# A GENERIC EXPERT SYSTEM FRAMEWORK WITH FUZZY BAYESIAN INFERENCE FOR MEDICAL CLASSIFICATION AND DIAGNOSIS IN CARDIALOGY

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**A GENERIC EXPERT SYSTEM FRAMEWORK WITH FUZZY BAYESIAN INFERENCE FOR MEDICAL CLASSIFICATION AND DIAGNOSIS IN CARDIALOGY**

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## Abstract

Medical knowledge is expanding fast and it is difficult for general practitioners to remain abreast of all medical domains. Also, access to domain specialist is limited due to availability and geographical constraints. In many situations the diagnosis in upon the decision of the general practitioner and in cases this has resulted in the problem of patient's misdiagnosis. The purpose of this research is to create an expert system as a decision support model which is capable of risk analysis for diagnosis based on the patient's demography and laboratory tests. The expert system is designed in compliancy with medical communications protocol such as HL7 and can be integrated to any HL7 compliant Electronic Medical records system to provide more intelligence in diagnosis.

Using linear scoring models and Fuzzy logic, the patient's demography and laboratory results will be used as rule bases. Such knowledge will be used as priors for a Bayesian engine to create the diagnostic spaces. Patient's information is compared in the space and the general practitioner can select between the possible hypotheses. Each diagnostic decision will be associated with a risk value. Using such scoring model provides a new semantic in diagnosis by providing risk values for every diagnosis made and by suggesting the most suitable treatment. Unlike many other existing expert systems, the architecture is designed in a generic standard which provides the capability to use the system for all medical domains. Achieving this generality has been a major goal achieved and its details are discussed in this document.

**Acknowledgements**

I would like to thank Dr. Alireza Sadeghian, who supported me in this research and taught me the great values and ethics of research. I also acknowledge Dr. William Melek's unconditional support for my research and thanking him for introducing and initiating the subject and core fundamentals of this research.

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# CHAPTER 1: INTRODUCTION

## 1.1 Motivation

Expansion of the medical knowledge has made it difficult for general practitioners to remain abreast of medicine outside a narrow field. Scheduling a meeting with a specialist has also proved to be a lengthy process due to time and availability constraints. In many cases the expert opinion is not also usually available in a timely fashion [1]. These constraints in many cases result in the patient's misdiagnosis. If there can be a decision support model that can assist the general practitioners in their diagnosis in specialized cases, the problem of misdiagnosis can be significantly reduced. Currently there is no systematic guideline for calculating the risk of a particular diagnosis. Creating a generic risk analysis paradigm for diagnosis can significantly enhance our health system and provide a reliable scoring model for measuring the correctness of each diagnosis.

## 1.2 Objective

The objective of this research is to create an expert system which acts as a reliable decision support engine in the process of medical diagnosis and can also be complied with standard medical communications protocols such as HL7. This means that the proposed expert system can be added to any existing Electronic Medical Records (EMR) system without a need for excessive integration. The architecture of the system is to be designed in a manner so that the system can be customized for different medical domains. Embedding such intelligence in healthcare platforms will propose a new semantic in medical diagnosis.

## 1.3 Background

Since early eighties, attempts have been made to develop computer programs which are capable of diagnosis. In recent years, research advanced considerably in developing expert systems for medical diagnosis. In [2], authors proposed an algebra-based expert system for diagnosis of Anorexia. In [3], Artificial Intelligence has been used in the form of Kohonen Self Organizing maps to design an expert system for disease classification. In [4], a design strategy for a self-adaptive brain tumor diagnostic system was developed. In [5], authors proposed a neural network-based learning system for Echocardiography diagnosis expert systems. In [6], an expert system for deafness was proposed. The Fuzzy set theory was used to develop a medical expert system for diagnosis of rheumatology in [7]. In [8], a weighted fuzzy reasoning algorithm was proposed for medical diagnosis. In [9], the authors conducted studies in adaptive abstraction in expert systems for medical diagnosis. In [10] and [11], a fuzzy rule-based system for decision support in pathology anatomist was developed. Similarly, a computer program for neural network-based weaning in Intensive Care Units (ICU) was developed in [12]. In [13], fuzzy set theory was used in pharmacokinetic modeling. Also, in [14], some guidelines for the use of fuzzy modeling and decision support expert system in medical diagnosis were proposed.

There has been a steady progress in creating expert systems capable of diagnosis; however, to our knowledge, there exists no generic expert system structure capable of accurately representing medical knowledge and extracting diagnosis in a specific multi-disease medical discipline [15].

## 1.4 Proposed Method

Most of the existing expert systems used for medical diagnosis suffer from the following drawbacks:

- Lack of generality:

  Majority of approaches are being targeted specifically for a given disease like breast cancer, diabetes, etc., whereas a medical discipline such as cardiology includes a wide spectrum of diseases each of which might present different requirements in terms of lab tests, physical examinations and patient medical history information needed to infer an accurate diagnosis. In other words, lack of generality in terms of providing tools for knowledge representation of multiple diseases in a medical domain is seen as a draw back [16].

- Limited Learning Capability:

  To incorporate new advances in medical knowledge, existing expert system approaches generally use artificial intelligence mechanisms such as bi-valued IF-THEN rules or fuzzy-logic inference in a form that often presents very limited freedom when adaptation and learning are required. Hence, the limited learning capability is seen as another drawback in the existing expert systems for medical diagnosis.

- Lack of generic reasoning models:

  Reasoning mechanisms proposed in the majority of the existing expert systems are often very specific for the particular domain. This means that they would only achieve suitable diagnosis of the specific disease for which the expert system was originally structured. In other words, a dedicated inference engine has been tied to every disease being represented into an expert system for medical diagnosis [17]. Therefore, the lack of generic reasoning mechanism capable of diagnosis is seen as another draw back.

- Lack of systematic guidelines in the design of the expert system:

  Having the medical knowledge in hand, the development process of an expert system is often hierarchical. The design sequence, hierarchy levels, and artificial intelligence schemes should all be integrated for the purpose of knowledge representation and reasoning [18].

Medical science has evolved through the integration of the experiences, thoughts, and beliefs of individuals over centuries. Since engineering is neither dedicated nor qualified to reconstruct the medical knowledge, the system developer cannot expect to have a better knowledge in this domain. Thus, the only option is to develop a sufficiently generic knowledge representation and inference tool that can employ any conceivable form of medical reasoning [19].

The aim of this research is to develop a novel expert system which imitates the reasoning methods of a physician to tackle the two levels of patients' medical care associated with diagnosis and treatment. The proposed expert system aims at providing diagnosis and treatment in the domain of cardiology. The majority of drawbacks presented above will be resolved in the proposed expert system design. To give the expert system more validity, two models of scoring systems are introduced. The proposed expert system utilizes these approaches to reach diagnosis more efficiently and with more accuracy.

Expert systems are designed to solve problems that normally require human intelligence [20]. These systems represent knowledge as a mathematical model or as a set of rules. These models and rules are then used to solve specific problems within a particular domain. The example domain considered in this research is medical diagnosis of the patients with clinical signs and symptoms of Cardio-Vascular categories.

The end users of such expert system are non-specialized general practitioners who directly interact with the patients. The proposed expert system is designed to simulate the expert knowledge of a specialized cardiologist. The system is used by the general physician to help diagnose the patient's disease(s) when access to the cardiologist is not available due to constraints.

It has been shown that when medical experts approach the problem of diagnosis, they quickly generate a small number of disease hypotheses [21] and then seek to verify or refute these hypotheses with further specialized examination and testing based on limited findings provided during the consultation [22]. The medical diagnosis reasoning process can be grouped into four key steps:

**1) Initial Gathering of patient's Subjective Information**

Subjective information refers to data such as past medical history of the patient, as well as present symptoms and complaints. They are first gathered by the medical experts. Such findings are referred to as "Subjective Evidence" since they can be used to indicate the possibility of certain diseases [23]. The process of knowledge gathering starts with the generation of medical records according to the domain related to medical knowledge. This knowledge acquisition will reduce the number of hypotheses by narrowing the scope of diagnosis. Figure 1.1. depicts the logic in acquisition of the preliminary medical knowledge.

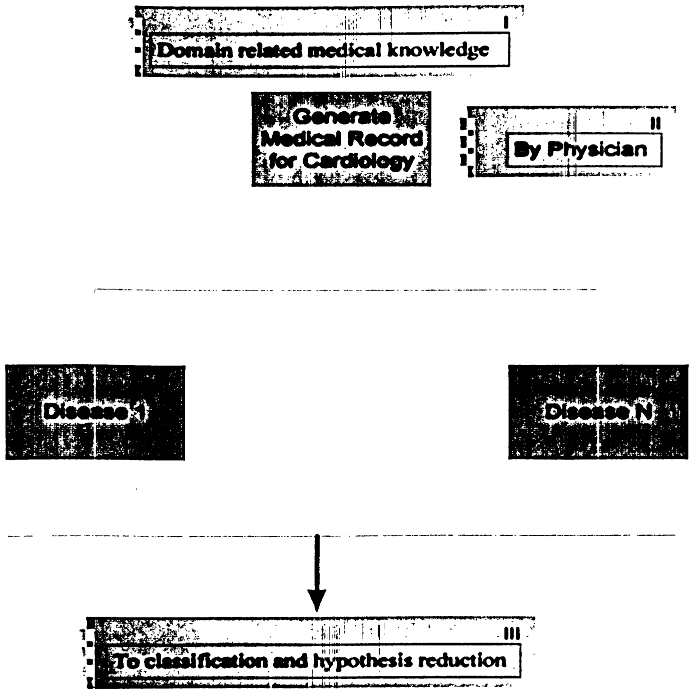



**Figure 1.1. Logic used by the physician in creating diagnosis between hypotheses.**

## 2) Generation of possible diagnosis list

After the initial examination, the medical expert generates a list of probable diagnoses that explains the patient's clinical signs and symptoms. The number of generated hypotheses is usually around five or six for experts, and considerably greater for non-experts [24]. The early generation of hypotheses is very important in the medical diagnostic reasoning since it is not possible for a medical expert to provide an effective consultation without having a scheme of potential problems and formulated hypotheses. An interim treatment is often prescribed to patients for highly suspected diseases until further objective evidence can be gathered to confirm or refute the disease . This early generation of hypothesis is very common strategy used in all fields of diagnostic reasoning and is illustrated in Figure 1.2.

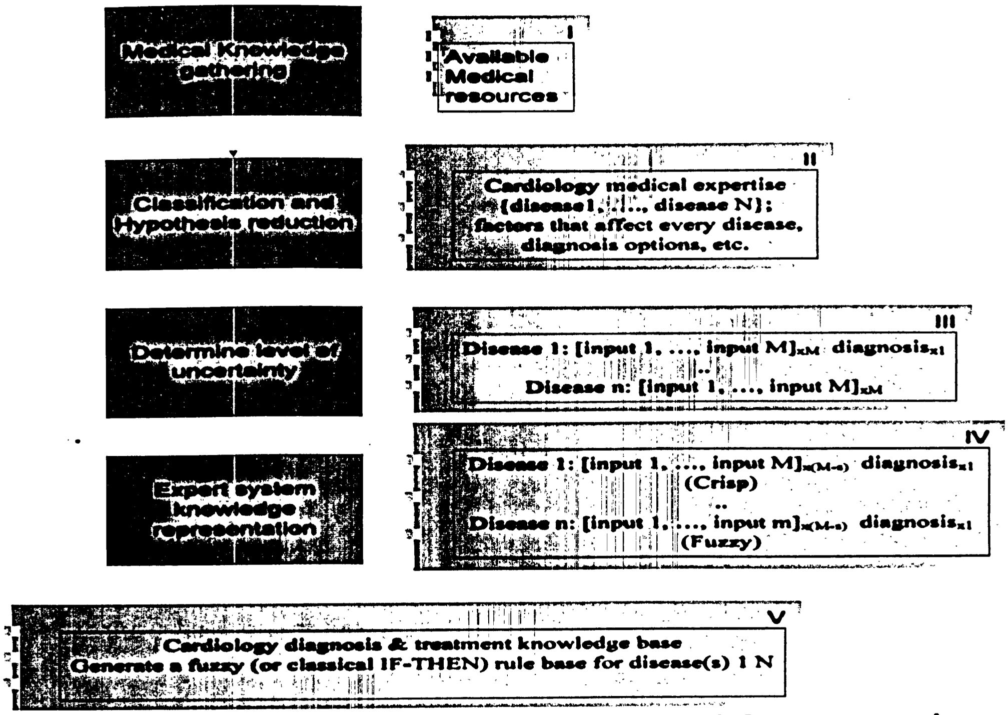



**Figure 1.2. Abstract process in medical knowledge representation.**

**3) Gathering of objective evidence**

Further information specific to the diagnosis of each disease is gathered to confirm or refute each disease in the probable diagnosis list. The objective evidence is usually in the form of laboratory tests, imaging studies or specific physical examination procedures [25]. Each particular disease is associated with certain number of lab tests, imaging studies and other medical findings.

**4) Hypothesis evaluation**

The subjective and objective data are grouped, weighted and scored based their relevance. This information is then used to verify or reject each disease in the probable diagnosis list. If the result does not explain patient's symptoms, the problem is reconsidered by forming new disease hypotheses and often further subjective and objective evidence are gathered.

The evaluation of a disease hypothesis is obtained through using available information and the medical expert's knowledge of the disease. This process is illustrated in Figure 1.3.

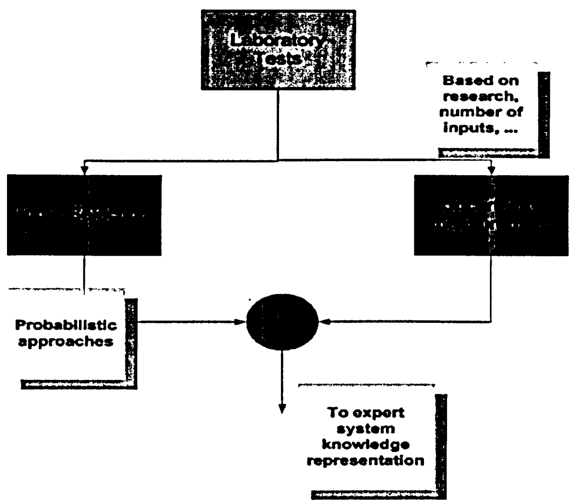



**Figure 1.3. Process of hypothesis evaluation**

The intended expert system follows the above diagnosis process primarily because:

1) The expert system should be able to allow the general physicians to follow their intuition, without a need for changing the regular course of their practice. The proposed expert system is designed to assist the physicians, not to replace them.

2) The system should have the ability to provide explanations and reasoning through the course of diagnosis, in addition to provide confidence measures for the physicians regarding the generated diseases hypotheses and probable diagnosis lists.

3) The ability to perform diagnosis based on incomplete information. According to the medical research and from the available laboratory tests, a number of lab tests will be selected. The uncertainty of the input selection will then be measured using fuzzy inference. The following diagram shows the general process of input selection and diagnosis.

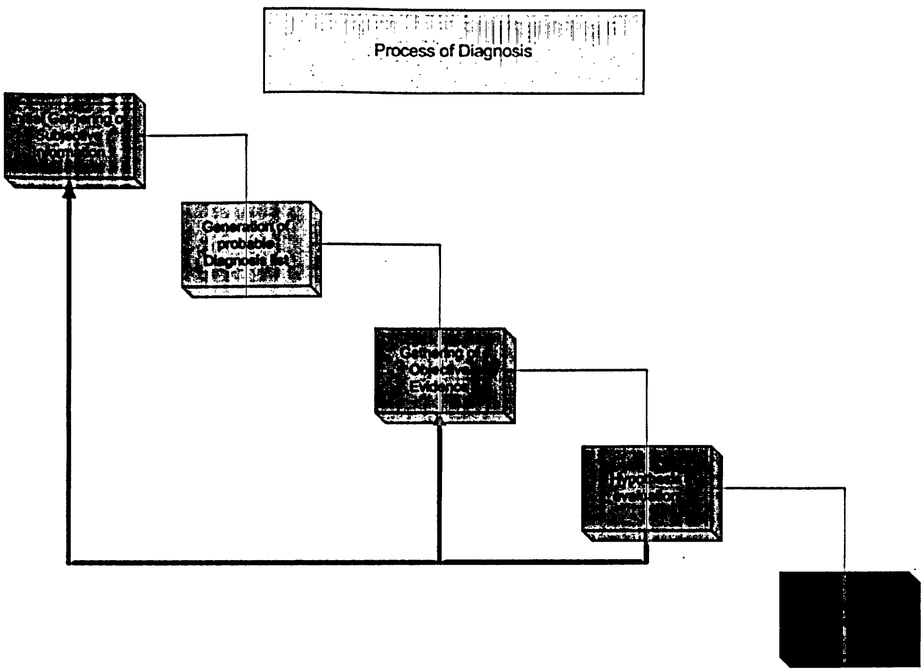



**Figure 1.4. Iterative process of diagnosis**

## 1.5. Thesis Outline

In chapter 2, a statistical approach will be discussed to obtain the score for the demographic analysis. Then a Fuzzy-based system will be introduced to obtain the score for lab and imaging analysis. In chapter3, a Bayesian approach is introduced to select between probable disease hypotheses by creating a decision space. In chapter 4, the simulations and results are shown. The conclusion of the research is written in chapter 5.

# CHAPTER 2: DIAGNOSTIC CLASSIFICATION USING SUBJECTIVE AND OBJECTIVE ANALYSIS

## 2.1 Introduction to Subjective Medical Information

Medical diagnostic reasoning, discussed in chapter 1, is rooted in the following 4 steps:

1. Subjective Analysis
2. Probable diagnoses list
3. Objective Analysis
4. Hypothesis Analysis

In Subjective level of diagnosis, symptoms and medical history of the patient is considered. The Objective Level of diagnosis uses fuzzy logic to evaluate the results of imaging studies and laboratory reports that are required to confirm or refute the disease diagnosis. Each of these suspected diseases are derived from the subjective level of diagnosis shown in Figure 1.4. The user has the overall control of the diagnostic process by adding or removing selected diseases from the list provided during the subjective level of diagnosis at various stages of the assessment even as early as the Physical Examination phase. Figure 2.1 shows how this model can be used to determine the level of uncertainty when a hypothesis is selected.

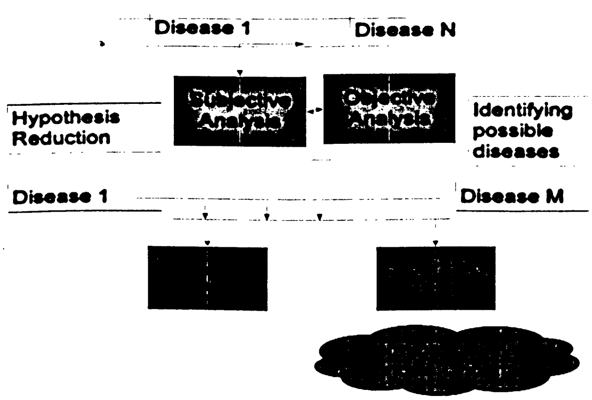



**Figure 2.1. Hypothesis reduction by performing the subjective and objective analysis**

Since the information gained during the physical examination is interpretative (for example: Irregular heart beat), the system is designed such way that the medical professionals could have the freedom of adding or removing diseases from the probable diagnosis list based on their findings and intuition. A feed-forward neural network can be used to capture the practice of the physician during physical examination. Such network will be trained to use the medical records stored in the knowledge base of the dedicated expert system. These records represent successful diagnosis and prognosis outcomes over a substantial period of time.

The neural network will assist the expert system in identification of diseases to which the system has been exposed to through training. This can be considered as a parallel processing assistance to the physical examiner. Complete architecture of the proposed expert system in addition to the proposed reinforcement protocol is shown in Figure 2.2.

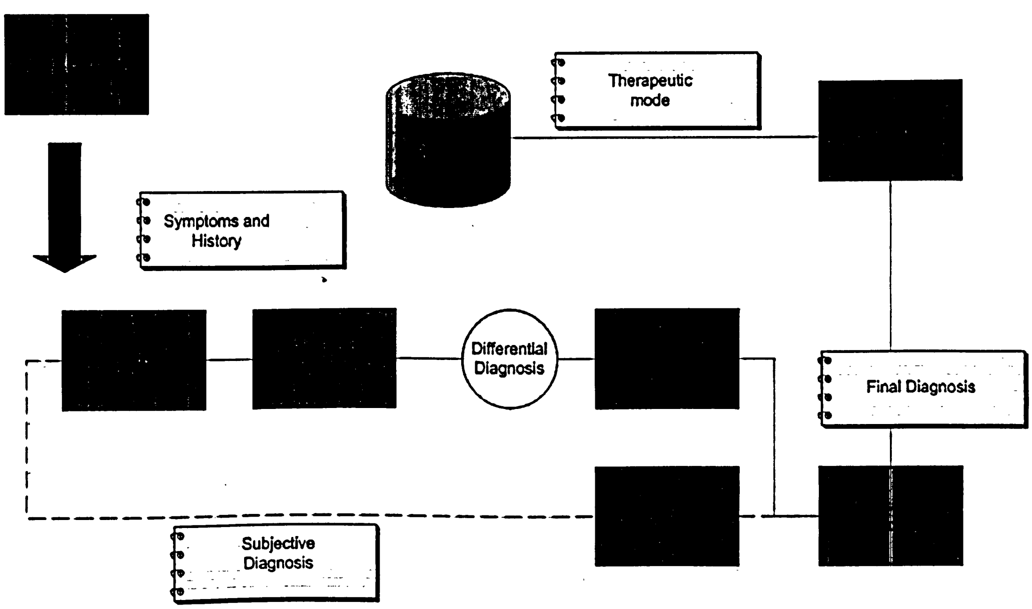



**Figure 2.2. Complete architecture of the proposed expert system**

The inputs to the Neural Network may include:

- Symptoms captured during chief complaints
- History findings of the patient
- Objective evidence from labs and imaging

The probability is presented to the physician during different stages of the diagnosis to assist the practitioner in the decision making process. The following scenario is an example of a patient's walkthrough:

### 2.1.1 Example Scenario – Patient Encounter I

1) Patient complains about:
   - Breathlessness on exertion
   - Chest Pain on Exertion on the left side

2) The above mentioned chief complaints will be stored by the physician in the Medical Record or the EMR.
3) Physician reviews patient's medical history.
4) The expert system applies the "Subjective Level" of diagnosis and a list of suspected diseases is generated.
5) The list is reviewed by the physician. Diseases may be added or removed from the list by the physician.
6) A list of lab tests is suggested based on the subjective information.
7) Physician determines if the suggested lab tests are required.
8) When the lab results are ready, the "Objective" fuzzy expert system is triggered.

9) The physician reviews and assess the suggested diagnoses.

10) The expert system will finally suggest a treatment advice for the confirmed diseases.

11) Physician reviews the confirmed diseases and may prescribe accordingly.

The above 11-step execution represents a common scenario during a patient encounter. Depending on the type of a doctor visit, the patient's encounter may not follow the exact sequence. A patient attending a routine checkup, for example, may undergo a physical examination and may not necessarily need an objective analysis.

### 2.1.2 Scoring System in Subjective Level

In the proposed expert system the subjective level of diagnosis utilizes a linear scoring system to generate a likelihood score for each disease based on the patient's demography. The total number of diseases obtained from Cardiology books and encyclopedias are 75 to 85 [26]. The proposed expert system identifies 75 most common cardiac diseases. For each of these diseases two scores are calculated:

- **A symptom score:** Calculated based on the symptoms and chief complaints
- **A History score:** Calculated based on the past medical history

Table 1 shows a sample of the subjective information.

**Table 1. A table of subjective information**

| History | Present symptoms |
|---|---|
| [illegible] | [illegible] |
| [illegible] | [illegible] |
| [illegible] | [illegible] |
| [illegible] | [illegible] |
| [illegible] | [illegible] |
| [illegible] | [illegible] |
| [illegible] | [illegible] |
| | [illegible] |

The subjective level of the expert system applies thresholds to these 2 scores to determine which of the 75 diseases should be added to the list of possible diagnosis. The disease will be added to the probable diagnosis list if the symptom score is above the set "Symptom Threshold" and the history score is above the set "History Threshold". During data analysis the diseases are ranked by the total number of history and symptom scores. The ranking is kept simple by maintaining the same symptom and history thresholds for each disease. The rank is determined by adding up the symptom score and the history score for each possible disease and then combining them into an overall score. Cutoffs applied to the maximum contribution from the symptom or history portions will be combined into the overall score. The cutoffs are applied to ensure that the ranking is not unfavorably skewed by diseases that have a very high history score and a low symptom score or vice versa. Most common diseases would have both a high history and high symptom score [27]. Figure 2.3.shows how diseases share symptoms and histories.

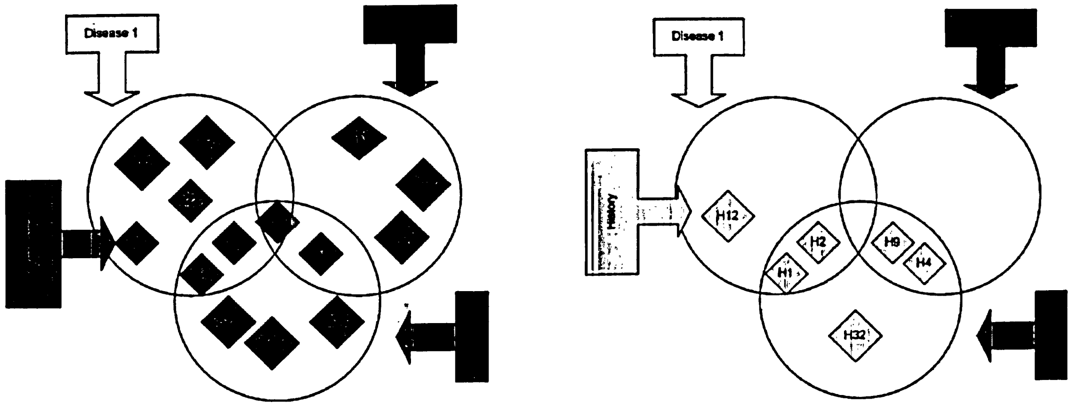



**Figure 2.3. Diseases share certain symptoms and histories**

The general diagnostic flow of the system is shown in Figure 2.4.

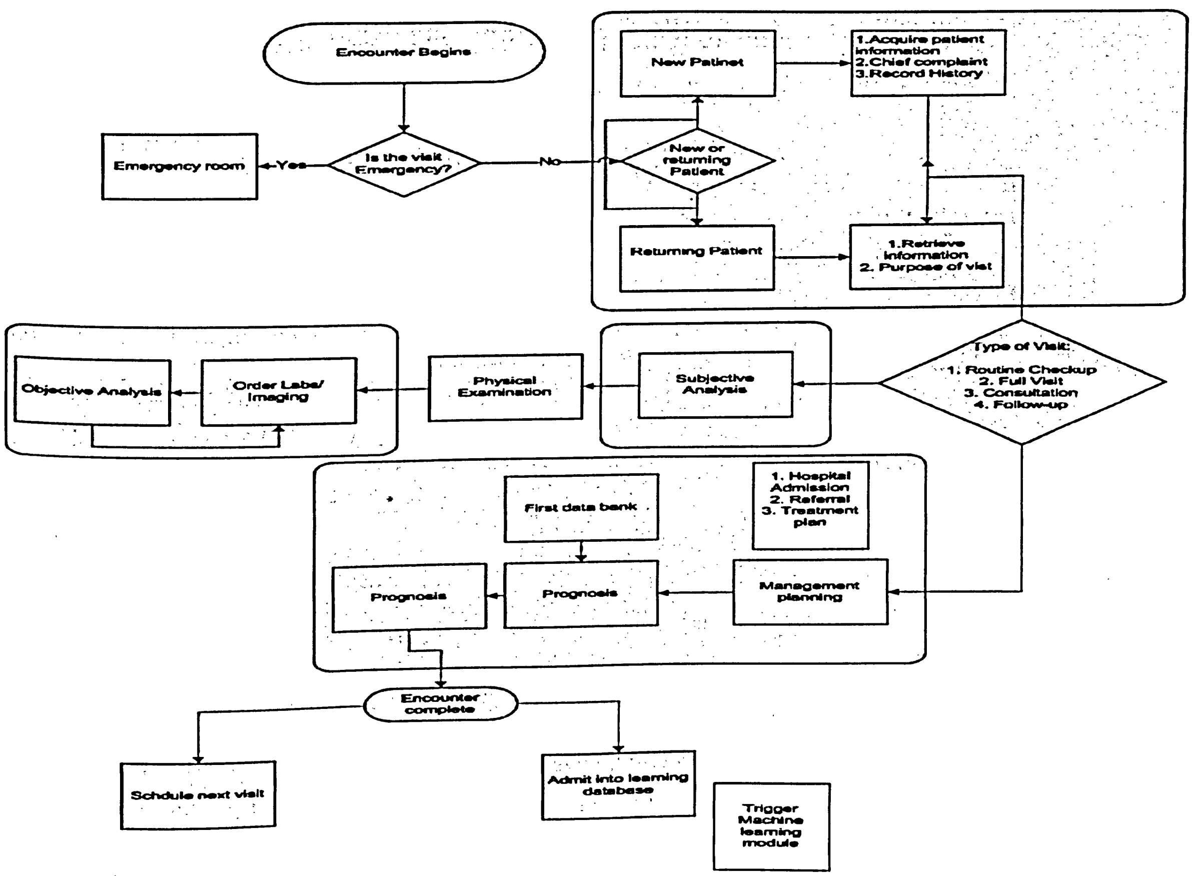



**Figure 2.4. Complete flow of the patient's encounter.**

## 2.2 Obtaining the Subjective Score

Various Artificial Intelligence techniques can be used for the "Subjective Analysis" including linear systems, Bayesian inference and Fuzzy Logic [28]. Since the target users of such expert systems are physicians, a model that corresponds with the thinking pattern of the physician is preferred. A simple scoring system can successfully represent this stage of diagnosis without complicating the diagnosis process. Once the preferred scoring method is chosen, a list of all the diseases is developed. The list covers the most common diseases in the field of cardiology. To give a better understanding, it is decided to group specific diseases into categories. After consultation with cardiologists and professionals 28 disease categories were selected in Cardiology in 10 classes. These 28 categories were then divided into 75 specific final diagnoses. Figure 2.5. shows the main 10 classes selected.

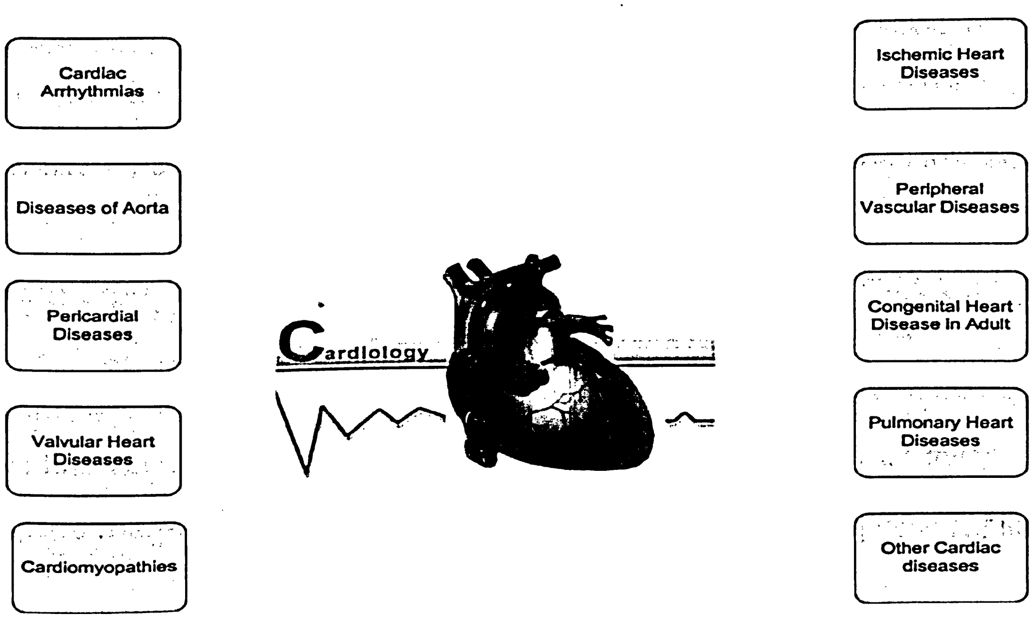



**Figure 2.5. Diseases are classified into 10 cardiac classes.**

Once the AI technique of a linear scoring system is chosen and the list of diseases to create a rule base is finalized, the actual scoring rules for each disease are relatively easy to develop. Two separate scores are calculated with two thresholds:

- A symptom score with a threshold of 50
- A history record with a threshold of 30

The simple IF-THEN statement that applies to every disease rule base is IF symptom score is > 50 AND history score is > 30 THEN disease is put into the probable diagnosis list. Once the physician assigns an appropriate score to each symptom or history item for each disease (Selection of $W_S$ and $W_H$ ) the subjective rule base is complete. Figure 2.6 shows completely how the subjective information is obtained.

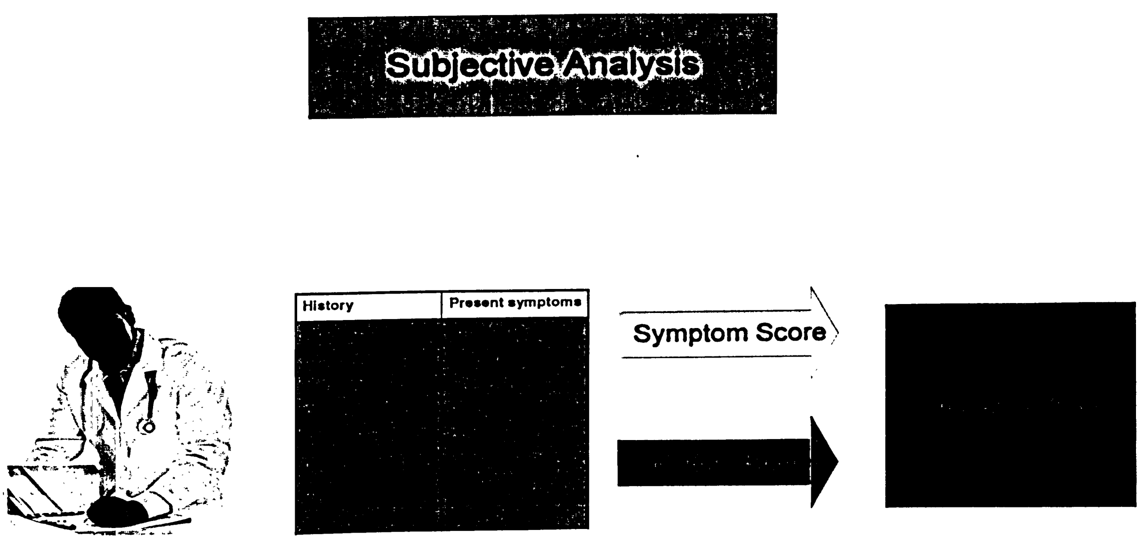



**Figure 2.6. Complete process of obtaining subjective information by the physician.**

## 2.3 Objective Analysis

After the physical examination and possible modification of the diagnosis list the "Objective level" of diagnosis begins. The expert system recommends specific laboratory tests along with possible imaging and other tests based on the obtained diagnosis list. This is achieved by relating the required tests to each of the 75 diseases mentioned earlier. Fuzzy logic rules are then used to interpret the results of the confirmatory tests and to determine weather each disease in the probable diagnosis list was present or absent. A separate fuzzy rule base is developed for each disease, to increase its modularity and to allow for easy updating of the rules [30]. To implement the fuzzy logic rule base, the First-Infer-Then-Aggregate (FITA) method with the Mamdani inference approach [31] is used.

The inputs for each rule base are often aggregated scores from each required lab test. The aggregated score for each test is determined by adding the scores of all the relevant findings for that test, where high scores are given to findings that indicate the presence of the disease. Tests with only one relevant finding do not need to be aggregated since the score for the single finding was used as an input. A final diagnosis index number for each suspected disease is generated using the FITA method [33]. This diagnosis index number is matched with a diagnosis as a treatment that outputted to the user. The diagnosis index is a continuous scale normalized from 0-1, where each disease has various ranges for the diagnosis index that matches particular diagnoses in words which will be outputted to the user.

A Fuzzy expert system seems appropriate for processing lab and imaging reports since medical terminologies in most labs are reported using terms such as "elevated" and "enlarged". These types of measurements can be better be handled using Fuzzy sets. One of the possible drawbacks of using Fuzzy Logic is its steep learning curve [34]. It is difficult and time consuming for a cardiologist to learn the fuzzy logic theory before being able to effectively develop and apply the rule bases. In order to shorten such learning curve for the physician, the standard method for developing fuzzy rule bases is modified. The FITA method for fuzzy inference appears to be appropriate for medical reasoning largely by the AI expert and knowledge engineer with limited input from the cardiologist. The Mamdani approach is chosen because it is more representative of the inference patterns used by the cardiologist.

The first step to develop the actual rule base is to choose relevant inputs for the 75 diseases considered in the expert system. This process is thought to be a relatively straightforward task for the cardiologist. The status of these inputs is also derived from lab reports and their associated terminologies. For instance, a lab report for Total Cholesterol reports the Total Cholesterol level as "Normal" for the range 120-200mg/ dL, "Low" for total Cholesterol levels less than 120 mg/ dL, and "High" for Total Cholesterol Levels greater than 200mg/dL [35]. For lab tests with several possible findings, an aggregated score is used as the input rather than using the individual findings. This ensures that the rule base size is kept reasonable as the number of rules increases exponentially with the number of inputs.

Developing Fuzzy Trapezoidal membership functions for the input states is carried out by spanning the membership functions of every input over its discourse with 0.5 membership overlap between adjacent membership grades [36]. The total number of rules for every disease is equal to the combination of all possible states of input (labs, imaging, etc) factors considered. The cardiologist assigns a final diagnosis number to specific combinations of the various input states, as this is similar a model in medical practice [37]. Therefore the output membership functions are trapezoids centered on the final diagnosis number provided by the expert.

The cardiologist assigns weights to the different lab test inputs based on the relative sensitivity of the various tests. These weights are incorporated into the fuzzy rule base. The cardiologist therefore fills out the "The Final Diagnosis Number" for all combinations of the input states

### 2.3.1 Fuzzy Expert System for Objective Diagnosis

Knowledge acquisition in fuzzy expert systems involves choosing a method of fuzzy inference that is most appropriate to the domain as well as in developing the fuzzy rule bas. There are four standard methods of inference available for fuzzy logic expert systems [38]. These methods are determined by the order in which inference and rule aggregation takes place and the meaning of the inference [39]. In short, there are two options available for the order in which inference from antecedents to consequent and rule aggregation takes place:

First infer each individual rule, and then aggregate the outcomes of each rule. Second is first aggregate all the inputs and outputs from different rules then infer each individual rule. The First Infer Then Aggregate (FITA) method is better suited to medical reasoning given that it closely resembles medical diagnosis process throughout the process and is more easily understood. This research examines the FITA approach only. There are also two options for assigning different "meanings" to the inference [40]:

- The Formal Logic Approach
- The Mamdani Approach

In this research the Mamdani approach is discussed. There are three steps in developing the rule base for fuzzy expert systems. Less than 8 relevant inputs are required for making a diagnosis. Once these relevant inputs are isolated, the various stages of the inputs need to be defined. To keep the number of rules covering all input combinations relatively low, the number of states is suggested to be between 2 to 6. Both the number of states (ie:High/Medium/Slow) as well as the fuzzy membership function associated with each state needs to be specified. During the final step the inputs are combined to generate a comprehensive rule base covering all combination of input states. Also, the domain expert assigns an output membership function to each rule and crosses out rules that are not applicable.Therefore depiction of each cardiac disease can be drawn as a weighted acyclic graph as shown in Figure 2.7 which is drawn based on Atrial Fibrilation.

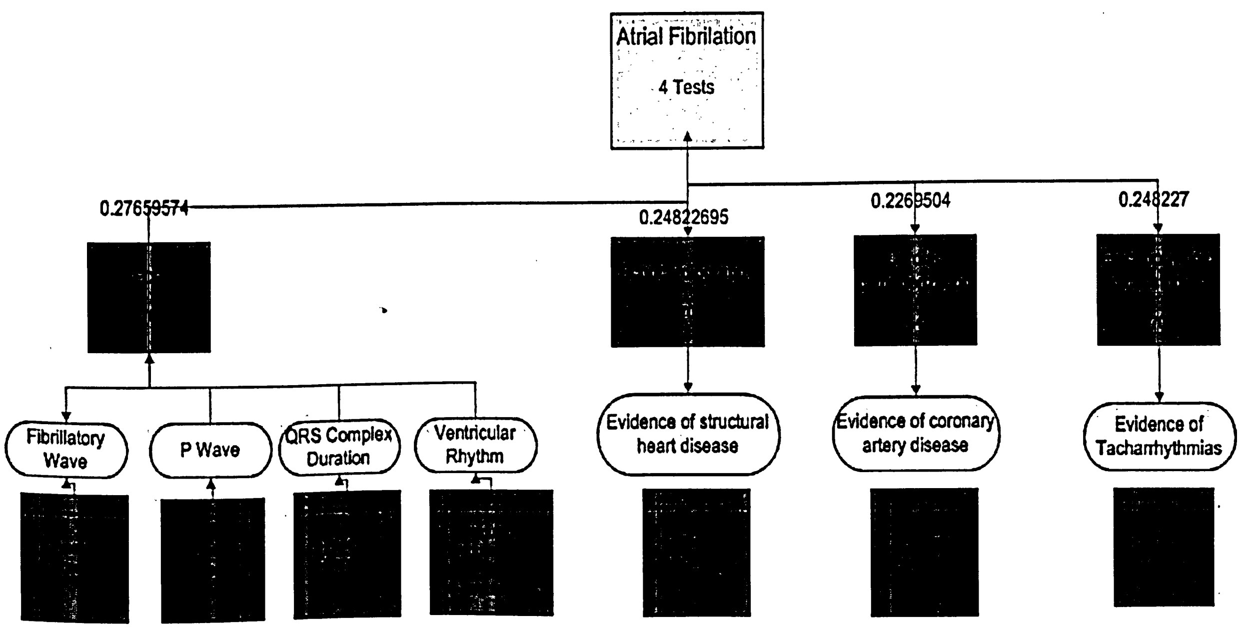



**Figure 2.7. Acyclic tree for representing the training cases for Atrial Fibrilation.**

Medical professionals with sufficient knowledge of fuzzy logic are required to accurately define the fuzzy membership functions. However, there might be problems associated with this approach since the performance of the system may be very subjective to individual human expert's intuition and a large time commitment is required from the medical experts. In some newer fuzzy expert systems [41], however the new definition of fuzzy sets has been accomplished through computer compilation of large amounts of data from many different sources and applying Fuzzy Cluster Method [42], [43].

The implementation of fuzzy inference within objective diagnosis involves the following four standard steps:

**1) Rule Firing and Antecedent aggregation**

Each rule is applied to a specific problem. The antecedents of each rule are aggregated to one numeric value, represented by 'A' in the 'IF THEN B' expression.

**2) Individual Rule Inference**

The value of the aggregated inputs for each single rule and the membership function of the consequent are combined using either the Mamdani or formal logic approach to inference.

**3) Aggregation of Inferred Consequent Membership Functions**

The resulting membership functions from the inference of each rule are aggregated together, usually with an 'OR' operator. Using an 'OR' operator to combine competing rules is semantically appropriate since in medicine it is common to say that either rule 1 OR rule 2 OR rule 3 is applied to a particular patient.

### 4) Deffuzification of Aggregated Consequent Membership Functions

Once all the inferred consequent membership functions have been aggregated into one membership function, this fuzzy membership function needs to be defuzzified to a crisp numeric answer. The following diagram depicts the steps in creating a fuzzy rule base.

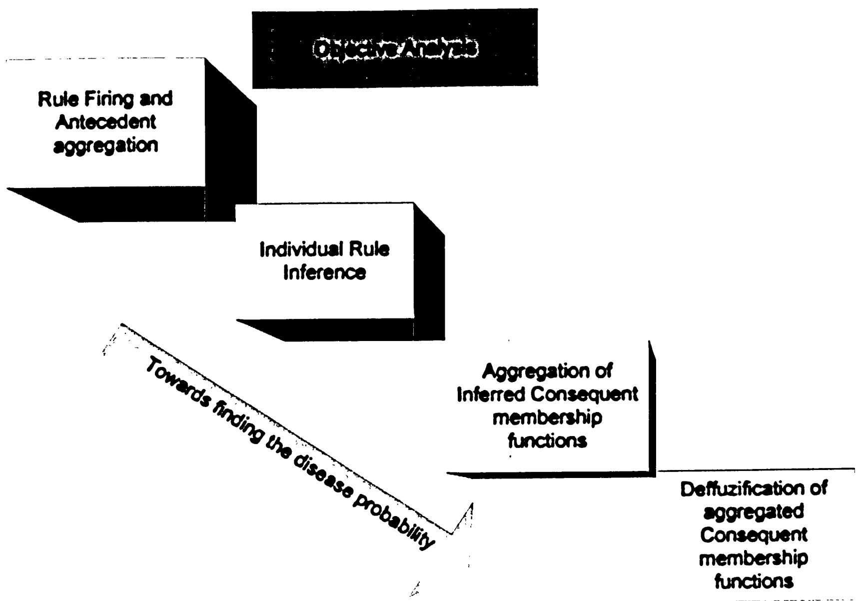



**Figure 2.8. Process of implementing fuzzy inference in objective analysis.**

The FITA method is chosen because it is a more common method and is easier to follow for the general practitioner once invoked in a rule base.

### 2.3.2 Case Study and Proof of Concept in Effectiveness of Fuzzy Inference

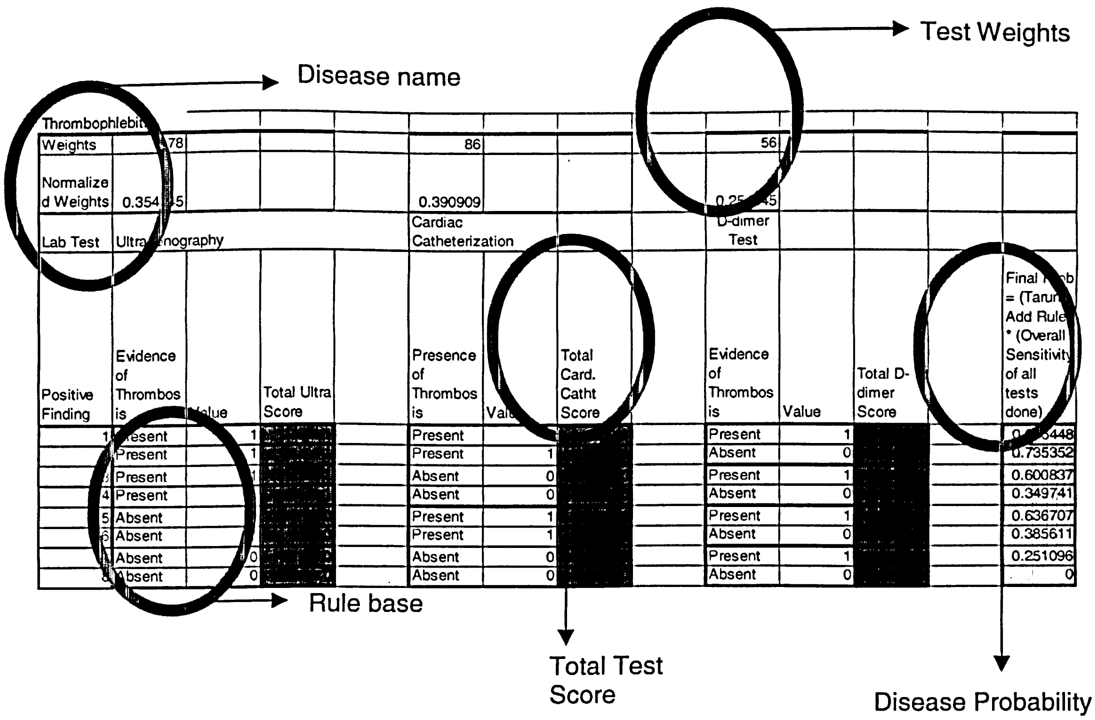
To justify the approach in designing a paradigm in obtaining objective evidence in diagnosis, the above mentioned steps were performed on an arbitrary cardiac disease called Thrombophlebitis. Table 2 shows the data format for the diagnosis of this disease. The disease name is shown on the top corner of the table. Thrombophlebitis is a disease which occurs when blood clots cause inflammation in one or more of the veins, typically in the legs [44]. It is classified under Peripheral Vascular diseases. The expert system suggests three tests to diagnose such disease in the objective level. These tests include:

- **D-dimer test**: A test for evaluating clot formation. It includes one finding which verifies if Thrombosis is either present or absent [44].

- **Cardiac Catheterization**: By inserting a plastic tube, blood pressure and oxygen level in the heart is measured. This test has one binary value [44].

- **Ultrasonography:** A test that uses sound waves and echoes to create images of the inside of the body. This test has one finding with a binary value [44].

  The last column of each test indicates the total score for that test.




| Thrombophlebit | | | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Weights | 78 | | | | 86 | | | | 56 | | | | |
| Normalized Weights | 0.354[illegible]5 | | | | 0.390909 | | | | 0.25[illegible]45 | | | | |
| Lab Test | Ultra[illegible]nography | | | | Cardiac Catheterization | | | | D-dimer Test | | | | |
| Positive Finding | Evidence of Thrombosis | Value | Total Ultra Score | | Presence of Thrombosis | Value | Total Card. Catht Score | | Evidence of Thrombosis | Value | Total D-dimer Score | | Final Prob = (Tarun Add Rule * (Overall Sensitivity of all tests done) |
| 1 | Present | 1 | | | Present | [illegible] | | | Present | 1 | | | [illegible]448 |
| | Present | 1 | | | Present | 1 | | | Absent | 0 | | | 0.735352 |
| 3 | Present | 1 | | | Absent | 0 | | | Present | 1 | | | 0.600837 |
| 4 | Present | [illegible] | | | Absent | 0 | | | Absent | 0 | | | 0.349741 |
| 5 | Absent | [illegible] | | | Present | 1 | | | Present | 1 | | | 0.636707 |
| 6 | Absent | [illegible] | | | Present | 1 | | | Absent | 0 | | | 0.385611 |
| [illegible] | Absent | 0 | | | Absent | 0 | | | Present | 1 | | | 0.251096 |
| [illegible] | Absent | 0 | | | Absent | 0 | | | Absent | 0 | | | 0 |

**Table 2. Training cases for diagnosis of Thrombophlebitis**

### 2.3.3 Test Weights

Test weights are assigned by the medical specialist, in this case the cardiologist. These numbers are obtained in accordance with cardiology references and are passed to the expert system through the doctor's perception. Data is weighted and numbered from 0 to 100 based on its importance. For instance on the above example, D-dimer test is given the value of 56 and Cardiac Catheterization is given the value of 86. This implies that the latter test has more significance in obtaining the probability of the disease compared to the former test. The test weights are then normalized and used in calculating the final probability of the diseases.

### 2.3.4 Rule Bases and the Total Test Score for Each Lab Test

In order to complete the rule base for the use of fuzzy inference, the findings of each test should be obtained and combined with other required tests to create a comprehensive probability combination. As it can be seen, the first lab test is D-dimer test with only one (binary) finding with a binary value. The first input in the Thrombophlebitis table can be seen in Table 3. The only finding for D-dimer test is "Evidence of Thrombosis" which can be either "Present" or "Absent". If evidence of the finding is Present, the Value of the findings will be 1, if Absent it will be zero. Since there is only one finding for this test, the total score for the test is equal to available finding. If there were more findings per test, the total test score would have been equal to the summation of all the findings. Table 3 shows the first input to the objective table.

**Table 3. First input for the diagnosis of Thrombophlebitis**

| Thrombophlebitis | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|
| Weights | | | | | | | 56 | | |
| Normalized Weights | | | | | | | | | |
| Lab Test | | | | | | | D-dimer Test | | |
| Positive Finding | | | | | | | Evidence of Thrombosis | Value | Total D-dimer Score |
| 1 | | | | | | | Present | 1 | 1 |
| 2 | | | | | | | Absent | 0 | 0 |
| 3 | | | | | | | Present | 1 | 1 |
| 4 | | | | | | | Absent | 0 | 0 |
| 5 | | | | | | | Present | 1 | 1 |
| 6 | | | | | | | Absent | 0 | 0 |
| 7 | | | | | | | Present | 1 | 1 |
| 8 | | | | | | | Absent | 0 | 0 |

The Second test will be Cardiac Catheterization which will be the second input to the Thrombophelibits table:

**Table 4. Second input for the diagnosis of Thrombophlebitis**

| | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|
| Weights | | | | 86 | | | 56 | | |
| Normalized Weights | | | | | | | | | |
| Lab Test | | | | Cardiac Catheterization | | | D-dimer Test | | |
| Positive Finding | | | | Presence of Thrombosis | Value | Total Card. Catht Score | Evidence of Thrombosis | Value | Total D-dimer Score |
| 1 | | | | Present | 1 | 1 | Present | 1 | 1 |
| 2 | | | | Present | 1 | 1 | Absent | 0 | 0 |
| 3 | | | | Absent | 0 | 0 | Present | 1 | 1 |
| 4 | | | | Absent | 0 | 0 | Absent | 0 | 0 |
| 5 | | | | | | | | | |
| 6 | | | | | | | | | |
| 7 | | | | | | | | | |
| 8 | | | | | | | | | |

It can be seen that the total number of rules being created after the second input is equal to the number of the first test multiplied by the findings of the second test, which in this case is $2.2 = 4$. We can conclude that the total number of rules equals to the number of all the lab findings.

The third and last input is the Ultrasonography with one possible finding of binary value. After creating all the combinations, the final input in the table will be shown as Table 5.

**Table 5. Final input for the diagnosis of Thrombophlebitis**

Thrombophlebitis

| | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|
| Weights | 78 | | | 86 | | | 56 | | |
| Normalized Weights | | | | | | | | | |
| Lab Test | Ultrasonography | | | Cardiac Catheterization | | | D-dimer Test | | |
| Positive Finding | Evidence of Thrombosis | Value | Total Ultra Score | Presence of Thrombosis | Value | Total Card. Catht Score | Evidence of Thrombosis | Value | Total D-dimer Score |
| 1 | Present | 1 | 1 | Present | 1 | 1 | Present | 1 | 1 |
| 2 | Present | 1 | 1 | Present | 1 | 1 | Absent | 0 | 0 |
| 3 | Present | 1 | 1 | Absent | 0 | 0 | Present | 1 | 1 |
| 4 | Present | 1 | 1 | Absent | 0 | 0 | Absent | 0 | 0 |
| 5 | Absent | 0 | 0 | Present | 1 | 1 | Present | 1 | 1 |
| 6 | Absent | 0 | 0 | Present | 1 | 1 | Absent | 0 | 0 |
| 7 | Absent | 0 | 0 | Absent | 0 | 0 | Present | 1 | 1 |
| 8 | Absent | 0 | 0 | Absent | 0 | 0 | Absent | 0 | 0 |

The next step is to create a normalized weight for the lab tests and calculate the final probability for each combinations and rules.

### 2.3.5 Normalized Weight for Each Disease

Normalized weight of each disease is a measurement with maximum value of 1 and is calculated by dividing the test weights by the total sum of all tests required for the disease. If we denote the disease with $D$, the labs related to the disease with $L$, the findings for each lab with $f$, the assigned weight for each lab with $w$ and the Normalized weight for each lab $i$ with $N$, we can say:

$$N = \frac{w_i}{\sum_{1}^{n} w_n} \qquad (2.4)$$

For instance the normalized weight for Ultrasonography in Thrombophlebitis is equal to:

$$N_{\text{Ultrasonography-Thrombophlebitis}} = \frac{78}{78+86+56} = 0.354545455$$

### 2.3.6 Disease Probability

The disease probability for each combination of findings will be equal to the summation of each individual weighted test score multiplied by the multiplication of the percentage of each disease weight as it is shown in the following formula:

$$P = \left[ \sum_{i=1}^{n} S_n / 1.\omega_n \right] . \left[ 1 - \left( \prod_{j=1}^{m} 1 - W_m / 100 \right) \right] \tag{2.5}$$

After calculating the disease probability, the next input on the Thrombophlebitis will look like the following figure:

**Table 6. Calculating the final probability based on the findings**

| Thrombophlebitis | | | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Weights | 78 | | | | 86 | | | | 56 | | | | |
| Normalized Weights | 0.354545 | | | | 0.390909 | | | | 0.254545 | | | | |
| Lab Test | Ultrasonography | | | | Cardiac Catheterization | | | | D-dimer Test | | | | |
| Positive Finding | Evidence of Thrombosis | Value | Total Ultra Score | | Presence of Thrombosis | Value | Total Card. Catht Score | | Evidence of Thrombosis | Value | Total D-dimer Score | | Final Prob = (Tarun's Add Rule) * (Overall Sensitivity of all tests done) |
| 1 | Present | 1 | 1 | | Present | 1 | 1 | | Present | 1 | 1 | | 0.986448 |
| 2 | Present | 1 | 1 | | Present | 1 | 1 | | Absent | 0 | 0 | | 0.735352 |
| 3 | Present | 1 | 1 | | Absent | 0 | 0 | | Present | 1 | 1 | | 0.600837 |
| 4 | Present | 1 | 1 | | Absent | 0 | 0 | | Absent | 0 | 0 | | 0.349741 |
| 5 | Absent | 0 | 0 | | Present | 1 | 1 | | Present | 1 | 1 | | 0.636707 |
| 6 | Absent | 0 | 0 | | Present | 1 | 1 | | Absent | 0 | 0 | | 0.385611 |
| 7 | Absent | 0 | 0 | | Absent | 0 | 0 | | Present | 1 | 1 | | 0.251096 |
| 8 | Absent | 0 | 0 | | Absent | 0 | 0 | | Absent | 0 | 0 | | 0 |

Disease probability for one rule base

After the completion of the data table, a set of rule bases will be created to be used by the fuzzy inference engine and to create a knowledge base for the disease which in this scenario is Thrombophelbitis.

Following the procedures mentioned in section 2.3.4, the fuzzy logic is created using the following procedures:

- Assigning the number of input membership functions
- Obtaining antecedents parameters
- Preparing a list of rule indices
- Reshaping the antecedents matrix
- Defining the consequent trapezoidal membership

After generating the fuzzy logic, the system will be trained based on the complete information. This training will enable the system to diagnose a case with incomplete information which is usually the case. This means that the system is capable of diagnosis even at times where the information is incomplete. The patient provides certain subjective and objective information to the physician. Upon completion, this information is entered into the expert system for further processing. After performing the training and obtaining an error rate between 0 to 0.5 % or 99.5% accuracy level, the training can be terminated and the diagnosis rules can be utilized. Before creating the fuzzy trapezoids which represent the complete information, the error rate should be measured to validate the diagnosis [45].

Figure 2.9 shows how the predicted diagnosis is aligned with the system's generated rules. Since the error rate obtained in this example is zero, both the prediction and expertise are overlapping.

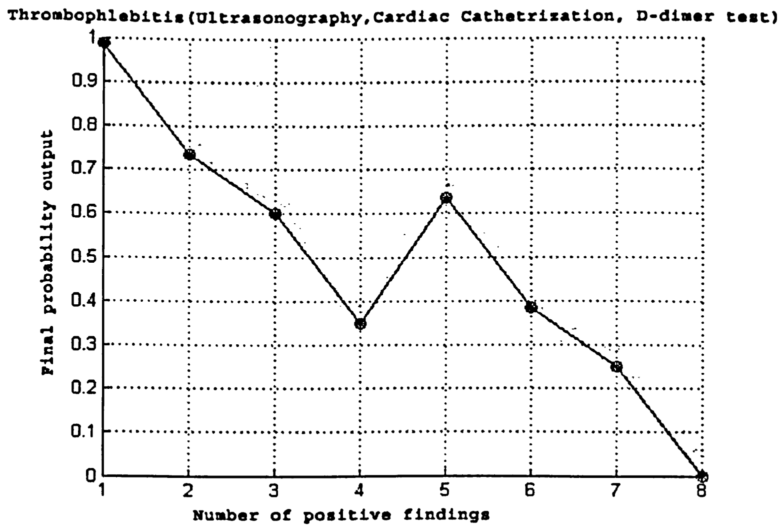



**Figure 2.9. Predicted diagnosis vs. system's generated rules in Thrombophlebitis.**

The following example shows the evaluations in Arterial Hyper-tension with 3 tests and error rate of 0. Each circle in the graph represents one rule and 48 diagnostic rules in total.

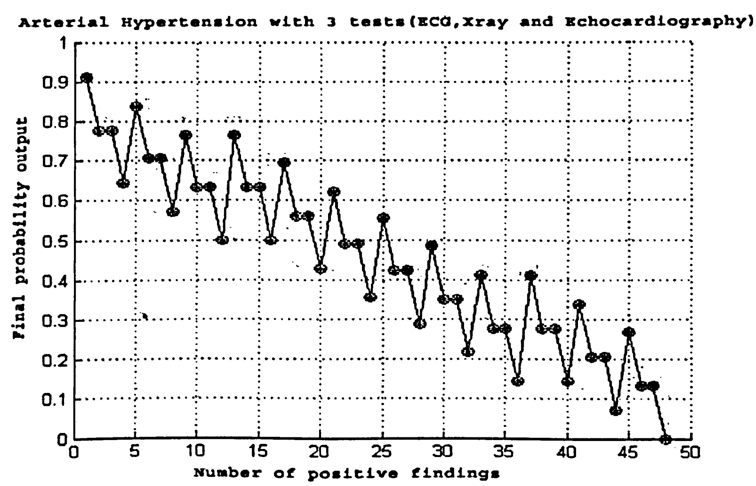



**Figure 2.10. Predicted diagnosis in Arterial Hypertension with 3 tests.**

The subsequent example shows evaluations for an atrial disease called Atrial premature beats. As it can be seen rules are created without achieving the zero error rate. Since the error rate is more than 0.5% the model cannot be accepted for the diagnosis engine and further training is required to achieve a smaller error rate.

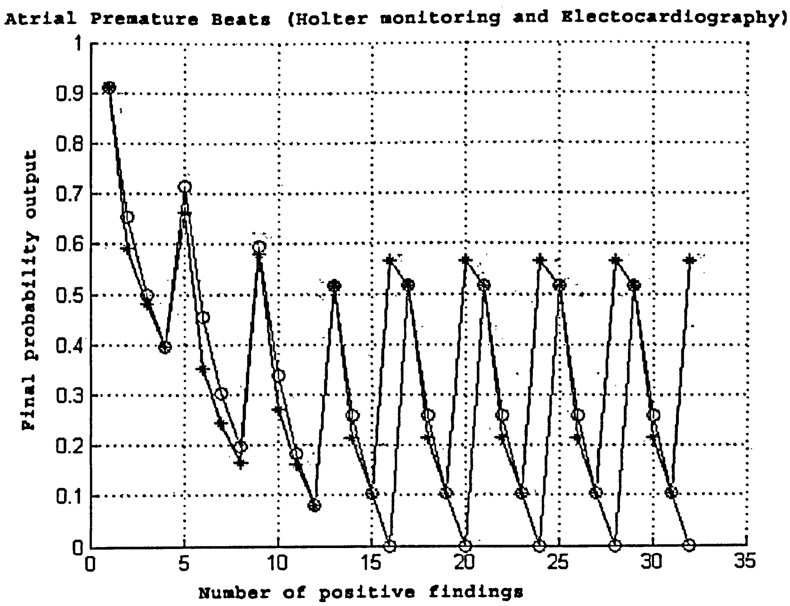



**Figure 2.11. Predicted diagnosis with 0.03 error rate.**

Once the rules are approved and the error rate is accepted, the fuzzy trapezoidal function will be drawn as shown in Figure 2.12. These trapezoids represent the knowledge base for the objective analysis of each disease. The following out put is based on Thrombophlebitis.

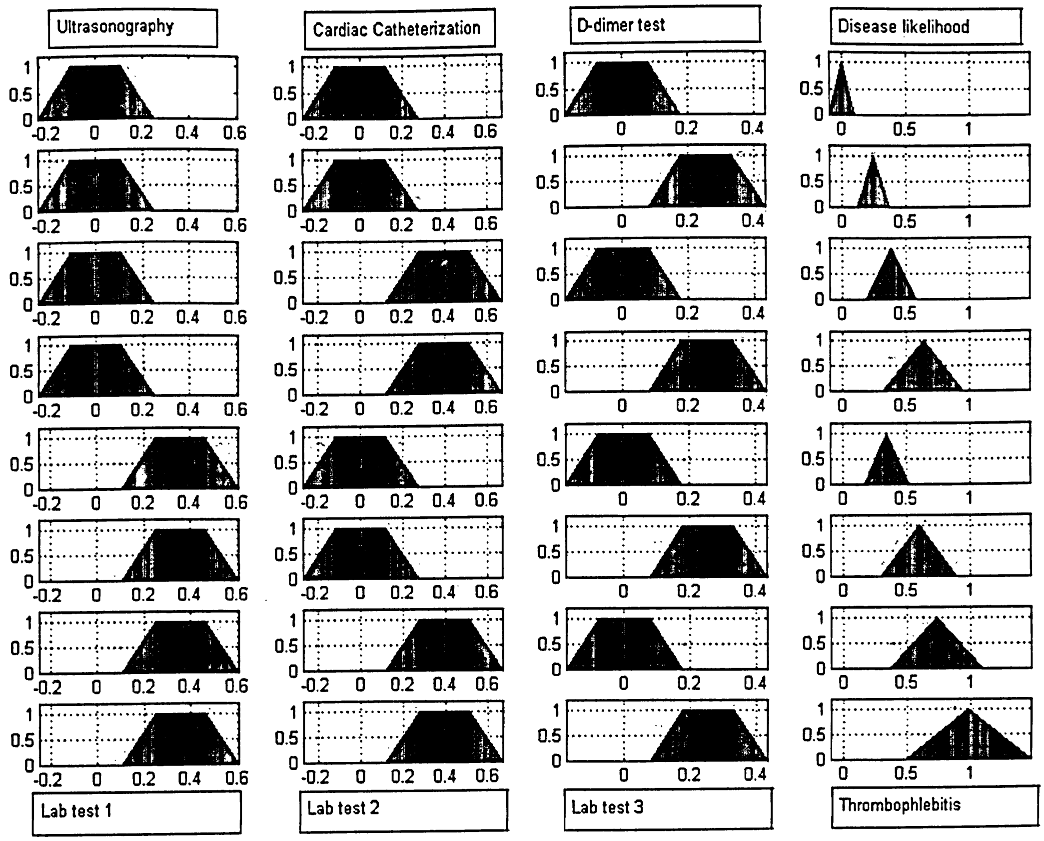



**Figure 2.12. Trapezoid membership functions for Thrombophlebitis.**

Each row on the trapezoidal output represents a row on the tables. The first row of the table represents the first row of the trapezoidal output. This is shown in the Figure 2.13 below.

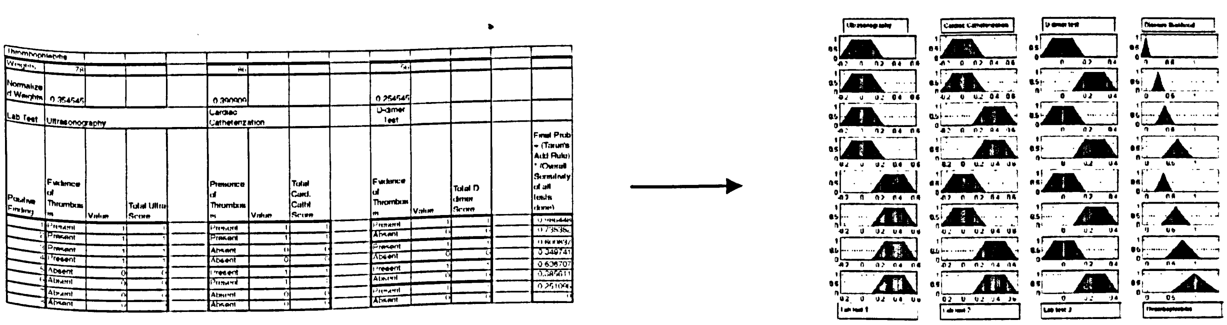


**Figure 2.13. Creation of the trapezoidal membership functions from objective tables.**

In Figure 2.13 it is observed that the derived trapezoidal output from the fuzzy inference is easier to perceive compared to the initial objective data. Therefore using the fuzzy expert system, patient's objective information is transformed into a meaningful logic that can be utilized as a set of rules for diagnosis of patients who follow the same pattern. Using Bayesian statistics, we will be able to measure the similarity between potential diseases and to find the most probable one.

In this research, the training cases for all cardiac diseases are developed and tested. There are a total number of 312 tables and fuzzy rule bases created which due size constraints are attached to this document as a CD-ROM.

# CHAPTER 3: BAYESIAN DIAGNOSIS

## 3.1 Introduction

In chapter 2, the likelihood of the disease was obtained by implementing a fuzzy inference. However, there are instances that the system proposes two or more diseases with high probability. Using Bayesian decision protocol, the physician will be able to choose between the high probable diseases with more confidence. Bayesian models can be considered efficient in such situations as they help to choose the most probable diagnosis in the derived probable hypotheses list as discussed in chapter 3. The goal of this chapter is to help develop intuition for probabilistic inference, its meaning, working and its practical implications for medical decision making. The Bayesian engine for this expert system should achieve following goals:

- Ability to perform multiple lab analysis
- Ability to decide between an array of probable diagnosis
- Ability to utilize a loss function to measure diagnosis risk

## 3.2 Bayesian Approach in Diagnosis

The most important aspect of Bayesian modeling is that all uncertainties are represented by probability distributions [46]. In medical decisions there are different sources of uncertainty that need to be understood and quantified. These include variations in prognosis from patient to patient, sampling variability in experimentation, heterogeneity of results across different studies, imperfect expert knowledge of critical quantities or mechanisms, and so forth [47]. There are of course differences among these uncertainties. These differences and their practical implications are recognized in

Bayesian modeling [47]. In this research Bayesian model is used to give a higher confidence to the user when the decision is between multiple high-probability diagnoses. This is achieved by creating a diagnosis space where the correct diagnosis can be plotted within the most confident decision region.

### 3.2.1 Decision Rules

Using the score obtained from the Subjective and Objective analysis, a prior score is obtained for all the probable diseases in the list of probable hypotheses. This score acts as the prior information for the diseases. If we denote each disease with $\omega_i$, in the decision between two probable diagnoses we can say:

Disease 1: $\omega_1$

Disease 2: $\omega_2$

If the prior likelihood of these two diseases are the same, by denoting the posterior probability with $P(\omega_i)$ which is the score derived from the Subjective and Objective analysis, we can say that the probability of the diseases based on the equivalent probability prior is:

$$P(\omega_1) = P(\omega_2) \tag{3.1}$$

However, if the posterior probability is different in the probable diagnosis list, the decision with the higher posterior probability will be chosen:

If ( $P(\omega_1) > P(\omega_2)$ )

  Decide $\omega_1$

Else

  Decide $\omega_2$

### 3.2.2 Decision Rule Based on the Diagnosis Prior

In most medical decisions, prior information is not sufficient to prioritize between multiple likely diseases. Therefore a more thorough analysis is required to create a higher confidence in the physician's decision. Usually physicians order more objective tests or review the details of the current tests for such decisions.

If the system is supposed to choose between two likely diseases namely $\omega_1$ and $\omega_2$, a shared lab analysis is selected such as $x$ which acts as a criteria in choosing between the two diseases. Using $x$, a class conditional probability [48] is defined which can be denoted as follow:

$$P(x \mid \omega_1) \tag{3.2}$$

This means that the probability density function for lab test $x$, given that the state of diagnosis is $\omega_1$. By choosing a lab result, $x$ from the list of the shared labs between $\omega_1$ and $\omega_2$, we can say:

$P(x \mid \omega_1)$ AND $P(x \mid \omega_2)$ describe the difference between the two arbitrary diseases based on the lab result $x$.

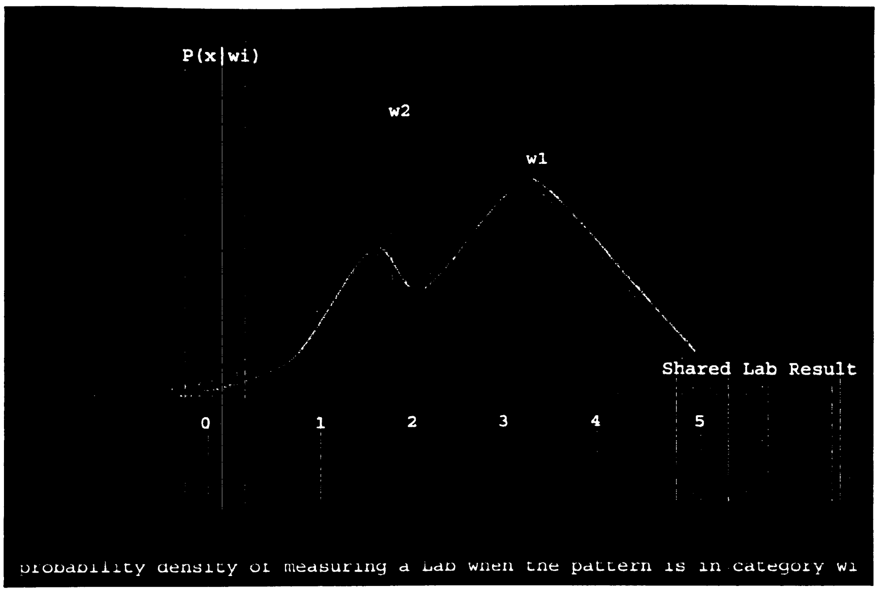



**Figure. 3.1. Probability density of measuring a Lab with two probable diseases**

Suppose that we know the prior probability of the disease $w_j$ is $P(\omega_j)$ and its conditional probability based on lab result $x$, is $P(\omega_j \mid x)$. By analyzing the value of $x$ , we would like to measure the diagnosis probability as in (3.3) based on the Bayes Formula [49]:

$$P(\omega_j \mid x) = P(x \mid \omega_j).P(\omega_j) / P(x) \qquad (3.3)$$

By denoting the number of hypotheses with $n$, it can be concluded that:

$$P(x) = \sum_{j=1}^{j=n} P(x \mid \omega_j) P(\omega_j) \qquad (3.4)$$

This means that if we are deciding between two possible diagnoses we can say:

$$P(x) = \sum_{j=1}^{j=2} P(x \mid \omega_j) P(\omega_j) \qquad (3.5)$$

Therefore we can conclude that the posterior probability of the disease is equal to the prior likelihood of the disease divided by the lab evidence. This is shown on Figure 3.2

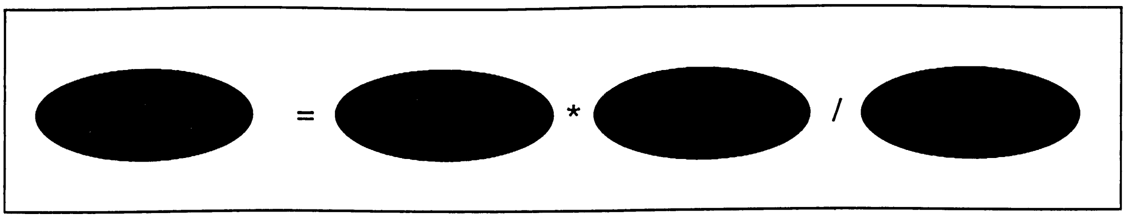



**Figure. 3.2.A. Obtaining the posterior information**

By a simple algebra we can derive Figure 3.2.B:

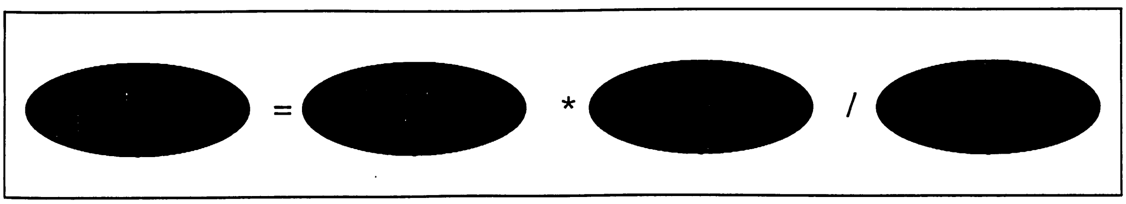



**Figure. 3.2.B. Obtaining the likelihood of the disease**

Bayes Formula shown in (3.3) shows that by observing the value of lab result $x$, we can convert the prior probability $P(\omega_j)$ to a posterior as $P(x \mid \omega_j)$ - the probability of the state of disease being the diagnosis $\omega_j$. We call $P(x \mid \omega_j)$ the likelihood of disease $\omega_j$ with respect to $x$. The lab evidence mentioned in Figure 5.3? is merely a scale factor that guarantees that the posterior probabilities sum to one as shown in Objective Analysis section.

### 3.2.3 Calculation of Error in Deciding Between Hypotheses

A simple logic in deciding between two probable diagnoses using a shared lab result is to choose the diagnosis with higher posterior probability. This means that if the correct disease is $\omega_i$ and we choose $\omega_j$ instead, the probability of error is $P(\omega_j \mid x)$.

So in deciding between two diseases we can say that if $x$ is an observation from a lab test:

$$\begin{array}{ll} \text{If } P(\omega 1 \mid x) > P(w2 \mid x) \longrightarrow \text{True state of disease: } \omega 1 \\ \text{If } P(\omega 1 \mid x) < P(\omega 2 \mid x) \longrightarrow \text{True state of disease: } \omega 2 \end{array} \quad (3.6)$$

For example if the decision is between $\omega 1$ and $\omega 2$ by having the prior values of 2/3 and 1/3 we can say:

Disease Priors :
$P(\omega_1) = 2/3$
$P(\omega_2) = 1/3$
$x = \text{Labx result}$
$P(\omega_1) = 0.92$
$P(\omega_2) = 0.08$
$P(\omega 1) + P(\omega 2) \cong 1$

Therefore in deciding between two hypotheses we can say:

$$\begin{array}{l} P(error \mid x) = P(\omega_1 \mid x) \text{ If decision is } \omega_2 \\ P(error \mid x) = P(\omega_2 \mid x) \text{ If decision is } \omega_1 \end{array} \quad (3.7)$$

$x$ is the shared lab result and $\omega_i$ is the diagnosis.

Therefore the probability of error can be written as:

$$P(error \mid x) = \min[P(\omega 1 \mid x), P(\omega 2 \mid x] \quad (3.8)$$

### 3.2.4 Risks and Loss Functions in diagnosis

In order to enhance the proposed system, the Bayesian engine should be able to diagnose more than two states of diseases using multiple features. So far the engine has been proposed based on two states of diseases and one lab. In order to gain such goal, following features should be added to the expert system:

- Ability to use more labs as a shared feature
- Ability to decide between more than two diseases
- Introducing a loss function which is more general than the probability of error

Allowing the use of more than one feature requires replacing the scalar $x$ by a feature vector such as $X$ , where $X$ is in a $d$ -dimensional Euclidean space $R^d$ called the feature space. Allowing more than two state of nature provides us with the more confidence when deciding between diseases. Allowing actions in addition to classification allows the possibility of rejection which means refusing to take decisions in close cases. The Loss Function states exactly how costly each action is and is used to convert a probability determination into a decision.

Let $\{\omega_1, \omega_2, \ldots, \omega_c\}$ be the set of diagnoses

$\{\alpha_1, \alpha_2, \ldots, \alpha_a\}$ be the set of diagnostic decisions

$\lambda(\alpha i \mid \omega j)$ will be the potential loss for taking decision $\alpha i$ when the true diagnosis is $\omega$j

The Bayesian risk is calculated as: $R =$ Sum of All $R(\alpha_i \mid x)$ for i = 1,...,a

The goal of a successful diagnosis will be reducing the risk as much as possible, therefore in order to reduce such risk we can say:

Minmizing R $\leftrightarrow$ Minimizing $R(\alpha_i \mid x)$ for i = 1,...,a (3.9)

Based on (3.10) following can be obtained as a rule for risk calculation:

$$R(\alpha i \mid x) = \sum_{j=1}^{j=c} \lambda(\alpha i \mid \omega j) P(\omega j \mid x) \quad \text{For } i = 1,\ldots,a \tag{3.10}$$

This means that the diagnosis action $\alpha_i$ is taken when $R(\alpha_i \mid x)$ is minimum.

Let us consider these facts when applied to the special case of two-category diagnosis. Diagnostic action $\alpha_1$ corresponds to deciding that the true state of disease is $\omega_1$ and diagnostic action $\alpha_2$ corresponds to deciding that it is $\omega_2$. Let $\lambda ij = \lambda(\alpha_i \mid \omega_j)$ be the loss incurred for deciding $\omega_i$ when the true disease is $\omega_j$. Based on (3.10) we can say:

$$\begin{aligned} R(\alpha_1 \mid x) &= \lambda_{11} P(\omega_1 \mid x) + \lambda_{12} P(\omega_2 \mid x) \\ R(\alpha_2 \mid x) &= \lambda_{21} P(\omega_1 \mid x) + \lambda_{22} P(\omega_2 \mid x) \end{aligned} \tag{3.11}$$

Therefore a simple diagnosis rule is If $\mathrm{R}(\alpha 1|\mathrm{x}) < \mathrm{R}(\alpha 2|\mathrm{x})$, Diagnostic action will be $\alpha_1$ and the selected disease will be $\omega_1$. In terms of posterior probabilities we choose the disease $\omega_1$ if:

$$(\lambda_{21} - \lambda_{11}) P(\omega_1 \mid x) > (\lambda_{12} - \lambda_{22}) P(\omega_2 \mid x) \tag{3.12}$$

Using (3.13), we will be able to create a threshold which can be used as a criteria in deciding optimal decisions. If the likelihood ratio exceeds the threshold value independent of the pattern of $x$ we can say:

$$\text{If } \frac{P(x \mid \omega 1)}{P(x \mid \omega 2)} > \frac{\lambda 12 - \lambda 22}{\lambda 21 - \lambda 11} \bullet \frac{P(\omega 2)}{P(\omega 1)} \tag{3.13}$$

This form of decision as shown in (3.14) focuses on the $X$ -dependence of the probability densities. $P(X \mid \omega_j)$ is a function of $\omega_j$. Using this we can form the likelihood ratio $\frac{P(x \mid \omega 1)}{P(x \mid \omega 2)}$. Therefore the Bayesian decision rule discussed earlier can be interpreted as calling for deciding $\omega_1$, if the likelihood ratio exceeds a threshold value that is independent of the observation $X$.

## 3.3 Di/Polychotomizer Functions for Diagnosis Selection

In order to distinguish between the diseases, a disease classifier should be implemented which is capable of analyzing the disease's probabilities using a pattern classifier. The pattern classifier is analyzing the probable diseases by a given set of lab results. The lab results will be stored as a set of discriminant functions $g_i(x), i = 1,...,c$. The classifier is said to assign a feature vector $X$ to class $\omega_i$ if

$$g_i(x) > g_j(x) \text{ for all } j \neq i \tag{3.14}$$

The classifier is viewed as a network or machine that computes $c$ discriminant functions and selects the category corresponding to the largest discriminant. The discriminant functions can be created in different forms but the decision rules are equivalent.

The result of the decision rules is to divide the feature space into $c$ decision regions, $\Re 1,...,\Re c$. If $g_i(x) > g_j(x)$ for all $j \neq i$ then $X$ is in $\Re_i$ and the decision rule assigns $X$ to $\omega_i$. Figure 3.4 shows the logic of such classifier machine.

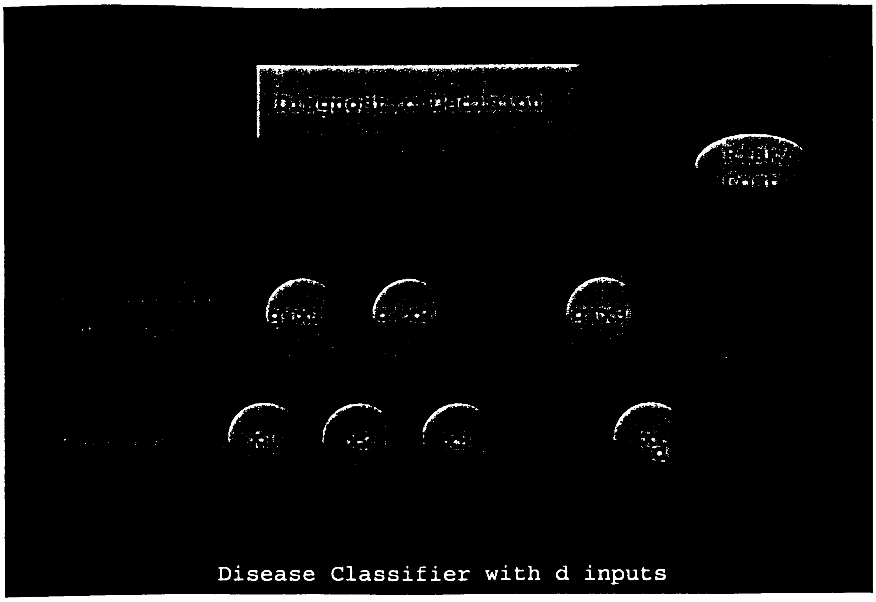



**Figure 3.3. A diagnostic classifier with d inputs**

Figure (3.4) is based on a multi-category diagnosis case where $x_1,...x_c$ are the Hypotheses and $g1(x),...gc(x)$ are the discriminant functions. In many Bayesian research [50] a two-category classification has been given a separate treatment. A classifier that places a pattern in one of only two categories is called a dichotomizer. In a dichotomizer, instead of using two discriminant functions $g_1$ and $g_2$ and assigning $X$ to $\omega_1$ if $g_1 > g_2$, it is proposed to define a single discriminant function such as:

$$\begin{aligned} & g(x) = P(\omega_1 \mid x) - P(\omega_2 \mid x) \\ & g(x) = g_1(x) - g_2(x) \\ & \text{If } g(x) > 0 \Rightarrow x \in \omega_1 \\ & \text{else } x \in \omega_2 \end{aligned} \tag{3.15}$$

This means: Choose disease $\omega_1$ if g(x)>0 otherwise choose disease $\omega_2$

Therefore, a dichotomizer can be viewed as a machine that computes a single discriminant function $g(x)$, and classifies $x$ according to the sign of the lab result. Using such dichotomizer function the Bayesian feature space can be shown as Figure (3.7) in which a two dimensional two-category classifier are shown along with two hyperbolic decision boundaries $\Re_1$ and $\Re_2$. The ellipses mark where the density is $1/e$ times at the peak of the distribution [50].

### 3.4 Diagnostic Spaces

Using the paradigms mentioned, we will be able to create the diagnosis space in which the less probable diagnoses are eliminated and the most probable ones can be selected within decision boundaries defined. Using the Bayesian model, a decision space will be created. Using the probability priors, certain decision boundaries are created and the true state of disease will be plotted in this space. Depending in which decision boundary, the diagnosis will be plotted, the true state of disease will be diagnosed.

In accordance with the data obtained through subjective and objective analysis, a disease space is created in which the less likely diagnoses are eliminated and the decision is performed among the most probable diseases. Such diagnosis space is shown in Figure 3.4. Diseases belongs to the same cardiac class are grouped separately and they will be analyzed using the dichotomizer function. At the end, the value of $g(x)$ is calculated the highest $g(x)$ is selected as the main diagnosis.

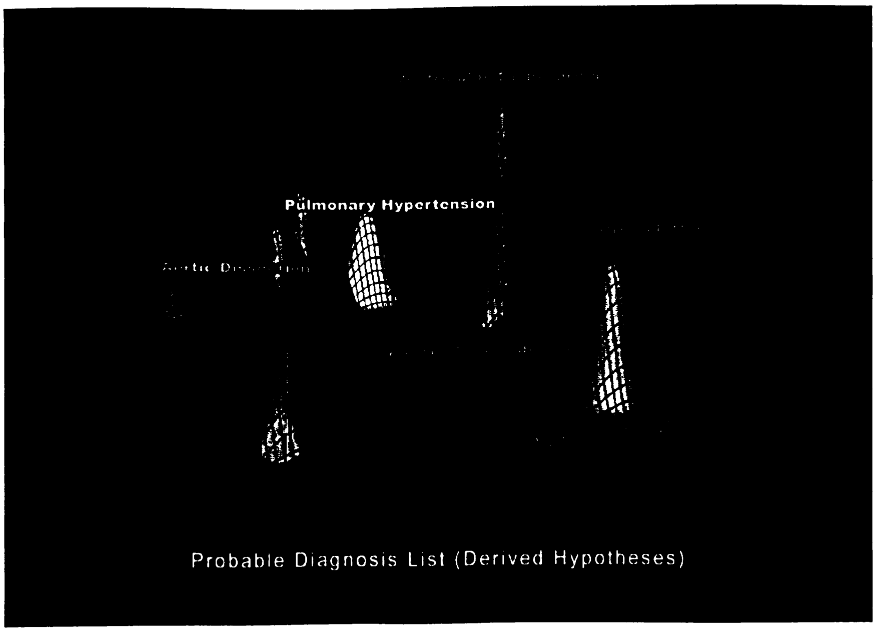



**Figure. 3.4. Derived Hypotheses from the probable diagnosis list**

Regardless of weather the prior probabilities are equal or not, it is not actually necessary to compute distances. Expansion of the quadratic form $(x-\mu_i)^t(x-\mu_i)$ [XX], yields the following discriminant functions obtained from [51]:

$$gi(x) = -\frac{1}{2\sigma^2}[x'x - 2\mu_i{}^t x + \mu_i{}^t \mu_i] + \ln P(\omega_i) \tag{3.16}$$

Where $\mu = \varepsilon[x] = \int xp(x)dx$ and (3.17)

$$\sigma^2 = \varepsilon[(x-\mu)^2] = \int_{-\infty}^{\infty} (x-\mu)^2 p(x)dx \tag{3.18}$$

Figure (3.6) shows how the decision is made between two diseases from Cardiomyopathies with one shared lab test, ECG.

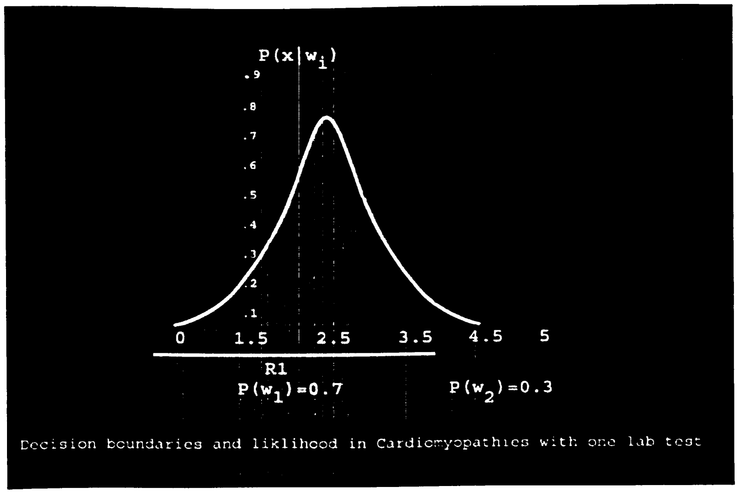



**Figure. 3.5. Decision in Cardiomyopathies with one shared lab test**

Figure 3.7 shows how such diagnosis space is created along with the decision boundaries in decision making between two diseases with two shared labs from Cardiac Arrhythmias.

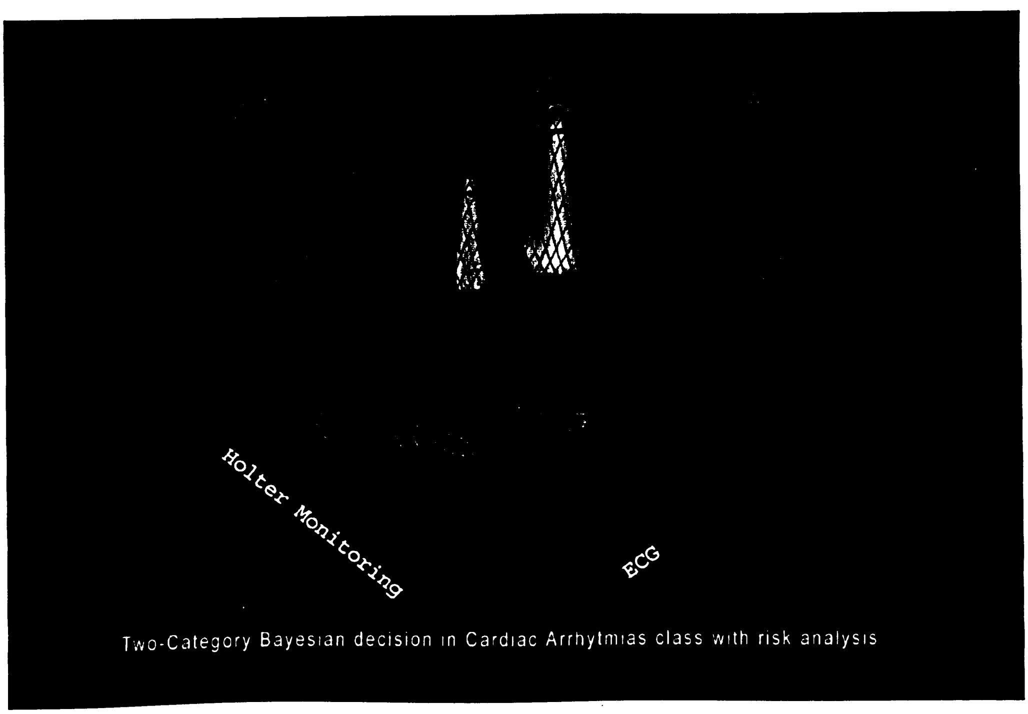



**Figure. 3.6. Two-Category decision in Cardiac Arrhytmias.**

By using the score obtained from the Objective lab analysis, a point will be selected on this space using two set of lab results. For instance deriving data from the patient's subjective/objective analysis, a point is plotted in the decision boundary of $\Re_1$ as follow.

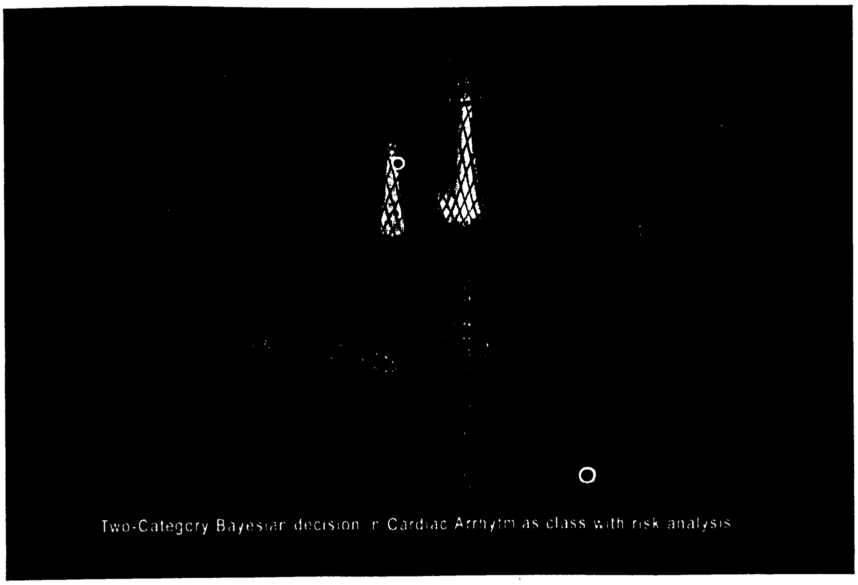


**Figure. 3.7. True state of disease in Cardiac Arrhytmias space**

Following the same paradigm but with 3 shared labs, the decision boundaries and the diagnosis space will look like Figure 3.8.

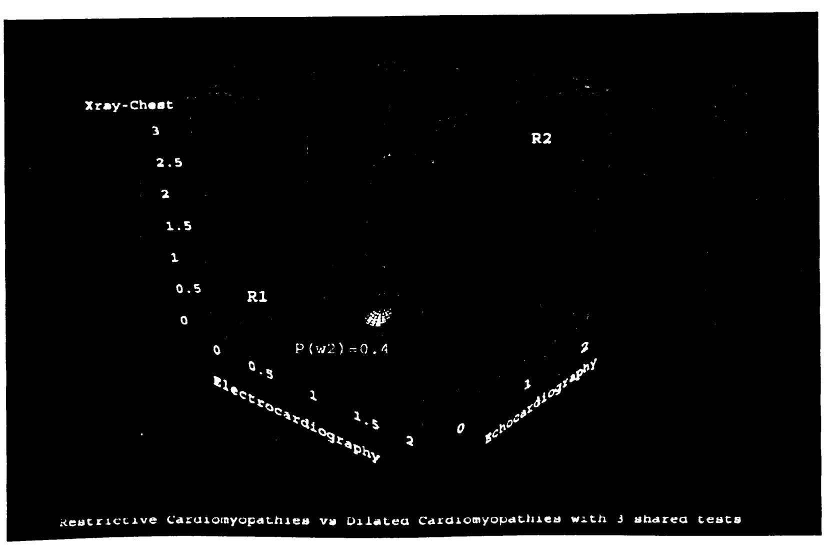



**Figure. 3.8. Decision space in Cardiomyopathies with 3 shared labs.**

In this chapter, using a Bayesian inference, we can create a diagnosis space which could assist in creating the correct decision between the two possible diseases. This method allows us to analyze the likelihood of the diseases with minimum of 1 and maximum of three shared features which in this case are lab results. Also possibilities can be measured in such diagnostic spaces with more than 2 hypotheses. For instance, diagnostic decision in Ischemic heart diseases between 4 probable diseases will look like Figure 3.9.

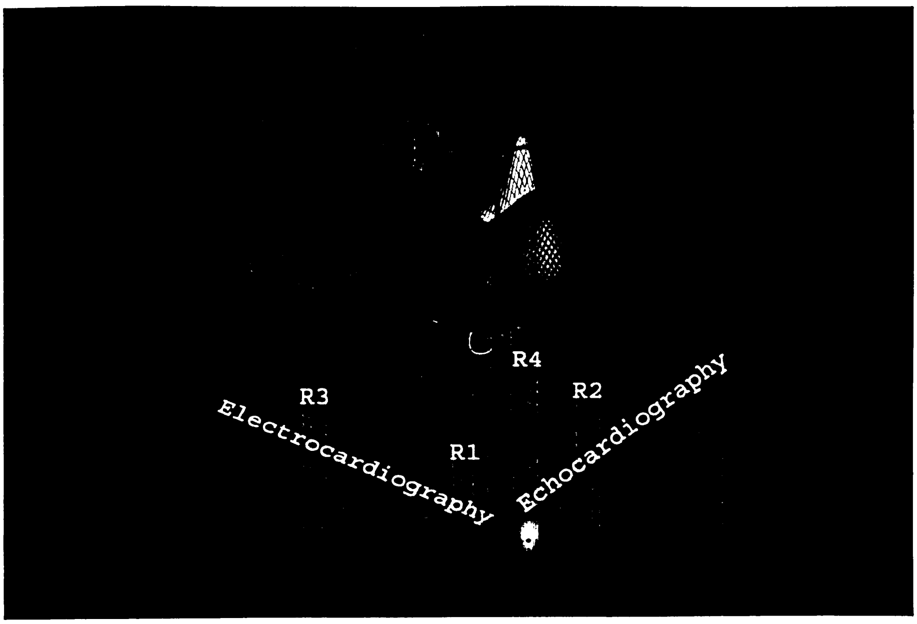



**Figure. 3.9. Decision between four hypotheses in Ischemic Heart diseases.**

# CHAPTER 4: RESULTS AND SIMULATIONS

## 4.1 Case Studies

In this chapter, three case studies are shown in different cardiology classes. The series are performed using one, two and three shared features respectively in each class. Due to the limited access to patient's data, the given inputs are selected from 10% of the rule base tables.

### 4.1.1 First Case Study: $\sum_i = \sigma^2 I$ (Equal Variance)

This case study is performed in Pericardial diseases class based on the following lab tests.

| | | |
|---|---|---|
| ECG | Xray | Echocardiography |

Between two likely hypotheses of:

| | |
|---|---|
| Acute Pericarditis: R1 | Constrictive Pericarditis: R2 |

Referring to tables of Appendix III, following diagnosis space in Figure XX is obtained:

Based on one shared lab result ECG, the decision boundaries are equal.

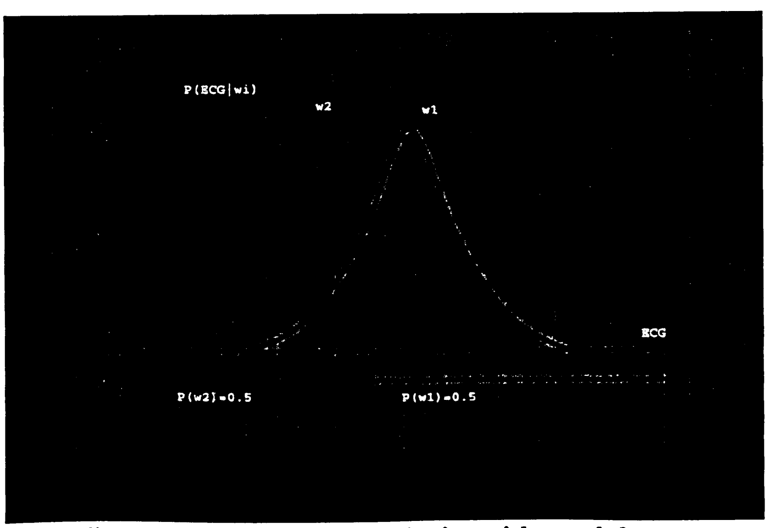



**Figure 4.1. Decision boundaries with one lab test.**

Based on two shared lab results , ECG and Xray, diagnosis space in Figure 4.2 is obtained.

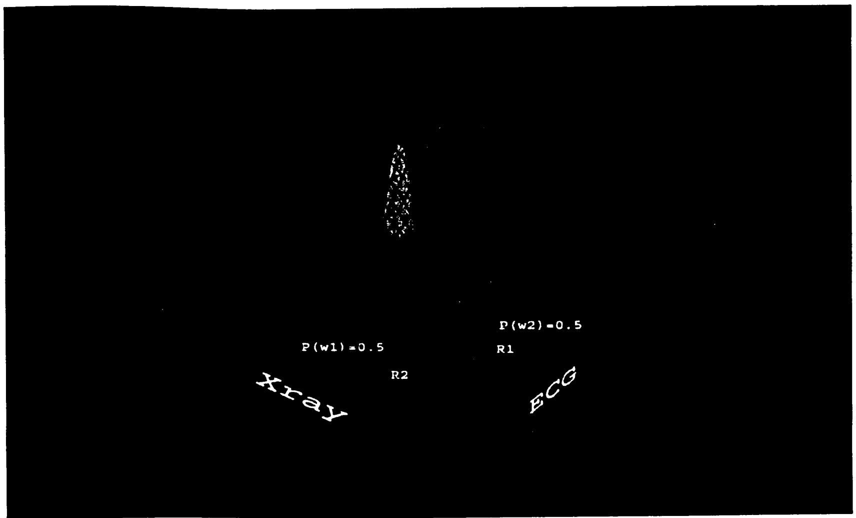



**Figure 4.2. The decision space with two lab tests in Vulvular Hearth diseases**

Plotting arbitrary information from Pericardial diseases, results in Figure 4.3.

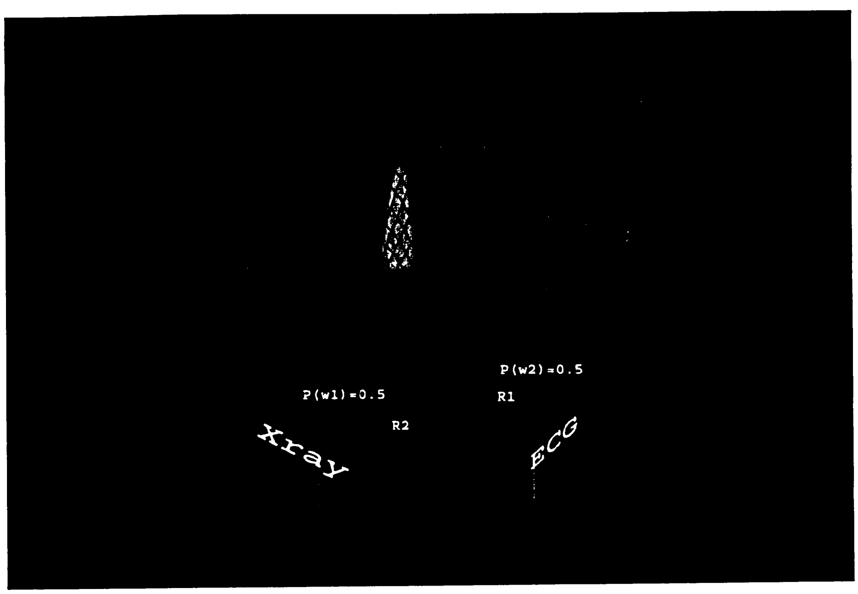



**Figure 4.3. The true state of diagnosis in the decision space.**

Using the same paradigm and by incorporating 3 lab results, ECG, Xray and Echocardiography result in the diagnosis space shown in Figure 4.4.

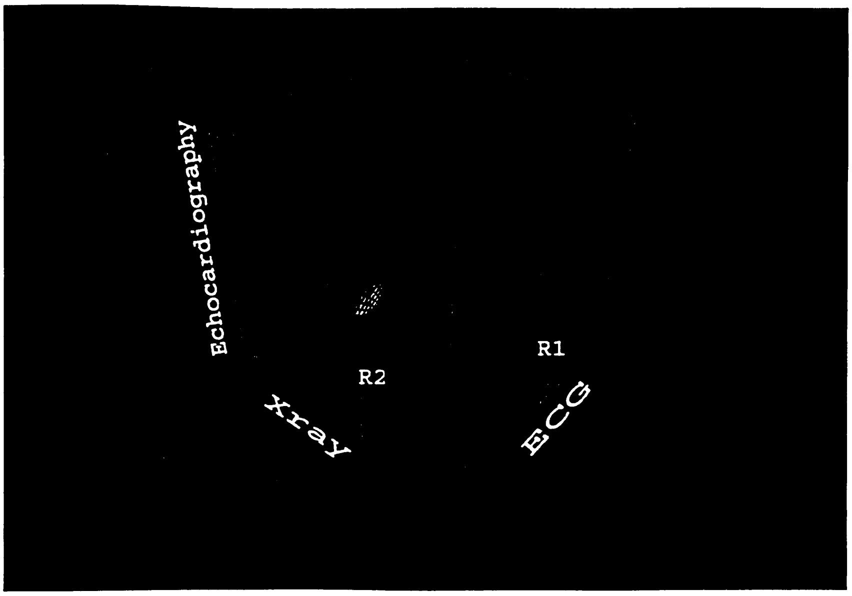



**Figure 4.4. Decision space with 3 shared lab results.**

Plotting a patient's information from pericardial diseases shows that the diagnosis is in the R1 region therefore selecting the true state of diagnosis as Acute Pericarditis.

### 4.1.2 Second Case Study: $P(w_i) > P(w_j)$

There are instances where the prior probability of one disease is bigger than the other. In this case the information from the class Vulvular Heart Diseases between Tricsupid Stenosis and Mitral Regurgitation are obtained.

The diagnosis space will be created as follow based on one, two and three shared lab features.

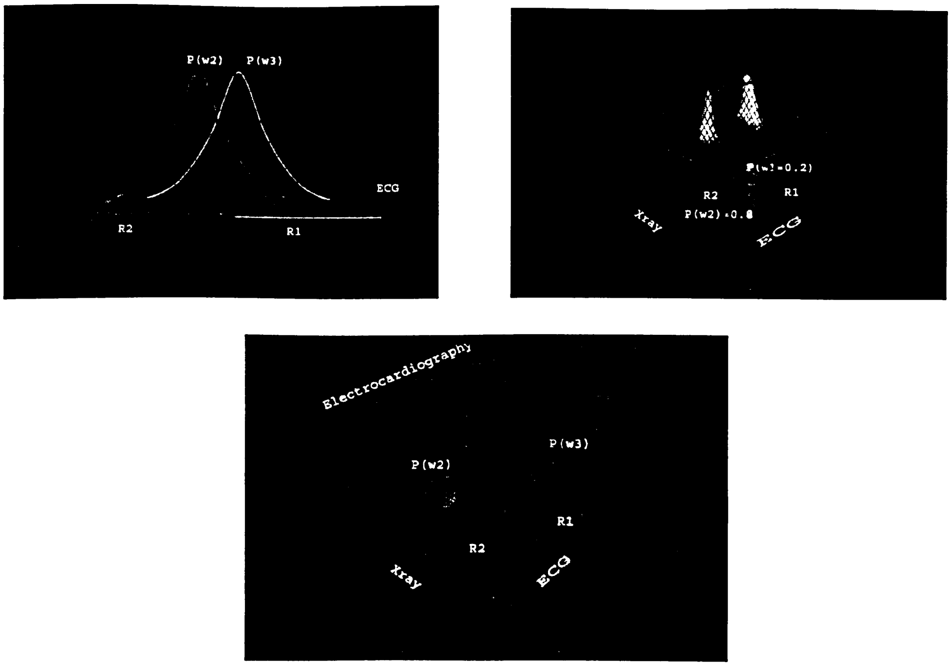



**Figure 4.5. Decision spaces in Vulvular heart diseases.**

In decision between Pulmonary Stenosis and Tricuspid Regurgitation, the set of results will be shown as Figure 4.6.

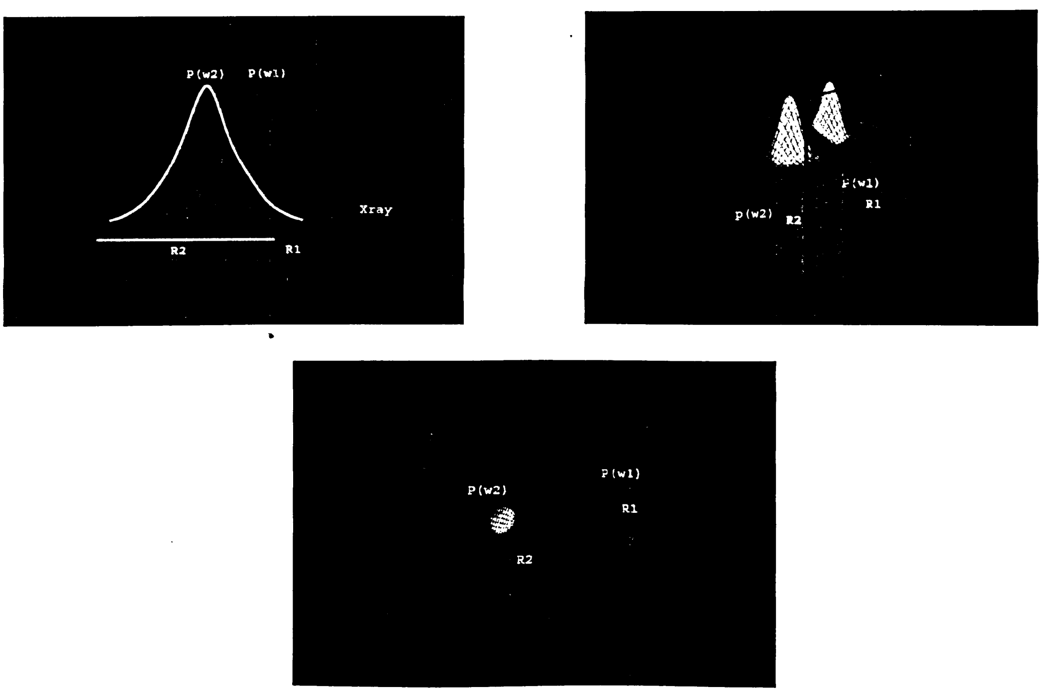



**Figure 4.6. The decision regions in pulmonary diseases.**

### 4.1.3 Third Case Study: Overlapping of Diagnostic Decision

In decision between Pulmonary Hypertension and Pulmonary Edema, it was observed that the decision boundaries overlap. This is shown in Figure 4.7.

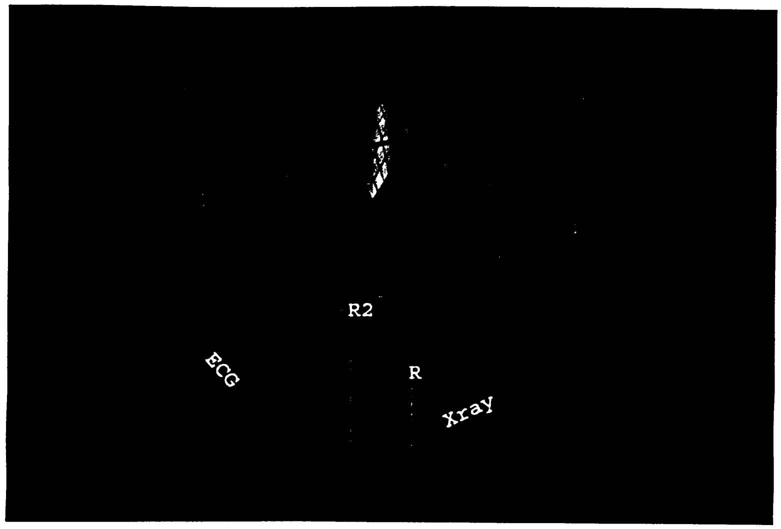



**Figure 4.7. Overlapping of the regions in Pulmonary diseases**

For the complete set of diagnostic spaces, refer to the CD-ROM attached to this document.

# CHAPTER 5: CONCLUSIONS

## 5.1 Summary

The proposed expert system obtains patient's demography including history and symptoms using a linear scoring system. A fuzzy model is designed to obtain the probable diagnosis list according to related lab test. The main reason that a fuzzy system is used instead of a look up table is that the proposed inference engine provides less complicated rules compared to the equivalent set of rules from a lookup table. By using the tables, the system is trained with complete information. Creation of fuzzy rules allows patient's diagnosis when information is not complete. The logic in objective analysis is based on reduction of the hypotheses as shown in Figure 5.1.

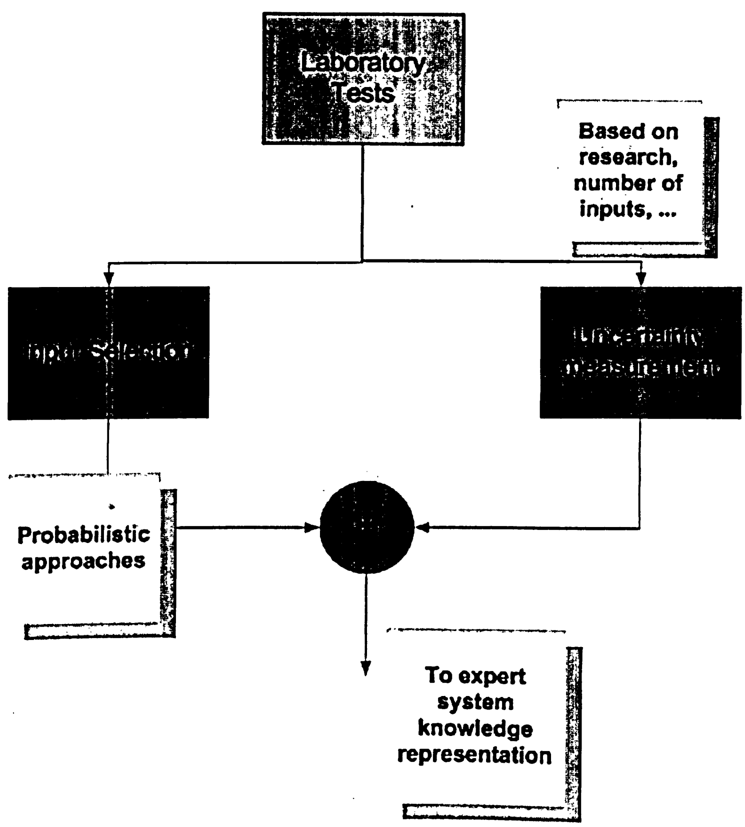



**Figure 5.1. Objective analysis by reducing the amount of hypotheses.**

Scores obtained from the subjective and objective analysis are then used to acquire a probability score for each disease based on the patient's demography and lab results as shown in Figure 5.2.

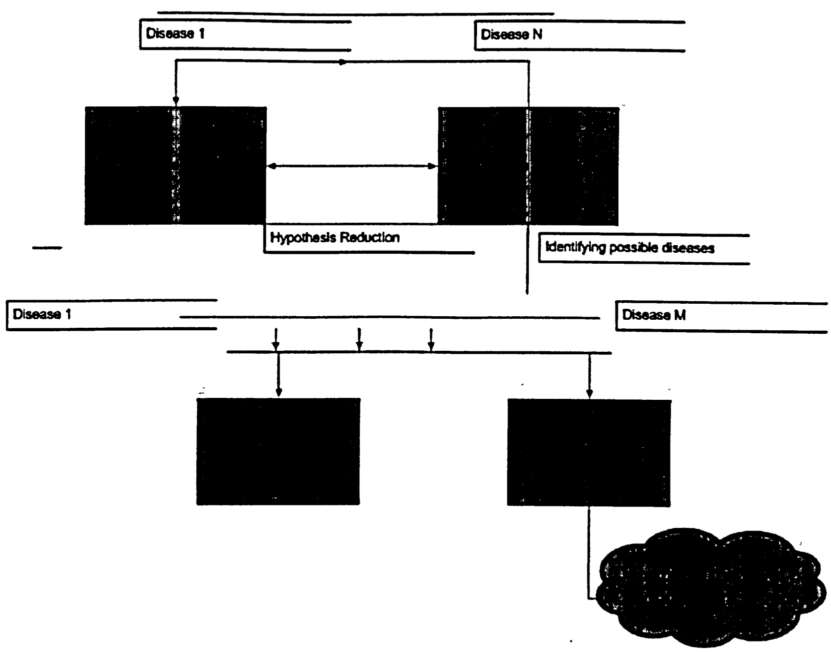



**Figure 5.2. Determining the level of uncertainty by combining the subjective and objective analysis.**

The subjective analysis is a linear score and the objective analysis is a set of fuzzy rules. Later the information is used to create the diagnostic space. Using these scores a probable diagnosis list is created with less than ten diseases. However, such scores do not correspond to a crisp result and the decision will be made by the practitioner.

In order to improve such expert system, a Bayesian engine is introduced to select the most probable disease in the probable diagnosis list with minimum risk and maximum confidence. Figure 5.3 shows the process of the expert system before incorporating the Bayesian engine.

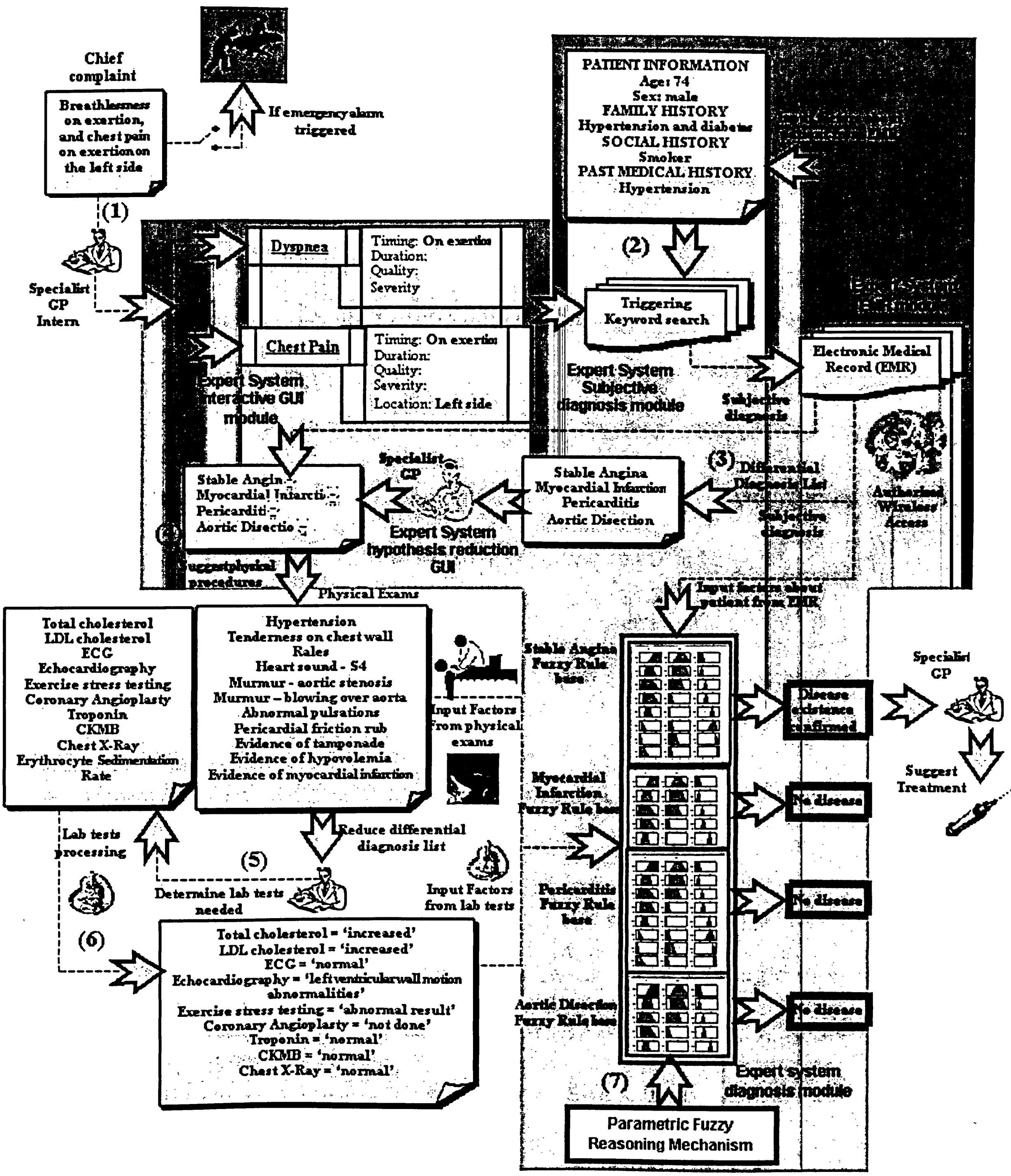



**Figure 5.3. Process of diagnosis before incorporating the Bayesian decision.**

The Bayesian engine will recalculate the probability of diseases existing in the probable diagnosis list using shared lab results. Current Bayesian engine has the capability of measuring the probability by using up to 3 shared lab results. The more lab results are available to the Bayesian engine, the more diagnosis will be performed with higher confidence.

### 5.1.1 Contributions of the Research

1. This research is proposing the implementation of a generic paradigm in diagnosis and prognosis. It can be adapted to any other medical domain than cardiology.

2. This research provides a complete template and framework for creating an efficient expert system such as the data relations and rule sets.

3. The predicted diagnosis is selected by the expert system with minimal risk.

4. Introduced framework has the capability of processing missing information when complete patient's data is not available.

5. Hierarchical structure of the system reduces amount of misdiagnosis. This means that if there is an error in the Subjective Analysis, the Objective Analysis detects it. And if there is an error in the Objective Analysis, the Bayesian Analysis detects it. Therefore reliability of the framework is achieved using this paradigm.

## 5.2 Suggestions for Future Research

Creating adaptability and reinforcement for the system and improving the statistical methods described in chapter can be considered the major aspects of improvement for this research. The model described in Figure 2.2 can be considered a model for creating such reinforcement and adaptation. It is also imperative that data can be obtained from a medical entity to prove the integrity of the system. Improving the Fuzzy inference engine also is important for providing more precise diagnostic spaces.

The system has the capability to perform transparently, therefore by creating a proper graphical interface, usability and learning capability of the system can become satisfactory for the user.

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