Expert System, Fuzzy Logic System and Neural Networks in the Detection of Coronary Artery Disease

R.JAIN\textsuperscript{1}, J MAZUMDAR\textsuperscript{1} and B MORAN\textsuperscript{2}

Dept. of Applied Mathematics, The University of Adelaide \textsuperscript{1}
Dept. of Mathematics, The Flinders University of SA \textsuperscript{2}

(Received 10 March 1996; revised and accepted 15 June 1996)

Abstract: This paper presents a comparative study of expert system, fuzzy logic system and neural networks in the detection of coronary artery disease. It is evident from this study that expert system can be useful in training and providing expert assistance to the user. Fuzzy logic system simplifies the knowledge base in the system. Neural networks are faster and have generalisation capability.

Keywords: expert system, fuzzy logic, neural networks, medical diagnosis

1. INTRODUCTION

Artificial intelligence techniques are getting wide acceptance in diagnosis related applications in medicine, sciences and other disciplines. Recent studies pertaining to medicine on non-invasive acoustical detection of coronary artery disease are encouraging.

Artificial intelligence can be defined as the ability to learn, modify and improve in an uncertain environment. The main idea behind the artificial intelligence techniques is knowledge acquisition, knowledge representation and knowledge processing. The main technique used for this purpose is called neural computing or NNet's. Neural networks originally grew out of the desire to understand the function of the biological brain. Artificial neural networks try to mimic the working of the human brain in a limited sense. One of most important property of artificial neural networks is their ability to generalise. It means that they can successfully interpret data which have not previously been seen before and provide a sensible result. Ofcourse, there are limits to the generalisation ability and the work is in progress in this direction all over the world. The second important property of the artificial neural networks is their parallelism means greater speed of operation. Artificial neural networks memory is distributed all over the network which is like an intelligent behaviour. These networks are not usually programmed during training but they learn the information presented to them.

The main purpose of this paper is to present a comparative study pertaining to non-invasive acoustical detection of coronary artery disease using expert system, neural networks and fuzzy logic system.
2. LITERATURE REVIEW

This section provides a brief sample review of some of the reported work on heart disease.

KARDIO-E for Diagnosis Of Cardiac Arrhythmias

KARDIO-E [10] is an expert system for electrocardiographic diagnosis of cardiac arrhythmias. This expert system can be used as a diagnostic tool in the routine assessment of ECG recordings in preventive or systematic examinations. Its performance is equivalent to that of a specialist of internal medicine. The tool can be used for instructions of electrocardiography in education.

Preceptor for Prognostic Indices

Preceptor [11] expert system shell is reported in a study of prognostic indices in stroke to support clinical decision-making. The system has a capacity of 350 litres of clinical data and 400 rules. Although this expert system was developed to standardise diagnosis for medical purposes, the developers believe that this expert system will also be valuable as an aid to learning and decision making in the management of stroke patients. It is planned to extend the knowledge-base to enable this tool to assist in selecting appropriate methods of rehabilitation as well as diagnosis.

Knowledge-Based System For The Diagnosis Of Leukaemia

A knowledge-based system is reported in [1] for the diagnosis of leukaemia. The idea is to classify the cases of leukaemia on the basis of the specific cell markers detected by monoclonal antibodies and related laboratory tests. The antibodies required for the tests are now commercially available but the interpretation of the results is not simple. The system was developed with the help of an expert immunologist over the period of two years. This system also includes a variety of rare and typical cases.

Expert System Tool for Thyroid Function Test

A tool for the interpretation of thyroid function tests [2] is developed to increase diagnostic accuracy by improved test strategies. This rule based tool incorporates all of the most commonly used thyroid function tests. This tool also includes the facility to stipulate the decision and reference ranges for the tests used in the local laboratory.

Hybrid System in Medical Diagnosis

Sphinx system [8] is a hybrid medical diagnostic tool using fuzzy and logical inferences. This knowledge-based tool is able to generate hypotheses using heuristics based on fuzzy pattern matching procedures. This system is applied in the area of therapeutics of diabetes and in the diagnosis of cancer. This system can also be used as a teaching aid.

EEG Data Analysis

A hybrid neural net/knowledge-based tool to analyse EEG data is reported in [12]. The idea is to use neural net as a front-end processor of sensor data for a knowledge-based system. The tool focuses on the domain of signal processing, specifically the recognition/removal of artefacts (noise) from EEG signals.

Fuzzy Control for Postoperative Pain Relief

A study exploring the application of fuzzy control for the relief of postoperative pain was reported in [5]. This study reports the implementation of the tool in two phases. In the first phase a fuzzy controller takes the system to setpoint, and in the second phase, a controller functions in a semiclosed-loop to maintain the analgesic. The controller was implemented in the OPS-83 and in Microsoft-C.

Fuzzy Sets in Diagnosing Coronary Artery Stenosis

This work reports the use of fuzzy logic to represent perfusion defects and to generate expert rules in diagnosing coronary artery stenosis [4]. The retrospective data was collected from 91 patients. The random 64 scans were chosen for training and the remaining 27 scans for testing data. It is shown that fifteen rules generated using fuzzy set theory perform as well as 68 rules specified by cardiologists in diagnosing coronary artery stenosis.

Survival Prediction Tool for Cardiopulmonary Resuscitation (CPR)

This software tool uses artificial neural network to predict failure to survive following in-hospital cardiopulmonary resuscitation [6]. This study considers the age, sex, heart rate, and 21 other clinical variables of 218 adult patients at a 295-bed hospital. It is shown that neural network based software tool gave a positive predictive value of 97% for the prediction of failure to survive following CPR.
Neural Network for Identifying The Presence of Myocardial Infarction

The effect of the input clinical variables for the diagnosis of the presence of acute myocardial infarction using neural network is reported in [3]. It is shown in this study that neural network appears to place diagnostic importance on clinical variables that have not been shown previously to be highly predictive or infarction.

It is obvious from this selective and brief literature review that there is not a single technique which has answer to all the problems. Thus it is useful to compare various artificial intelligence based techniques (expert system, fuzzy logic and neural network) in diagnosis.

3. INTELLIGENT DIAGNOSIS

In recent years, a great improvement has taken place in medical diagnosis. A large number of intelligent diagnostic techniques are reported in the literature. These intelligent techniques are able to improve or maintain an acceptable level of performance in the presence of uncertainty. The main ingredients of these intelligent techniques are knowledge acquisition, knowledge representation and knowledge processing. Some of the tools used for this are expert systems, fuzzy logic and artificial neural networks.

The following is a brief introduction of these tools.

(a) EXPERT SYSTEM TOOL

Expert system also called knowledge-based system [14] is a software tool which can simulate the performance of a human expert in a limited sense. Figure 1 shows a simplified diagram of a typical expert system. It contains the knowledge-base, the inference engine and the user interface. Knowledge base consists of a set of rules derived from human expert and/or literature. The function of the inference engine is to go through the knowledge base and activate the rules to produce the conclusion. There is a provision to provide a reasoning mechanism and explanation for displaying the rules which were used to reach a conclusion. The user interface connects the expert system to the outside world. There are various methods to represent the knowledge in the knowledge base. The most popular and widely used method is using production rules. The basic of production rule is

IF  
A₁, A₂, ..., Aₙ  
Then  
B₁, B₂, ..., Bₙ

In the classic MYCIN expert system, a typical rule is:

IF  
1. There is an organism that requires therapy, AND  
2. Consideration has been given to the possible existence of additional organisms requiring therapy, even though they have not actually been recovered from any current cultures

THEN: Do the following:

1. Compile the list of possible therapies that, based upon sensitivity data may be effective against the organisms requiring treatment, and
2. Determine the best therapy recommendations from the compiled list.

OTHERWISE: Indicate that the patient does not require therapy.

(b) FUZZY LOGIC SYSTEM

Fuzzy Logic [13] was first developed by Zadeh to automate various types of activities from designing a motor car to diagnosing a patient. In the classic Boolean logic, the information is expressed in binary form, i.e. true or false (1 or 0). In fuzzy logic the information is presented in a form which resembles like human thinking. For example:

Patient has HIGH fever.

The word HIGH is resembles more like a way humans express things.

In fuzzy logic one has to indicate the degree to which a variable is a member of a set. This is done by using a degree-of-membership variable, often represented by μ. For example:

\[ μ_A(x) = [0,1] \]

This means that the degree of membership of the element \( x \) in the fuzzy set \( A \) range from 0 to 1.

Figure 2 shows an example of the degree of membership of fever \( F \).

As an example, let us consider the following rule.

IF  
fever is HIGH

THEN  
seek medical advice immediately

The fuzzy inference engine searches through the knowledge base and draws conclusion.

The most commonly used operators in fuzzy logic theory are

- Union  \[ μ_A \text{ or } B = \max(μ_A, μ_B) \]
- Intersection  \[ μ_A \text{ and } B = \min(μ_A, μ_B) \]
- Complement  \[ μ_{\text{not } A} = 1 - μ_A \]

It is shown in reference [4] that fifteen rules generated with fuzzy set theory perform as well as 68 rules
specified by cardiologists in diagnosing coronary artery stenosis using thallium-201 scientigrams.

![Figure 1](image1)

**Figure 1** A simplified representation of an expert system.

![Figure 2](image2)

**Figure 2** Degree of membership of fever $F^*$ to the fuzzy set high.

(C) ARTIFICIAL NEURAL NETWORKS

In the 1980's artificial neural networks [7] have re-emerged as a tool in making intelligent decisions in diagnosis. These networks are capable to learn from examples and can generalise in the sense that they can make close conclusions pertaining to the data not seen before. Figure 3 shows a typical three layer network. The input layer consists of two neurons. It accepts the input data and pass it on to the hidden layer. The hidden layer process this data and pass it on the output layer. The actual output from the output layer is compared. With the desired output and the difference between the two, usually called the error is fed back to the network to adjust the weights. This learning process repeats till the difference between the desired output and the actual output reaches to a predetermined value. This state of the network is called the trained state. In this state, the network should be able to produce the desired output for the given input data and the limited new input data.

The multiple layer perceptron (MLP) is a feedforward neural network having an input layer, one or more hidden layers and one output layer. The backpropagation learning algorithm (BP) is widely used to train MLP. The BP is a supervised learning procedure. The training data set consists of input and the desired output data. The input data is presented to the input layer and the generated output is used with the desired output to calculate the error. This error is propagated back into the network for the modification of the weights of the hidden and output layers. Again the error is computed. This process is repeated until the error is decreased to the prespecified value. It is an usual practice to minimize the sum of square of the error using the least mean square (LMS) procedure. The error is expressed as

$$E = \frac{1}{2}(d_k - O_k)^2$$

Where

$d_k = \text{desired output}$

$O_k = \text{actual output}$

The objective here is to compute the derivative of the error function $E$ with respect to the weight in the network and the then change the weights accordingly to minimise the error. The weight change equation is

$$W_{jk}(t+1) = (1-\alpha)\eta_d\delta_k + \alpha W_{jk}(t)$$

where, $\alpha$ = momentum term which accounts for the affects of the past weight changes on the current direction of movement in weight space ($0<\alpha<1$).

$\eta = \text{learning rate}$

$O_j = \text{Output of layer j}$

$W_{jk} = \text{weights between layers j and k}$

$\delta_k = \text{error signal at an output unit k}$

4. CASE STUDY

Our study considers the data pertaining to the application of ARMA method to acoustic detection of coronary artery disease. Patients are classified as being either normal or abnormal. Table 1 illustrates the data of 20 patients (10 normal and 10 abnormal). For every patient, three parameters are listed which can be used to distinguish between the normal and the abnormal patients.
Expert System - We have used VP-expert system shell to develop the prototype expert for distinguishing between the normal and abnormal patient. VP-Expert version 2.0 is a cheap educational version of the VP-Expert tool by Paperback Software International. It includes a built-in text editor for rule development. It has a useful inductive facility to derive rules directly from examples in data files. It uses backward and forward chaining in its problem solving process. To simplify the knowledge base we have arranged the variables of table 1 into four classes as illustrated in table 2.

Using the categorisation of the patient data table, we have constructed the rule table as shown in table 3. (Refer Appendix 1 for rules)

Fuzzy logic - We have used a simple fuzzy logic system to enable us to determine if a patient is normal or abnormal. The grade of membership functions used for p2, ap and apr are shown in Figure 4.

A computer program is written in Pascal to implement the normal/abnormal patient data using fuzzy logic. (Appendix 2)

Neural Network - Our case study involves the use of two layer neural networks as a classifier system for categorising the patients into the normal and abnormal category. The data pertaining to the normal/abnormal patient of Table 1 is classified into four categories as Big (B), Medium (M), Small (S), and very Small (VS) as illustrated in table 2. Table 4 shows the coding of every variable of the patient data.

We have considered three variables for each patient in our training set. The coding for each variable are concatenated to form a six-bit input string as shown in table 5. The single-bit output string consists of 0 and 1 and is codified as:

\[
\begin{align*}
1 & \quad \text{normal patient} \\
0 & \quad \text{abnormal patient}
\end{align*}
\]

The simple problem requires the use of a two layer neural network. The input layer consists of 6 neurones and the output layer contains 1 neuron. We have used a small set of training data in our experiments. We have achieved 100% generalisation ability in our experiments. We have implemented our software using Pascal language. Our research is directed on a data set from Cleveland Clinic Foundation USA. This database contains 303 instances, of which 164 with goal values 0, 55 with values 1, 36 with value 2, 35 with value 3, and 13 with value 4. Our initial results show the generalisation accuracy on the test set of 85% on a training set of 202 instances and test set of 101 instances. We will report our new results in our next paper. power of the artificial neural networks comes from their ability of generalisation. They need no programming and can work with some missing data.
Figure 4 Grades of membership functions used to distinguish normal patients from abnormal.

### Table 1

<table>
<thead>
<tr>
<th>Patient</th>
<th>p2</th>
<th>ap</th>
<th>apr</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>630.4</td>
<td>11569.2</td>
<td>0.1</td>
</tr>
<tr>
<td>2</td>
<td>326.5</td>
<td>2123.0</td>
<td>2.5</td>
</tr>
<tr>
<td>3</td>
<td>274.9</td>
<td>4818.0</td>
<td>2.1</td>
</tr>
<tr>
<td>4</td>
<td>151.0</td>
<td>6294.2</td>
<td>1.5</td>
</tr>
<tr>
<td>5</td>
<td>111.7</td>
<td>2329.9</td>
<td>1.6</td>
</tr>
<tr>
<td>6</td>
<td>111.2</td>
<td>1856.0</td>
<td>4.0</td>
</tr>
<tr>
<td>7</td>
<td>110.6</td>
<td>2673.8</td>
<td>0.7</td>
</tr>
<tr>
<td>8</td>
<td>99.0</td>
<td>1221.0</td>
<td>0.9</td>
</tr>
<tr>
<td>9</td>
<td>96.3</td>
<td>754.8</td>
<td>1.2</td>
</tr>
<tr>
<td>10</td>
<td>96.2</td>
<td>1162.0</td>
<td>2.1</td>
</tr>
<tr>
<td>11</td>
<td>25.9</td>
<td>607.3</td>
<td>4.0</td>
</tr>
<tr>
<td>12*</td>
<td>12.0</td>
<td>766.6</td>
<td>16.2</td>
</tr>
<tr>
<td>13*</td>
<td>6.1</td>
<td>798.6</td>
<td>13.8</td>
</tr>
<tr>
<td>14*</td>
<td>4.0</td>
<td>520.2</td>
<td>0.8</td>
</tr>
<tr>
<td>15*</td>
<td>3.2</td>
<td>491.0</td>
<td>45.0</td>
</tr>
<tr>
<td>16*</td>
<td>2.8</td>
<td>361.7</td>
<td>17.0</td>
</tr>
<tr>
<td>17*</td>
<td>2.8</td>
<td>247.3</td>
<td>10.2</td>
</tr>
<tr>
<td>18*</td>
<td>2.5</td>
<td>331.2</td>
<td>3.9</td>
</tr>
<tr>
<td>19*</td>
<td>2.4</td>
<td>312.7</td>
<td>11.8</td>
</tr>
<tr>
<td>20*</td>
<td>1.8</td>
<td>705.8</td>
<td>0.2</td>
</tr>
</tbody>
</table>

* = normal patients
p2 = amplitude of the second peak (pressure in dB)
ap = absolute area between 400 and 800 Cycles per second (units of pressure Cycles per second)
apr = ratio of ap below 400 Cycles per second over ap above 400 Cycles per second

### Table 2

<table>
<thead>
<tr>
<th>Category</th>
<th>p2</th>
<th>ap</th>
<th>apr</th>
</tr>
</thead>
<tbody>
<tr>
<td>Big (B)</td>
<td>&gt; 150</td>
<td>&gt; 1500</td>
<td>&gt; 30</td>
</tr>
<tr>
<td>Medium (M)</td>
<td>50 - 150</td>
<td>500 - 1500</td>
<td>15 - 30</td>
</tr>
<tr>
<td>Small (S)</td>
<td>10 - 50</td>
<td>300 - 500</td>
<td>5 - 15</td>
</tr>
<tr>
<td>Very Small (VS)</td>
<td>&lt; 10</td>
<td>&lt; 300</td>
<td>&lt; 5</td>
</tr>
</tbody>
</table>
Rule table

<table>
<thead>
<tr>
<th>patient</th>
<th>p2</th>
<th>ap</th>
<th>apr</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>B</td>
<td>B</td>
<td>VS</td>
</tr>
<tr>
<td>2</td>
<td>B</td>
<td>B</td>
<td>VS</td>
</tr>
<tr>
<td>3</td>
<td>B</td>
<td>B</td>
<td>VS</td>
</tr>
<tr>
<td>4</td>
<td>M</td>
<td>B</td>
<td>VS</td>
</tr>
<tr>
<td>5</td>
<td>M</td>
<td>M</td>
<td>VS</td>
</tr>
<tr>
<td>6</td>
<td>M</td>
<td>M</td>
<td>VS</td>
</tr>
<tr>
<td>7</td>
<td>M</td>
<td>M</td>
<td>VS</td>
</tr>
<tr>
<td>8</td>
<td>M</td>
<td>M</td>
<td>VS</td>
</tr>
<tr>
<td>9</td>
<td>M</td>
<td>M</td>
<td>VS</td>
</tr>
<tr>
<td>10</td>
<td>M</td>
<td>M</td>
<td>VS</td>
</tr>
<tr>
<td>11</td>
<td>S</td>
<td>M</td>
<td>VS</td>
</tr>
<tr>
<td>12</td>
<td>S</td>
<td>M</td>
<td>M</td>
</tr>
<tr>
<td>13</td>
<td>VS</td>
<td>M</td>
<td>VS</td>
</tr>
<tr>
<td>14</td>
<td>VS</td>
<td>M</td>
<td>VS</td>
</tr>
<tr>
<td>15</td>
<td>VS</td>
<td>S</td>
<td>B</td>
</tr>
<tr>
<td>16</td>
<td>VS</td>
<td>S</td>
<td>M</td>
</tr>
<tr>
<td>17</td>
<td>VS</td>
<td>VS</td>
<td>S</td>
</tr>
<tr>
<td>18</td>
<td>VS</td>
<td>VS</td>
<td>S</td>
</tr>
<tr>
<td>19</td>
<td>VS</td>
<td>S</td>
<td>S</td>
</tr>
<tr>
<td>20</td>
<td>VS</td>
<td>M</td>
<td>VS</td>
</tr>
</tbody>
</table>

Table 4: The coding scheme of variables

<table>
<thead>
<tr>
<th>Category</th>
<th>Code</th>
</tr>
</thead>
<tbody>
<tr>
<td>Big (B)</td>
<td>11</td>
</tr>
<tr>
<td>Medium (M)</td>
<td>10</td>
</tr>
<tr>
<td>Small (S)</td>
<td>01</td>
</tr>
<tr>
<td>Very Small (VS)</td>
<td>00</td>
</tr>
</tbody>
</table>

Table 5: Training set for neural network

<table>
<thead>
<tr>
<th>Patient</th>
<th>p</th>
<th>ap</th>
<th>apr</th>
<th>outputdata</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>1</td>
<td>11</td>
<td>00</td>
<td>0</td>
</tr>
<tr>
<td>2</td>
<td>1</td>
<td>11</td>
<td>00</td>
<td>0</td>
</tr>
<tr>
<td>3</td>
<td>1</td>
<td>11</td>
<td>00</td>
<td>0</td>
</tr>
<tr>
<td>4</td>
<td>1</td>
<td>11</td>
<td>00</td>
<td>0</td>
</tr>
<tr>
<td>5</td>
<td>1</td>
<td>11</td>
<td>00</td>
<td>0</td>
</tr>
<tr>
<td>6</td>
<td>1</td>
<td>11</td>
<td>00</td>
<td>0</td>
</tr>
<tr>
<td>7</td>
<td>1</td>
<td>11</td>
<td>00</td>
<td>0</td>
</tr>
<tr>
<td>8</td>
<td>1</td>
<td>11</td>
<td>00</td>
<td>0</td>
</tr>
<tr>
<td>9</td>
<td>1</td>
<td>11</td>
<td>00</td>
<td>0</td>
</tr>
<tr>
<td>10</td>
<td>1</td>
<td>11</td>
<td>00</td>
<td>0</td>
</tr>
<tr>
<td>11</td>
<td>1</td>
<td>11</td>
<td>00</td>
<td>0</td>
</tr>
<tr>
<td>12</td>
<td>0</td>
<td>00</td>
<td>01</td>
<td>1</td>
</tr>
<tr>
<td>13</td>
<td>0</td>
<td>00</td>
<td>01</td>
<td>1</td>
</tr>
<tr>
<td>14</td>
<td>0</td>
<td>00</td>
<td>01</td>
<td>1</td>
</tr>
<tr>
<td>15</td>
<td>0</td>
<td>00</td>
<td>01</td>
<td>1</td>
</tr>
<tr>
<td>16</td>
<td>0</td>
<td>00</td>
<td>01</td>
<td>1</td>
</tr>
<tr>
<td>17</td>
<td>0</td>
<td>00</td>
<td>01</td>
<td>1</td>
</tr>
<tr>
<td>18</td>
<td>0</td>
<td>00</td>
<td>01</td>
<td>1</td>
</tr>
<tr>
<td>19</td>
<td>0</td>
<td>00</td>
<td>01</td>
<td>1</td>
</tr>
<tr>
<td>20</td>
<td>0</td>
<td>00</td>
<td>01</td>
<td>1</td>
</tr>
</tbody>
</table>

5. CONCLUSION

We have attempted in this study to compare three intelligent techniques (expert system, fuzzy logic system and Neural network) in the detection of coronary artery disease. It is obvious from this study that expert systems cannot generalise. Knowledge acquisition is a difficult problem and the expert systems do not work properly with insufficient knowledge.
The fuzzy logic provides a basis for human reasoning and requires the less number of rules than the expert system for implementing a given medical system. The power of artificial neural networks comes from their ability of generalisation. They need no programming and can work with some missing data.

ACKNOWLEDGEMENTS

Thanks are due to the reviewers for very useful comments. These comments have improved the quality of this paper.

REFERENCES


APPENDIX 1

ACTIONS
DISPLAY "This expert system will diagnose if a patient is normal or abnormal based on data entered by the user."
FIND CONDITION
DISPLAY "Based on the data which you entered the patient has been diagnosed as [CONDITION].";

RULE 0
IF P2=Big AND AP=Big AND APR=VerySmall
THEN CONDITION=abnormal;

RULE 1
IF P2=Medium AND AP=Big AND APR=VerySmall
THEN CONDITION=abnormal;

RULE 2
IF P2=Medium AND AP=Medium AND APR=VerySmall
THEN CONDITION=abnormal;

RULE 3
IF P2=Small AND
AP=Medium AND
APR=VerySmall
THEN CONDITION=abnormal;

RULE 4
IF P2=Small AND AP=Medium AND APR=Medium
THEN CONDITION=normal;

RULE 5
IF P2=VerySmall AND AP=Medium AND APR=Small
THEN CONDITION=normal;

RULE 6
IF P2=VerySmall AND AP=Small AND APR=Big
THEN CONDITION=normal;

RULE 7
IF P2=VerySmall AND AP=Small AND APR=Big
THEN CONDITION=normal;

RULE 8
IF P2=VerySmall AND AP=Small AND APR=Medium
THEN CONDITION=normal;

RULE 9
IF P2=VerySmall AND AP=VerySmall AND APR=Small
THEN CONDITION=normal;

RULE 10
IF P2=VerySmall AND AP=VerySmall AND APR=Small
THEN CONDITION=normal;

RULE 11
IF P2.Help>150
THEN P2=Big;

RULE 12
IF P2.Help<=150 AND P2帮助企业>50
THEN P2=Medium;

RULE 13
IF P2帮助企业<50 AND
APPENDIX 2

program medic;
{uses fuzzy logic to determine if a patient is normal or abnormal}
uses Crt;

CONST MAXELEMENTS=5;

TYPE MemArray = array[1..MAXELEMENTS] of real;
MemberType = array[1..2] of MemArray;

CONST
p2MemInit:MemberType=((2,1,10,100,0),(1,1,20,150,0))
; apMemInit:MemberType=((2,1,500,800,0),(1,2,600,1000,0))
; aprMemInit:MemberType=((1,1,1,4,0),(2,1,1,3,0));

var p2Mem,apMem,aprMem:MemberType;
dum:char;
p2,ap,apr:real;

procedure InitialiseMembershipFunctions(var p2Mem,apMem,aprMem:MemberType);
{ defines the membership functions for the different fuzzy sets}
the first entry in the array denotes the shape of the membership
function: 1=s-shaped
2=z-shaped
3=spike-shaped
the second entry represents a multiplication factor, which in the
initial phase is 1 for all membership functions }

begin
p2Mem:=p2MemInit;
apMem:=apMemInit;
aprMem:=aprMemInit;
end; {InitialiseMembershipFunctions}

procedure GradeMembership(Fuset:MemArray; x:real;
VAR grade:real);
{ calculates the grade of membership to membership
function Fuzset of a certain value for x }

function s(Fset:MemArray; x:real):real;
var result:real;
begin
if x<Fset[3] then result:=0;
if x>Fset[4] then result:=Fset[2];
if (Fset[3]<=x) and (x<=Fset[4]) then
result:=(Fset[2]*(x-Fset[3]))/(Fset[4]-Fset[3]);
function z(Fset:MemArray; x:real):real;
var result:real;
begin
if x<Fset[3] then result:=Fset[2];
if x>Fset[4] then result:=0;
if (Fset[3]<=x) and (x<=Fset[4]) then
result:=(Fset[2]*(Fset[4]-x))/(Fset[4]-Fset[3]);
z:=result;
end; (z)

function spike(Fset:MemArray; x:real):real;
var result:real;
begin
if x<Fset[3] or (x>Fset[5]) then result:=0;
if (Fset[3]<x) and (x<Fset[4]) then
result:=(Fset[2]*(x-Fset[3]))/(Fset[4]-Fset[3]);
if (Fset[4]<x) and (x<=Fset[5]) then
result:=(Fset[2]*(Fset[5]-x))/(Fset[5]-Fset[4]);
 spike:=result;
end; (spike)

begin
if Fuzset[1]=1 then grade:=s(Fuzset,x);
if Fuzset[1]=2 then grade:=z(Fuzset,x);
if Fuzset[1]=3 then grade:=spike(Fuzset,x);
end; [GradeMembership]

procedure DetermineCondition(p2,ap,apr:real);
var
p2Normal,p2Abnormal,apNormal,apAbnormal:real;
aprNormal,aprAbnormal,SumNormal,SumAbnormal:real

begin
GradeMembership(p2Mem[1],p2,p2Normal);
GradeMembership(p2Mem[2],p2,p2Abnormal);
GradeMembership(apMem[1],ap,apNormal);
GradeMembership(apMem[2],ap,apAbnormal);
GradeMembership(aprMem[1],apr,aprNormal);
GradeMembership(aprMem[2],apr,aprAbnormal);
SumNormal:=p2Normal+apNormal+aprNormal;
SumAbnormal:=p2Abnormal+apAbnormal+aprAbnorm al;
writeln;writeln;writeln;
if SumNormal>=SumAbnormal then writeln('Patient has been diagnosed as normal')
else writeln('Patient has been diagnosed as abnormal');
writeln;writeln('Press q to quit or any other key to begin again');
dum:=ReadKey;
end; [DetermineCondition]

begin [main]
InitialiseMembershipFunctions(p2Mem,apMem,aprMem);
repeat

ClrScr;
writeln("******************************************************************************
******************************************************************************

* This program enables you to determine if a patient is normal or abnormal *

******************************************************************************
******************************************************************************

* Written by Ravi Jain, 20/12/1995 *

******************************************************************************
******************************************************************************

* Use a simple fuzzy logic algorithm to diagnose the patients condition *

******************************************************************************
******************************************************************************

writeln;
writeln;
writeln;
write('What is the amplitude of the second peak (p2)? ');readln(p2);
write('What is the absolute area between 400 and 800 Cycles per second (ap)? ');readln(ap);
write('What is the ratio of ap below 400 Cycles per second over ap above 400 Cycles per second (ap)? ');readln(ap);
DetermineCondition(p2,ap,apr);
until dum='q';
ClrScr;
end.

R.K.JAIN
R.K.Jain is presently with the Department of Applied Mathematics, University of Adelaide, South Australia. He is researching the intelligent techniques including expert systems, fuzzy systems and genetic algorithms in medical diagnosis.
E-mail: ravi@maths.adelaide.edu.au

J.MAZUMDAR
J.Mazumdar received the B.Sc.(Hons.) and M.Sc. degrees from the University of Patna, India, and the PhD degrees from Moscow State University Russia. He joined the University of Adelaide, South Australia, in 1966 where he is currently an Associate Professor involved in teaching and research in solid mechanics and biomechanics. He has published nearly 130 papers in these fields. He is an elected member of the American Academy of Mechanics and a fellow of the Australian College of Physical Scientists and Engineers in medicine and a fellow of the Institution of Engineers, Australia.
Mailing address: University of Adelaide, GPO Box 498, Adelaide, 5001, South Australia.
E-mail: Jmazumda@maths.adelaide.edu.au

BILL MORAN
Bill Moran is Professor of Mathematics at Flinders University at Flinders University of South Australia and Head of the Medical Signal Processing Group of the Cooperative Research Centre for Sensor Signal and Information Processing. He has published over 100 papers in refereed journals in various areas of mathematics and applications. He is a Fellow of the Australian Academy of Sciences.