T_j - O_j) ; \]
//compute the error
for each unit j in the hidden layers, from the last to the first hidden layer
Err_j = O_j(1-O_j) \sum_k Err_k W_{jk};
//compute the error with respect to the next higher layer, k
for each weight W_{ij} in network{
  \Delta W_{ij} = (l) Err_j O_i;  //weight increment
  W_{ij} = W_{ij} + \Delta W_{ij};  //weight update
}
for each bias \Theta_j in the network{
  \Delta \Theta_j = (l) Err_j;  //bias increment
  \Theta_j = \Theta_j + \Delta \Theta_j;  //bias update
}

6.10 Back Propagation Neural Network for classification of clinical datasets

The performance of BPN is studied for the optimum feature set, selected by the feature selection process. Single hidden layered network is not converging for the input patterns. This may be due to complexity of input feature vectors or insufficient representation of samples in the training data. Hence, two hidden layered neural network architecture is used. The 12 features are given to the input layer neurons. The first hidden layer consists of 25 neurons (12*2 +1) and second hidden layer consist of 12 neurons. The output layer consists of 3 neurons to indicate whether the input pattern is mild, moderate or gangrenous appendicitis. The proposed two hidden layered back propagation neural network is implemented using C++.

The parameter learning rate and moment are chosen by repeatedly conducting the experiment based on convergence. The learning rate for input and hidden layer are 0.4, moment is 0.2 and the error allowed is 0.01. Binary sigmoid function is used. For training two disjoint set of clinical data sets, training-pattern and training-testing patterns are used.

Weight adjustments are based on the training pattern, however at intervals of 10 iterations during training, the error is computed using training-testing patterns. As long as the error for the training-testing pattern decreases training continues. When error begins to increases, the net is
starting to memorize the training patterns too specifically (and staring to lose its ability to generalize). At this point, training is terminated.

After successful training with 400 epochs, 100 feature vectors are given and satisfactory results are obtained. Training takes 60 seconds. New pattern is tested within a minute. Compared to other neural networks BPN takes longer time for training. The performance measures of BPN for the 2230 feature vector are tabulated. The Table-6.5 gives the confusion matrix representation of the results obtained by Fuzzy logic rule based classifier.

<table>
<thead>
<tr>
<th>Correct Class</th>
<th>Classified as</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Mild appendicitis</td>
</tr>
<tr>
<td>Mild appendicitis</td>
<td>174</td>
</tr>
<tr>
<td>Moderate appendicitis</td>
<td>43</td>
</tr>
<tr>
<td>Gangrenous Appendicitis</td>
<td>0</td>
</tr>
</tbody>
</table>

Accuracy is low compared to fuzzy logic based classifier. Time taken for training is comparatively more. Memory requirements are more compared to Fuzzy logic classifier. It is expected that BPN may give good response if it is trained with more number of representative samples.

**6.11 Experimental Results**

The proposed Neuro Fuzzy logic rule based classifier system was experimented for several test cases and the results obtained are graphically represented. The graph in Figure-6.9
shows the comparison of the clinical attribute values for patients with different types of appendicitis. Based on clinical attributes it was found that the pain site is usually right iliac fossa (RIF) pain in all the three classes. Guarding, rigidity, RIF tenderness and rebound tenderness was present in high value among the patients suffering with Gangrenous appendicitis. Pain shift, foetor and rebound tenderness was present in low value among the patients suffering with mild appendicitis.

**Figure 6.9 Clinical attribute values for Patients with different types of appendicitis**

The graph in Figure-6.10 shows the comparison of the Biochemical attribute values for patients with different types of appendicitis for the sample test cases. Based on the biochemical Tests it was found that high white blood cell count and high neutrophil count indicates the severity of the appendicitis. Patients with high WBC and neutrophil count have a high probability of severe appendicitis.
Figure 6.10 Biochemical attribute values for Patients with different types of appendicitis

6.12 Chapter Conclusions

Our study shows that Fuzzy logic rule based classifier can provide high degree more than of positive predictive value and thus diagnostic accuracy in the prediction of the type of appendicitis. We were able to classify the patients to different classes of appendicitis namely mild, moderate and severe appendicitis based on the various input parameters namely the pain site, pain nature, nausea, previous surgery, RIF tenderness, rebound tenderness, guarding, rigidity, Temperature, White blood cell count and Neutrophil count. The results predicted by Fuzzy Logic-based classifier has high accuracy rate compared with the Back Propagation Neural Network based classifier. The proposed scoring system for Neuro fuzzy logic classifier was also very effective in detecting the severity of the appendicitis of the patients.