Fuzzy Logic via Computing with Words in Gynaecology Diseases

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This Thesis is submitted for the award of degree of

Doctor of Philosophy (Ph.D.)

Under the guidance of

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Dedicated with love to my loving daughter **Sneha**, for her great patience and sparing me at the cost of her joy and to my all time motivation and inspiration, **Shailesh**, my better half, for his constant unstinted support and whole hearted involvement…..

Certificate of Guide

This is to certify that the work incorporated in the dissertation "**Fuzzy Logic Via Computing with Words in Gynaecology Diseases**" submitted by Anjali Shailesh Sardesai was being carried out under our guidance and supervision. The material obtained from other sources is duly acknowledged in this dissertation. I consider this work to be worthy for the award of the Degree of Doctor of Philosophy in Computer Science.

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Research Co-guide	**Research Co-guide**	**Research guide**

Date:

Declaration

I, Anjali Shailesh Sardesai, declare that the conceptual framework of this Thesis has been developed on the detailed literature review as shown in the bibliographical references. I have quoted several notes, opinions and other information from various books, journals, periodicals and other reference material with clear mention of the source of information in references. Apart from these, all the opinions, hypothesis, remarks, inferences, analysis and interpretations in this Thesis are my own and are original creations.

I also declare that the work in the Thesis entitled "**Fuzzy Logic Via Computing with Words in Gynaecology Diseases**" is a record of independent research work carried out by me during the period 7th July 2011 till date under the guidance and supervision of **Dr. Vilas Kharat**, Head, Department of Computer Science, SPPU, **Dr. Pradip Sambarey**, Head, Department of Gynaecology and Obstetrics, B.J. medical Government College, Pune and **Dr. Ashok Deshpande**.

This work has not been previously submitted for the award of any diploma, degree, associate ship or any similar title.

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Acronyms

Acronym	Full Form
AAH	Adenomatous hyperplasia
ALL	Acute Lymphoblastic Leukemia
ANC	Absolute Neutophil count
AUB	Abnormal Uterine Bleeding
BP	Blood pressure
C/O	Complaint of
CaCx	Cervical Cancer
CADIAG	Computer Assisted DIAGnosis
CCD	Charg-Coupled Device
CC-EMG	Electro-myogram of the corpora cavernous
CDSS	Clinical Decision Support System
CHMM	Concept Hierarchy Memory Model
CPRS	Computerised Patient Record System
CPT	Complete Perineal Tear
CW / CWW	Computing With Words
DM	Diabetes Mellitus
DnC	Dilation and Caesarean section
DSS	Decision Support System
DUB	Dysfunctional Uterine Bleeding
ECG	ElectroCardioGram
EEG	ElectroEphaloGraphy
EMR	Electronic Medical Record System
ERA	Early Referrals Application
FCA	Fuzzy Concept Analysis
FCM	Fuzzy C-Means

Acronym	Full Form
FELF	System in Fuzzy Set
FIS	Fuzzy Inference System
FLMP	Fuzzy Logical model of perception
FST	Fuzzy Set Theory
FWCM	Fuzzy Weighted C-Means
GIDEON	Global Infectious Disease and Epidemiology Network
GSI	Genuine Stress Incontinence
GV	Gravid Patient
H/O	History of
HB	Hemoglobin
HIV	Human Immunodeficiency Virus
ICC	Intra-class correlation
ICU	Intensive Care Unit
IFS	Intuitionistic Fuzzy Sets
IUD	Intra Uterine Device
LCT	Lactational Amenorrhea
LIFE	Laboratory for International Fuzzy Engineering
LMP	Last Menstrual Period
LNL	Linguistic Natural Language
LSCS	Lower (uterine) Segment Caesarean Section (Caesarean)
M/S	married Since
MDDS	Medical Decision Diagnostic System
MDSS	Medical Decision Support System/ Medical Diagnostic Support System
MMC	Missed Menstrual Cycles
MP	Menopaused Patient
MRI	Magnetic Resonance Imaging
MTP	Medical Termination of Pregnancy

Acronym	Full Form
NL	Natural Language
OB/GYN	Obstetrics and Gynaecology
P/V	Pelvic
PBS	Painful Bladder Syndrome
PCOS	Polycystic Ovarian Syndrome
PICU	Pediatric Intensive Care Unit
PID	Pelvic Inflammatory Disease
PMC	Previous Menstrual Cycle
PMDD	Premenstrual Dysphonic Disorder
PMP	PreMenstrual Period
PMS	PreMenstrual Syndorme
POP	Pelvic Organ Prolapse
PUFF	Pulmonary Function System
QMR	Quick Medical Reference
RESAC	Real Time Expert System for Advice and Control
RMC	Regular Menstrual Cycles
SCM	Support Center Machines
SELF	System in Fuzzy Sets
SGC	Short Gap Cycles
STD	Sexually Transmitted Disease
T1FIS	Type 1 Fuzzy Inference System
T2FIS	Type 2 Fuzzy Inference System
UPT	Urine Pregnancy Test
USG	Ultra Sound Graph
VNITLD	Vietnam National Institute of Tuberculosis and Lung Diseases
VR	Virtual Reality
WHO	World Health Organization

Publications

[1] Sardesai A, Kharat V, Sambarey P, Deshpande A. Fuzzy Logic Based Formalisms for Gynaecology Disease Diagnosis. ***Journal of Intelligent Systems*** ISSN No: 2191-026X DOI 10.1515/jisys-2015-0001 (2016) 283-295.

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[9] Sardesai A, Kharat V, Sambarey P, Deshpande A. Comparative Analysis of Fuzzy C-Mean and Fuzzy Similarity Measures in a typical Study of Initial Screening Model for Gynaecology Patients. (Communicated)

Preface

Over the past decades, use of soft computing techniques such as Fuzzy Logic based methods, Neural Networks, Genetic Algorithms and alike have significant and growing impacts on environmental fields, health care systems, control systems etc. On careful scrutiny of relevant research efforts, it is observed that there has been limited use of these methods in medical decision support systems especially in Gynaecology. With this backdrop, an attempt has been made in this dissertation to demonstrate practical utility of Prof. Lotfi Zadeh's Fuzzy Set Theory and a few statistical methods in 'Gynaecology Disease Diagnosis'.

The good quality of clinical information, which is required for better clinical diagnostics, is based on the experience of the medical practitioner. The suggested perception based modeling by the authors incorporates over forty years of experienced knowledge base of eight gynaecologists which helped to increase the overall percentage of the accuracy of the model.

Looking at the increasing evidences of the use of computer aided clinical decision support system, the authors believe that the Three Stage Approach detailed in the Thesis on **'Fuzzy Logic via Computing with Words in Gynaecology Diseases'** is a better proposition in medical diagnosis system, especially in the field of Gynaecology.

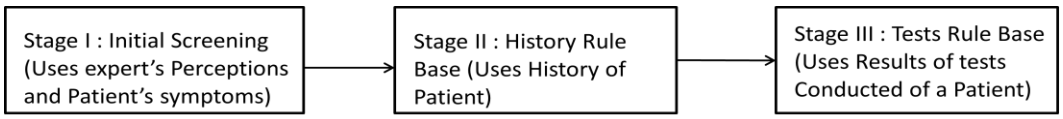

Figure: Three Stage Approach

Outcome of the research is summarized as follows:

- The success rate of the system is 95.13% for 226 patients that were observed during the study, which seemingly to be relatively better for the 'Medical Decision Support System'.
- A new formalism to simulate differential diagnosis process for Gynaecology diseases is being developed.

- Development of a novel 3 stage diagnosis approach for Gynaecology disease diagnosis is carried out.
- Modeling the domain experts' perceptions using non statistical approach is done.
- The experts are classified using fuzzy relational calculus.
- The cause-effect relationship between Symptoms and Gynaecology Diseases is analyzed.
- The patients are classified using fuzzy similarity measures, crisp similarity measures and FCM; and analysis of these classified patients is carried out.
- The concept of "reference group" to compute weighting factor in FCM is applied.
- The overall output is in the direction of real time application in Gynaecology Disease Diagnosis.

The system which is being developed during this research work is a simulation of differential diagnosis process which can be proved to be of great help for the medical students to understand the differential diagnosis process. The development of software has achieved some level of machine intelligence in medical diagnosis and it might help to general physicians / gynaecologists to arrive at correct disease diagnosis in Gynaecology.

The concept can be further inherited for the other branches of medicine with necessary. For the specific branch of medicine the identification of, diseases, signs & symptoms as well as tests to be conducted. The expert's perceptions for Initial Screening Stage are to be gathered for the effective implementation of the derived concept and developed software.

Nonetheless, it is to be noted that this work can be further extended for exhaustive study using various computing techniques to enhance the model accuracy.

The biggest room in this world is the room for improvement!

Chapter 1

Introduction

Dealing with uncertainty has been one of the major objectives of scientific research over a period of time. Successes of probability theory have high visibility in achieving some of the objectives of decision research. But what is not widely recognized is that these successes mask a fundamental limitation – the inability to operate on what may be called as perception–based / imprecise or more concretely fuzzy information. Computing with words via Fuzzy Logic is a method for reasoning, computing and decision-making. The information is described in a natural language in which the perception is well described.

The twentieth century medical science has embrace nineteenth century Boolean Probability Theory which is based upon two-valued Aristotelian logic. The bi-valued von Neumann structured computational architectures have led to a bivalent epidemiological methodology that govern medical decision making. Fuzzy Logic is based on twentieth century multi-valued logic. It contains the computational structures that are content addressed and adaptively modified which have advanced a new scientific paradigm for the twenty-first century (Helgason & Jobe, 1988). Decision making in an imprecise / fuzzy an environment has wide applications in several areas of science and technology including medical sciences.

The medical diagnostic process can be viewed as a process by which a clinician assigns a label to a patient. This assignment is based on the information; the clinician/physician collects from patient, and his present knowledge of medical science.

The diagnosis of a disease involves several levels of uncertainty and imprecision, and it is inherent to medicine. A single disease may manifest itself quite differently, depending on the patient as well as with different intensities. A single symptom may correspond to different diseases. On the other hand, several diseases present in a patient may interact and interfere with the usual description of any of the diseases. The best and most precise description of disease entities uses linguistic terms that are also imprecise and vague (Klir & Yuan, 1995). However, diseases like gynecological ones involve multiple related causal factors, which are not easy to represent using conventional statistical methods.

By 'symptoms', we mean information received from the patient, in particular, only through interviews. By 'diagnosis', we mean a label or a word used by the clinician to describe and synthesize the medical status of a patient. The tactical knowledge of experts (perceptions) is needed for this synthesis. In nut shell, the study is based on the information obtained from patients and the perceptions of experts that are invariably expressed in linguistic terms.

The medical knowledge mainly consists of symptom-disease relationship which forms one type of imprecision and uncertainty in the process of diagnosis and the type is knowledge related to patient's state. The physician generally gathers data about the patient from the past history, physical examination, results of laboratory test and other investigative procedures such as Ultrasonic, X-ray etc. The information provided by each of these sources carries with it varying degrees of uncertainty. The symptoms and past history narrated by the patient may be subjective, exaggerated, under estimated or incomplete. Also, mistakes may be made in the physical examination and symptoms may be overlooked. Nonetheless, the measurements supplied by laboratory tests are usually of limited precision and the exact borderline between normal and abnormal pathological result is often unclear. The diagnostic tests require a correct interpretation of the results (Abbod, Keyserlingk, Linkens & Mahfouf, 2001; Torres & Nieto, 2006). Thus the state and symptoms about the disease narrated by the patient can be known by the physician with only a limited degree of precision. By considering the uncertainty in the observed symptoms of the patient and uncertainty in the relation of the symptom to a disease entity, it is not easy task for a physician to describe that the diagnosis is accurate. However, the study reported in this sequel is primarily focused on only the tactic

knowledge of the identified eight gynaecologists and on the linguistic descriptions of the symptoms by the patients about the systems.

It is noted that inherent uncertainty in the form of vagueness or fuzziness which is resident in Gynaecology, essentially implies that the use of fuzzy set theoretic operations and the concept of statistical multivariate data analysis in medical decision making needs to be explored. The aspiration to better understand and teach this difficult and important technique of medical diagnosis has encouraged attempts to model the process with the use of Fuzzy Set Theory (Klir & Yuan, 1995). One of the important and prime characteristic of Fuzzy Set Theory is its capability of representing knowledge in a linguistic way. With the help of this capability a system can be expressed by simple, human-friendly rules, known as interpretability. This makes Fuzzy Set Theory important from medical point of view.

Besides the foregoing discussion, this Chapter contains the discussion about an overview of the Gynaecology, Three Stage Approach, need and relevance of the research, objectives of the research, assumptions and limitations and an outline of the Thesis.

1.1 Gynaecology: An Overview

Genecology or Gynaecology (science of women) refers to the health of the Female Reproductive System such as: Uterus, Vagina, and Ovaries, while Obstetrics deals with care of women's reproductive tracts and their children during pregnancy (prenatal period), child birth and the postnatal period. The research study presented in this sequel refers only to the medical diagnosis in Gynaecology.

If we look at the information about gynaecological diseases and conditions including *Uterine Fibroid* tumours, *Ovarian Cysts*, *Polycystic Ovarian Syndrome* (*PCOS*), *Endometriosis*, and *Vulvodynia* as well as many other female reproductive system abnormalities, we get: Cervical Health, Common Uterine Conditions, Diseases of the Uterus, Ovarian Conditions, Vaginal Health different category counts (Datta, 2009) and their related symptoms for which a Disease x Symptom relation can be formed.

With the increase in volume of patient information being made available to physicians from new technologies, the process of analyzing it and determining appropriate therapeutic actions has become increasingly difficult. It is somewhat complex

for a gynaecologist to reach to a proper diagnosis due to uncertainty / fuzziness/ ambiguity in the complaints to disease entity. The descriptions of disease entities use linguistic expressions that are inherently imprecise/ vague/ fuzzy and these form the scaffold of the medical knowledge of a physician. The latter utilizes his medical knowledge to analyze the information for a patient and arrives at a diagnosis. This process of medical diagnosis is characterized by different stages of uncertainty viz. information concerning the symptoms (s) of a patient (p), symptom (s) - diseases (d) association, and the indicated diagnosis (d) itself.

1.2 Three Stage Approach

In our view, overall approach in Gynaecology disease diagnosis could be divided into three distinct stages as shown in Figure 1.1. Stage I refer to Initial Screening Stage in order to arrive at a single disease diagnosis for the patients, and based only on the subjective information provided by the patients to the physician. In stage II, the patient who has not received a single diagnostic label in stage I, is further investigated for single disease diagnosis using parameters like past history, pre-menstrual changes, last menstrual period, marital status, parity etc. If output at the end of stage II fails to arrive at a single disease diagnosis for a patient then physical examination and various tests like ultra-sonography, X-ray, blood tests, etc. are conducted and the test results are processed in stage III.

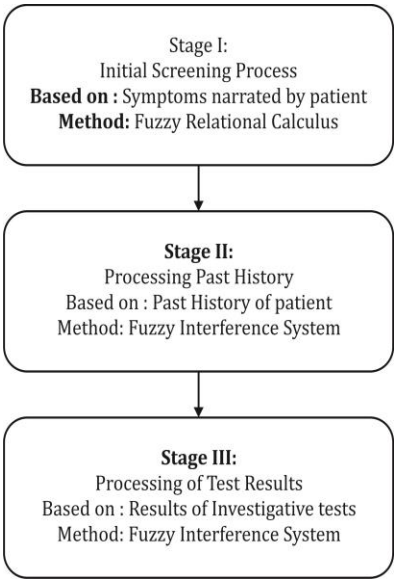

Figure 1.1 Overall approach of Gynaecology disease diagnosis

1.3 Need and Relevance

- The Exponential growth of patients suffering from gynaecological diseases across the globe, in general and especially in lower middle class with special reference to India prompted the research team to initiate the study with an objective to assist relatively new gynaecologists or general physicians / clinicians in decision making. Gynaecology refers to abnormalities or diseases of female reproductive system such as, uterus, vagina and ovaries, while Obstetrics deals with abnormalities or diseases during pregnancy (prenatal period), child birth and the postnatal period. The information about gynaecological diseases and conditions include *Uterine Fibroid* (tumours), *Ovarian Cysts*, *Polycystic Ovarian Syndrome* (*PCOS*) and *Endometriosis*. Also, it consists of many other female reproductive system abnormalities which can be referred to different disease categories as cervical health, common uterine conditions, diseases of the uterus, ovarian conditions and vaginal health.

- According to the definition issued by the World Health Organization (WHO), health is a state of complete physical, mental, and social well-being, and not merely the absence of disease or infirmity. The loss of health can be seen in its three forms: disease, illness, and sickness. To deal with imprecision and uncertainty, we have at our disposal the Fuzzy Logic. Usually, the symptoms belonging to different diseases do overlap with each other and very small variations are observed among them. This could be the reason why the physician may diagnose a patient with disease x instead of y. It is understood that physicians count on their experience and intuition and not on strong and rational rules to deduce from the patients data to a disease. (Horrocks, Mccann, Satniland, Leaper & Dombal, 1972). This emphasizes the need of automation in the process of diagnosis.

- It can be stated that inherent uncertainty in the form of vagueness/fuzziness which is resident in Gynaecology, calls for exploration of the possibility of using fuzzy set theoretic operations and the concept of statistical multivariate data analysis in medical decision making.

- To process large volume of data, data analysis is considered as very important tool because processing large volume of data is very tough job. To be precise, data mining

is the analysis of datasets that are observational and are aiming at *a.* finding out unsuspected relationships among datasets *b.* summarizing the data in such a fashion in order to make the same understandable and useful to the data users.

1.4 Objectives of the research

i. In the developing countries, respective Governments usually run medical camps in villages/ towns, wherein people undergo medical check-ups even for Gynaecology. The software developed as a result of the study can be used effectively for the initial screening of mass investigative process.

ii. In medical colleges, the software can be used as a demonstrating, learning tool for the students to teach process of differential diagnosis. Also, it can help to assist a general physician or a new gynaecologist in the diagnosis process.

iii. From the viewpoint of the policy, a physician is advised by the decision makers to follow the standard guidelines in medical diagnosis- may be for health insurance reasons. Experience shows that, in spite of adhering to these medical procedures, a physician with inadequate experience (may be some of those physicians with several years of experience) sometimes does commit a mistake in diagnosing a patient. The case in point herein is the gynaecological diseases.

iv. The developed software is simulation of differential diagnosis process which can be a useful prototype model in medical colleges in the teaching-learning process.

v. Mendel (2007) stated that "*Words can mean different things to different people*". This fact leads to classify the gynaecologists as their perceptions could be different in assigning linguistic hedges in defining symptoms, *For example Sever pain in abdomen*. Similarly, patients can also be classified depending on the narration of the complaints.

vi. The final objective of the proposed research is to develop complete application software to be helpful to general physicians.

1.5 Assumptions and Limitations

Assumptions:

i. Thirty One most commonly gynecology diseases are considered.

ii. Medical being a fuzzy science, some vagueness and uncertainty is assumed in experts' opinion, patients' narration and dissimilar behavior of human body with respect to different situation, which might lead to fuzzy diagnosis.

Limitations:

i. The tactic knowledge of identified gynaecologists is the basis of research study especially in Stage I.

ii. If the symptoms of a patient are not related to Gynecology related issues, the software will not diagnose since the disease-symptom set does not match and it outputs *'Unspecific Disease*'.

1.6 Organization of the Thesis

The Thesis has been organized in seven Chapters. Each Chapter starts with a prologue and is further divided into sections. Each section is detailed with a distinct objective.

Chapter 1 Introduction

The Chapter starts with importance of Medical diagnosis process, fuzziness, uncertainty in Medical diagnosis and a brief about Gynaecology. The chapter also briefs about the need and relevance of the research, objectives and the assumptions and limitations of the study. The chapter focuses on the differential diagnosis process, Three Stage Approach, overall working of the system and a note on classification of experts and patients.

Chapter 2 Critical Literature Review

This chapter focuses on study and analysis of different Medical Decision Support Systems with using Soft Computing Techniques. Use and analysis of different classification methods are also covered in this chapter.

Chapter 3 Gynaecology Diseases: An Overview

This chapter briefs about the Gynaecology: the delimitation, history of Gynaecology and Gynaecology diseases. It details about the Gynaecology diseases considered in the study, various tests to be conducted for confirmation of the disease.

Chapter 4 Mathematical Preliminaries and Techniques Used

A brief account on Computing with Words (CW), Fuzzy Set Theoretic Operations, Fuzzy Relational Calculus, Fuzzy Inference System (FIS), Fuzzy Similarity Measures Crisp Similarity Measures, Fuzzy C-Mean and Inter-Rater Reliability (Kappa Coefficient) and all the methods used in the research explained in this chapter.

Chapter 5 Soft Computing Methods for Gynaecology Disease Diagnosis

The objective of this chapter is to simulate the differential diagnosis process using Fuzzy Relational Calculus and Fuzzy Inference System. The Experts' classification is carried out using Fuzzy Similarity Measures which is confirmed using Inter-rater reliability Statistics. Fuzzy and Crisp Similarity Measures along with Fuzzy C-Means are used to classify the patients.

Chapter 6 Results and Discussion

The result of case studies carried out in the study is discussed in adequate details.

Chapter 7 Concluding Remarks and Scope for Further Research

The research findings are concluded in this Chapter and also the further scope of research is presented in brief.

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Chapter 2

Critical Literature Review

This chapter briefs about the evolution of Fuzzy Logic, Possibility Theory and Computing with Words. The chapter also details about the various application areas of Fuzzy Logic in general and Medical Decision Support System in particular. The various classification techniques are also focused in the chapter.

Fuzzy set theory is very widely and effectively used in medical expert systems, medical decision support systems. Fuzzy set theory and Fuzzy Logic has been proved to be very applicable and suitable in developing knowledge-based systems in medicine. Some of those are diagnosis of diseases in Western medicine, the interpretation of sets of medical findings, mixed diagnosis of integrated western and eastern medicine, syndrome differentiation in eastern medicine, the optimal selection of medical treatments integrating western and eastern medicine and for real-time monitoring of patient data (Phuong & Vladik, 2000).

2.1 Evolution of Fuzzy Logic

According to Aristotelian logic, any given proposition or state can be expressed by only two logic values: true-false, black-white, 1-0. In real life, most of the times the things are grey, neither black nor white. So, it is convenient to consider intermediate values which can be termed as multivalued logic.

The polish logician Jon Lukasiewicz, in 1920, narrated the principles of multivalued logic. He proposed that statements can take on fractional truth values between the ones and zeros of binary logic. In 1937, quantum philosopher Max Black applied multivalued logic to lists or sets of objects and that was the first time fuzzy set curves were drawn

which were called as "Vague". Almost 30 years later Prof. Lotfi A. Zadeh published "Fuzzy Sets" (Zadeh, 1965), a landmark paper that gave the field its name. Prof. Zadeh applied Lukasiewicz logic to every object in a set. He proposed a complete algebra for fuzzy sets.

Fuzzy sets were not used much until mid-1970. In 1970's, Ebrahim H. Mamdani designed a fuzzy controller for a steam engine. The use of term "Fuzzy Logic" was being started since then for different applications worldwide. There in only one constraint on Fuzzy Logic i.e. sum of the object's degree of membership in complementary groups must be one.

Classical logic has proved very useful for solving formal problems specified in two-valued terms. Fuzzy Logic is proving useful for quasi-formal problems involving gradual transitions between various system states. While describing the vagueness, this classical logic (binary logic) often fails. Fuzzy Logic offers more graceful alternatives. Computers do not reason as the brains do. Computers 'reason' when they are represented using either zeros or ones (true / false). In contrast, the vague assertions, or claims involving uncertainties or value judgments, can be reasoned by human brain. Fuzzy Logic is a branch of machine intelligence that helps computers to capture these vague assertions and uncertainties. (Kosko & Isaka, 1993).

Uncertainty is a challenging part in human's everyday life. The main cause of uncertainty is the information deficiency. Information may be incomplete, fragmentary, not fully reliable, vague, contradictory or deficient in some other way. These various information deficiencies may result in different types of uncertainty. Rudolf Seising (2006) stated that the history of philosophy and medical diagnosis is concerned with the phenomenon of vagueness in the physician's 'style of thinking'. When physicians make a diagnosis, the use of fuzzy sets and fuzzy systems to create a model of such reasoning can be well suited.

2.1.1 Possibility Theory and its use

Possibility theory is one of the uncertainty theories dedicated to the handle incomplete information. It is similar to probability theory because it is based on set-functions. It differs from the probability theory as it uses a pair of dual set functions called possibility and necessity measures instead of only one.

The "Theory of Possibility" was expressed by Zadeh (1978). In Zadeh's view, possibility distributions were meant to provide a graded semantics to natural language statements. Possibility and necessity measures can also be the basis of partial belief that parallels probability. The possibility theory refers to the study of Maxitive and Minitive set-functions, respectively called possibility and necessity measures.

2.1.2 Computations with Computing with Words

Charles S. Pierce stated that "vagueness is no more to be done away with in the world of logic than friction in mechanics." Likewise, Bertrand Russell retorted, "everything is vague to a degree you do not realize till you have tried to make it precise." Vagueness and equivocation are integral features of any human system of communication. The concept of fuzzy set focuses on the vagueness that is essential to natural language. A approach behind a linguistic Fuzzy Logic approach is that we can use natural language to express a logic in which the truth values of propositions are expressed in natural language terms such as true, very true, less true, less false, very false, and false etc., instead of a numerical scale, (Zadeh, 2002) which is essentially computation of words rather than numbers.

In general, Computing refers to manipulation of numbers and symbols. In contrast, computing with words (CW) is a methodology in which the objects of computation are words and propositions drawn from a natural language. Computing with words is the human capability to perform a wide variety of physical and mental tasks without any measurements and any computations. This capability is the brain's ability to manipulate perceptions; perceptions of distance, size, weight, color, speed, time, direction, force, number, truth, likelihood and other characteristics of physical and mental objects. Computing with words provides a basis for a computational theory of perceptions. The measurements are crisp whereas perceptions are fuzzy (Zadeh, 2002).

2.2 Classification: the review

Due to the rapid development on medical devices, the traditional data analysis has become inefficient and is replaced, as a necessity, by compute based analyses. Statistical methods, Fuzzy Logic, neural networks and machine learning algorithms are being tested on many medical prediction problems to provide a better decision support system

(Albayrak & Amasyali, 2003). Processing large volume of data is tough and complex for data analysis. In the field of software, data analysis is considered as a very useful and important tool. Data analysis can be done with the help of data mining tools, pattern recognition, image analysis, bioinformatics, machine learning various clustering methods etc. Data clustering is a method of data description which is commonly used for data analysis, classifying data, finding clusters of a dataset based on similarities in the same cluster and dissimilarities between different clusters (Rao & Vidyavathi, 2010).

In conventional clustering, each point of the dataset is put to exactly one cluster. In contrast, the clustering algorithm partitions set of data into different groups according to the similarity. Clustering is considered as classification of similar objects. There are three major types of clustering processes viz. the hierarchical, partitioning and mixture model methods. The choice of application of a particular method depends on the type of output desired, the known performance of the method with particular type of data, available hardware and software facilities and size of the dataset (Rao & Vidyavathi, 2010; Ghosh & Dubey, 2013).

The role of Clustering technique in data analysis and interpretation is very important. The data is grouped in clusters in such a way that the data objects within the cluster are similar to each other and are dissimilar to data objects from other clusters. The well-known Fuzzy clustering algorithms such as Bezdek's Fuzzy C-Means (FCM) and Li, *et. al.*'s (2008), Fuzzy Weighted C-Means (FWCM**)** (Bezdek, 1981; Li, Huang, Kuo & Hung, 2008) are based on Euclidean distance. These fuzzy clustering algorithms can only be used to detect the data classes with the same super spherical shapes (Liu, Jeng, Yih & Yu, 2009).

2.3 Headway of Fuzzy Control

In past couple of decades, the application of fuzzy control has been used in wide variety of applications. The interest in fuzzy systems was initiated by Seiji Yasunobu and Soji Miyamoto of Hitachi in 1985 in Japan to provide fuzzy control systems for the Sendai railway. In 1987, system was developed to control acceleration, braking and stopping of the vehicle when the line opened. Takeshi Yamakawa used fuzzy control in an "inverted pendulum" experiment in the same year. Matsushita vacuum cleaners,

Hitachi washing machines, auto focusing camera which uses Charge-coupled device (CCD), Mitsubishi industrial air conditioner are some of the applications developed in Japan using fuzzy controllers.

The world wide range of other applications of Fuzzy Controllers are: character and handwriting recognition, optical fuzzy systems, robots, including one for making Japanese flower arrangements, voice-controlled robot helicopters, inverted pendulum problem, control of flow of powders in film manufacture, elevator systems, automated space docking system by NASA, energy efficient electric motors, low power refrigerators, improved automotive transmissions, and so on. In 1995, Maytag introduced an "intelligent" dishwasher based on a fuzzy controller and a "one-stop sensing module". The various areas where the use of fuzzy controllers was started are: Washing machines, automatic focusing for video cameras, automatic TV tuner, servo motor control, automotive anti-skid brake, Artificial Intelligence, machine learning, robotics, knowledge based decision making processes etc. It also involves medical diagnosis, business forecasting, traffic control, network management, image processing, signal processing, computer vision, geology and many more (Costa, De Gloria, Faraboscho, Pagni & Rizzotto, 1995).

2.4 Fuzzy Logic in Medicine and Health Care

The past study shows that since 1970, lot of work has been carried out in the development of Knowledge Based/ Rule Based Expert System in medical diagnosis in many countries. E. Sanchez (1976; 1977; 1979) developed the diagnostic models involving fuzzy relations representing the medical knowledge between the symptoms and diseases. Fuzzy cluster analysis was used by Esogbue and Elder (1980) to model medical diagnostic. Meenakshi and Kaliraja (2011) have extended Sanchez's approach for medical diagnosis using the representation of an interval valued fuzzy matrix. They have also introduced the arithmetic mean matrix of an interval valued fuzzy matrix and directly applied Sanchez's method of medical diagnosis on it. Porchelvi, Selvavathi&Vanitha implemented the approach of fuzzy matrices for the diagnosis of hypotension and anemia (Porchelvi, Selvavathi & Vanitha, 2015).

Adlassnig (1980; 1982; 1986) found two fuzzy relationships to describe medical knowledge as the relationship between symptoms S_i and diseases D_j, namely *Occurrence* which is how often does S_i occur with D_j and *Confirmability* is how strongly does S_i confirm D_j (Mahdi, Razali, Al-wakil, 2011). Neog & Sut in 2011 introduced a matrix representation of fuzzy soft set and extended Sanchez's approach for medical diagnosis using their notion of fuzzy soft complement. University of Vienna Medical School contributed pioneered research developments in the medical diagnosis. (Adlassnig, Kolarz, Scheithauer, Effenberger & Grabner, 1985; Adlassnig, 1986; Adlassnig, Kolarz, Scheithauer & Grabner 1986; Adlassnig 1988; Sageder, Boegl, Adlassnig, Kolousek & Trummer, 1997; Brein, Adlassnig & Kolousek, 1998; Adlassnig, 2001).

Edward Samuel and Balamurugan (2012) proposed a new method based on Sanchez's method for medical diagnosis using the notion of IFS theory. The method of Intuitionistic medical diagnosis involves Intuitionistic fuzzy relations as defined in (Samuel & Balamurugan, 2012). Many such applications based on compositional rule of inference, Intuitionistic fuzzy sets are been developed in past 4 decades.

J. F. Yao and J.S. Yao in 2001 used interval estimation to get fuzzy number and applied compositional rule of inference for medical diagnosis. Intuitionistic Fuzzy Sets (Szmidt & Kacprzyk, 2001; Agarwal, Hanmandlu & Biswas, 2011), Intuitionistic Fuzzy relation (Cuong & Phong, 2014), Intuitionistic Fuzzy Sets based method for traditional Chinese medicine diagnosis (Wu, 2011) are some of the cases where research is carried out in Medical diagnosis.

Connectivity analysis methodology is suitable to find representative symptoms of a disease. This methodology describes connections between symptoms in and then chooses the group of symptoms that have strong interconnections between elements of a group. Tatiana Kiseliova, in 2009, investigated the analogy between connectivity analysis and cluster analysis based on fuzzy equivalence relations. In the research work presented by Rotshtein & Rakytyanska (2008) depicted the restoration and the identification of the causes (diagnosis) through the observed effects (symptoms) on the basis of fuzzy relations and Zadeh's compositional rule of inference.

The use of Fuzzy Logic was evolved in Medical field for diagnosis of various diseases and many medical applications. Steimann (Steimann 1997; Kuncheva &

Steimann, 1999; Steimann, 2001), Innocent (Innocent, John & Garibaldi, 2004; Innocent & John, 2004), Torres and Nieto (2006), Seising (2006) observed and further analysed the rapid growth of relevant research in this field. Fuzzy Logic is being used in almost all the branches and sub-branches of medicine since almost 4 decades very effectively. The details are as follows (Abbod, Keyserlingk, Linkens & Mahfouf, 2001).

i. Internal medicine

The use of Fuzzy Logic in internal medicine has given birth to the well-known knowledge-based expert system, MYCIN, CADIAG in which the medical information is derived from medical records taken from a hospital information system. Other expert systems which utilize Fuzzy Logic include SPHINX (Fieschi, Joubert, Fieschi & Roux 1982), RENOIR (Belmonte-Serrano, Sierra & Lopezde-Mantaras, 1994), and CLINAID (Kohout, Bandler, Anderson &Trayner, 1986).

ii. Cardiology and Vascular Surgery

The initial work was related to cardiovascular investigation and fuzzy concepts (Kalmanson & Stegall, 1975), the use of fuzzy set theory in evaluation of cardiac functions (Joly, Sanchez, Gouvernet & Valty, 1980) and ECG analysis (Jagannathan, Bourne, Jansen & Ward, 1982) and analysis of cerebro-vascular disease (Dong, Zhou & Wang, 1987). In 1990's, the system TOTOMES was developed to assess cardiovascular dynamics during ventricular assistance (Yoshizawa, Takeda, Yambe & Nitta, 1994). Other applications are: coronary artery disease fuzzy classifier (Jain, Mazumdar & Moran, 1998; Lovelace, Cios, Sala & Goodenday, 1998; Akay Y., Akay M., Welkowitz & Kostis, 1994), ECG classification and diagnosis (Pedrycz, Bortolan & Degani, 1991; Kerre, 1989; Degani, 1992; Degani & Bortolan,1989; Degani & Bortolan, 1990), diagnosis and treatment of heart disease (Hudson, Cohen & Deedwania, 1994; Adeli & Neshat, 2010; Wagholikar & Deshpande, 2008), Fuzzy Rule base system for Congenital Heart disease (Kaya, Oran & Arslan, 2011), mining Cardiological systems and developing association rules (Zuhtuogullari & Allahverdi, 2011), multi-stage diagnosis using myocardial infraction (Kurzynski, 2004), a diagnostic system for Valvulae Heart Diseases (Anbe & Tobi, 1999).

iii. Intensive Care

An expert system based on Fuzzy Logic was designed as a warning system in the pediatric intensive care unit (PICU) (Si, *et.al.*, 1998). Based on Fuzzy Logic, many automated systems have been developed, which are able to distinguish between critical situations and artifact (Wolf *et. al.*, 1996; Henkind, Yager, Benis & Harrison, 1987; Becker, *et.al.*, 1994). Another expert named FLORIDA is developed which determines the physiological condition of patients in Intensive Care Unit (ICU) using Fuzzy Logic and knowledge bases (Pilz, 1995; Pilz & Engelmann, 1999). For on-line monitoring of patients in ICU, a system for breath detection was developed based on fuzzy sets and non-invasive sensor fusion (Cohen, Webster, Northern, Hu & Tompkins, 1994).

iv. Pediatric

There are a very limited amount of applications which use expert systems, fuzzy modeling and fuzzy control in Pediatric branch (Koprinska, Pfurtscheller, & Flotzinger, 1996). To predict the need for advanced neonatal resuscitation efforts in the delivery room the fuzzy expert system is used. This system relates the maternal medical, obstetric and neonatal characteristics to the clinical conditions of the newborn, providing a risk measurement of need of advanced neonatal resuscitation measures (Reis, Ortega & Silveira, 2004; Ifeachor & Outram, 1994).

v. Endocrinology

In 1978, a system of an inference engine was applied to treatment of diabetic patients (Buisson, *et.al.*, 1987). An expert system (PROTIS) used for deduction of fuzzy rules was developed for treatment of diabetes (Soula, Vialettes & San Marco, 1983; Turnin, *et. al.*, 1992). The decision support systems for treatment of diabetic out-patients using fuzzy classification were described by Stadelmann, Abbas, Zahlmann, Bruns & Hennig (1990) and Lekkas & Mikhailov (2010). A knowledge-based system was developed for monitoring diabetics, consisting of fuzzy rules and hierarchical neural networks (Zahlmann, Schubert, Obermaier & Mann, 1997). The expert systems such as Diagnosis of Hypothyrodism (Khanale & Ambiwade, 2011), Rheumatic disorders (Moens & Korst, 1991) and Liver disorders (Neshat, Yaghobi, Naghibi & Esmaelzadeh, 2008) are effectively implanted using Fuzzy Logic formalisms.

vi. Oncology

Magnetic resonance image analysis for tumor treatment planning (Vaidyanathan, Velthuizen, Clarke & Hall, 1994) and *Ovarian Cancer* (Wallace, *et. al.*, 1997) has been attempted. Fuzzy systems are developed for the diagnosis of *Ovarian Cancer* (Redman, Duffy, Bromham & Francis, 2011), staging of *Cervical Cancer* (Mitra P., Mitra S. & Pal, 2000), early detection of *Esophageal Cancer* (Hebert, *et. al.*, 2006), management of *Urological Cancer* (Abbod, Catto, Linkens & Hamdy, 2007), management of *Lung Cancer* (Lavanya, Durai & Iyengar, 2011), diagnosis of *Prostate Cancer* (Saritas, Allahverdi & Sert, 2003; Saritas, Allahverdi & Sert, 2013; Seker, Obetayo, Petrovic & Naguib, 2003), multi-criteria fuzzy assignment for *Acute Leukemia* diagnosis (Belacel, Vincke, Scheiff & Boulassel, 2001). Generally, image clustering analysis is mostly applied for determining the brain tumor segmentation (Velthuizen, 1997). Lastly, a fuzzy reasoning algorithm has been used to diagnose Breast tumors using 3-D ultrasonic echographic images (Cios, Goodenday, Shah & Serpen, 1996). The diagnosis and management of breast cancer is focused by many researchers in terms of diagnosis and detection (Reyes & Sipper, 1999; Sahan, Polat, Kodaz & Güneş, 2006; Saleh, Barakat & Awad, 2011) and prognosis methods (Seker, Obetayo, Petrovic & Naguib, 2003).

vii. Gerontology

Gerontology applications have been mainly developed for the use of Fuzzy Logic for clustering. The same research group has used different approaches for different subjects (Manton & Woodbury, 1995). A fuzzy relational system was used to implement the databases for building a veterinary expert system (McLeish, Cecile & Lopez, 1989).

viii. General Practice

In general practice, Fuzzy Logic can be used to assist physicians to define relationships between patients by applying fuzzy clustering (Sedbrook, H. Wright & R. Wright, 1993). Some more applications of Fuzzy Logic are Back pain (Kadhim, Alam & Kaur, 2011), diagnosis of chicken pox and measles (Mahdi, Razali & Salih, 2011), asthma (Zarandi, Zolnoori, Moin & Heidarnejad, 2010). Diagnostic decision support system for *Tuberculosis* (Soundararajan, Sureshkumar & Anusuya, 2012), hypertension

management (Djam & Kimbi, 2011a; Djam & Kimbi, 2011b; Mondal & Raha, 2015) are also developed.

ix. Invasive Medicine

a. Surgery

The surgery branch has benefited greatly by advanced diagnostic tools which include advanced image processing, patho-physiological reasoning as well as improved control mechanisms and simulating systems in anesthesia. Fuzzy Logic is used in the Virtual Reality (VR) simulation as an indirect application (Ota, Loftin, Saito, Lea & Keller, 1995). To create the new image of the patient in Plastic surgery, use of Fuzzy Logic based unsupervised segmentation has given an added advantage (Raposio, *et.al.*, 1997).

b. Anaesthesia

One feature of Fuzzy Logic control is its ability to adapt to the pharmaco-kinetic and pharmaco-dynamic parameter' changes of the patient which has been proved as a system for the delivery of the muscle relaxant pancuronium (Kern, Johnson & Westenskow, 1997). To reduce the usual strain on the anesthetist and to support intra-operative monitoring, intelligent monitoring and alarm systems have been proposed (Becker, *et.al.*, 1997). The first real-time expert system for advice and control (RESAC) in anesthesia was developed to advice on the concentration of inhaled volatile anesthetics (Greenhow, Linkens & Asbury, 1993). Direct application of Fuzzy Logic rule-based controllers has been implemented for controlling drug infusion to maintain an adequate level of anesthesia by monitoring blood pressure and muscle relaxation (Linkens, 1994; Isaka & Sebald, 1989; Isaka, Sebald, Smith & Quinn, 1988; Kamiri & Sebald, 1988; Oshita, Nakakimura & Sakabe, 1994). Evoked potentials were also used as a measure of depth of anesthesia for controlling drug infusion using Fuzzy Logic controllers (Boston, 1989; Nayak & Roy, 1998), and EEG monitoring (Nahm, *et.al.*, 1999). Fuzzy Logic is used to decide the amount of drug infused to maintain a constant depth of anesthesia (Abbod & Linkens, 1998).

c. Artificial organs

One of the early applications of Fuzzy Logic to artificial organs was reported by Saridis using fuzzy decision-making in prosthetic devices (Saridis, 1975; Saridis & Stephanou, 1997). Feng and Andrews (1994) developed an adaptive Fuzzy Logic controller. This controller has the ability to incorporate expert's knowledge in terms of fuzzy rules, which can be reinforced online by a learning algorithm. It was used to develop a system to predict the forces required for standing up and developing a closed-loop controller (Davoodi & Andrews, 1997; Andrews & Davoodi, 1997).

x. Regionally defined medical disciplines

a. Gynaecology

Tumor diagnosis, treatment of intra-uterine foetal distress, monitoring of preterm infants, and differentiating bursts of ultrasonic, data applications have all used fuzzy mathematics (Wolf, *et.al.*, 1996). A System in Fuzzy Set (SELF) has been devised as an extensive interactive system for medical decision help (Kohler, *et.al.*, 1988). SELF was first applied to the prescription of contraceptive methods, but it has now been tested in other specialties such as Gynaecology, Penology, Haematology etc. Another system based on Fuzzy Logic was developed which aids the diagnosis of *Breast Cancer* by analysing the lobulation (Kovalerchuk, Triantaphyllou, Ruiz & Clayton, 1997).

Mental disorders of women (Patel, Kirkwood, Pednekar, Weiss & Mabey, 2006), study of Gynaecological morbidities among the women (Inamdar, Sahu & Doibale, 2013), mathematical approach to diagnose Premenstrual Syndrome (Chattopadhyay & Acharya, 2011) are some other areas where Fuzzy Logic is applicable.

b. Dermatology

Kolles and Hudschen developed a decision support system that processes lexical fuzzy knowledge from standard pathology textbooks (Kolles & Hubschen, 1994). The degree of agreement between the approaches developed for differential diagnosis generated by the system quite high. In terms of classifying the structure and tissues in echocardiogram images, a multiple-feature, hierarchical, fuzzy and neural network fusion solution system has been developed by Brotherton, Pollard, Simpson & DeMaria (1994).

c. Dental medicine

Fuzzy inference for personal identification in medical theory has been demonstrated. The materials examined were mandibular and maxillary dental plaster models of adult males and females, and infant males and females. Teeth characteristics were used as inputs to a fuzzy inference program and the probability of maleness, obtained from the discriminate analysis, was set as the output object. Finally, a sex determination program for both permanent and deciduous teeth was constructed using a fuzzy inference software development tool. Each measured value was input to the program and the output results were compared with those of discriminate analysis (Takeuchi, 1993).

Diagnostic processes for tooth conservation are another application of Fuzzy Logic (Ito, 1997). Fuzzy expert system for diagnosis of periodontal dental diseases was developed in 2011 (Allahverdi, Akcan, 2011). In the field of dentistry skills, an expert system was developed for capturing the knowledge of dentists, then using fuzzy sets to exploit it as a commercial expert system (Sims-Williams, Mackin & Stephens, 1994).

d. Ophthalmology

In ophthalmology, fuzzy reasoning has been applied to eye movement. Prochazka (Prochazka, 1996) used Fuzzy Logic control in which the sensor motor behaves in biologically compatible way. Also, it was utilised for diagnosis of glaucoma which is one of the leading causes of blindness in the world (Losch, 1997).

e. Otology, rhinology, laryngology

In the field of otology and laryngology, a fuzzy expert system has been developed for classification of pharyngeal dysphagia (Suryanarayanan, Reddy & Canilang, 1995). Fuzzy analysis has been used to improve hearing aids. Neuro-fuzzy systems have been implemented to localise sounds in space and Fuzzy Logic based discrimination of spoken words has been investigated to improve cochlea implementation (Nandy, 1996).

f. Urology

The CC-EMG which communicates information on the autonomic cavernous innovation is interpreted mainly by evaluation of signal patterns of higher activity. An

evaluation of the patterns is derived from these features using Fuzzy Logic thereby diagnosing the erectile dysfunction (Gorek, Hartung & Stief, 1997). A fuzzy expert system has been developed mainly for diagnosis and treatment of a typical Adenomatous hyperplasia (AAH) of the prostate and its distinction from well differentiated prosthetic adenocarcinoma with small acinar pattern (Montironi, Bartels, Hamilton, & Thompson, 1996). Fuzzy Logic is also used in the management of urological cancer (Abbod, Catto, Linkens & Hamdy, 2007).

xi. Neuro-medicine

a. Neurology

The techniques used in the soft computing applications in neurology are: signal and image processing, clustering analysis, linguistic modeling, pharmacotherapy prediction, control of body movements by electrical stimulation, self-optimising and neuro-fuzzy networks for decision support (Rocha, 1990; Naranjo, Bremner, Bazoon & Turksen, 1997).

b. Psychology

The Fuzzy Logical model of perception (FLMP) fits the judgments from two features experiments significantly better than an additive model (Ellison & Massaro, 1997). Concept Hierarchy Memory Model (CHMM) is a neural network based model which is used for conceptual knowledge representation and common sense reasoning with fuzzy relations. Using a unified inferencing mechanism based on code string, CHMM performs an important class of commonsense reasoning, including concept recognition and property inheritance (Tan & Soon, 1996).

c. Psychiatry

An expert system to help physicians in administrative, diagnostic, therapeutic, statistical and scientific work has been developed. This system is based on Fuzzy Logic and backward chaining (Kovacs & Juranovics, 1995). A multivariate classification technique based on fuzzy-set mathematics was applied to the demographic, historical, and mental-state data on dementia praecox cases and manic-depressive insanity cases (Woodbury & Jablensky, 1995).

xii. Image and signal Processing

a. Signal Processing

Fuzzy Logic was early applied in medical systems for signal processing and thereby in dynamic state recognition and event prediction. Fuzzy Logic is mainly used for pattern recognition and fuzzy clustering of EEG, ECG and evoked potentials combination with or without Neural networks (Guiheneuc, Nguyen, Pereon & Genet, 1997). Some of the signal processing applications are monitoring the electrical responses of nerve fibres (Al-Holou & Joo, 1997), R-spike detection for rhythm monitoring (Molina, Urbaszek & Schaldach, 1997), clustering of gradient-echo functional MRI in the human visual cortex (Moser, Diemling & Baumgartner, 1997), magnetic resonance imaging (Mutch, *et.al.*, 1997), clustering approach to evoked potentials (Zouridakis, Jansen & Boutros, 1997), expert system for EEG interpretation (Riddington, Ifeachor, Allen, Hudson & Mapps, 1994), matrix-assisted laser desorption / ionization mass spectrometry (Jensen, Mortensen, Vorm & Mann, 1997), feedback control (Lin, 1996), improved monitoring of preterm infants (Wolf, *et.al.*, 1996), detection of rapid eye movement (Wallner, 1996), discrimination of vowels in the cochlear implant signal (Berger-Vachon, Gallego, Morgonand & Truy, 1995), pattern recognition methods to classify esophageal motility records (Abou-Chadi, Ezzat & Sif el-Din, 1994), rule-based labelling of computed tomography images (Cosic & Loncaric, 1997; Schmitt, *et.al.*, 1996; Lo, Chan, Lam & Poon, 1997), segmentation of ventricular angiographics images (Ruben, Mireille, Diego, Carlos & Javier, 1997) and medical image restoration (Hui, Wei & Chin, 1997).

b. Radiation Medicine

Diagnostic imaging and treatment planning for radiation were mainly concerned with image processing using fuzzy techniques i.e. matching two image volumes in terms of their surface elements (tiles). Fuzzy Logic has been used to register the surfaces of two volumes acquired by different medical imaging modalities (Butt, Acharya, Sibata & Shin, 1998). Diagnosis of chronic liver disease from liver scintiscans based on scintigraphic results by fuzzy reasoning gave a better accuracy in diagnosis than a conventional scoring system (Shiomi, Kuroki, Jomura, Ueda & Ikeoka, 1995). Sadati and Mortazavi developed a fuzzy system for modeling and optimisation of radiotherapy treatment planning (Sadati

& Mortazavi, 1995). A similar system was also developed which was based on 3-D radiotherapy of cancer patients (Waschek, Levegrun, Schlegel, Kampen & Engenhart-Cabillic, 1996). For prediction of radiation damage in organs, an expert system was also developed (Busch & Duhmke, 1998).

c. Radiology

Image processing, particularly, magnetic resonance images (MRI) is one of the most popular applications of Fuzzy Logic in medicine (Menhardt, Schmidt, Otttenberg, Kuhn & Imme, 1990; Serpico, Sturaro, Vernazza & Dellepiane, 1987; Clark, *et. al.*, 1994; Colin & Boire, 1997). This is due to the pioneering work of pattern recognition using Fuzzy Logic by Bezdek, Hall & Clarke (1993). Bezdek, Hall, Clark, Goldgof, & Clarke (1997) reported the use of fuzzy models for segmentation and edge detection in medical image data. Fuzzy C-Means clustering is also used in the applications like assigning the patients to different clusters of thyroid diseases. Albayrak & Amasyali (2003) examined unsupervised clustering methods to develop a medical diagnostic system. They used Fuzzy C-Means clustering to assign patients to different clusters of Thyroid diseases. They observed the importance of Fuzzy clustering methods for medical experts in diagnosis.

Fuzzy C-Means clustering for tissue differentiation along with a fuzzy model for segmentation and edge detection have been applied very successfully in many applications. The brain and the heart are most often investigated (Velthuizen, *et.al.*, 1995), together with *Breast Cancer* diagnosis (Kovarlerchuk, Triantaphyllou, Ruiz & Clayton, 1997), diagnosis of rheumatologic diseases (Boegl, *et.al.*, 1995), search for lung nodules (Carmody, Nodine & Kundel, 1980), and interpretation of X-ray Puorescence spectra (Abbott & Adams, 1996).

xiii. Laboratory

a. Biomedical laboratory tests

Fuzzy Logic was used in conjunction with neural networks in clinical laboratory computing with application to integrated monitoring (Guez & Nevo, 1996) and in clinical test database systems (Nishimura, Kambe, Futagami, Morishita & Tsubokura, 1991).

Fuzzy Logic can be used in the areas like Classification of constitution of blood, interpretation of patho-physiological background, controlling the bioprocess, analysis of tests, assistance in diagnosis and solving clinical problems with expert systems.

Many more such systems based on Medical reasoning and decision support, Anatomy, Pathology, Forensic medicine and genetics, Physiology, Pharmacology/biochemistry, Education, Nursing, Healthcare, Oriental medicine etc. have been developed using Fuzzy Logic as a tool and are in use till date. Expert anatomic knowledge, weighted fuzzy reasoning, pattern classification, support center machine method (SCM) and Web based multi-criteria DSS are some of the applications developed under Fuzzy Logic tree related to MDDS.

2.5 Fuzzy Expert Systems in Medical Diagnostic

The research in the field of knowledge based system continued for next decades which can be categorized into following types (Gulavani & Kulkarni, 2009).

- Rule Based reasoning and its application in medical diagnosis.
- Case based reasoning in medical diagnosis.
- Combination of rule based reasoning and case based reasoning.
- Fuzzy Logic with rule based reasoning.
- The relationship between inferencing and the other technologies of hypertext and text retrieval.
- FEL-EXPERT is a family of diagnostic rule-based shells using a Prospector-like model for uncertainty handling.
- Use of Artificial Intelligence in medical diagnosis
- Web based medical diagnostic applications

Using these techniques, many different Medical Diagnostic systems were developed, some of which are still in use. The details of these systems are as follows.

1. INTERNIST–I

INTERNIST is developed by Pople and Myers at the University of Pittsburgh in 1974. It is one of the first clinical decision support systems (CDSS) in general internal

medicine for the diagnosis of complex diagnosis problems. INTERNIST-I is a rule based expert system. It has a tree structure database which related diseases with symptoms. It uses patient observations to figure out a list of relative state of disease. In early 80's, it was used as a basis for the systems CADUCEUS and Quick Medical Reference (QMR), a commercialized diagnosis Decision Support System for internists (Miller, Pople & Myers, 1982; Wolfram, 1995).

2. MYCIN

MYCIN was the first well known rule based medical expert system developed by Shortliffe at Stanford University to help doctors. The objective was to help physicians in the diagnosis and treatment of meningitis and bacteremia infections. MYCIN was goal directed system, designed to use backward chaining reasoning strategy. Clinical knowledge in MYCIN is represented as an inference engine with set of around 600 IF-THEN rules with certainty factors attached to the diagnosis (Mycin, 2016).

The system asks questions to the physician via a long series of yes/no type of questions in textual form. After processing, it provides a list of possible culprit bacteria based on probability of each diagnosis. E-MYCIN an expert system "shells", was introduced in 1980s.

3. CADUCEUS

CADUCEUS is a medical expert system finished in mid-1980s by Harry Pople with the help of Dr. Jack Mayers to improve MYCIN. Instead of embracing all internal medicine, CADUCEUS eventually could diagnose 1000 diseases. Numbers of changes like incorporating adductive reasoning were made to deal with additional complexity of internal diseases (Winston & Prendergast, 1985).

4. QMR–Quick Medical Reference

QMR is developed from INTERNIST-I, to help physicians to diagnose adult diseases. It provides electronic access to more than 750 diseases. QMR uses more than 5,000 clinical findings to describe the features of diseases in the QMR knowledge base. Findings are in the form of medical history, symptoms, physical signs, and laboratory test results. For every disease profile in the QMR knowledge base an extensive review of the

primary medical literature was carried out. The inconsistencies or deficiencies were resolved by consultation with experts. QMR is used in hospital and office practice (Lemaire, *et.al.*, 1999).

5. PUFF–Pulmonary Function System

It is an expert system that diagnoses the results of pulmonary function tests. It was initially developed on the SUMEX computer using E-MYSCIN. Later it was rewritten to run on the hospital's own minicomputer. Initially it interprets set of pulmonary function (PF) test results, like volume of the lungs, the ability of the patient to move air into and out of the lungs, and the ability of the lungs to get oxygen into the blood and carbon dioxide out. Then it produces a set of interpretation statements and a diagnosis for the patient. The expertise of the staff still would be necessary to verify PUFF's output. Approximately 85% of the reports generated are accepted without modifications. PUFF's performance is good enough that it is used daily in clinical service (Aikins, Kunz, Shortliffe & Fallat, 1983).

6. ATHENA

ATHENA is developed by Stanford Medical Informatics, VA Palo Alto Health Care System and Stanford Center for Primary Care and Outcomes Research. It is a Decision Support System (DSS) which implements guidelines for hypertension. ATHENA DSS support blood pressure control and suggests guideline-concordant choice of drug therapy. In ATHENA DSS the clinical experts can customize the knowledge base so as to include new evidence. This knowledge base can also reflect local interpretations of guideline ambiguities. It can be integrated into a variety of electronic medical record systems. For this it uses its database mediator (Athenaeum) (Henriksen, Battles, Marks & Lewin, 2005).

7. CEMS

CEMS is the mental health decision support system. It is developed by the Institute of Living (the Mental Health Network of Hartford Hospital), Hartford, Connecticut, USA. The input to CEMS are clinical functions like evaluation, diagnosis, treatment, outcome assessment by allowing queries (e.g., of treatment protocols) and by monitoring data in

the central medical database for observance to more than 100 practice guidelines. In case the practice does not follow the guidelines, alert messages are sent to clinicians. A response is generated by changing the not-standard practice (Morelli, Bronzino & Goethe, 1987).

8. ERA–Early Referrals Application

ERA is a web-based decision support and cancer referrals system developed by Advanced Computation Laboratory, Cancer Research UK, London in collaboration with Infer Med Ltd., London. ERA is an interactive decision support tool to support General Practitioners. It identifies patients with suspected cancer that should be referred under the 2- week standard outlined by the Department of Health's "Referral Guidelines for Suspected Cancer" (Bury, Humber & Fox, 2001).

9. GIDEON (Global Infectious Disease and Epidemiology Network)

GIDEON is developed by the gideononline.com for diagnosis of infectious diseases, tropical diseases, epidemiology, microbiology and antimicrobial chemotherapy. The system generates a Bayesian ranked differential diagnosis based on signs, symptoms, laboratory tests, country of origin and incubation period; and can be used for diagnostic support and simulation of all infectious diseases in all countries. The data in GIDEON are derived from all peer-reviewed journals in the relative fields. The database incorporates 327 diseases, 205 countries, 806 bacterial taxa and 185 antibacterial agents (Berger & Blackman).

10. PERFEX–Knowledge Based Interpretation of Myocardial SPECT Imagery

The PERFEX project has as overall objective of developing a clinically useful, computer-based methodology to use in the diagnosis of heart disease. The methodology contains well established mathematical methods, visualization techniques and artificial intelligence approaches for representing medical knowledge and integrating visual, numeric, textual and temporal information. It automatically determines the orientation of left ventriculae myocardium (DISHA). It is aimed at extension and enhancement of a knowledge base for interpreting myocardial perfusion imagery and other relevant information. It is also intended towards prediction of resting perfusion from resting

thickening distributions through connectionist methods (Henriksen, Battles, Marks & Lewin, 2005).

11. Iliad

It is the expert system for internal medical diagnosis at the University of Utah, School of Medicine's Dept. of Medical Informatics. Iliad uses Bayesian reasoning to calculate the posterior probabilities of various diagnoses under consideration, given the findings present in a case. Iliad was developed initially for diagnosis in Internal Medicine. It now covers about 1500 diagnoses in this domain, based on several thousand findings. Iliad is used as a teaching tool for medical students. Iliad can be useful to a health care provider as a personal consultant and can suggest relevant diagnoses (Bury, Humber & Fox, 2001; Warner & Bouhaddou, 1994).

12. Isabel

Isabel is a web-based diagnosis decision support system created in 2001 by physicians to offer diagnosis decision support at the point of care. Isabel covers all ages (neonates to geriatrics) and all major specialties and sub-specialties in Internal Medicine, Surgery, Gynecology & Obstetrics, Pediatrics, Geriatrics, Oncology, Toxicology and Bioterrorism. Isabel is fast and easy to use & gives the clinician an instant list of likely diagnoses for a given set of clinical features like symptoms, signs, results of tests and investigations etc. Isabel has been interfaced with electronic medical record systems (EMR). It helps to answer clinical questions with up to date knowledge from textbooks and journals containing 11000 diagnosis and 4000 drugs and heuristics. In 2012, a separate version was developed for patients as a symptom checker. Isabel's diagnostic tool is capable of understanding ordinary English sentence constructions through the use of statistical natural language processing (Ramnarayan, *et.al.*, 2006).

13. LISA

LISA is a clinical information and decision support system for collaborative care in childhood acute lymphoblastic leukemia. A centralised Oracle database holds all patient information and accessible by health professionals from different sectors in different locations. Acute Lymphoblastic Leukemia (ALL) is the most common pediatric

malignancy. It is implemented using PROforma guideline development technology which was designed to provide advice about dose adjustments in the treatment of acute childhood lymphoblastic *Leukemia* (Bury *et. al*., 2004).

14. Expert System for the Diagnosis of neonatal jaundice for use by medical field personnel

The main objective of this system is to develop an expert system module that uses the clinical decision criteria of experts in the neonatology field to advice paramedical and semi-skilled personnel who require guidance to diagnose the etiology of neonatal jaundice. The project was developed using software package EXSYS (Multilogic Inc.). A rule-based system is used to build the decision tree that would aid the paramedical personnel to arrive at an appropriate etiology for hyperbilirubinemia in a neonate. The disadvantage of this model is that it becomes obsolete in a few years' time unless it is constantly being updated by developers (Dharmar, Srinivasan, Mital & Haque, 2002).

15. MEDUSA

MEDUSA is a fuzzy expert system for medical diagnosis of acute abdominal pain. The medical knowledge in this field is characterized by uncertainty, imprecision and vagueness. The hybrid concept of the system enables the integration of rule-based, heuristic and case-based reasoning on the basis of imprecise information. The central idea of the integration is to use case-based reasoning for the management of special cases, and rule-based reasoning for the representation of normal cases (Torbaghan & Meyer, 1994; Saleh, Barakat & Awad, 2011).

16. CADIAG-2

CADIAG-2 (Computer Assisted DIAGnosis) is a well-known rule-based expert system aimed at providing support in diagnostic decision making in the field of internal medicine (Adlassnig, 1980; Adlassnig, Kolarz, Scheithauer, Effenberger & Grabner, 1985; Adlassnig, 1986; Adlassnig & Akhavan-Heidari, 1989). Its design and construction was initiated in the early 80's at the Medical University of Vienna by K.P. Adlassnig. CADIAG-2 consists of the inference engine and the knowledge base. The inference engine (Muino, 2010) for alternative formalizations and analyses of CADIAG-2's

inference is based on methods of approximate reasoning in fuzzy set theory (Zadeh, 1965; Zadeh, 1975). The knowledge base consists of a set of IF-THEN rules intended to represent relationships between distinct medical entities: symptoms, findings, signs and test results on the one hand and diseases and therapies on the other. CADIAG-2's knowledge base is formalised as a probabilistic logic theory (Klinov, Parsia & Picado-Muino, 2010). It is highly unsatisfiable. It is unclear what action this calls for. Inconsistency in a knowledge base may capture critical information and maintaining it may be critical to the integrity of the represented knowledge (Gabbay & Hunter, 1991; Adlassnig, 2001; Klinov, Parsia & Picado-Muino, 2010).

17. DoctorMoon

It is a Fuzzy Logic rule based system for diagnosis of lung diseases. DoctorMoon has been programmed in Borland Delphi 4.0 and run on Microsoft Windows 9x. It's easy to install and has a friendly interface. The knowledge base of DoctorMoon is managed by a Borland Paradox Database consisting of 700 records, each represents a rule. Most of the rules in DoctorMoon were provided by doctors in the Vietnam National Institute of Tuberculosis and Lung Diseases (VNITLD). A program will browse the patient database to summarize the common syndromes that confirms or excludes a certain lung disease and then creates new rules. A large number of rules can be created very quickly in this way, but rules' accuracy is not high.

DoctorMoon had undergone much testing and the knowledge base had been corrected several times by conducting diagnostic tests, with the help of lung disease experts.

A patient database was created and has been updated. This database plays a crucial role in the automatic knowledge acquisition. In most cases, DoctorMoon drew the same conclusion as the last conclusion of the doctor in the records.

The evaluation found DoctorMoon's diagnoses to be acceptable and in order to improve system's performance in special cases, the knowledge base needs to be strengthened. The reasoning engine is good (Phuong & Vladik, 2000).

18. MedFrame/CADIAG IV

MedFrame/CADIAG-IV is a rule- and frame-based diagnostic and therapeutic consultation system. It is the latest successor of the CADIAG projects that started with a

system based on Boolean logic in 1968. MedFrame/CADIAG-IV consists of the following components (Kolousek, 1996):

- Patient management and general administration
- Database
- Knowledge base
- Inference engine
- Explanation tool
- User interface

It is designed as a multi-user, platform independent client/server system that is implemented by use of flexible object-oriented programming and modeling techniques. It is also equipped with a modern graphical user interface with multi-language capability and comprehensive help-functions. It is a platform independent system achieved by using Smalltalk Visual works. It's a SNOMED International based multi-user system in which the problem of users' access rights to data is overcame. It is made to communicate with other systems via computer networks and internet for smooth data exchange (Boegl, Leitich, Kolousek, Rothenfluh & Adlassnig, 1996; Sageder, Boegl, Adlassnig, Kolousek & Trummer, 1997; Adlassnig, 2001).

19. FuzzyTempToxoPert

This system interprets toxoplasmosis serology test results obtained for Toxoplasma gondii infections in pregnant women. It also provides therapeutic recommendations to avoid fetal damage or subsequent harm to the child. The system contains knowledgebase in the form of decision graph. Decision rules control the transition from one decision node to the next. Each transition step is activated by obtaining a further serological test result. To arrive at correct diagnostic interpretations, a minimal temporal distance from one test to the next has to be observed. These minimal distances are checked by applying fuzzy sets modeling temporal concepts (Adlassnig, 2001).

20. Medical Diagnostic Support System (MDSS)

MDSS, Medical Diagnostic Support System is a medical expert system applied to support the diagnosis and treatment of diabetes. It is the evidence-based medicine

approach, which is concerned with ensuring that strategies of proven clinical effectiveness are adopted by the system. It is a logic based system which adopts a forward, backward chaining inference mechanism. The system judges the possibility of illness, its severity and its potential complications including a statistical belief, based on the patient's symptoms and laboratory examinations. The system also gives prescriptions for treatment and makes useful indications and suggestions (Filho, 2008).

21. DxPlain

DXplain is a computer based diagnostic decision support system designed for those physicians who have lack of computer expertise. It was developed with the support and cooperation of the American Medical Association. The system is distributed to medical community through AMA/NET with the objective of collaboration with its physician-users whose comments, criticisms and suggestions, modification and enhancement of the knowledge-base is possible. It uses the Bayesian inference decision process to take into account one piece of clinical finding (such as a symptom or lab result) at a time, and then calculate the statistical probabilities of various potential diagnoses. The system accepts a list of clinical manifestations and processes diagnostic hypotheses. The program explains and justifies its interpretations and provides access to a knowledge-base concerning the differential diagnosis of signs and symptoms (Barnett, Cimino, Hupp & Hoffer, 1987; Iantovics, 2006).

22. Dr. Watson

It the experts system developed by IBM which uses natural language capabilities, hypothesis generation and evidence-based learning to support medical professionals as they make decisions. Watson starts by parsing the input to identify the key pieces of information. Watson then mines the patient data to find relevant facts about family history, current medications and other existing conditions. It combines this information with current findings from tests and instruments and then examines all available data sources to form hypotheses and test them. Watson can incorporate treatment guidelines, electronic medical record data, doctors and nurse's notes, research, clinical studies, journal articles, and patient information into the data that is available for analysis.

Watson will then provide a list of potential diagnoses along with a score that indicates the level of confidence for each hypothesis (Watson in Healthcare, 2016).

Few more diagnosis software are available online such as Expert opinion software for medical diagnosis and treatment, Artificial Intelligence in Medical Diagnosis, Reliable Clinical Diagnosis Support System, Doctor's Diagnosis, Version 2.0, Easy Diagnosis OnCoQuant, YourDiagnosis, MILORD, Resolution MD, SimulConsult, Support Center machine, TxDENT, Novel Diagnosis System (Iantovics, 2006), Human disease diagnosis an expert system (Hasan, Sher-E-Alam & Chowdhury 2010), etc.

2.6 Summary

Taking a review of all these systems and applications, it is observed that tremendous amount of work has been carried out in the field of medical diagnostic. Many expert systems, medical decision support systems have been developed and are in use. Some systems are generalized ones; some are specific to some branch of medicine. From expert's perspective, Gynaecology is the branch which is very specific and important from the uncertainty and vagueness point of view. This calls for more and detailed research in the Gynaecology disease diagnosis.

Study confirms that the differential diagnosis is the process which is inherently used in the diagnosis by the physicians. Differential diagnosis process invites the step wise diagnosis approach, particularly in the Gynaecology diseases. The need to simulate this process of differential diagnosis using different stages is essential.

Fuzzy Logic is based on the perceptions. Perceptions vary from person to person. More the experience of an expert, more accurate is the perceptions. The perception based diagnosis may give more accurate results in the medical diagnostic process.

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Chapter 3

Gynaecology Diseases: An Overview

This Chapter presents certain details about the Gynaecology as a branch of medical sciences. The details include the definition, history of Gynaecology and gynecological diseases. It also outlines the diseases that have been studied in the present work and various tests those are to be conducted for their diagnosis.

3.1 Introduction

The Kahun Gynaecological Papyrus (1800 B.C.) is the oldest known medical text of any kind. It deals with women's complaints, gynecological diseases, fertility, pregnancy, contraception, etc. The text is divided into thirty-four sections, each section deals with a specific problem and contains diagnosis and treatment. No prognosis is suggested. The treatments suggested are non-surgical, comprising application of medicines to the affected body part or oral medication. The womb is at times seen as the source of complaints manifesting themselves in other body parts.

Gynaecology or **Genecology** is the medical practice dealing with the health of the female reproductive systems (vagina, uterus and ovaries) and the breasts. Literally, outside medicine, it means "the science of women". Its counterpart is Andrology, which deals with medical issues specific to the male reproductive system (Gynaecology, 2016).

Obstetrics is the field of study concentrated on pregnancy, childbirth, and the postpartum period. As a medical specialty, obstetrics is combined with Gynaecology under the discipline known as Obstetrics and Gynaecology (OB/GYN) (Obstetrics, 2016).

3.2 Gynaecological disorders and diseases

The Gynaecological disorders affect the female reproductive system. The most common symptoms of Gynaecological disorders include pelvic pain, vaginal itching, vaginal discharge, abnormal vaginal bleeding, breast pain and lumps (Barad, 2016).

In a broad view, Gynaecological disorders* are classified into following types (Datta, 2009) as Pelvic Infections, Sexually Transmitted Diseases, Infections on Individual Pelvic Organs, Disorders of Menstrual Cycles, Abnormal Menstrual Bleeding, Displacement of Uterus, Benign Lesions of Vulva and Vagina, Benign Lesions of Cervix, Benign Lesions of Uterus, Benign Lesions of Ovary, Endometriosis and Adenomyosis, Genital Malignancy, Urinary Problems in Gynaecology, Genital Fistulae and Special Disorders.

**See Annexure 3.1 for more details on Gynaecological disorders.*

1. Pelvic infections

The infection of one pelvic organ usually spreads to the other more frequently. There is a direct communication of the peritoneal cavity to the exterior through the vagina. In spite of these, the frequency and intensity of pelvic infection is kept lowered by the defense mechanism. Some of the common pelvic infections are as follows.

a. Pelvic Inflammatory Disease (PID)
b. Infections following delivery and abortion
c. Infections following Gynaecological procedures
d. Infections following IUD
e. Infections secondary to other infections - Appendicitis

2. Sexually transmitted infections

Sexually transmitted diseases are caused by bacteria, viruses, protozoa, fungi and ectoparasites. These infections include those which are predominantly transmitted

through sexual contact from an infected partner. The various modes of transmission include sexual contact, placental (HIV, syphilis), blood transfusion or infected needles (HIV, hepatitis B or syphilis) or inoculation on the birth canal (gonococcal, chlamydial or herpes). Gynaecological morbidities associated with the sexually transmitted diseases (STDs) are normally high. Also the chronic pelvic infection, infertility, ectopic pregnancy, vulval and cervical neoplasia are long term sequelae.

3. Infections of individual pelvic organs

The vulval and perineal skin is usually resistant to common infection. But the defense is lost following constant irritation by the vaginal discharge or urinary incontinence. The vulval infection may be affected secondarily; the primary site may be elsewhere in the adjacent structures.

It is difficult to classify the vulval infection but the following aetiological classification is of great use.

- **a.** Vulval Infection
- **b.** Endometritis
- **c.** Acute Bartholinitis
- **d.** Pyometra
- **e.** Bartholin's Abscess
- **f.** Salpingitis
- **g.** Bartholin's Cyst
- **h.** Oophoritis
- **i.** Vaginal Infection (Vaginitis)
- **j.** Parametritis
- **k.** Vulvo-vaginitis in childhood
- **l.** Pelvic abscess
- **m.** Cervicitis
- **n.** Endometritis

4. Disorders of menstrual cycles

The menstrual disorders are nothing but the disruptive physical and/or emotional symptoms just before and during menstruation and include heavy bleeding, missed periods and unmanageable mood swings. These include:

a. Dysmenorrhoea: It is marked by painful periods, or menstrual cramps, pain during menstruation. It usually begins around when the menstruation starts. Symptoms typically last for less than three days. Also, the pain is usually in the pelvis or lower abdomen. Other symptoms may include back pain, diarrhea or nausea.

b. **Primary Dysmenorrhoea (Spasmodic):** In this disorder, there is no identifiable pelvic pathology.

c. **Secondary Dysmenorrhoea (Congestive)**: It is normally considered to be menstruation associated pain that occurs in the presence of pelvic pathology.

d. **Premenstrual Syndrome (PMS):** It is a psycho-neuro-endocrine disorder of an unknown aetiology and is often noticed just prior to menstruation. Also, there is a cyclic appearance of large number of symptoms during the last 7-10 days of the menstrual cycle.

5. Abnormal Menstrual Bleeding

It usually includes heavy menstrual bleeding (Menorrhagia), no menstrual bleeding (Amenorrhea) or bleeding in between periods (Metrorrhagia), painful menstrual periods (dysmenorrheal), Premenstrual Syndrome (PMS) and Premenstrual Dysphonic Disorder (PMDD).

a. **Menorrhagia (Hypermenorrhoea):** There is a cyclic bleeding that occurs at normal intervals and the bleeding is either excessive in quantity (> 80 ml) or excessive in duration or both.

b. **Polymenorrhoea (Epimenorrhoea):** Polymenorrhoea is defined as a cyclic bleeding where the cycle is reduced to an arbitrary limit of less than 21 days and remains constant with the same frequency. It is called epimenorrhagia if frequent cycle is associated with an excessive and prolonged bleeding.

c. **Metrorrhagia:** In metrorrhagia, irregular acyclic bleeding from the uterus is observed. The amount of bleeding varies. It is strictly concerned with the uterine bleeding. Menometrorrhagia is when the bleeding is quite irregular and excessive that the menses cannot be identified at all.

d. **Oligomenorrhoea:** In this case, the menstrual bleeding occurs more than 35 days and remains constant with the same frequency.

e. **Dysfunctional Uterine Bleeding (DUB):** It is a state of abnormal uterine bleeding without any clinically detectable organic systematic and iatrogenic cause.

6. Displacement of Uterus

The uterus is not a fixed organ in general. Minor variations in its position in any direction occur constantly with changes in posture, with straining and with full bladder or loaded rectum. The term displacement of uterus is used only when the uterus rests habitually in a position beyond the limit of normal variation.

a. Retroversion: It is the term used when the long axes of the corpus and cervix are in line and the whole organ turns backwards in relation to the long axis of the birth canal. Retro-flexion signifies a bending backwards of the corpus on the cervix at the level of internal os. The two conditions are usually present together and are loosely called retroversion or retro-displacement.

b. Pelvic Organ Prolapse (POP): The pelvic Organ Prolapse (POP) is one of the common clinical conditions observed in day-to-day gynecological practice, especially amongst the parous women. The entity includes descent of the vaginal wall and/or the uterus. It is in fact, a form of hernia.

7. Benign lesions of vulva and vagina

a. Vulval Epithelial Disorders: The term dystrophy was used to embrace several lesions in the vulva characterized by epithelial abnormalities, which result in either red or white appearance of the skin of the region. Usually within the spectrum, various patterns of epithelial changes may be found. The changes may be interchangeable in the same patient at different times or at different sites. The process may be reversible or may remain static.

b. Vulval Ulcers: The vulval ulcers are developed predominantly due to the sexually transmitted diseases and rarely due to specific causes. The malignant ulcer is also rare. The various aetiological factors related to vulval ulcers are STD related, idiopathic, Tuberculosis, Malignancy, systematic disease related or Dermatoses.

c. Miscellaneous swellings: These include vulval cysts, Iguinolabial hernia, vulval varicosities, elephantiasis vulvae, benign tumors of the vulva and endometriosis.

d. **Vaginal Cysts:** This is of rare occurrence since there is no gland in the mucous coat. However, small cysts may remain unnoticed. The common cysts that are found include Gartner's duct cyst and epithelial inclusion cyst.

e. **Vulval Pain Syndrome :** Vulval pain may be burning, stinging or irritation. It may be due to reasons like aphthous ulcer, vulval dermatoses, Herpes genitalis, pudendal or genitofemoral nerve neuralgia, vulvodynia, referred pain from urethral or vagina and vulval vestibulitis syndrome. Sometimes it is also psychological.

8. **Benign Lesions of the Cervix**

a. **Cervical Ectopy (Erosion):** It is a condition where the squamous epithelium of the ectocervix is replaced by columnar epithelium which is continuous with the endocervix. It is not an ulcer.

b. **Eversion (Ectropion):** In chronic cervicitis, there is thickening of the cervical musosa with underlying tissue odema. These thickened tissues tend to push out through the external os along the direction of least resistance. The entity is most marked where the cervix has already been laceracted. In such conditions, the longitudinal muscle fibres are free to act unopposed. As a result, the lips of the cervix curl upward and outwards to expoise the red looking endocervix so as to be confused with ectopy.

c. **Cervical Tear:** In this case, varying degrees of cervical tear is invariable during vaginal delivery. Also, one or both the sides may be torn or the tear may be irregular. If there is no superimposed infection and the tear is small, the torn surfaces may oppose leaving behind only a small notch. However, if infection supervenes, eversion occurs confusing the diagnosis of ectopy.

d. **Cervical Cysts:** These are of types like Nabothian cysts, Endometriotic cysts and Mesonephiric cysts.

e. **Elongation of the Cervix:** The normal length of a cervix is about 2.5 cm. The vaginal and the supravaginal parts are of equal length. The elongation may affect either part of the cervix.

9. Benign Lesions of the Uterus

a. Fibroid: It is not only the most common benign tumor of the uterus but is the most common benign solid tumor in females. Histologically, this type of tumor is composed of smooth muscle and fibrous connective tissue, so named as uterine leiomyoma, myoma or fibromyoma.

b. Body or Corporeal Fibroid: In this case, the uterus is enlarged and the shape is distorted by multiple nodular growths of varying sizes. Occasionally, there may be uniform enlargement of the uterus by a single fibroid. Also, the feel is firm.

c. Cervical Fibroid: It normally appears in the non-pregnant state and the symptoms are predominantly due to pressure effect on the surrounding structure.

d. Fibroid Polyp, Placental Polyp, and Malignant Polyp: The fibroid polyp may arise from the body of the uterus or from the cervix. In the case of Placental polyp, a retained bit of placental tissue when adherent to the uterine wall gets organized with the surrounding blood clots. The mass so formed is in fact not pedunculated. The malignant polyp may undergo secondary malignant changes on benign polyps.

10. Benign Lesions of the Ovary

a. Ovarian Enlargement: It is broadly of two types: Non-neoplastic, and Neoplastic (Benign). In the non-neoplastic, the enlargement of the ovary is usually due to accumulation of fluid inside the functional unit of the ovary. The incidence of ovarian tumor amongst Gynaecolgical admission varies from 1 to 3%. The principal ovarian tissue components are: epithelial cells derived from the coelomic epithelium, Oocytes derived from the primitive germ cell and mesenchymal elements from the gonadal stroma.

b. Borderline Epithelial tumors of the ovary: Borderline Epithelial tumors have got some but not all features of malignancy. They are of low malignant potential.

c. Paraovarian Cyst: Paraovrian cyst may arise either from the vestigial remnants of Wolffian in the mesosalpinx or even from the peritoneal inclusions or from tubal epithelium. In such a case, the ovary is separated and the uterine tube is stretched over the cyst.

11. Endometriosis and Adenomyosis

The presence of functioning endometrium in sites other than uterine mucosa is called *Endometriosis*. It is not a neoplastic condition although malignant transformation is possible. *Adenomyosis* is a condition where there is ingrowth of the endometrium, both the glandular and stromal components, directly into the myometrium.

12. Premalignant lesions

a. Premalignant Vulval Lesions: These include vulval intraepithekial neoplasia, Paget's disease, Lichen sclerosus, squamous cell hyperplasia and condyloma accuminata.

b. Premalignant Endometrial Lesion: There is an ample evidence that both the endometrial hyperplasia and carcinoma are oestrogen dependent. The long-term unopposed oestrogen, particularly around the time of menopause, often leads to various types of endometrial hyperplasia.

13. Genital malignancy

- **a.** Vulval Carcinoma
- **b.** Sarcoma Uterus
- **c.** Vaginal Carcinoma
- **d.** Endometrial carcinoma
- **e.** Carcinoma cervix
- **f.** Carcinoma Fallopian Tube
- **g.** Sarcoma Botryoides
- **h.** (embryonal rhabdomyosarcoma)
- **i.** Malignant Ovarian tumor (Ovarian Cancer)

14. Urinary problems in Gynaecology

- **a.** Urinary Incontinence
- **b.** Reflex Incontinence
- **c.** Genuine Stress Incontinence (GSI)
- **d.** Painful Bladder Syndrome (PBS)
- **e.** Urge Incontinence
- **f.** Urinary Track Infections
- **g.** Overactive Bladder
- **h.** Dysuria
- **i.** Voiding Disorder
- **j.** Frequency of Urination
- **k.** Overflow Incontinence
- **l.** Urethral Caruncle

15. Genital fistulae

a. **Genitourinary Fistula:** Geniyourinary fistula is an abnormal communication between the urinary and genital track either acquired or congenital with involuntary escape of urine into the vagina.

b. **Urethrovaginal Fistula:** A urethrovaginal fistula is an abnormal passageway between female urethra and vagina. The fistula is often developed after incontinence surgery, surgical treatment of urethral diverticulas, prolonged labor or obstetric interventions. Other causes include trauma (pelvic fractures, long-term catheterization etc.), and tumors or the complications of cancer treatment such as surgery and radiation.

c. **Rectovaginal Fistula:** The Abnormal communication between the rectum and vagina with involuntary escape of flatus and / or faeces into the vagina is called rectovaginal fistula.

16. Genital track injuries

The genital track and the adjacent pelvic organs are subjected to strain of vaginal delivery either spontaneous or assisted. The injury is more in areas of inadequate antenatal and intra-natal care. These injuries are caused by:

a. **Old complete perineal tear (CPT):** A tear of the perineal body involving the sphincter ani externus with or without involvement of the anorectal mucosa is called as complete perineal tear.

b. **Coital injuries:** The nature of coital injuries include (i) minor haemorrhage, due to tearing of the hymen or bruising of the vagina or urethra may occur at defloration (ii) severage haemorrhage, if the tear spreads to involve the vestibute or the region of the clitoris and (iii) rupture of the vault of the vagina exposing the peritoneal cavity.

c. **Rape:** In this case, the rape victims may be of any age group.

17. Amenorrhea

An Amenorrhea means the absence of a menses.

a. **Primary Amenorrhea:** It is described in case a girl who has not yet menstruated by her 16 years of age is having Primary Amenorrhea rather than delayed menarche.

b. **Secondary Amenorrhea:** It is the absence of menstruation for 6 months or more in a woman whose normal menstruation has already been established.

c. **Polycystic Ovarian Syndrome (PCOS):** It is a syndrome manifested by amenorrhea, hirsutism and obesity associated with enlarged polycystic ovaries. In fact, POCS is multifactorial and polygenic in condition.

d. **Premature Ovarian Failure:** It is defined when ovarian failure occurs before the age of forty.

18. Special disorders

a.	Abnormal Vaginal Discharge	**b.**	Breast in Gynaecology
c.	Pruritus Vulve	**d.**	Breast Carcinoma
e.	Pelvic pain	**f.**	Psychosexual Problems
g.	Acute Pelvic pain	**h.**	Vaginismus
i.	Chronic Pelvic pain	**j.**	Dyspareunia
k.	Trappedn (Residual) Ovarian Syndrome	**l.**	Abdominopelvic lump
m.	Ovarian Remnant Syndrome	**n.**	Adnexal Mass
o.	Postmenopausal Bleeding	**p.**	Hirsutism
q.	Low Backache	**r.**	Galactorrhoea

3.3 Description, Symptoms and Tests for 31 selected diseases

Out of these Gynaecological diseases, the present study focuses on thirty one most commonly occurring diseases. The selection is based on the medical results and experts' opinions. The reason, in selecting the most commonly occurring diseases, is to get the maximum number of patients as an input to the developed software so that the reliability of the software can be tested rigorously.

3.3.1 List and Description of Diseases

The details of the selected 31 diseases are presented below (Diseases and Conditions, 2016; Health A-Z, 2016; Medicine, 2016).

1. **Uterine Prolapse:** If the muscles or ligaments get stretched or become weak, they are no longer able to support the uterus thereby causing prolapse. *Uterine Prolapse* occurs when the uterus sags or slips from its normal position and into the vagina (birth canal).
2. **Endometriosis:** The presence of functioning endometrium in sites other than uterine mucosa is called endometriosis. It is not neoplastic condition, although malignant transformation is possible.
3. **Vaginal Yeast Infection:** A *Vaginal Yeast Infection* is a fungal infection that causes irritation, discharge and intense itchiness of the vagina and the vulva: the tissues at the vaginal opening. It is a type of *Vaginitis* or inflammation of the vagina.
4. **Ovarian Cyst:** *Ovarian Cysts* are fluid-filled sacs or pockets within or on the surface of an ovary. Women have two ovaries, each about the size and shape of an almond, located on each side of the uterus. Eggs (ova) develop and mature in the ovaries and are released in monthly cycles during child bearing years.
5. **Urinary Track Infection:** An *Urinary Tract Infection* (UTI) is an infection in any part of urinary system; kidneys, ureters, bladder and urethra. Most infections involve the lower urinary tract: the bladder and the urethra. Women are at greater risk of developing an UTI than men.
6. **Vulval Cancer:** *Vulval Cancer* is a type of cancer that occurs on the outer surface of the female genitalia. The vulva is the area of skin that surrounds the urethra and vagina, including the clitoris and labia. *Vulvar Cancer* commonly forms as a lump or sore on the vulva that often causes itching. Though it can occur at any age, *Vulvar Cancer* is most commonly diagnosed in older women.
7. **Uterine Cancer (Menopaused):** *Endometrial Cancer* develops when cells in the endometrium begin to grow out of control and can then invade nearby tissues or spread throughout the body. *Endometrial Cancer*, or cancer of the endometrium, is a cancer that develops in the inner lining of the uterus (womb). This lining is called the endometrium. Cancer is the uncontrolled growth of cells that invade and cause damage to surrounding tissue.

8. **Uterine Cancer (PeriMenopausal):** Similar to *Uterine Cancer* (Menopaused), but the woman is menstruating and has not yet received menopause. Her age is Perimenopausal, she shows some of the symptoms of Menopause.

9. **Menopause:** *Menopause* is a normal condition that all women experience as they age. The term "Menopause" can describe any of the changes a woman goes through either just before or after she stops menstruating, marking the end of her reproductive period. It is the period in a woman's life (typically between the ages of 45 and 50) when menstruation ceases.

10. **Premenstrual Syndrome (PMS):** *Premenstrual syndrome* (PMS) refers to the physical and emotional symptoms that occur within one to two weeks before a woman's period. Symptoms often vary among women and resolve around the start of bleeding. Common symptoms include acne, tender breasts, bloating, feeling tired, irritability and mood changes. Often symptoms are present for around six days. A woman's pattern of symptoms may change over the time. Symptoms do not occur during pregnancy or following Menopause.

11. **Ovarian Cancer:** *Ovarian Cancer* is a cancer that begins in an ovary. It results in abnormal cells that have the ability to invade or spread to other parts of the body. When this process begins, symptoms may be vague or not apparent, but they become more noticeable as the cancer progresses. These symptoms may include bloating, pelvic pain, and abdominal swelling, among others. Common areas to which the cancer may spread include the lining of the abdomen, lining of the bowel and bladder, lymph nodes, lungs, and liver.

12. **Pelvic Inflammatory Disease (PID):** *Pelvic Inflammatory Disease*, commonly called PID, is an infection of the female reproductive organs. PID is one of the most serious complications of a sexually transmitted disease in women: It can lead to irreversible damage to the uterus, ovaries, fallopian tubes or other parts of the female reproductive system and is the primary preventable cause of infertility in women.

13. **Cervical Cancer (Stage I):** *Cervical Cancer* is a cancer arising from the cervix. It is due to the abnormal growth of cells that have the ability to invade or spread to other parts of the body. Early on, typically no symptoms are seen. Later, symptoms may

include abnormal vaginal bleeding, pelvic pain or pain during sexual intercourse. While bleeding after sex may not be serious, it may also indicate the presence of cervical cancer.

14. **Dysfunctional Uterine Bleeding (DUB):** Abnormal uterine bleeding (formerly, *Dysfunctional Uterine Bleeding* (DUB) is irregular uterine bleeding that occurs in the absence of recognizable pelvic pathology, general medical disease or pregnancy. It reflects a disruption in the normal cyclic pattern of ovulatory hormonal stimulation to the endometrial lining. The bleeding is unpredictable in many ways. It may be excessively heavy or light and may be prolonged, frequent or random.

15. **Endometritis:** *Endometritis* is an inflammation of the endometrium, the inner lining of the uterus. It is usually due to an infection. The uterus, or womb, is a major reproductive organ in women. It is where the fetus develops during pregnancy.

16. **Uterine Fibroid:** *Uterine Fibroids* are noncancerous growths of the uterus that often appear during childbearing years. *Uterine Fibroids* are very common non-cancerous (benign) growths that develop in the muscular wall of the uterus. They can range in size from very tiny (a quarter of an inch) to larger than a cantaloupe. Occasionally, they can cause the uterus to grow to the size of a five-month pregnancy. In most cases, there are more than one fibroid in the uterus. While fibroids do not always cause symptoms, their size and location can lead to problems for some women, including pain and heavy bleeding.

17. **Polycystic Ovaries:** *Polycystic Ovarian Syndrome* is a problem in which a woman's hormones are out of balance. It can cause problems with periods and make it difficult to get pregnant. *Polycystic ovarian Syndrome* (PCOS) is a common endocrine system disorder among women of reproductive age. Women with PCOS may have enlarged ovaries that contain small collections of fluid called follicles which are located in each ovary as seen during an ultrasound examination.

18. **Adenomyosis:** *Adenomyosis* is a medical condition characterized by the presence of ectopic glandular tissue found in a muscle. Adenomyosis, also called to as '*Uterine Endometriosis*', is a benign disease confined to the uterine muscle. Endometrial cells from the lining of the endometrial cavity migrate from that lining, most commonly

into the posterior side or back wall of the uterus. As these cells respond to monthly hormonal changes, blood can get trapped in the myometrium producing a hard and enlarged uterus. Adenomyosis is most frequently seen in women in their early to middle 40s and is often associated with hormone imbalance, usually an excessive estrogen supply.

19. **Ectopic Pregnancy:** In 1 out of every 50 pregnancies, the fertilized egg stays in the fallopian tube. It is called an *Ectopic Pregnancy* or a *Tubal Pregnancy*. In rare cases, the fertilized egg attaches to one of the ovaries, the cornua (or horn) of the uterus or even the cervix. Ectopic pregnancies require emergency treatment.

20. **Lecuorrhoea:** *Lecuorrhoea* or *Leukorrhea* is a thick, whitish, or yellowish vaginal discharge. There are many causes of *Leukorrhea*, the usual one being estrogen imbalance. The amount of discharge may increase due to vaginal infection or STDs, and also it may disappear and reappear from time to time. This discharge can keep occurring for years in which case it becomes more yellow and foul-smelling; it is usually a non-pathological symptom secondary to inflammatory conditions of vagina or cervix.

21. **Hyperprolactinemia:** *Hyperprolactinemia* is a condition in which a person has higher-than-normal levels of the hormone prolactin in the blood. The main function of prolactin is to stimulate breast milk production after childbirth, so high prolactin levels are normal in pregnancy.

22. **Haematometra:** *Haematometra* or *Hematometra* is a medical condition involving collection or retention of blood in the uterus. An imperforate hymen or a transverse vaginal septum most commonly causes it.

23. **Rectovaginal Fistula:** Abnormal communication between the rectum and vagina with involuntary escape of flatus and / or faeces into the vagina is called *Rectovaginal Fistula*.

24. **Cervictis:** *Cervicitis* is an inflammation of the cervix, the lower, narrow end of the uterus that opens into the vagina. *Cervicitis* is common. A number of factors, including infections, chemical or physical irritations, and allergies, may cause it.

25. **Abortion:** The termination of a pregnancy after, accompanied by, resulting in, or closely followed by the death of the embryo or fetus: as (**a**) spontaneous expulsion of a human fetus during the first 12 weeks of gestation (**b**) induced expulsion of a human fetus (**c)** expulsion of a fetus by a domestic animal often due to infection at any time before completion of pregnancy.
26. **Primary Amenorrhea:** A young girl who has not yet menstruated by her 16 years of age is having *Primary Amenorrhea* rather than delayed menarche.
27. **Secondary Amenorrhea:** It is the absence of menstruation for 6 months or more in a woman whose normal menstruation has been established.
28. **Pubertal Menorrhagia:** Menstrual abnormality in adolescents. The periods may be heavy, irregular or scanty initially. Eventually, majorities of these teenage girls establish a normal cycle and are fertile.
29. **Premature Menopause:** Also termed as premature ovarian failure and is defined as ovarian failure occurring before age of forty.
30. **UPT to be done:** For a fertile woman, when the menses are absent for about 28-60 days, normal diagnosis is chances of pregnancy so UPT is suggested.
31. **Lactational Amenorrhea:** *Lactational Amenorrhea* is the temporary postnatal infertility that occurs when a woman is amenorrheic (not menstruating) and fully breastfeeding.

3.3.2 Symptoms related to selected 31 diseases

Symptoms related to the selected diseases are presented in Table 3.1.

Table 3.1 Diseases selected in the present study and their symptoms

D1. Uterine Prolapse	D2. Endometriosis
▪ Something coming out of vagina, increased frequency of micturition ▪ Backache ▪ Vaginal bleeding between periods	▪ Backache ▪ Pain in lower abdomen ▪ Painful Menstruation ▪ Painful intercourse

▪ Painful intercourse ▪ Bladder /bowl complaints	▪ Bladder / bowl complaints
D3. Vaginal Yeast Infection	**D4. Ovarian Cyst**
▪ Burning micturation ▪ Vaginal bleeding between periods ▪ Painful intercourse ▪ Vaginal itching / Burning ▪ Vulval itching ▪ White discharge	▪ Pelvic pain ▪ Swelling in abdomen ▪ Nausea ▪ Vomiting ▪ Painful intercourse ▪ Bowl/bladder complaints ▪ Pain in abdomen
D5. Urinary Track Infection	**D6. Vulval Cancer**
▪ Fever ▪ Increased urinary frequency ▪ Cloudy/bloody urine ▪ Pain/ burning with urination	▪ Vaginal bleeding ▪ Spotting ▪ Fatigue ▪ Lump in vulva ▪ Itching of vulva ▪ Cut/soar in vulva ▪ Skin changes
D7. Uterine Cancer (Menopaused)	**D8. Uterine Cancer (PeriMenopausal)**
▪ Vaginal bleeding between periods ▪ Spotting ▪ Bleeding after menopause	▪ Vaginal bleeding between periods ▪ Spotting ▪ Heavy/abnormal vaginal bleeding ▪ Heavy/excessive menstrual bleeding ▪ Irregular periods
D9. Menopause	**D10. Premenstrual Syndrome (PMS)**
▪ Muscle ache ▪ Painful intercourse	▪ Mood swings ▪ Headache

▪ Bleeding between periods ▪ Spotting ▪ Heavy/excessive menstrual bleeding ▪ Vaginal discharge ▪ Hot flashes ▪ Mood swings ▪ Headache ▪ Fatigue ▪ Male pattern baldness ▪ Difficulty concentration ▪ Forgetfulness ▪ Irritable hostile aggressive behavior with outbursts of anger ▪ Sleep problems ▪ Pain/burning with urination ▪ Urinary incontinence ▪ Increase in fat ▪ Irritability depression ▪ Diminished interest in sex ▪ Thinning of scalp hair ▪ Bone loss ▪ Loss of muscle mass ▪ Reduced fertility	▪ Breast tenderness ▪ Fatigue ▪ Swelling ▪ Loss of appetite ▪ Constipation ▪ Gas ▪ Clumsiness ▪ Diarrhea ▪ Food cravings ▪ Less tolerance for noise and lights ▪ Confusion/mental changes ▪ Difficulty concentration ▪ Feeling of sadness or hopelessness ▪ Feeling of tension, anxiety or giddiness ▪ Forgetfulness ▪ Irritable, hostile, aggressive behavior with outbursts of anger ▪ Poor judgment ▪ Poor self image, feeling of guilt, increased self fear ▪ Sleep problems ▪ Slow, sluggish, lethargic movement
D11. Ovarian Cancer	**D12. Pelvic Inflammatory Disease (PID)**
▪ Increased frequency of micturition ▪ Backache ▪ Pain in abdomen ▪ Pelvic pain	▪ Burning micturition ▪ Increased frequency of micturition ▪ Backache ▪ Pain in abdomen

▪ Gas ▪ Constipation ▪ Indigestion ▪ Nausea ▪ Vomiting ▪ Swelling ▪ Weight gain ▪ Weight loss ▪ Irregular menses ▪ Heavy/excessive menstrual bleeding ▪ Vaginal bleeding between periods ▪ Increased body hair	▪ Pelvic pain ▪ Loss of appetite/full quickly/difficulty in eating ▪ Fever ▪ Nausea ▪ Chills ▪ Fatigue ▪ Vomiting ▪ No menses ▪ Painful menstruation ▪ Irregular menses ▪ White discharge
D13. Cervical Cancer (Stage I)	**D14. Dysfunctional Uterine Bleeding (DUB)**
▪ Heavy/excessive menstrual bleeding ▪ Bleeding after menopause ▪ Vaginal bleeding between periods ▪ Bleeding after intercourse ▪ White discharge with foul smell	▪ Weakness ▪ Fatigue ▪ Irregular menses ▪ Heavy/excessive menstrual bleeding ▪ Vaginal bleeding between periods ▪ Spotting ▪ Passage of clots ▪ Increased body hair ▪ Hot flashes ▪ Mood swings ▪ Vaginal dryness
D15. Endometritis	**D16. Uterine Fibroid**
▪ Pain in lower abdomen ▪ Pelvic pain	▪ Increased frequency of micturition ▪ Pain in lower abdomen

▪ Constipation ▪ Generalized body pain ▪ Distension in abdomen ▪ Fever ▪ Vaginal bleeding between periods ▪ White discharge ▪ Bladder/bowl complaints	▪ Gas ▪ Constipation ▪ Painful menstruation ▪ Irregular menses ▪ Continuous menstruation ▪ Heavy/excessive menstrual bleeding ▪ Vaginal bleeding between periods ▪ Passage of clots ▪ Painful intercourse
D17. Polycystic Ovaries	**D18. Adenomyosis**
▪ No menses / menses absent ▪ Irregular menses ▪ Decreased breast size ▪ Deepening of voice ▪ Increased body hair ▪ Thinning of hair on head ▪ Enlargement of clitoris ▪ Pimples ▪ Infertility	▪ Painful intercourse ▪ Heavy menstrual bleeding ▪ Painful menstruation ▪ Perimenopausal
D19. Ectopic Pregnancy	**D20. Leucorrhoea**
▪ Mild cramping on one side of pelvis ▪ Pain in lower abdomen ▪ Shoulder area pain ▪ Back ache ▪ Vaginal bleeding between periods ▪ Intense pressure on rectum ▪ Fainting	▪ White discharge ▪ Weakness ▪ Constipation ▪ Headache ▪ Irritation ▪ Black patches under eyes

▪ Distension in abdomen ▪ Breast tenderness ▪ Nausea ▪ No menses	
D21. Hyperprolactinemia	**D22. Haematometra**
▪ Infertility ▪ Milk secretion from breast ▪ Irregular periods	▪ Pain in abdomen ▪ Uterine enlargement ▪ Infertility ▪ Irregular menses ▪ Menses absent
D23. Rectovaginal Fistula	**D24. Cervicitis**
▪ Passing of air and stool through vagina ▪ Vaginal itching burning ▪ Vaginal discharge ▪ Painful urination	▪ Vaginal discharge ▪ Vaginal bleeding between periods ▪ Vaginal itching ▪ Pain during intercourse ▪ Spotting ▪ Burning micturition ▪ Pain in abdomen
D25. Abortion	**D26. Primary Amenorrhea**
▪ Fertile ▪ Perimenopausal ▪ Continuous flow ▪ MAG	▪ Permenarche ▪ Puberty
D27 Secondary Amenorrhea	**D28 Pubertal Menorrhagia**
▪ Fertile ▪ PMC	▪ Premenarche ▪ Puberty ▪ Excessive flow

	▪ Irregular menses ▪ SGC
D29. Premature Menopause	**D30. UPT to be done**
▪ Fertile ▪ Perimenopausal ▪ MP	▪ Fertile ▪ MMC
D31. Lactational Amenorrhea	
▪ Fertile ▪ Amenorrhea after child's birth	

3.3.3 Tests required for partially diagnosed diseases

Few symptoms in some of the gynecologic diseases overlap due to which the state of the disease becomes unclear. The confirmed diagnosis can be made with the help of clear cut understanding of the state of internal organs related to the symptoms. Various pathological test, imaging tests and/or radiological tests are of great help to diagnose the disease correctly. Table 3.2 shows the tests required to be undergone by a patient to receive the confirmed diagnosis for some of the diseases.

Table 3.2: Tests suggested/ required for the partially diagnosed diseases

Disease	**Tests**	**Description**
Uterine Prolapse	Pelvic Examination	Cervix in lower part of vagina
		Cervix drops out of vaginal opening
		Bladder, front wall of vagina, rectum, back wall of vagina entering vaginal area
		Urethra and bladder lower in pelvis
		Mass (if caused by tumor)
Endometriosis	Transvaginal USG	Pucker black, powder burn, blueberry cyst
	Pelvic laparoscopy	Blue berry cyst, pigmented lesion
Vaginal Yeast Infection	KOH test	Thin walled yeast like structure, hyphae and budding cells
Ovarian Cyst	USG pelvis	Ovarian cyst, uterus normal
	CT scan	Cystic lesion in ovary of various size

Disease	Tests	Description
	Doppler flow studies	Increase S/D, pulsactile index
	MRI ovary	Cystic lesion
	Harmone levels – estradiol, testosterone, HCG	Polymbroyma - increased HCG Estrodiol increased granulasa cell tumor
	Serum HCG	Embroyoma
Urinary Track Infection	Urinalysis/microscopic	Puss cells in urine
	Urine culture	Presence of bacteria in urine on growth
	CBC	Neutrophilia, lymphocytosis
Vulval Cancer	Biopsy	Squamous cell carcinoma
	Pap smear	Ca cervix may associated
	Cystoscopy (bladder & urethra)	Metastasis lesion in bladder or uterus
	Proctoscopy (rectum & anus)	Metastasis lesion / growth
	X-Ray pelvic	Pelvic hydromeplrososil
	CT Scan	involvement pelvic lymph node and other pelvic organs
	MRI pelvis	involvement pelvic lymph node and other pelvic organs
Uterine Cancer (Menopaused)	2 tissue biopsy (endometrial biopsy)	Endometrial hyperplasia / adenocarcinoma
	Transvaginal USG	Endometrial hyperplasia ET > 4 mm
Uterine Cancer (PeriMenopausal)	2 tissue biopsy (endometrial biopsy)	Endometrial hyperplasia / adenocarcinoma
	Transvaginal USG	Endometrial hyperplasia ET> 16 mm
Ovarian Cancer	CA-125 blood test (1)	> 35 mIU 7200 mIU/ml
	Complete blood count & blood chemistry	Eib increased
	CT scan or MRI of pelvis or abdomen	Ovarian mass, irregular, multilocular
	USG pelvis	Ovarian mass, complex, cyst or irregular mass
	Pelvic laparoscopy (for small lumps)	Solid, hard irregular mass
	Exploratory laparotomy	Large irregular hard mass

Disease	Tests	Description
	Biopsy	Cysto-adeno-carcinoma, squamous cell carcinoma and mucinous cysto-adeno-carcinoma
Pelvic Inflammatory Disease(PID)	CRP : c- reactive Protein	Raised
	Erythrocyte sedimentation rate (ESR)	Raised
	WBC count	Raised WBC count, Neutrophilia, lymphocytosis
	Culture of vagina or cervix	Culture positive for gonorrhea, streptococi, Tuberculoses
	Pelvic USG	Uterus bulky, T.O mass
	CT Scan	Inflamed tubes, ovaries, hydrosalpiv
	Laproscopy	Tubo-ovarian masses
Cervical Cancer (Stage I)	Papsmear	Malignant cells, dysplastic cells
	Endocervical curettage (ECC)	Malignant cells, dysplastic cells
	Cx Biopsy	Malignant cells, squamous cell carcinoma
Dysfunctional Uterine Bleeding(DUB)	Blood clotting profile	Increased prothrombin time, decreased platelet count
	Hormone tests (FSH, LH)	May be raised or decreased
	Progesterone	Level decreases
	Endometrial biopsy	Secretary or proliferate changes
	Transvaginal USG	Bulky uterus or normal size
Adenomyosis	Hysterectomy	Uterine tissue present
	Transvaginal USG	Enlarged and tender uterus
		Multiple small cysts in myometrium
	MRI	Thickened junctional zone present
		Multiple small cysts in myometrium
Uterine Fibroid	USG Pelvis	Fibroid (absent, small, medium, Large)
	CBC	Anemic condition
	MRI	Fibroid(absent, small, medium, Large) Thickened junction Zone not present
Endometritis	USG Transvaginal	Thickened, heterogeneous Endometrium
	MRI	Intra-cavitary fluid present
		Ecogenic mass
		Enlarged uterus

Disease	Tests	Description
		High Signal Intensity
		Ecogenic mass
Cervicitis	vaginal fluid test	Bactria present / absent
	Cervical fluid test	Bactria present / absent
PCOD	Pelvic USG	Enlarged ovaries Small Cysts

3.4 Data collection at a glance

When a patient approaches gynaecologist, she narrates the complaints (symptoms) that she is suffering from. This information alone from a Gynaecology patient is not sufficient for a doctor. Some more information called '*History*' is also required which plays important role in differential diagnosis process. The information required is:

Age, Menarche, Married Since (in years), Last Menstrual Period (LMP), PMC, Previous Menstrual Cycle (PMC) Flow, Parity details, some significant history such as hypertension (BP), Diabetics, Tubectomised, Hysterectomy done, laproscopy done and history of any major / minor surgery.

Some of the terms used in history taking process are as follows.

a. **Polymenorrhoea (Epimenorrhoea) :** Cyclic bleeding where the cycle is reduced to an arbitrary limit of less than 21 days and remains constant at that frequency. If frequent cycle is associated with excessive and prolonged bleeding, it is called epimenorrhagia.

b. **Metrorrhagia :** Irregular acyclic bleeding from the uterus. Amount of bleeding is variable. It strictly concerns uterine bleeding. Menometrorrhagia is when the bleeding is so irregular and excessive that the menses cannot be identified at all.

c. **Oligomenorrhoea:** Menstrual bleeding occurring more than 35 days and which remains constant at that frequency.

The information related to history and complaints received from patient is recorded in specific format as below.

a. Complaints :

1. If complaint is : *Pelvic White discharge* then it is noted as *c/o p/v white discharge.*
   Similarly,
2. Excessive bleeding → c/o menorrhagia
3. Absent Menses → c/o Amenorrhoea
4. Painful menses → Dysmenorrhoea
5. Polymenorrhoea → Cyclic bleeding, reduced menstrual cycle
6. Metrorrhagia → irregular, excessive cyclic bleeding
7. Oligomenorrhoea → Menstrual bleeding > 35 days

b. History :

1. **Age** → age in years
   35 yrs
2. **Menarche** → at which year
   Menarche → 13 yrs
3. **M/S** → Married since number of years
   e.g., M/S 7 yrs
4. **LMP** → Date of last menses started
   e.g., LMP : 12 /12 2015
5. **PMC** → number of days of flow / nature (regular / irregular / normal / scanty / excessive / continuous/ painful/ painless)
   e.g., PMC : 6 D / RMPL → PMC Flow for 6 days and it was **R**egular, **M**oderate, **P**ain**L**ess.
   PMC : 2-3 D / IRSPF → PMC Flow for 2-3 days and it was **Ir****R**egular, **S**canty, **P**ain**Ful**.
6. **H/O** → BP, Diabetes , tubectomised, hysterectomised, or any other major/ minor surgery
7. **Information about parity** → $P_iL_jA_kD_l$ Where P indicates number of parity, L is number of children alive, A indicates number of abortions held and D indicates number of children dead. Here i = j + k + l. After this details about each parity is mentioned as :
   G1: age of child / (M/F) / (FTND/ LSCS) / (LnW / D) / (Home / Hospital)

For some pregnancy abortion is carried out then mention it as MTP or in case of miscarriage mention as 'Miscarriage'

'G' indicate Gravid

FTND : FT Normal Delivery

LSCS : Caesarian done

LnW : Live and Well

D : Dead

Nulligravidia : A women having 0 parity (No child)

e.g., 1. ***G1 : 12 yrs / F / FT-LSCS / LnW / Hospital*** → First child 12 years old, Female, Caesarian in hospital, Live and well

e.g., 2. ***G2 : MTP*** → Second child MTP done (Aborted)

e.g., 3. ***G3 : 10 yrs / M / FTND / D / Home*** → Third child 10 years old, Male, Normal Delivery in hospital, Dead.

❐❐❐

Chapter 4

Mathematical Preliminaries and Techniques Used

Modeling of the uncertainty and vagueness that is present in medical systems can be best implemented by using fuzzy set theory and Fuzzy Logic. It is important implement perception based modeling. Computing with Words is a method to deal with linguistic valuations unlike conventional systems. CW deals with reasoning, computing and decision making in natural language

This chapter focuses on various mathematical formalisms like fuzzy relational calculus, Fuzzy Logic, fuzzy similarity measures, Fuzzy C-Means, Inter-Rater reliability and Gower's Coefficient in detail which are used in the research.

4.1 Computing with Words

Expert's knowledge (usually in linguistic terms / words), symptoms of the patients and investigating tests are the back bone of medical disease diagnosis in general and Gynaecology disease diagnosis in particular. Medical documentation is invariably expressed in words and not in numeric terms. Therefore computing with words forms an integral part of medical disease diagnosis.

4.1.1 Terminology

Computing is defined as manipulation of numbers and symbols. Computing with Words (CWW / CW), is a methodology in which the objects of computation are words and propositions drawn from a natural language, e.g. *cold, hot, far, heavy, not very tall* etc. Computing with words provides a basis for a computational theory of perceptions. When perceptions are described in words, manipulation of perceptions is reduced to computing with words (CW) (Zadeh, 2002). According to Zadeh, CWW is a methodology in which the objects of computation are words and propositions drawn from a natural language.

Computing with words are mainly used when the available information is too imprecise to justify the use of numbers and when there is a tolerance for imprecision which can be exploited to achieve tractability, robustness, low solution cost and better rapport with reality.

Figure 4.1 depicts the levels of complexity in CW. Computing with words covers the two levels of complexities (CW-1 and CW-2). The first complexity is due to Linguistic Natural Language (LNL), known as Fuzzy Logic and the second level is Natural Language (NL) which is still under development. The concept of Precisiation of the meaning deals with CW methodology. It has been envisaged to employ appropriate facets of CW methodology in Gynaecology diseases.

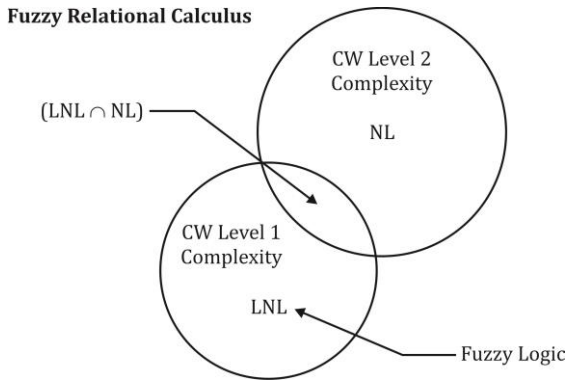


Figure 4.1: Perception based modeling using Computing with Words

4.1.2 Use of linguistic hedges

Prof. Zadeh proposed the use of linguistic modifier which is commonly used. Amongst which we use linguistic hedge ‘very’ to indicate ‘very often’ and ‘very seldom’

linguistic terms (Ross 1995; Sardesai, 2012). The concentration operator takes the form as:

$$A_{very}(x) = A^2(x) \quad (4.1)$$

E.g. consider the statement "Jane is old". To transform this statement to "Jane is very old." we use linguistic hedge '*very*' which is defined as $\mu_{(very)}A(x) = \mu_A(x)^2$. So if $\mu_{old}(Jane) = 0.8$, then $\mu_{veryold}(Jane) = 0.64$.

In linguistics, fundamental linguistic terms are often modified with adjectives (nouns) or adverbs (verbs) like *very*, *low*, *slight*, *more or less*, *fairly*, *slightly*, *almost*, *barely*, *mostly*, *roughly*, *approximately*. These modifiers are called as
'linguistic hedges': that is, the singular meaning of linguistic term is modified, or hedged, from its original interpretation. In the use of fuzzy sets as the calculus of interpretation, the linguistic hedges play role of modifying the membership function for a basic linguistic term (Ross, 1995).

4.2 Fuzzy Set Theory and Fuzzy Logic

Computers can understand only true and false values where as human being can interpret the degree of truth or degree of falseness. These human actions can be interpreted by Fuzzy Logic so is called as machine learning or artificial intelligence.

4.2.1 Classical Sets and Fuzzy Sets

The father of fuzzy set theory is an American Professor *A. Zadeh.* In 1965 when he presented the seminal paper on fuzzy sets, he showed that Fuzzy Logic unlike classical logic can realize values between 0 (false) and 1 (true). He transformed the crisp (classical) set into the continuous set. The fuzzy sets have movable boundaries i.e., elements of fuzzy set represent true false value and also represent the degree of truth or degree of falseness for each input (Ross 1995; Sardesai, 2012).

Classical Sets: The classical sets can be represented by various ways as follows (Ross 1995; Sardesai, 2012).

a. List method: A set is defined by naming all its members. Used only for finite sets.

A set A whose members are a_1, a_2, a_3,....a_n , is written as:

$A = \{a_1, a_2, a_3, ...a_n\}$

b. Rule method: A set is defined by a property satisfied by its members.

It is expressed as : $A = \{x \mid P(x)\}$

where "|" means such that and P(x) means a proposition of the form "x has a property P", i.e., A is defined by this notation as the set of all elements of X for which the proposition P(x) is true.

It is required that the property P such that for any given $x \in X$, the proposition P(x) is either true or false.

c. Characteristic function method: A set is defined by a function called as characteristic function, that declares which elements of X are members of the set and which are not. Set A is defined by its characteristic function χ_A, as follows –

$$\chi_A(x) = \begin{cases} 1, \text{ for } x \in A \\ 0, \text{ for } x \notin A \end{cases}$$

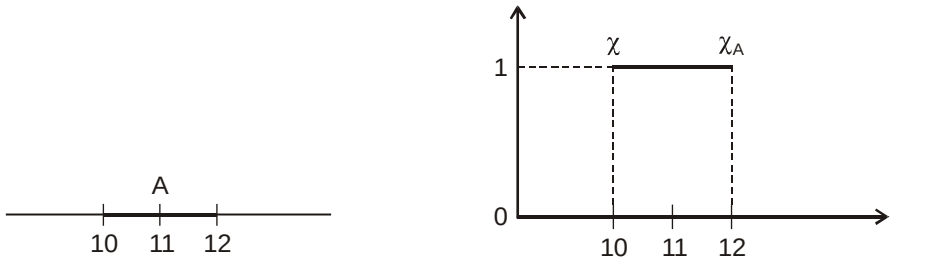
i.e., that characteristic function maps elements of X to elements of the set {0, 1}, which is formally expressed by,

$\chi_A: X \rightarrow \{0, 1\}$ for each $x \in X$

When $\chi_A(x) = 1$, x is declared to be a member of A.

When $\chi_A(x) = 0$, x is declared to be a non-member of A.

Consider an example Set A = {10, 11, 12}. The membership function χ is as shown in Figure 4.2.



(a) Set A **(b) Height membership function (χ_A) for a crisp set A**

Figure 4.2: Crisp set representations

Fuzzy Sets:

a. A fuzzy set $\underset{\sim}{A}$ is defined by an ordered pair, a binary relation:

$$\underset{\sim}{A} = \{(x, \mu_{\underset{\sim}{A}} (x))) \mid x \in X , \mu_{\underset{\sim}{A}} (x) \in [0,1]\}$$

Where $\mu_{\underset{\sim}{A}} (x)$ is a membership function which specifies grade or degree to which any element x in $\underset{\sim}{A}$ belongs to the fuzzy set $\underset{\sim}{A}$.

$\underset{\sim}{A}$is a fuzzy set, X is Universe or universe of Discourse.

Elements with 0 degree of membership in a fuzzy set are usually not listed in the fuzzy set.

b. If the universe of discourse X is **discrete and finite**, Fuzzy set $\underset{\sim}{A}$ is represented as follows.

$$\underset{\sim}{A} = \left\{ \frac{\mu_{\underset{\sim}{A}} (x_1)}{x_1} + \frac{\mu_{\underset{\sim}{A}} (x_2)}{x_2} + \ldots. \right\} =$$

c. If the universe of discourse X is **continuous and infinite**, Fuzzy set $\underset{\sim}{A}$ is represented as follows.

$$\underset{\sim}{A} = \left\{ \int \frac{\mu_{\underset{\sim}{A}} (x)}{x} \right\}$$

In both the above notations, the horizontal bar is not quotient but it is a delimiter where Denominator $\rightarrow$ element of universe.

Numerator in each term $\rightarrow$ the membership value in set A associated with the element of the universe indicated in the denominator.

The summation symbol ($\sum$) is not algebraic summation, it denotes collection or aggregation of each element. The "+" sign is not algebraic "addition" but it denotes collection or aggregation of each element. The integral sign ($\int$) is not algebraic integral but it is a continuous function-theoretic aggregation operator for continuous variables.

Membership Function: If x is an element in the universe, is a member of fuzzy set $\underset{\sim}{A}$, then this mapping is given by membership function which is represented mathematically as follows (Ross & Parkinson, 2002).

$\mu_{\underset{\sim}{A}}(x) \in [0, 1]$

And it is shown graphically as shown in Figure 4.3

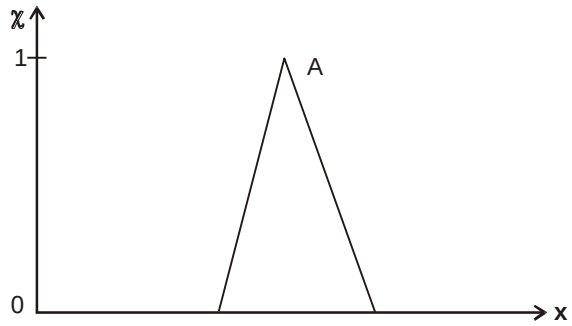


Figure 4.3: Membership Function

The symbol $\mu_{\underset{\sim}{A}}(x)$ is the degree of membership of element x in fuzzy set $\underset{\sim}{A}$.

$\mu_{\underset{\sim}{A}}(x)$ is the value on the unit interval that measures the degree to which element x belongs to fuzzy set $\underset{\sim}{A}$.

i.e., $\mu_{\underset{\sim}{A}}(x)$ = degree to which $x \in \underset{\sim}{A}$.

Comparative Analysis: Classical Sets and Fuzzy Sets

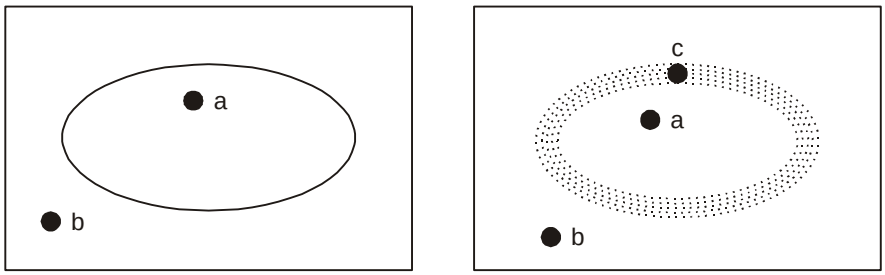
- A fuzzy set is a set containing elements that have varying degrees of membership in the set where as in classical sets degree of membership in a set is either 0 or 1 (Ross & Parkinson, 2002).
- Elements in a fuzzy set can also be members of other fuzzy sets on the same universe because of their partial membership. Where the members of crisp set would not be members unless their membership was full or complete (i.e., their membership value = 1).
- Zadeh extended the notation of binary membership to accommodate various **"degrees of membership"** on the real continuous interval [0, 1]. The point 0 confirms "No membership" and point 1 confirms "full membership". The infinite number of values between these 2 endpoints 0 and 1 represent various degrees of membership for an

element x in some set on the interval. Crisp set woks on binary membership viz. 0 and 1 (Ross & Parkinson, 2002).

- The fuzzy set is normally denoted with a tilde understrike ($\underset{\sim}{A}$), Crisp set is denoted as A.
- The membership function of fuzzy set maps elements of Fuzzy Set $\underset{\sim}{A}$ to real numbered value in the interval 0 to 1. The membership function of crisp set maps elements of fuzzy set A to either 0 or 1.
- For the crisp sets, the transition for an element in the universe between membership and non-membership in a given set is quick and well defined (crisp). The transition of the element in the fuzzy set it is gradual. This gradual transition conforms to the fact that the boundaries of fuzzy set are vague and ambiguous. So the membership of such an element is measured by a function that describes the vagueness and ambiguity.

- **Membership function in comparison with Crisp Set**

The boundary of crisp set A is an unambiguous line. A fuzzy set $\underset{\sim}{A}$ is prescribed by vague or ambiguous properties so its boundaries are ambiguously specified.



(a) Crisp set boundary **(b) Fuzzy set boundary**

Figure 4.4 Set Boundaries

Figure 4.4 (a) shows clear boundary of a crisp set A on the same universe X

Region inside the boundary represents the full membership of A.

Region outside the boundary represents the non membership of A.

So, χ_A (a) = 1 and χ_A (b) = 0, Where χ_A is characteristic function.

Figure 4.4 (b) shows vague, ambiguous boundary of a fuzzy set $\underset{\sim}{A}$ on the same universe X. Shaded region represents the boundary region of $\underset{\sim}{A}$. Region inside the shaded region represents the full membership of $\underset{\sim}{A}$. Therefore, point a is full member of set $\underset{\sim}{A}$ and point b is not a member of set $\underset{\sim}{A}$.

So, $\mu_{\underset{\sim}{A}}$ (a) = 1 and $\mu_{\underset{\sim}{A}}$ (b) = 0 Where $\mu_{\underset{\sim}{A}}$ is membership function.

Region outside shaded region represents the non-membership of $\underset{\sim}{A}$. The point c, which is on boundary region, is ambiguous, shows partial membership. So it must have some intermediate value of membership on the interval [0, 1].

As the point c moves closer to central (unshaded) region, the membership value of point c approaches to 1, i.e., towards full membership and as the point c moves closer to leaving the boundary region of the set $\underset{\sim}{A}$, the membership value approaches towards 0 (Ross 1995; Sardesai, 2012).

4.2.2 A Primer on Formal Concept Analysis

Concepts are necessary for expressing human knowledge. Any knowledge management process depends on a comprehensive formalization of concepts. Fuzzy Concept Analysis (FCA) offers such formalization by mathematizing the idea of concept as a unit of two parts:

1. Extent refers to a set of objects (say, a patient), expressed as say X.
2. Intent covers a set of attributes (say, symptoms), described by a patient to a physician as say Y.

The set of objects and attributes together with their relation to each other form a "formal Concept". There are two basic outputs of FCA, namely a concept lattice and attribute implications.

Formal Context: A formal context is a triplet (X, Y, I) where X is a set of objects, Y is a set of attributes and I is the binary relation between X and Y i.e. (x, y) $\in$ I.

For a set A $\subseteq$ X of objects and a set B $\subseteq$ Y of attributes, we define:

The set of all attributes from Y shared by all the objects from A:

$A^{\uparrow} = \{y \mid \text{for each } x \in A, (x, y) \in I\}$

The set of all objects from X sharing all the attributes from B:

$B^{\downarrow} = \{x \mid \text{for each } y \in B, (x, y) \in I\}$

From the operators $\uparrow$ and $\downarrow$ are two compositions $\uparrow\downarrow$ and $\downarrow\uparrow$ can be obtained. The operator $\uparrow\downarrow$ maps the power set $\Phi(X)$ of X onto itself and $\downarrow\uparrow$ maps the power set $\Phi(Y)$ of Y onto itself.

If (X, Y, I) be a formal context and $A_1, A_2, A_3 \subseteq X$ then it can be proved that

$A_1 \subseteq A_2 \rightarrow A_1^{\downarrow} A_2^{\downarrow}$

$A \subseteq A^{\uparrow\downarrow}$

Note: In medical documentation X refers to patients, Y is symptoms and I refer to the intensity of symptom low, medium, high and so on.

4.2.3 Fuzzy Relational Calculus (Compositional Rule of Inference)

The definitions of fuzzy sets and fuzzy operations are well known and therefore, not discussed in this section. This section very briefly describes fuzzy relational calculus used in the study (Sardesai, Kharat, Deshpande & Sambarey, 2016; Klir & Yuan, 1995; Ross, 1995; Fuller & Zimmermann, 1993).

A fuzzy relation *R* is maps the elements from the elements from universe X to universe Y and S is the relation that maps the elements from universe Y to Z. The membership functions $\mu_R(x, y)$ and $\mu_S(y, z)$ give the strength of the mapping. Fuzzy max–min composition is defined in terms of the function-theoretic notation in the following manner:

$$\mu_T(x, z) = \vee_{y \in Y}(\mu_R(x, y) \wedge (\mu_S(y, z)) \tag{4.2}$$

Definition 1: Let $R \subset X \times Y$ and $S \subset Y \times Z$ be fuzzy relations, the max-min composition R o S is defined by

$$R \circ S = \{((x, z), \max_{y} \{\min_{x,z} \{ f_R(x, y), f_S(y, z)\}\}) \mid x \in X, y \in Y, z \in Z\} \tag{4.3}$$

4.2.4 Fuzzy Similarity Measures

Clustering is considered as classification of similar objects. It is partitioning of datasets into clusters so that data in each cluster shares some common trait. The

hierarchical, partitioning and mixture model methods are the three major types of clustering processes that are applied for data organization. Fuzzy similarity measures provide one of the effective mechanisms for clustering / classification by means of two methods viz. Cosine Amplitude method and Max-Min method.

a. Cosine Amplitude Method

It makes use of a collection of say n data samples. These data samples form a data array, $X = \{x_1, x_2, ...x_n\}$. Each of the elements x_i, in the data array X is itself a vector of length m, i.e.

$$X_i = \{ x_{i1}, x_{i2},.....x_{im}\} \quad (4.4)$$

Each of the data samples is considered as a point in m-dimensional space. Each of these points need m coordinates for a complete description. Each element of a relation r_{ij}, is calculated by a pair-wise comparison of two data samples, say x_i and x_j. The strength of the relationship between data sample x_i and data sample x_j is given by the membership value $r_{ij} = \mu_R(x_i, y_j)$ resulting a relation matrix of size n x n. The relation will be reflexive and symmetric so is a tolerance relation. The Cosine Amplitude method calculates r_{ij} as (Ross, 1995).

$$r_{ij} = \frac{\left|\sum_{k=1}^{m} x_{ik}x_{jk}\right|}{\sqrt{\left(\sum_{k=1}^{m} x^2{}_{ik}\right)\left(\sum_{k=1}^{m} x^2{}_{jk}\right)}} \quad \text{, Where } 0 \leq r_{ij} \leq 1 \quad (4.5)$$

Close inspection of Equation 5 reveals that this method is related to dot product for the cosine function. When two vectors are collinear (most similar), their dot product is unity. When the two vectors are at right angles to each other (most dissimilar), their dot product is zero.

b. Max-min Method

The method is similar to Cosine Amplitude method. It is computed by a simple min and max operations on pairs of the data points x_{ij} and is given by (Ross, 1995).

$$r_{ij} = \frac{\sum_{k=1}^{m} \min(x_{ik},x_{jk})}{\sum_{k=1}^{m} \max(x_{ik},x_{jk})} \quad (4.6)$$

c. Fuzzy Tolerance to Fuzzy Equivalence Relation Transformation

A fuzzy relation, *R* on a single universe *X* is tolerance relation if the relation is reflexive and symmetric. The relation R is a fuzzy equivalence relation or a similarity relation if all three of the following properties hold:

Reflexivity $\mu_R(x_i, x_i) = 1$ (4.7)

Symmetry $\mu_R(x_i, x_j) = \mu_R(x_j, x_i)$ (4.8)

Transitivity $\mu_R(x_i, x_j) = \lambda_1, \mu_R(x_j, x_k) = \lambda_2 \rightarrow \mu_R(x_i, x_j) = \lambda$ where $\lambda \geq \min[\lambda_1, \lambda_2]$ (4.9)

The similarity measures methods generate the n x n relation which is usually observed as Fuzzy tolerance relation. In order to defuzzify Fuzzy Tolerance relation to it the relation needs to be transformed to Fuzzy Equivalence relation using transitivity closure operation expression. A fuzzy tolerance relation can be transformed into fuzzy equivalence relation by at most (*n*-1) compositions using Equation 4.10.

Fuzzy $R^{n-1} = R_1 \text{ o } R_1 \text{ o} \ldots\ldots \text{o } R_1 = R$ (4.10)

The distinction between Fuzzy relations and Equivalence relations is that the former describe the interactions between variables and the later categorize the elements which are equivalent under the relation into disjoint classes. For an equivalence class, the members in a class are similar to each other to degree 1. A similarity class is defined as a fuzzy set in which the membership grade of any single element is the similarity of that element to element x. A similarity class becomes equivalent class when all the members of similarity class are similar to each other with the degree 1 within a class and with degree 0 outside a class.

A Fuzzy relation *R* can be represented in terms of its α-cuts by the formula $\cup\alpha$, $\alpha\in_{(0,1]}R$. If *R* is a similarity relation then each α-cut, ${}^{\alpha}R$ is a crisp equivalence relation. Thus, to get the similarity between the elements to the degree α, any similarity relation *R* can be used by taking an α- cut ${}^{\alpha}R$ for any value $\alpha\in$ (0,1). Each of these equivalence relations created is a crisp equivalence relation which forms patrician X. These partitions are continued such that π (${}^{\alpha}R$) is a refinement of π (${}^{\beta}R$) if and only $\alpha \geq \beta$.

Following definitions support the explanations.

Definition 2: A fuzzy relation R on R x R is called is a *fuzzy compatible* or *tolerance* or *proximity relation* if it satisfies reflexive and symmetric conditions.

Definition 3: A fuzzy relation R on R_x R is called a fuzzy equivalence relation if the following three conditions hold,

1. R is reflexive, if $f_R(x,x)=1, \forall x \in X$.
2. R is symmetric, if $f_R(x,y) = f_R(y,x), \forall x,y \in X$.
3. R is transitive, if $R^{(2)}$ = (R o R) $\subset$ R, or more explicitly

$$f_R(x,z) \geq \max_y \left\{ \min_{x,z} \{ f_R(x,y),\ f_R(y,z) \} \right\}, \forall x,y,z \in X \tag{4.11}$$

Definition 4: Let R be a fuzzy relation on X x Y, i.e.

$R = \{((x,y),\ f_R(x,y)) \mid (x,y) \in X \times Y\}$, the α-cut matrix R_α is denoted by

$$R_\alpha = \{((x,y),\ f_R(x,y)) \mid f_R(x,y) = 1, if\ \_\ f_R(x,y) \geq \alpha;$$

$$f_R(x,y) = 0; if\ \_\ f_R(x,y) < \alpha, (x,y) \in X \times Y, \alpha \in [0,1]\} \tag{4.12}$$

4.3 Type 1 Fuzzy Inference System (T1FIS)

Fuzzy inference is the process of establishing the mapping from a given input to an output using Fuzzy Logic. The process of fuzzy inference involves fuzzification, defuzzification, implication and aggregation.

Fuzzification:

Fuzzification is a process of changing real scalar value into a fuzzy value. This is achieved with the different types of fuzzifiers or different types of membership functions viz. Singleton fuzzifier, Triangular membership function, Trapezoidal membership function, Gaussian membership function, Bell shaped membership function, Z-shaped membership function, Sigmoidal membership function, S-shaped membership function, π_1 membership function and π_2 membership function. In the research, Trapezoidal membership function is used.

Trapezoidal membership function

By a trapezoidal membership function we mean the regular uncertain set fully determined by a quadruplet (a, b, c, d) of crisp numbers with a < b < c < d whose membership function as shown in Equation 4.13.

$$\mu_A = x \begin{cases} 0, & x \le \alpha \\ (x-\alpha)/(\beta-\alpha), & \alpha \le x \le \beta \\ 1, & \beta \le x \le \gamma \\ (\delta-x)/\delta-\gamma), & \gamma \le x \le \delta \\ 0, & x \ge \delta \end{cases} \quad (4.13)$$

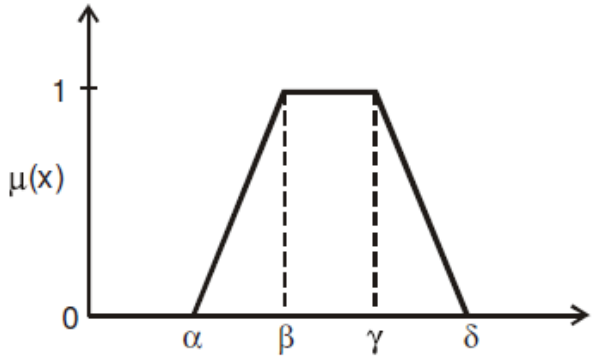


Figure 4.5 Trapezoidal membership function

A schematic of a Fuzzy Inference System (FIS) is shown in Figure 4.6.

Consider a multi-input, multi output system. Let the input vector $x = (x_1, x_2,..... x_n)^T$ and $y = (y_1, y_2,..... y_m)^T$ be the output vector. The linguistic variable x_i in the universe of discourse *U* is characterized by:

$$T(x) = \{Tx^1, Tx^2, Tx^3,.....Tx^k \} \quad (4.14)$$

and

$$\mu(x) = \{\mu x^1, \mu x^2, \mu x^3,..... \mu x^k \} \quad (4.15)$$

where T(x) is a term set of x, i.e., it is the set of names of linguistic values of x, with each being a fuzzy member and the membership function μx^i defined on *U*. The linguistic variable *y* in the universe of discourse *V* is characterized by:

$$T(x) = \{Ty^1, Ty^2, Ty^3,.....Ty^k \}, \quad (4.16)$$

where T(x) is a term set of y, i.e., *T is* the set of names of linguistic values of y, with each Ty^i being a fuzzy membership function μx^i defined on *V* (Ross 1995, Sardesai 2012).

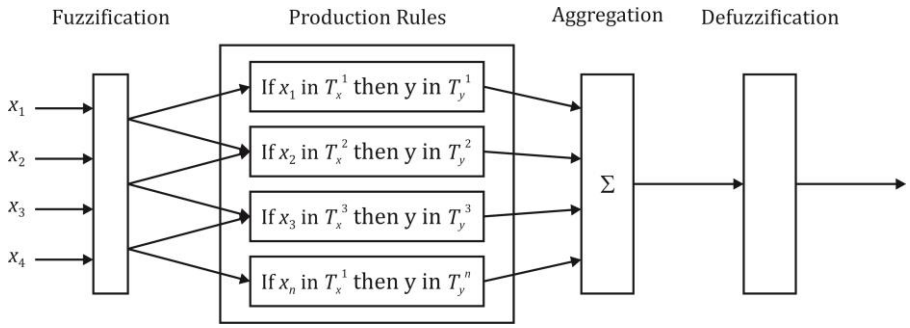


Figure 4.6 Schematic diagram of FIS

Mamdani type fuzzy inference system is used in this research which uses centre of gravity as defuzzification method. Software is developed to simulate the Mamdani type Fuzzy Inference System.

Defuzzification:

Defuzzification is a method used to convert the fuzzy quantity to crisp quantity, which exactly opposite to fuzzification which converts crisp value to fuzzy value. Some of the defuzzification methods are Max Membership principle, Centroid method, Weighted average method, Mean max membership, Center of sums, Center of largest area and First (or last of maxima). Center of Gravity defuzzification method is used in the study.

4.4 Inter-Rater Reliability

In statistics, inter-rater reliability is the degree of agreement among raters. It gives a score of homogeneity, or agreement, is present in the ratings given by judges. If various raters do not agree, either the scale is defective or the raters need to be re-trained. The different statistics used to determine inter-rater reliability are: joint-probability of agreement, inter-rater correlation, concordance correlation coefficient, intra-class correlation and Cohen kappa and the related Fleiss' kappa (Fleiss Kappa, 2016).

Joint-probability of agreement

It considers that the data are nominal and does not believe that the agreement may be based on chance. It is calculated as the number of times each rating (e.g. 1, 2, ... 5) is assigned by each rater divided by the total number of ratings.

Concordance correlation coefficient

In statistics, the concordance correlation coefficient measures the agreement between two variables, e.g., to evaluate reproducibility or for inter-rater reliability.

Intra-class correlation (ICC)

In statistics, the intra-class correlation is a descriptive statistic that can be used when quantitative measurements are made on units that are organized into groups.

Cohen kappa and the related Fleiss' kappa

Cohen's Kappa Coefficient is a statistical method which measures inter-rater agreement for qualitative (categorical) items. Cohen's kappa works for two raters where as Fleiss kappa works for any fixed number of raters. Fleiss kappa improves upon the joint probability, in which the amount of agreement that could be expected to occur through chance is taken into account. It suffers from the problem of the joint-probability where in the data is treated as nominal and it is assumed that the ratings have no natural ordering (Fleiss & Cohen, 1973).

Fleiss' kappa :

In our research, we have considered fixed number of experts/raters so to find the reliability we used Fleiss kappa. Fleiss kappa (named after Joseph L. Fleiss) is a statistical measure for assessing the reliability of agreement between a fixed number of raters when assigning categorical ratings to a number of items or classifying items.

Fleiss kappa is a generalisation of Scott's pi statistic. Fleiss' kappa works for any number of raters where as Scott's pi and Cohen's kappa work for only two raters. Fleiss' kappa gives categorical ratings to a fixed number of items. But it can be used only with binary or nominal-scale rating to check the consistency between the ratings (Fleiss, 1981; Fleiss Kappa, 2016). The kappa κ, can be defined as follows.

$$\kappa = \frac{\bar{P}-\bar{P}_e}{1-\bar{P}_e} \tag{4.17}$$

The factor 1- $\bar{P}_e$ gives the degree of agreement that is attainable above chance, $\bar{P} - \bar{P}_e$ gives the degree of agreement actually achieved above chance.

If the raters are in complete agreement then K = 1 .If there is no agreement among the raters (other than what would be expected by chance) then K ≤ 0. Landis and Koch (1977) gave the following table for interpreting κ values which is used as benchmark scale for Kappa's value (Table 4.1).

Table 4.1: Benchmark scale for Kappa's value

κ	**Interpretation**
< 0	Poor Agreement
0.01 – 0.20	Slight Agreement
0.21 – 0.40	Fair Agreement
0.41 – 0.60	Moderate Agreement
0.61-0.80	Substantial Agreement
0.81 – 1.0	Almost Perfect Agreement

4.5 Gower's Coefficient

The method is based on the fact that if comparison is possible between the measurable / non-measurable variables. In crisp Gower's Coefficient, the non-measurable variables are considered and in fuzzy approach at least one measurable parameter must be present. The method calculates s_{ij} as follows.

$$S_{ij} = \frac{\sum_{k=1}^{p} w_{ijk} S_{ijk}}{\sum_{k=1}^{p} w_{ijk}} \text{ where } S_{ijk} = 1 - ([x_{ik} - x_{jk}] / R_k) \quad (4.18)$$

The calculation is weightage is based on the fact that if the comparison between i & j is possible. If comparison is possible $w_{ij} = 1$ otherwise it is 0.

4.6 Fuzzy C-Mean

Clustering techniques are mostly unsupervised methods that can be used to organize data into groups based on similarities among the individual data items. Clustering of numerical data forms the basis of many classification and system modeling algorithms.

The purpose of clustering is to identify natural groupings of data from a large data set to produce a concise representation of a system's behavior, modeling algorithms. The purpose of clustering is to identify natural groupings of data from a large data set to produce a concise representation of a system's behavior. Clustering refers to identifying the number of subclasses of c clusters in a data universe *X* comprised of n data samples, and partitioning *X* into *c* clusters ($2 \leq c < n$). Note that $c = 1$ denotes rejection of the hypothesis that there are clusters in the data, whereas $c = n$ constitutes the trivial case where each sample is in a ''cluster'' by itself. There are two kinds of c-partitions of data: hard (or crisp) and soft (or fuzzy). For numerical data one assumes that the members of each cluster bear more mathematical similarity to each other than to members of other clusters. Two important issues to consider in this regard are how to measure the similarity between pairs of observations and how to evaluate the partitions once they are formed.

One of the simplest similarity measures is distance between pairs of feature vectors in the feature space. If one can determine a suitable distance measure and compute the distance between all pairs of observations, then one may expect that the distance between points in the same cluster will be considerably less than the distance between points in different clusters. Several circumstances, however, mitigate the general utility of this approach, such as the combination of values of in compatible features, as would be the case, for example, when different features have significantly different scales. The clustering method defines ''optimum'' partitions through global criterion function that measures the extent to which candidate partitions optimize a weighted sum of squared errors between data points and cluster centers in feature space. Hard C-means is employed to classify data in a crisp sense. By this we mean that each data point will be assigned to one, and only one, data cluster. The problem of hard C-mean lies in assigning the point on the line of symmetry to a class. Which class should this point belong to? Whichever class the algorithm assigns this point to; there will be a good argument that it should be a member of the other class.

Alternatively, the argument may revolve around the fact that the choice of two classes is a poor one for this problem. Three classes might be the best choice, but the physics underlying the data might be binary and two classes may be the only option (Ross, 2009). The solution to the above problem is Fuzzy C-Means (FCM). This technique was

originally introduced by Jim Bezdek in 1981 (Bezdek, 1981) as an improvement on earlier clustering methods. It provides a method that shows how to group data points that populate some multidimensional space into a specific number of different clusters (Bezdek, Ehrlich & Full, 1984).

This method uses concepts in *n*-dimensional Euclidean space to determine the geometric *closeness* of data points by assigning them to various clusters or classes and then determining the distance between the clusters. FCM is a data clustering technique in which a dataset is grouped into *n* clusters with every data point in the dataset belonging to every cluster to a certain degree. For example, a certain data point that lies close to the centre of a cluster will have a high degree of belonging or membership to that cluster and another data point that lies far away from the centre of a cluster will have a low degree of belonging or membership to that cluster. Thus, each data point belongs to a cluster to some degree that is specified by a membership grade. To introduce this method, define a sample set of *n* data samples that we wish to classify: $X = \{\boldsymbol{x}_1, \boldsymbol{x}_2, \boldsymbol{x}_3, \ldots, \boldsymbol{x}_n\}$. Each data sample, $\mathbf{x}_i$, is defined by *m* features, i.e., $\boldsymbol{x}_i = \{x_{i1}, x_{i2}, x_{i3}, \ldots x_{im}\}$ where each $\boldsymbol{x}_i$ in the universe *X* is an *m* dimensional vector of *m* elements or *m* features. Since all the *m* features can have different units, in general, we have to normalize each of the features to a unified scale before classification. In a geometric sense, each $\boldsymbol{x}_i$ is a *point* in *m*-dimensional feature space, and the universe of the data sample, *X*, is a *point set* with *n* elements in the sample space.

FCM Algorithm

FCM algorithm works by assigning membership to each data point corresponding to each cluster centre on the basis of distance between the cluster and the data point. More the data is near to the cluster centre more is its membership towards the particular cluster centre. Clearly, summation of membership of each data point should be equal to one. The algorithm is based on minimization of the following objective function.

$$J_m(\underset{\sim}{U}, v) = \sum_{i=1}^{c} (\mu_{ik})^{m'} (d_{ik})^2 \quad \text{Where} \quad d_{ik} = d(x_k - v_i) = \left[\sum_{j=1}^{m} (x_{kj} - v_{ij})^2 \right]^{1/2} \qquad (4.19)$$

Where μ_{ik} is the membership of the k^{th} data point in the i^{th} class. J_m can have large number of values the smallest one of which is best associated with the best clustering. The distance measure, d_{ik} in Equation (4.19), a Euclidean distance between the i^{th} cluster center and the k^{th} data set (data point in m-space).

A new parameter is introduced in Eq. (4.19) called a weighting parameter, m' (Bezdek 1981) which ranges in $m' \in [1, \infty)$. This parameter controls the amount of fuzziness in the classification process. According to many studies, the takes values in the interval: $m' \in [2, 2.5]$.

$\mathbf{v}_i$ is the i^{th} cluster center, which is described by m features (m coordinates) and can be arranged as, $\mathbf{v}_i = \{v_{i1}, v_{i2}, \ldots, v_{im}\}$. The cluster centers are calculated using Equation 4.20.

$$v_{ij} = \frac{\sum_{k=1}^{n} \mu_{ik}^{m'} \cdot x_{kj}}{\sum_{k=1}^{n} \mu_{ik}^{m'}} \qquad (4.20)$$

The fuzzy c-partitions can be obtained using Equation 4.20.

Update the partition matrix for the each step, $\underset{\sim}{U}^{(r)}$ as follows:

$$\mu_{ik}^{(r+1)} = \left[\sum_{j=1}^{c} \left(\frac{d_{ik}^{(r)}}{d_{jk}^{(r)}} \right)^{2/(m'-1)} \right]^{-1} \text{ for } I_k = \phi \qquad (4.21)$$

Or

$\mu_{ik}^{(r+1)} = 0$ for all classes i where $i \in \underset{\sim}{I}_k$

where

$I_k = \{i \mid 2 \le c < n; d_{ik}^{(r)} = 0\}$

And

$\underset{\sim}{I}_k = \{1, 2, \ldots, c\} - I_k$

And

$$\sum_{i \in I_k} \mu_{ik}^{(r+1)} = 1$$

The optimum fuzzy *c*-partition will be the smallest of the partitions described in Equation 4.22.

$$J_m^* (\underset{\sim}{U}^*, v^*) = \min_{Mf_c} J (\underset{\sim}{U}, v) \qquad (4.22)$$

❐❐❐

Chapter 5

Soft Computing Methods for Gynaecology Disease Diagnosis

5.1 Prologue

This chapter describes the soft computing techniques used in the simulation of differential diagnosis process for gynecological disease.

Differential Diagnosis Process

A differential diagnostic procedure is a systematic diagnostic method used to identify the presence of a disease entity where multiple alternatives are possible. This method is essentially a process of elimination or at least a process of obtaining information that shrinks the "Possibility" of candidate conditions to negligible levels, by using evidences such as symptoms, patient's history, and medical knowledge to adjust epistemic confidences in the mind of the diagnostician (or, for computerized or computer-assisted diagnosis, the software of the system) (Differential Diagnosis, 2016). The differential diagnosis process is presented in Figure 5.1.

The process is explained as follows.

i. When a patient approaches a physician, he/she narrates the general symptoms.
ii. The thought process of the doctor starts after listening the symptoms.
iii. The symptoms are in two forms viz. complaints and past history.
iv. Complaints may be suggestive, exaggerated, underestimated or incomplete.
v. Past history may be underestimated or incomplete.

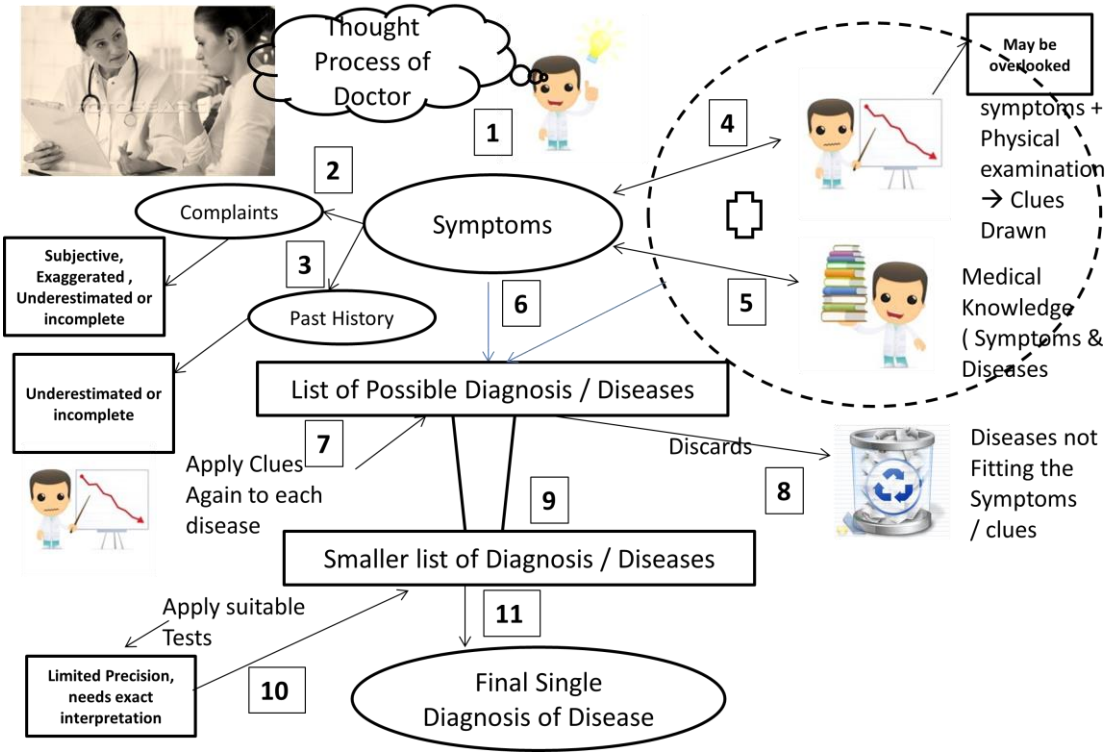


Figure 5.1 Differential Diagnosis Process

The study is based on the simulation of this differential diagnosis process especially in gynecological diseases. We have developed the model which mainly depends on the perceptions of experts and their knowledgebase. In the case of gynecological disease diagnosis, a 'Three Stage Approach' has been devised. Following is an exhaustive exposition of these three stages.

Three Stage Approach:

Stage I refers to Initial Screening Stage which deals with symptoms narrated by the patient. The computational procedure to collate perception based information is the compositional rule of inference with focus on max-min composition method. If the method does not indicate a single disease diagnosis, the output of Stage I become an input to Stage II, which considers history parameters of the patient and the computational procedure using Type 1 fuzzy inference system, to arrive at a likely single disease diagnosis. If the computations do not result into single disease diagnosis, then the output of Stage II becomes an input to Stage III, which deals with the results of various tests

suggested for the patient. Fuzzy Rule base system using Type 1 fuzzy inference system is designed for Stage III. The working of the model is shown in the Figure 5.2.

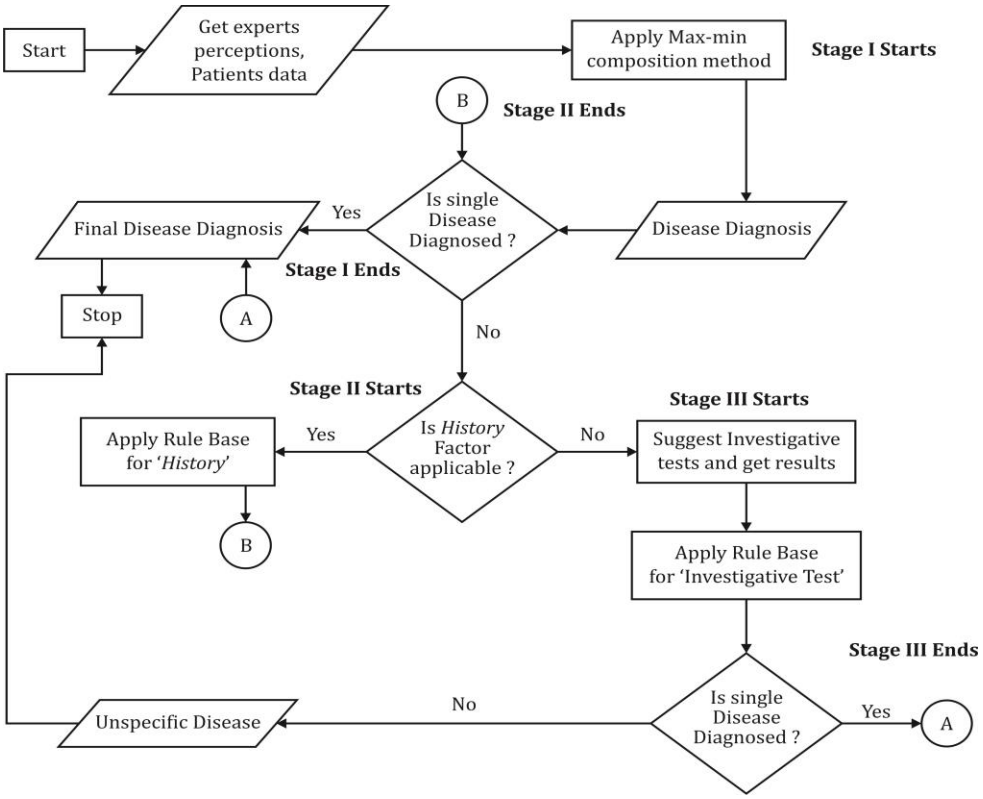


Figure 5.2 Three Stage Approach

The generic algorithm for three stage approach is as follows.

i. Get the perceptions from experts and collect patient's data.

ii. Apply max-min composition method to get the two Indication matrices.

iii. Diagnose a disease. Check if a single disease is diagnosed. If yes, it is the final diagnosis. Stage I (Initial Screening) and the diagnosis process terminate.

iv. If single disease is not diagnosed, the diagnosis process continues. Check if the '*History'* parameter is applicable to the patient.

v. If '*History*' parameter is applicable, apply rule base for '*History*' using Type 1 Fuzzy Inference System.

vi. Check if the output is single disease. If yes, it is the final diagnosis. Stage II (History Rule base) and the diagnosis process terminate.

vii. If the output is not a single disease even at Stage II, further investigative tests are suggested and the test results are obtained.

viii. Test Rule base is applied on the conducted test results to get the final diagnosis.

ix. If the single disease diagnosis is achieved after application of Test Rule base, it is the final diagnosis. Stage III (Test Rule base) and the diagnosis process terminate.

x. If the desired output is not obtained even at Stage III, the model gives output as '*Unspecific Disease*'.

Classification:

Experts are classified based on their perceptions and patients are classified as per the symptoms they possess. The methods such as Fuzzy Similarity Measures, Gower's Coefficient and Fuzzy C-Means are used for the classification (Figure 5.3).

The process of classification is divided into four parts. The first part focuses on classifying the experts depending upon their perceptions related to symptom-disease relationship. The second part of the case study initiates classifying the patients by using Fuzzy Similarity based classification method which is dependent on the narrated symptoms. The third part is based on patient's classification by using statistical approach, the Gower's Coefficient, and the fourth part is fuzzy clustering method based on Fuzzy C-Means clustering to classify patients.

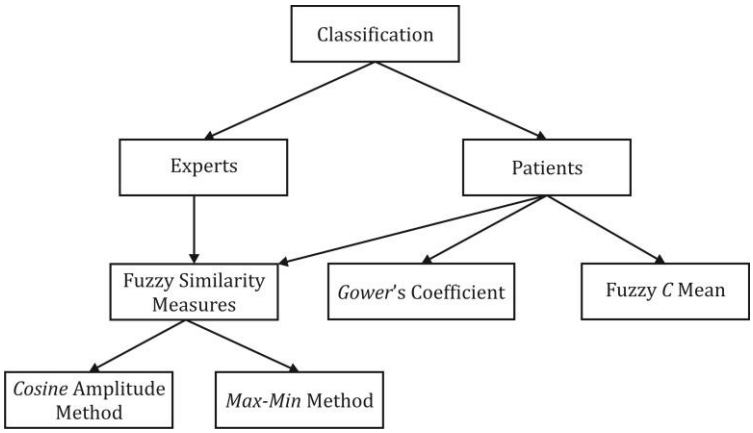


Figure 5.3 Classification details

The remaining chapter is organized in five sections. Section 1 introduces Perception Based Modeling. The three stage approach is covered in next three sections and Classification is presented in last section.

5.2 Perception Based Modeling

Eight different gynecologists' perceptions were collected from Pune, Ahmednagar, Ambejogai and Pimpri. These perceptions are used as Master Input Data for the Initial Screening Stage to get the diagnosis at Stage I. This is called Experts' knowledgebase.

These are the perceptions of the experts developed over more than 30 years of their experience in the fields of Gynaecology. We modeled these perceptions to diagnose a patient in the Initial Screening stage.

5.2.1 Fuzzy Occurrence and Confirmability Relations

The computational framework proposes two types of fuzzy relations which exist between symptoms (*s*) and diseases (*d*). These are: Fuzzy Occurrence Relation (R_o) and Fuzzy Confirmability Relation (R_c). The first provides knowledge about the tendency or frequency of a symptom when the specific disease is present; it corresponds to the question,

"*How often does symptom, 's' occur with disease 'd'?"*

The second fuzzy relation describes discriminating power of the symptom to confirm disease; it corresponds to the question,

"How strongly does symptom,'s' confirm disease 'd'?".

The distinction between Occurrence and Confirmability is useful because a symptom may often occur in given disease but the presence of this symptom may not confirm the disease where as the presence of the same symptom in some other disease may confirm the disease. On the other hand, another symptom may occur rarely but the presence of this symptom confirms the presence of disease.

As an example, in a disease *Uterine Prolapse,* the symptom '*Something Coming out of vagina' 'Always*' occurs and the presence of this symptom '*Always*' confirms the disease. Another symptom of Uterine Prolapse is '*Increased Frequency of Micturition',* which 'Always' occurs but not necessarily confirms the disease every time. Instead, it 'Very Often' confirms the disease. Similar is the case with '*Backache',* which is '*Always*' present in the patient but does not confirm the disease but '*Often*' confirms it.

Physician use natural language to note the symptoms which are received from patient like 'symptom 's_i' is always seen in disease d_j, symptoms 's_i' is never seen in disease d_j'

etc. The data in two relations, Fuzzy Occurrence (R_o) and Fuzzy Confirmability (R_c) relation contain the opinion about disease-symptom which is collected from the physicians in the linguistic form. The model uses similar terms to describe terms linguistically as a beauty of Fuzzy Logic to deal with human language. The linguistic terms used are A – *Always*, O – *Often*, NS – *Not Specific*, S – *Seldom*, N – *Never*.

With this, the Fuzzy Occurrence and Confirmability relations takes the form of statements as - "Symptom 's' *Always* occurs in disease 'd' and *Not Specific* confirms the disease".

To model the linguistic terms mathematically, membership grades of 1, 0.75, 0.5, 0were assigned in fuzzy sets R_o and R_c for the linguistic terms *Always*, *Often*, *Not Specific*, and *Never* respectively. The use of Equation 4.1 is designed to get the membership values to linguistic hedge *Very* as: 0.5625 & 0.0625 to *Very Often* and *Very Seldom* respectively. Upon defining the relations and linguistic hedges, opinions were received from many experts for the R_o and R_c relations.

As an illustration, the Fuzzy Occurrence and Confirmability relation values accepted from Expert E_1 are as shown in Table 5.1.

Table 5.1: Occurrence and Confirmability values for disease Ovarian Cyst

D4 **Ovarian Cyst**	Pelvic Pain	Swelling in Abdomen	Nausea	Vomiting	Painful Intercourse	Bladder/ Bowl Complaint	Pain in Abdomen
Occurrence Relation	VO	A	S	S	VO	VO	A
Confirmability Relation	O	A	S	S	O	O	A

The data clearly indicates that for disease *Ovarian Cyst*, the symptoms *Swelling in Abdomen*, and *Pain in Abdomen* Always occur and they Always confirm the disease at Initial Screening Stage. As these two symptoms overlap in multiple diseases, further investigations are of course required for the final diagnosis. But the symptoms *Pelvic Pain*, *Painful Intercourse* and *Bowl / Bladder Complaint* Very Often occur and Often confirm the disease. The values Seldom indicate that the symptoms *Nausea* and *Vomiting*

are neither very prominent in the disease nor they play a prominent role in confirmation of disease.

Table 5.2: Occurrence and Confirmability values for disease Uterine (Endometrial) Cancer (Perimenopausal)

Uterine (Endometrial) Cancer (Peri Menopausal)	Vaginal bleeding between periods	Spotting	Heavy/abnormal vaginal bleeding	Heavy/ excessive menstrual bleeding	Irregular periods
Occurrence Relation	VO	O	A	A	O
Confirmability Relation	US	S	VO	VO	S

Table 5.3: Occurrence and Confirmability values for disease Rectovaginal Fistula

Rectovaginal Fistula	Passing of air and stool through vagina	Vaginal itching, burning	White discharge	Burning Micturition
Occurrence Relation	A	US	S	S
Confirmability Relation	A	O	US	S

From the tables as demonstrated above, two relations matrices each of size 123 x 31 (123 symptoms and 31 diseases) are constructed viz. Fuzzy Occurrence Relation matrix and Fuzzy Confirmability Relation matrix, wherein all the linguistic hedges used (*A, VO, O, US, S, VS, N*) are replaced by respective membership grades (1, 0.5625, 0.75, 0.5, 0.25, 0.0625,0). These matrices are then used for the further computations. The sample Fuzzy Occurrence Relation and Fuzzy Confirmability Relation for 9 selected diseases and related 17 symptoms are as shown in Table 5.4 and Table 5.5 respectively.

Table 5.4: Fuzzy Occurrence Relation (Case Study example)

	D_1	D_2	D_3	D_4	D_5	D_6	D_7	D_8	D_9
S_1	0	0	0	0	0	0.5625	0.75	1	0
S_2	0	0	0.75	0	0	0	0	0.5625	0
S_3	0	0.5625	1	0	0	0	0.5625	1	0

	D_1	D_2	D_3	D_4	D_5	D_6	D_7	D_8	D_9
S_4	0	0	1	1	0	0	1	0.5625	0
S_5	0	0	0.75	0	0.5625	0	0	0.75	0
S_6	0	0	1	1	1	0	0	0	0
S_7	0.0625	0	1	0	1	0.5625	0	0	0
S_8	0	0	1	0	1	0	0	0	0
S_9	0.5625	0.5625	0.75	1	0	0.75	1	0	0
S_{10}	0	0	0	0	0.75	0	0	0	0.5625
S_{11}	1	0	0	0	0	1	0	0.5625	1
S_{12}	1	0	0	0	0	0.5625	0	0	0
S_{13}	0.75	0	0	0	0	0.5	0	0	0
S_{14}	0	1	0	0	0	0	0	0	0
S_{15}	0	0.5625	0	0	0	0	0.75	0	0
S_{16}	0	1	0	0	0	0.5	0	1	0
S_{17}	0	0	0	0	0	0	0	0.0625	0

Table 5.5: Fuzzy Confirmability Relation (Case Study example)

	D_1	D_2	D_3	D_4	D_5	D_6	D_7	D_8	D_9
S_1	0	0	0	0	0	0.5625	0.75	0.75	0
S_2	0	0	0.75	0	0	0	0	0.75	0
S_3	0	0.75	0.75	0	0	0	0.5625	1	0
S_4	0	0	1	1	0	0	1	0.5625	0
S_5	0	0	0.75	0	0.5625	0	0	0.75	0
S_6	0	0	1	1	1	0	0	0	0
S_7	0.0625	0	1	0	1	0.5625	0	0	0
S_8	0	0	1	0	1	0	0	0	0
S_9	0.75	0.75	0.75	1	0	0.75	1	0	0
S_{10}	0	0	0	0	0.75	0	0	0	0.5
S_{11}	1	0	0	0	0	1	0	0.5625	1
S_{12}	1	0	0	0	0	0.5625	0	0	0
S_{13}	0.75	0	0	0	0	0.5	0	0	0
S_{14}	0	1	0	0	0	0	0	0	0
S_{15}	0	0.75	0	0	0	0	0.75	0	0
S_{16}	0	1	0	0	0	0.5	0	1	0
S_{17}	0	0	0	0	0	0	0	0.25	0

These Fuzzy Occurrence relation and Fuzzy Confirmability relation are used in the classification of experts based on their perceptions as described the in Section 5.1.3.

5.2.2 Experts' Classification

No two persons think alike. Even the twins do not think alike. This is known as a Consistency Principle. This fact leads to classifying the gynaecologists because their perceptions could be different in assigning linguistic hedges in defining symptoms. Based on over two decades of experience, the domain experts confirmed that there are 31 commonly observed gynaecological diseases and 123 related symptoms.

The gynaecologists/experts recorded their perceptions linguistically with corresponding membership values (shown in bracket) as A- Always (1), VO - Very Often (0.5625), O - Often (0.75), NS - Not Specific (0.5), S - Seldom (0.25), VS - Very Seldom (0.0625) and N - Never (0).

We assume that if in a disease d_i, a symptom s_j is absent, the Fuzzy Occurrence and Confirmability relation entries for the $[d_i, s_j]$ will have membership value 0. Such entries in the tables are not further considered in the analysis for the obvious reason.

Algorithm 1: Expert's Classification

1. Get expert's perceptions in the form of Confirmability relation matrix (symptom x disease relation) (Table 5.5) and assign membership grades for the linguistic hedges used in the perceptions recorded by the experts.
2. Generate the relation matrix D_i/S_j, Disease-Symptom combination (for all diseases and all symptoms) x expert's perceptions from the Confirmability relation matrix. The obtained matrix (D_i/S_i) x E is on two universes viz., expert and D/S, so normalize the matrix.
3. Apply similarity measures: Cosine Amplitude method and Max-Min method to generate a tolerance relation (R).
4. Check if the relation R is equivalence (Equation 4.11):
   The relation R is *Reflexive*, if $\mu_R (x_i, x_i) = 1 \; \forall \; x_i$.
   The relation is *Symmetric*, if $\mu_R (x_i, x_j) = \mu_R (x_j, x_i) \; \forall \; i, j$.

To check if the relation R is *Transitive* i.e. $\mu_R (x_i, x_j) = \lambda_1$ and $\mu_R (x_j, x_k) = \lambda_2 \rightarrow \mu_R (x_i, x_k) = \lambda$, Where $\lambda \geq \min [\lambda_1, \lambda_2]$

5. If not an equivalence relation, then perform $R^2 = R \circ R$ (Equation 4.10) and go to step 4 otherwise go to step 6.
6. Apply α-cuts to the obtained equivalence relation and classify the experts.
7. Stop.

** See Annexure 5.1 for Classification Program Screenshot*

Case Study Example

To perform Fuzzy Similarity Measures based classification of gynaecologists, the perceptions recorded by 8 experts for the Confirmabiliy relation matrix (Sardesai, Kharat, Deshpande & Sambarey, 2015) is used. The matrix has the elements *Experts x Disease-Symptom* combination viz. D_i/S_j (disease Di is confirmed when symptom Si occurs) for i = 1 to 31 and j = 1 to 123.

The obtained matrix (D_i/S_i) x E is on two universes viz., expert and D/S. Therefore, the similarity measures using Cosine Amplitude is the right kind of formalism to be used to compute Fuzzy Similarity relations between, in this case, eight gynaecologists and D/S.The table contains 31 x 123 rows and 8 columns (experts) (Table 5.6).

Table 5.6: Disease / Symptom and Experts Confirmability Values (31 x 123 x 8)

D/S	E_1	E_2	E_3	E_4	E_5	E_6	E_7	E_8
D_1S_1	A	VO	A	A	A	A	A	A
D_1S_3	N	N	N	N	N	N	N	N
D_1S_4	VO	O	O	O	O	NS	NS	O
D_1S_5	O	NS	NS	NS	S	NS	NS	VO
D_1S_{18}	N	N	N	N	N	N	N	N
D_1S_{36}	O	VS	S	S	S	S	S	NS
D_1S_{40}	NS	VS	VS	VS	VS	VS	VS	VS
D_1S_{47}	A	O	O	VO	VO	VO	O	NS
D_1S_{61}	N	N	N	N	N	N	N	N
….								
D_5S_1	N	N	N	N	N	N	N	N
D_5S_3	A	A	A	A	A	A	A	A

D_5S_4	O	O	VO	VO	VO	A	VO	A
D_5S_5	N	N	N	N	N	N	N	N
D_5S_{18}	S	VO	VO	VO	VO	VO	VO	VO
D_5S_{36}	N	N	N	N	N	N	N	N
D_5S_{40}	N	N	N	N	N	N	N	N
D_5S_{47}	N	N	N	N	N	N	N	N
D_5S_{61}	A	S	S	O	O	O	O	A
…..								

To explain the computational procedure of similarity measure, out of 8 experts and 31 x 123 (disease x symptom) entries, a sample set of 5 experts and 18 (disease x symptom) entries are considered (Table 5.7). For the case study, the Confirmability Relation values as mentioned in Table 5.7 are used for multiple experts. In this typical study, 2 diseases and their related symptoms are considered instead of all 31 diseases and 123 symptoms. Remaining symptom values are '0' for the particular disease and are omitted (Sardesai, Kharat, Deshpande & Sambarey, 2015).

Table 5.7: Table of Disease / Symptom and Experts Confirmability Values

D/S	**E_1**	**E_2**	**E_3**	**E_4**	**E_5**
D_1S_1	A	VO	A	A	A
D_1S_3	N	N	N	N	N
D_1S_4	VO	O	O	O	O
D_1S_5	O	US	US	US	S
D_1S_{18}	N	N	N	N	N
D_1S_{36}	O	VS	S	S	S
D_1S_{40}	US	VS	VS	VS	VS
D_1S_{47}	A	O	O	VO	VO
D_1S_{61}	N	N	N	N	N
D_5S_1	N	N	N	N	N
D_5S_3	A	A	A	A	A
D_5S_4	O	O	VO	VO	VO
D_5S_5	N	N	N	N	N
D_5S_{18}	S	VO	VO	VO	VO
D_5S_{36}	N	N	N	N	N
D_5S_{40}	N	N	N	N	N

D/S	E_1	E_2	E_3	E_4	E_5
D_5S_{47}	N	N	N	N	N
D_5S_{61}	A	S	S	O	O

Application of the Cosine Amplitude method (Equation 4.5) is as shown below.

r_{12} = (1*0.5625 + 0*0 + 0.5625*0.75 + 0.75*0.5 + 0*0 + 0.75 * 0.0625 + 0.5 *0.0625 + 1*0.75 + 0*0 + 0*0 + 1*1 + 0.75*0.75 + 0*0 + 0.25*0.5625 + 0*0 +0*0 +0*0+1*0.25) / √ (6.3191 * 3.6404) = 0.950788.

Similarly, the computed value for r_{13} is 0.6141. Table 5.8 presents matrix R with size 5x5.

Table 5.8: Fuzzy Tolerance Relation Obtained Using Cosine Amplitude Method

R =

	x_1	x_2	x_3	x_4	x_5
x_1	1	0.950788	0.6141	0.6556	0.6199
x_2	0.950788	1	0.96211	0.9358	0.9247
x_3	0.6141	0.96211	1	0.96674	0.763246
x_4	0.6556	0.9358	0.96674	1	0.99297
x_5	0.6199	0.9247	0.763246	0.99297	1

The above relation R is *Reflexive*, as $\mu_R (x_i, x_i) = 1 \; \forall \; x_i$.

The above relation is *Symmetric* as $\mu_R (x_i, x_j) = \mu_R (x_j, x_i) \; \forall$ i, j.

We check if the above relation R is *Transitive* i.e.

$\mu_R (x_i, x_j) = \lambda_1$ and $\mu_R (x_j, x_k) = \lambda_2 \rightarrow \mu_R (x_i, x_k) = \lambda$

Where $\lambda \geq \min [\lambda_1, \lambda_2]$

Let i = 1, j= 2, k= 3, $\mu_R (x_i, x_j) = \lambda_1 = 0.950788$ $\mu_R (x_j, x_k) = \lambda_2 \rightarrow = 0.96211$ $\mu_R (x_i, x_k) = \lambda \rightarrow 0.6556$

So $\lambda \leq \min [\lambda_1, \lambda_2]$.

This relation is not transitive, so relation R is Fuzzy Tolerance relation. This is transformed to Fuzzy Equivalence relation using the defined procedure of R o R till the resultant Fuzzy Equivalence relation R is obtained. Table 5.9 presents the final Fuzzy Equivalence relation.

Table 5.9: Fuzzy Equivalence Relation Obtained From Fuzzy Tolerance Relation (Cosine Amplitude Method)

R =

	x_1	x_2	x_3	x_4	x_5
x_1	1	0.950788	0.950788	0.950788	0.950788
x_2	0.950788	1	0.96211	0.96211	0.96211
x_3	0.950788	0.96211	1	0.96674	0.96674
x_4	0.9507 88	0.96211	0.96674	1	0.99297
x_5	0.950788	0.96211	0.96674	0.99297	1

Application of Max-Min method (Equation 4.6) is as shown.

r_{12}= (min(1 , 0.5625) + min(0 , 0) + min(0.5625 , 0.75) + min(0.75 , 0.5) + min(0 , 0) + min(0.75 , 0.0625) + min(0.5 , 0.0625) + min(1 , 0.75) + min(0 , 0) + min(0 , 0) + min(1 , 1) + min(0.75 , 0.75) + min(0 , 0 + min(0.25 ,0.5625)+ min(0 , 0) + min(0 , 0) + min(0 , 0)+ min(1 , 0.25)) / (max(1 , 0.5625) + max(0 , 0) + max(0.5625 , 0.75) + max(0.75 , 0.5) + max(0 , 0) + max(0.75 , 0.0625) + max(0.5 , 0.0625) + max(1 , 0.75) + max(0 , 0) + max(0 , 0) + max(1 , 1) + max(0.75 , 0.75) + max(0 , 0 + min(0.25 ,0.5625) + max(0 , 0) + max(0 , 0) + max(0 , 0)+ max(1 , 0.25))

= 0.626984

Using the relation in Equation 4.6, we get 5 x 5 matrix of Fuzzy Tolerance relation (Table 5.10).

Table 5.10: Fuzzy Tolerance Relation Obtained Using Max-Min Method

	x_1	**x_2**	**x_3**	**x_4**	**x_5**
1	1	0.626984	0.723577	0.764228	0.731707
2	0.626984	1	0.923077	0.954545	0.909091
3	0.723577	0.923077	1	0.947917	0.90625
4	0.764228	0.954545	0.947917	1	0.958333
5	0.731707	0.909091	0.90625	0.958333	1

The above relation R is Reflexive, as: $\mu_R (x_i, x_i) = 1 \ \forall \ x_i$'s

The above relation is Symmetric, as: $\mu_R (x_i, x_j) = \mu_R (x_j, x_i) \ \forall$ i, j

We check if the above relation R is Transitive, i.e.

$\mu_R (x_i, x_j) = \lambda_1$ and $\mu_R (x_j, x_k) = \lambda_2 \rightarrow \mu_R (x_i, x_k) = \lambda$

Where $\lambda \geq \min [\lambda_1, \lambda_2]$

Let i = 1, j = 3, k = 2

$\mu_R (x_i, x_j) = \lambda_1 = 0.723577$

$\mu_R (x_j, x_k) = \lambda_2 \rightarrow = 0.923077$

$\mu_R (x_i, x_k) = \lambda \rightarrow 0.626984$

So $\lambda \leq \min [\lambda_1, \lambda_2]$

Therefore the relation is not transitive. This is transformed to Fuzzy Equivalence relation using the defined procedure of R o R till we get the resultant Fuzzy Equivalence relation R. Table 5.11 presents the final Fuzzy Equivalence matrix.

Table 5.11: Fuzzy Equivalence Relation Obtained From Fuzzy Tolerance Relation (Max-Min Method)

R =

	x_1	x_2	x_3	x_4	x_5
x_1	1	0.731707	0.731707	0.731707	0.731707
x_2	0.731707	1	0.947917	0.954545	0.954545
x_3	0.731707	0.947917	1	0.947917	0.947917
x_4	0.731707	0.954545	0.947917	1	0.958333
x_5	0.731707	0.954545	0.947917	0.958333	1

Table 5.12 and Table 5.13, respectively represent fuzzy equivalence relations obtained using Cosine Amplitude method and Max-Min method with the help of the software developed by the authors for 31 x 123 (disease x symptom) entries and 8 experts applied to Table 5.7.

Table 5.12: Fuzzy Equivalence Relation Obtained for 31 x 123 D_iS_j entries x 8 experts (Cosine Amplitude Method)

	E_1	E_2	E_3	E_4	E_5	E_6	E_7	E_8
E_1	1	0.888	0.9	0.906	0.901	0.913	0.91	0.935
E_2	0.888	1	0.975	0.952	0.937	0.951	0.937	0.892
E_3	0.9	0.975	1	0.955	0.946	0.954	0.95	0.904
E_4	0.906	0.952	0.955	1	0.976	0.981	0.97	0.906
E_5	0.901	0.937	0.946	0.976	1	0.969	0.969	0.909
E_6	0.913	0.951	0.954	0.981	0.969	1	0.973	0.917

	E_1	E_2	E_3	E_4	E_5	E_6	E_7	E_8
E_7	0.91	0.937	0.95	0.97	0.969	0.973	1	0.907
E_8	0.935	0.892	0.904	0.906	0.909	0.917	0.907	1

Table 5.13: Fuzzy Equivalence Relation Obtained for 31 x 123 D_iS_j entries x 8 experts (Max-Min Method)

	E_1	E_2	E_3	E_4	E_5	E_6	E_7	E_8
E_1	1	0.784	0.784	0.784	0.784	0.784	0.784	0.795
E_2	0.784	1	0.937	0.894	0.894	0.894	0.894	0.784
E_3	0.784	0.937	1	0.894	0.894	0.894	0.894	0.784
E_4	0.784	0.894	0.894	1	0.938	0.95	0.938	0.784
E_5	0.784	0.894	0.894	0.938	1	0.938	0.938	0.784
E_6	0.784	0.894	0.894	0.95	0.938	1	0.938	0.784
E_7	0.784	0.894	0.894	0.938	0.938	0.938	1	0.784
E_8	0.795	0.784	0.784	0.784	0.784	0.784	0.784	1

In the present work, the domain knowledge of eight different experts was used. The experts' agreement is computed using the well-established Fuzzy Similarity Measures. As there are multiple experts/raters involved in the study, the need to find the consistency among the experts/individuals arises due to the variability among human nature. '*Inter-Rater reliability*' can be thought of as the extent of agreement among data collectors as in Section 5.1.3.

5.2.3 Inter-Rater reliability

Inter-Rater reliability is a concern in most studies because different people collecting data may experience and interpret the phenomena of interest differently.

The Kappa statistic is frequently used to test inter-rater reliability. Since eight experts/raters were considered, the better option to choose is Fleiss Kappa model of inter-rater reliability (Inter-rater reliability, 2016; McHugh, 2015).

For the computational procedure of Fleiss Kappa, the results from our Initial Screening Stage were used, which in turn depend on the expert's knowledgebase for the diagnosis process. In Initial Screening stage (Stage I), we diagnosed all the patients using each expert's knowledgebase separately. The outcome of this is patients diagnosis, may be a single disease diagnosed or multiple diseases diagnosed. The multiple disease

diagnosed patients are passed to Stage II and Stage III. The single disease diagnosed patients whose diagnosis is purely based on the expert's judgment are considered as input to Fleiss Kappa model. The algorithm is as follows.

Algorithm: Fleiss Kappa Model

1. Let the number of experts n = 8.
2. List the number of patients with single disease diagnosis, (here p = 69).
3. List the possible diseases for the single disease diagnosed patients (Here d = 17). Here we add one more output to the list of diseases as "Unspecific Disease", as in some cases, the model gives output as "Unspecific Disease". Therefore, d becomes 18.
4. Create a p x d table. The entry (p_i, d_j) is a number 'n' indicating number of experts diagnosed disease d_j for patient p_i (Table 5.14). In the table, the entry (p_1, d_1) = 6 indicates that 6 experts have diagnosed patient p1 with the disease d_1 (*Uterine Prolapse*) and (p_1, d_{18}) = 2 indicates that 2 experts have diagnosed patient p1 with the disease d_{17} (*Unspecific Disease*). None of the experts have diagnosed the patient for remaining diseases, so the cell contains value 0. The row sum of the patient p_1 row must be equal to number of experts in consideration.
5. Calculate the reliability of the experts for the individual patient using :

   $R_i = \sum_{j=1}^{d} p_i d_j$ – n / (n * n-1)

   = (($p_i d_1$^2)+ ($p_i d_2$^2)+ ($p_i d_3$^2)+ ($p_i d_4$^2)+ ($p_i d_5$^2)+ ($p_i d_6$^2)+ ($p_i d_7$^2)+ ($p_i d_8$^2)+ ($p_i d_9$^2)+ ($p_i d_{10}$^2)+ ($p_i d_{11}$^2)+ ($p_i d_{12}$^2)+ ($p_i d_{13}$^2)+ ($p_i d_{14}$^2)+ ($p_i d_{15}$^2)+ ($p_i d_{16}$^2)+ ($p_i d_{17}$^2)) – n) / (n * n-1)
6. Calculate P_BAR = R_i / (1 – p).
7. Calculate $P_e = \sum_{j=1}^{d} ((\sum_{i=1}^{p} p_i d_j$ / (p – n)) ^ 2).
8. Calculate Kappa Coefficient κ = (P_BAR – P_e) / (1 – P_e) (Equation 4.17).
9. Find the expert's agreement using the interpretations given by Landis and Koch (1977) which are as presented in Table 4.1.

Table 5.14 demonstrates the p x d table entries which are used for calculation of Kappa Coefficient.

Table 5.14: p x d entries for Kappa Coefficient calculation

	D_1	D_3	D_5	D_9	D_{12}	D_{13}	D_{14}	D_{19}	D_{20}	D_{23}	D_{25}	D_{26}	D_{27}	D_{28}	D_{29}	D_{30}	D_{31}	UD
P_1	**6**	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	**2**
P_2	0	0	0	0	0	0	0	0	0	0	**7**	0	0	0	0	0	0	**1**
P_5	0	0	**1**	0	**1**	0	0	0	0	0	0	0	0	0	0	0	0	**6**
P_6	0	**7**	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0
P_9	0	0	0	0	**1**	0	0	0	0	0	0	0	0	0	0	0	0	**7**
P_{13}	0	0	0	0	0	0	0	0	0	0	**7**	0	0	0	0	0	0	**1**
….																		
P_{225}	0	0	0	0	0	0	0	0	0	0	0	0	**7**	0	0	0	0	**1**
P_{226}	0	0	0	0	0	0	**1**	0	0	0	0	0	**6**	0	0	0	0	**1**

Classification of experts is initial part of the study, which is baseline for the Stage I of differential diagnosis process (Section 5.3) which is designated as Initial Screening Model.

5.3 Stage I : Initial Screening

Initial Screening is the one of the early steps in the process of differential diagnosis which is followed very commonly by medical professionals. It is possible that the model may diagnose one or more diseases, based on the inputs from the patients. The possibility of differential diagnosis cannot be ruled out, as the s-d relationship in fuzzy relational calculus is based only on the perceptions of the patients without further medical tests.

To follow the Initial Screening part of research study, the data on patient/symptom matrix is collected from three different hospitals in Pune and Ambejogai, India, by interviewing the patients so as to avoid collecting happenstance data in statistics. During the personal conversation with the patients, questions were asked about their complaints, past history, age, Last Menstrual Period (LMP), Pre-Menstrual Changes (PMC) details, number of children, history about hypertension, Diabetics etc.

The data of 226 patients was initially scanned by the experts and are presented in the table of the form s x p. In this table, the patient's symptoms are recorded linguistically as High severity (1), Moderate severity (0.5), Low severity (0.25) and No Symptom present (0). A sample set of 9 patients is considered for computational demonstration (Table 5.15). The max-min procedure is followed and the software developed is using C#

DOTNET as platform to process the information set (Sardesai, Kharat, Deshpande & Sambarey, 2012).

Table 5.15: Patient Symptom Relation (Case Study Example)

	P_1	**P_2**	**P_3**	**P_4**	**P_5**	**P_6**	**P_7**	**P_8**	**P_9**
S_1	0	0	0	0	0	0.5	0	0	0
S_2	0	0	0	0	0	0	0	0	0
S_3	1	0	0	0	1	0	0	0	1
S_4	1	0	0	0	1	1	0	0	0.5
S_5	0	1	0	0	0	0	0	0	0
S_6	0	0	0	0	0	0	1	0	0
S_7	0	0	0	0	0	0	0	0.5	0
S_8	0	0	0	0	0	0	1	0	0
S_9	0	0	0	0	0	0	0	0	0
S_{10}	0	0	0	0	0	0	0	0	0
S_{11}	0	1	0	1	0	1	0	0	0
S_{12}	0	0	0	0	0	0	0	0	0
S_{13}	0	0	0	0	0	0.5	0	0	0
S_{14}	0	0	0	0	0	0	0	0	0
S_{15}	0	0	0	0	0	0	0	0	0
S_{16}	0	1	1	0	0	0	0.5	0.5	0
S_{17}	0	0	0	0	0	0	0	0	0.5

5.3.1. Algorithm for Stage I (Initial Screening Stage)

1. Get expert's perceptions in the form of Fuzzy Occurrence relation (R_o) and Fuzzy Confirmability relation (R_c) matrix.
2. Assign membership grades to the linguistic hedges received from the experts.
3. Collect patients' data in the form of symptoms in linguistic form in a relation P: s x p and assign membership grades.
4. Apply max-min composition as $R`_o = R_o$ o P and $R`_c = R_c$ o P to get Fuzzy Occurrence Indication Relation $R`_o$ and Fuzzy Occurrence Confirmability Relation $R`_c$.
5. If the entry $R`_o [d_i, p_j] = R`_c [d_i, p_j] = 1$ (α-cut = 1), display result: Patient P_j is suffering from disease d_i.

6. Repeat step 5 ∀ i = 1 to 31 for patient p_j.
7. Stop.

*See Annexure 5.2a for Initial Screening Stage Program Screenshot,
5.2b Initial Screening Stage Program Code Snippet.

5.3.2 max-min composition

To explain the computational procedure, a sample set of 9 diseases (out of 31 identified), 17 related symptoms (out of 123) are considered as shown in Table 5.4 and Table 5.5. We presuppose that if symptom s_j is not a symptom of disease d_i, then the Fuzzy Occurrence and Confirmability relation entries for the [d_i, s_j] will be 'Never' i.e. '0'. In this illustrative example, 'Never' or '0' entry symptoms are not considered as they result in '0' value after the application of max-min calculation. (Table 5.4 and Table 5.5). Similar is the case with Patient-Symptom relationship (Table 5.15).

*See Annexure 5.3 for Disease names and Symptoms related to Table 5.4 and 5.5 entries.

Typical max-min calculation procedure using Equation 4.3 is as follows.

(X_1,Z_4) = Max (min(0,0), min(0,0), min(0,0), min(0,0), min(0,0), min(0,0), min(0.0625,0), min(0,0), min(0.5625,0), min(0,0), **min(1,1),** min(1,0), min(0.75,0), min(0,0), min(0,0), min(0,0), min(0,0))

= Max(0,0,0,0,0,0,0,0,0,0,1,0,0,0,0,0,0)

= 1

(X_2,Z_1) = Max (min(0,0), min(0,0), **min(0.5625,1),** min(0,1), min(0,0), min(0,0), min(0,0), min(0,0), min(0,0), min(0.5625,0), min(0,0), min(0,0), min(0,0), min(0,0), min(1,0), min(0.5625,0), min(1,0), min(0,0))

= Max(0,0,0.5625,0,0,0,0,0,0,0,0,0,0,0,0,0,0)

= 0.5625

Using this procedure, we have obtained Fuzzy Occurrence Indication Relation (Table 5.16) and Fuzzy Confirmability Indication Relation (Table 5.17). These Indication relation table are used to arrive at the diagnosis further.

Table 5.16: Disease Fuzzy Occurrence Indication Matrix (P X D)

	P_1	**P2**	**P3**	**P4**	**P5**	**P6**	**P7**	**P8**	**P9**
D_1	0	1	0	1	0	1	0	0.0625	0

D_2	0.5625	1	1	0	0.5625	0	1	0.5	0.5625
D_3	1	0.75	0	0	1	0.75	1	0.75	1
D_4	1	0	0	0	1	1	1	0	0.75
D_5	0	0	0	0	0	0	1	0.75	0
D_6	0	1	0.5	1	0	1	0. 5	0.75	0
D_7	1	0	0	0	1	1	0	0	0.5625
D_8	1	1	1	0.5625	1	0.5625	0.75	0.5	1
D_9	0	1	0	1	0	1	0	0	0

Table 5.17: Disease Fuzzy Confirmability Indication Matrix (P X D)

	P_1	**P_2**	**P_3**	**P_4**	**P_5**	**P_6**	**P_7**	**P_8**	**P_9**
D1	0	1	0	1	0	1	0	0	0
D2	0.75	1	1	0	0.75	0	0.75	0.5	0.75
D3	1	0.75	0	0	1	0.75	1	0.75	1
D4	1	0	0	0	1	0	1	0	0.75
D5	0	0	0	0	0	0	1	0.75	0
D6	0	1	0.5	1	0	1	0.75	0.5625	0
D7	1	0	0	0	1	1	0	0	0.5625
D8	1	1	1	0.5625	1	0.5625	0.75	0.5	1
D9	0	1	0	1	0	1	0	0	0

The output of Initial Screening Stage is Single Disease or Multiple Diseases Diagnosis. In case of Multiple Diseases Diagnosis the received output is passed as input to check if the *History* parameter is applicable to Stage II (Section 5.3).

5.4 Stage II : *History* Rule Base

The output of Initial Screening may be a single disease diagnosed or multiple diseases diagnosed. In the latter case, to diagnose the patient further, there was a need to search for the factors which the Gynaecology diagnosis is heavily dependent on. It was evident that the diagnostic efforts in Gynaecology heavily depend on some of the factors/ history such as: Age of the patient, Last Menstrual Periods (LMP), Pre-Menstrual Cycle (PMC), Irregular/Regular nature of menses, Married/Unmarried status of the patient and parity. These factors collectively decide some of the diseases. Therefore, there was a need to define fuzzy sets for such factors (Sardesai, Kharat, Deshpande & Sambarey, 2014).

5.4.1 Defining *History* Parameters

In the field of medical diagnosis, the history of the patient plays vital role. In Gynaecology diseases, the history may consists mainly of age of the lady, the graph of menstrual flow, menstruation period, marital status, parity etc. Therefore, 5 fuzzy sets namely, Age, LMP, PMC_Flow, Marital Status, Parity are defined which are as below:

1. ***Age*** **:** Age is represented by a term set =
   {PreMenarche, Early Fertile, Fertile, PeriMenopausal, Menopaused}
2. ***PMC_Flow*** **:** PMC_Flow is represented by a term set =
   {Nil, Scanty, Moderate, Excessive, Contineous}
3. ***Marital_Status*** **:** Marital_Status is represented by a term set =
   {Unmarried, Early, Normal, Late}
4. ***Parity*** **:** Parity is represented by a term set =
   {Nil, Low, Moderate, High}
5. ***LMP*** **:** LMP is represented by a term set =
   {PMP, SGC, RMC, MMC, PMC, LCT, GV, MP}

5.4.2 Fuzzy Sets for *History* Parameter

Upon defining the term sets, for each of the term set the membership functions (Table 5.18) are defined by consulting the experts.

Table 5.18: Membership functions defined for each term set

Age	
PreMenarche	10-17 years
Early Fertile	13-26 years
Fertile	16-50 years
PeriMenopausal	40-55 years
Menopaused	50 years onwards
PMC_Flow	
Nil	0 days

Scanty	Less than 2 days
Moderate	1-5 days
Excessive	4-10 days
Continuous	6-15 days onwards
Marital Status	
Unmarried	0 years
Early	10-20 years
Normal	18-25 years
Late	23-40 years
Parity	
Nil	0
Low	0-3 children
Moderate	1-4 children
High	More than 3 children
LMP (Last Menstrual Period)	
PMP (Pre-Menstrual Period)	1-30 days
SGC (Short Gap Cycles)	10-20 days
RMC (Regular Menstrual Cycles)	20-30 days
MMC (Missed Menstrual Cycles)	28-90 days
PMC (Prolonged Menstrual Cycles)	55-210 days
LCT (Lactational Amenorrhea)	More than 280 days
GV (Gravid Patient)	0-280 days
MP (Menopaused Patient)	150-800 days

**See Annexure 5.4 for Fuzzy Sets for History parameter (Figures A.1 - A.5).*

5.4.3 Fuzzy Rules for *History* Parameter

From the above defined 5 fuzzy sets, 72 fuzzy rules are defined, some of which are as follows.

Rule 1 If (age is PM AND LMP is MMC) Then Secondary Amenorrhea Present

Rule 2 If (age is PM AND LMP is PMC) Then Secondary Amenorrhea Present

Rule 6 If (age is EF AND LMP is PMC) Then Secondary Amenorrhea Present

Rule 24 If (M_Status is Unmarried AND Age is PR AND PMC_Flow is C) Then Pubertal Menorrhagia Present

Rule 25 If (M_Status is Unmarried AND Age is PR AND PMC_Flow is E) Then Pubertal Menorrhagia Present

Rule 26 If (M_Status is Unmarried AND Age is PR AND PMC_Flow is S) Then Pubertal Menorrhagia Present

Rule 27 If (M_Status is Unmarried AND Age is EF AND PMC_Flow is C) Then Pubertal Menorrhagia Present

Rule 28 If (M_Status is Unmarried AND Age is EF AND PMC_Flow is E) Then Pubertal Menorrhagia Present

Rule 29 If (M_Status is Unmarried AND Age is EF AND PMC_Flow is S) Then Pubertal Menorrhagia Present

Rule 30 If(Age is PM AND PMC_Status is IRR AND PMC_Flow is S AND LMP is MMC) Then Perimenopausal Present

Rule 31 If(Age is PM AND PMC_Status is IRR AND PMC_Flow is S AND LMP is PMC) Then Perimenopausal Present

Rule 32 If(Age is PM AND PMC_Status is IRR AND PMC_Flow is M AND LMP is MMC) Then Perimenopausal Present

Rule 54 If(PMC_Flow is LCT AND Age is F AND Parity is High) Then Lactational Amenorrhea Present

Rule 55 If(PMC_Flow is LCT AND Age is EF AND Parity is Low) Then Lactational Amenorrhea Present

Rule 56 If(PMC_Flow is LCT AND Age is EF AND Parity is Moderate) Then Lactational Amenorrhea Present

Rule 57 If(PMC_Flow is LCT AND Age is EF AND Parity is High) Then Lactational Amenorrhea Present

Rule 70 If(LMP is M AND Age is PM) Then Menopause Present

Rule 71 If(LMP is M AND Age is M) Then Menopause Present

Rule 72 If(LMP is M AND Age is F) Then Menopause Present

5.4.4 Algorithm for Stage II

1. Get input from Initial Screening (Stage I) model (Patient having multiple diseases diagnosed).
2. Accept *History* parameter values from the patient.
3. Calculate membership value for each fuzzy set and every term set defined under *History* parameter which is accepted in linguistic form.

   Use fuzzy sets defined, identify the type of the fuzzy set, find the values of α, β, γ and δ. Use the following formulae for the respective fuzzy set type.

   All the fuzzy sets are Trapezoidal fuzzy sets so we use Equation 4.13 calculate membership value.
4. Use Mamdani type Fuzzy Inference System using center of gravity as a defuzzification method.
5. Display the result.
6. Stop.

5.4.5. Stage II Case study

From the output of Initial Screening, we could observe that the *History* parameter could be applied to 30 patients. The following tables demonstrate application of *History* parameter Rule base to these patients (Sardesai, Kharat, Deshpande & Sambarey, 2016).

1. **Patient 20 :** Age = 35 (F=1),

   LMP = 57 days (PMC = 0.4, MMC=1, GV = 1)

Table 5.19: Fuzzy Rules fired for Patient P_{20}

Antecedent	**Rule applied**	**Min**	**Result of min**	**Max of all**	**Consequent**
If (age is PM AND LMP is MMC)	If (age = 0 AND LMP = 1)	min(0,1)	0	Max (0,0,1,0.047619, 0,0) = 1	Secondary Amenorrhea Present with possibility 1
If (age is PM AND LMP is PMC)	If (age = 0 AND LMP = 0.4)	Min(0,0.4)	0		

Antecedent	**Rule applied**	**Min**	**Result of min**	**Max of all**	**Consequent**
If (age is F AND LMP is MMC)	If (age = 1 AND LMP = 1)	Min(1,1)	1		
If (age is F AND LMP is PMC)	If (age = 1 AND LMP = 0.4)	Min (1, 0. 4)	0.4		
If (age is EF AND LMP is MMC)	If (age = 0 AND LMP = 1)	min(0,1)	0		
If (age is EF AND LMP is PMC)	If (age = 0 AND LMP = 0.4)	Min(0,0.4)	0		
If(LMP is M AND Age is PM)	If(LMP = 0 AND Age is 0)	Min (0, 0)	0	Max (0, 0,0)	Menopause Present with possibility 0
If(LMP is M AND Age is M)	If(LMP = 0 AND Age is 0)	Min (0,0)	0		
If(LMP is M AND Age is F)	If(LMP = 0 AND Age is 1)	Min (0,1)	0		
If (age is EF AND LMP is GVAND PMC_Flow is N)	If (age = 0 AND LMP = 1 AND PMC_Flow =1)	Min(0, 1,1)	0	Max(0,1,0) = 1	UPT to be done Present with possibility 1
If (age is F AND LMP is GV AND PMC_Flow is N)	If (age = 1 AND LMP = 1 AND PMC_Flow =1)	Min(1, 1,1)	1		
If (age is PM AND LMP is GV AND PMC_Flow is N)	If (age = 0 AND LMP = 1 AND PMC_Flow =1)	Min(0, 1,0)	0		

2. **Patient 100 :** Age = 25 (F=1, EF = 0.2) ,
   LMP = 1500 days
   No Rule fired

3. **Patient 103:** Age = 22 (F=1, EF = 0.8) ,
   LMP = 205 days (PMC = 0.2, GV = 1)

Table 5.20: Fuzzy Rules fired for Patient P_{103}

Antecedent	**Rule applied**	**Min**	**Result of min**	**Max of all**	**Consequent**
If (age is PM AND LMP is MMC)	If (age = 0 AND LMP = 0)	min(0,0)	0	Max(0,0,0, 0.2, 0, 0) = 0.2	Secondary Amenorrhea Present with possibility **0.2**
If (age is PM AND LMP is PMC)	If (age = 0 AND LMP = 0.2)	Min(0, 0.2)	0		
If (age is F AND LMP is MMC)	If (age = 1 AND LMP = 0)	Min(1,0)	0		
If (age is F AND LMP is PMC)	If (age = 1 AND LMP = 0.2)	Min (1, 0.2)	0.2		
If (age is EF AND LMP is MMC)	If (age = 0.8 AND LMP = 0)	min(0,1)	0		
If (age is EF AND LMP is PMC)	If (age = 0.8 AND LMP = 0.2)	Min(0, 0.2)	0		
If (age is EF AND LMP is GVAND PMC_Flow is N)	If (age = 0.8 AND LMP = 1 AND PMC_Flow =1)	Min(0.8, 1,1)	0.8	Max(0.8,1,0) = 1	UPT to be done Present with possibility 1
If (age is F AND LMP is GV AND PMC_Flow is N)	If (age = 1 AND LMP = 1 AND PMC_Flow =1)	Min(1, 1,1)	1		
If (age is PM AND LMP is GV AND PMC_Flow is N)	If (age = 0 AND LMP = 1 AND PMC_Flow =1)	Min(0, 1,0)	0		

4. Patient 90:

Age = 27 (F = 1, EF = 0.1)

LMP: 70 days (MMC = 1, PMC = 1, GV = 1),

PMC_Flow (E = 1)

Table 5.21: Fuzzy Rules fired for Patient P_{90}

Antecedent	**Rule applied**	**Min**	**Result of min**	**Max of all**	**Consequent**
If (Age is F AND LMP is MMC AND PMC_Flow is S)	If (Age =1 AND LMP =1 AND PMC_Flow =0)	Min (1,1 ,0)	0	Max (0, 0.35. 0.0. 0.26667, 0, 0, 0.1, 0,0,0.1, 0,0,0,0) = 0.35	Incomplete Abortion Present With possibility 0.35
If (Age is F AND LMP is MMC AND PMC_Flow is E)	If (Age =1 AND LMP =1 AND PMC_Flow =1	Min (1,1,1)	1		
If (Age is F AND LMP is MMC AND PMC_Flow is C)	If (Age =1 AND LMP =1 AND PMC_Flow =0)	Min (1,1,0)	0		
If (Age is F AND LMP is PMC AND PMC_Flow is S)	If (Age =1 AND LMP =1 =0.619048 AND PMC_Flow =0)	Min (1, 0. 619048, 0)	0		
If (Age is F AND LMP is PMC AND PMC_Flow is E)	If (Age =1 AND LMP =0. 619048 AND PMC_Flow =1)	Min (1, 0.619048, 1)	0.619048		
If (Age is F AND LMP is PMC AND PMC_Flow is C)	If (Age =1 AND LMP =0. 619048 AND PMC_Flow =0)	Min (1, 0. 619048, 0)	0		
If (Age is EF AND LMP is MMC AND PMC_Flow is S)	If (Age =0.1 AND LMP =1 AND PMC_Flow =0)	Min (0.1, 1, 0)	0		
If (Age is EF AND LMP is MMC AND PMC_Flow is E)	If (Age =0.1 AND LMP =1 AND PMC_Flow =1)	Min (0.1, 1, 1)	0.1		
If (Age is EF AND LMP is MMC AND PMC_Flow is C)	If (Age =0 AND LMP =1 AND PMC_Flow =0)	Min (0, 1, 0)	0		

Antecedent	**Rule applied**	**Min**	**Result of min**	**Max of all**	**Consequent**
If (Age is EF AND LMP is PMC AND PMC_Flow is S)	If (Age =0.1 AND LMP =0.619048AND PMC_Flow =0)	Min (0.1, 0. 619048, 0)	0		
If (Age is EF AND LMP is MMC AND PMC_Flow is E)	If (Age =0.1 AND LMP =0.35AND PMC_Flow =1)	Min (0.1, 0.35, 1)	0.1		
If (Age is EF AND LMP is PMC AND PMC_Flow is C)	If (Age =0.1 AND LMP= 0. 619048 AND PMC_Flow =0)	Min (0.1, 0. 619048, 0)	0		
If (age is EF AND LMP is GV AND PMC_Flow is E)	If (age = 0.1 AND LMP = 1 AND PMC_Flow =1)	Min(0.1, 1,1)	0	Max(0,1,0) = 1	Incomplete Abortion Present with possibility 1
If (age is F AND LMP is GV AND PMC_Flow is E)	If (age = 1 AND LMP = 1 AND PMC_Flow =1)	Min(1, 1,1)	1		
If (age is PM AND LMP is GV AND PMC_Flow is E)	If (age = 0 AND LMP = 1 AND PMC_Flow =1)	Min(0, 1,1)	0		

5. Patient 129 : Age = 45 (PM=1, F= 0.71429) ,

PMC: 35 days (MMC = 1),

Parity = 2 (Low =1, Moderate = 1)

M_Status = Early = 1

PMC_Status = IRR

Table 5.22: Fuzzy Rules fired for Patient P_{129}

Antecedent	**Rule applied**	**Min**	**Result of min**	**Max of all**	**Consequent**
If(age is PM AND	If(age = 1 AND	Min (1,1,0)	0	Max(0, 0,	Cervical

Antecedent	**Rule applied**	**Min**	**Result of min**	**Max of all**	**Consequent**
M_Status is Early AND Parity is High)	M_Status =1 AND Parity = 0)			1, 0) = 1	Cancer Present with possibility 1
If(age is M AND M_Status is Early AND Parity is High)	If(age =0 AND M_Status = 1 AND Parity is 0)	Min (0,1,0)	0		
If(age is PM AND M_Status is Early AND Parity is Moderate)	If(age =1 AND M_Status = 1 AND Parity is 1)	Min (1,1,1)	1		
If(age is M AND M_Status is Early AND Parity is Moderate)	If(age =0 AND M_Status = 1 AND Parity is 1)	Min (0,1,1)	0		
If(age is PM AND M_Status is Late AND Parity is Low)	If(age =1 AND M_Status =0 AND Parity =1)	Min (1,0,1)	0	Max(0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0) = 0	Endometrial Cancer Present with possibility 0 → Endometrial Cancer NOT PRESENT
If(age is PM AND M_Status is Late AND Parity is nil)	If(age =1 AND M_Status =0 AND Parity =0)	Min (1,0,0)	0		
If(age is PM AND M_Status is Normal AND Parity is Low)	If(age =1 AND M_Status=0 AND Parity 1)	Min (1,0,1)	0		
If(age is PM AND M_Status is Normal AND Parity is Nil)	If(age =1 AND M_Status =0 AND Parity =0)	Min (1,0,0)	0		
If(age is PM AND M_Status is Unmarried AND Parity is Low)	If(age =1 AND M_Status =0 AND Parity =1)	Min (1,0,1)	0		
If(age is PM AND M_Status is	If(age =1 AND M_Status =0 AND	Min (1,0,0)	0		

Antecedent	**Rule applied**	**Min**	**Result of min**	**Max of all**	**Consequent**
Unmarried AND Parity is Nil)	Parity =0)				
If(age is M AND M_Status is Late AND Parity is Low)	If(age =0 AND M_Status =0 AND Parity =1)	Min (0,0,1)	0		
If(age is M AND M_Status is Late AND Parity is nil)	If(age =0 AND M_Status =0 AND Parity =0)	Min (0,0,0)	0		
If(age is M AND M_Status is Normal AND Parity is Low)	If(age =0 AND M_Status =0 AND Parity =1)	Min (0,0,1)	0		
If(age is M AND M_Status is Normal AND Parity is Nil)	If(age =0 AND M_Status =0 AND Parity =0)	Min (0,0,0)	0		
If(age is M AND M_Status is Unmarried AND Parity is Low)	If(age =0 AND M_Status =0 AND Parity =1)	Min (0, ,0,1)	0		
If(age is M AND M_Status is Unmarried AND Parity is Nil)	If(age =0 AND M_Status =0 AND Parity =0)	Min (0, ,0,0)	0		
If (Age is PM AND PMC_Status is IRR AND PMC_Flow is E AND LMP is MMC)	If (Age =1 AND PMC_Status =1 AND PMC_Flow =0.5 AND LMP =1)	Min (1, 1, 0.5, 1)	0.5	Max(0.5, 0, 1, 0,0,0,0,0) = 1	DUB Present
If (Age is PM AND PMC_Status is IRR AND PMC_Flow is E AND LMP is PMC)	If (Age =1 AND PMC_Status =1 AND PMC_Flow =0.5 AND LMP =0)	Min (1, 1, 0.5, 0)	0		

Antecedent	**Rule applied**	**Min**	**Result of min**	**Max of all**	**Consequent**
If (Age is PM AND PMC_Status is IRR AND PMC_Flow is C AND LMP is MMC)	If (Age =1 AND PMC_Status =1 AND PMC_Flow =1 AND LMP =1)	Min (1, 1, 1, 1)	1		
If (Age is PM AND PMC_Status is IRR AND PMC_Flow is C AND LMP is PMC)	If (Age =1 AND PMC_Status =1 AND PMC_Flow =1 AND LMP =0)	Min (1, 1, 1, 0)	0		
If (Age is F AND PMC_Status is IRR AND PMC_Flow is C AND LMP is MMC)	If (Age =0.72429 AND PMC_Status =1 AND PMC_Flow =1 AND LMP =1)	Min (0. 72429, 1, 1, 1)	0		
If (Age is F AND PMC_Status is IRR AND PMC_Flow is C AND LMP is PMC)	If (Age =0.72429 AND PMC_Status =1 AND PMC_Flow =1 AND LMP =0)	Min (0. 72429, 1, 1, 0)	0		
If (Age is F AND PMC_Status is IRR AND PMC_Flow is E AND LMP is MMC)	If (Age =0.72429 AND PMC_Status =1 AND PMC_Flow =0.5 AND LMP =1)	Min (0.72429,1, 0.5, 1)	0.5		
If (Age is F AND PMC_Status is IRR AND PMC_Flow is E AND LMP is PMC)	If (Age =0.72429 AND PMC_Status =1 AND PMC_Flow =0.5 AND LMP =0)	Min (0.72429, 1, 0.5, 0)	0.5		

6. Patient 153 : Age = 20 (F=1, EF = 1),

M_Status = Unmarried= 1,

PMC_nature = IRR =1,

PMC_flow = (S = 1)

Table 5.23: Fuzzy Rules fired for Patient P_{153}

Antecedent	**Rule applied**	**Min**	**Result of min**	**Max of all**	**Consequent**
If (PMC_Status is IRR AND Age is EF and PMC_nature = PF)	If (PMC_Status =1 AND Age =1 and PMC_nature = 1)	Min (1,1 1)	1	Max (1, 1)	Endometriosis or Fibroid present with possibility 1
If (PMC_Status is IRR AND Age is F and PMC_nature = PF)	If (PMC_Status =1 AND Age =1 and PMC_nature = 1)	Min (1,1 1)	1		

The patients not receiving Single Disease Diagnosis even at Stage II are input to Stage III. Also the patients for whom the History parameter cannot be applied are directly passed as input to Stage III at which the diagnosis is made based on the results of investigative tests (Section 5.4).

5.5 Stage III : *Test* Rule Base

In the process of differential diagnosis, ruling out of diseases is an important task. The diseases which are not filtered by stage I and II, are passed on to Stage III in which the investigative tests are suggested by the gynaecologist and based on the test results, the diseases are ruled out and single disease diagnosis is confirmed. The investigative tests are not required for all the diseases. We shortlisted the diseases for which investigative tests are required and the same are confirmed by the gynaecologists.

5.5.1 Defining *Tests* for Diseases

The investigative tests are broadly categorized in the tests related to pathology, histopathology, imaging tests, physical examination. After detailed discussions with gynaecologists, radiologists and pathologists, the tests required to be conducted for the disease are framed out. Some of which are shown in Table 3.2.

5.5.2 Defining *Test* Parameters

As the symptoms overlap among the diseases, one symptom occurs in multiple diseases which need differential diagnosis to rule out the diseases and arrive at single disease diagnosis. In many of the gynaecological diseases, the differential diagnosis is achieved by comparing the test results. Some of the tests are also common for certain diseases. The results obtained upon conducting those tests for a patient certainly derives correct diagnostic.

Based on the diseases selected for the study, multiple tests were pointed out, the best possible parameters for the tests were defined and the fuzzy sets were defined for all the tests and related parameters. Eighteen diseases were selected for which tests were required to be performed. Out of 75 term sets defined for 18 tests, some of the tests and related term sets are as listed below.

1. **TransVaginal USG Blueberry Cyst :** TransVaginal USGBlueberry Cyst is represented by a term set = { Present, Absent }
2. **TransVaginal USG ET:**TransVaginal USGET is represented by a term set = { GT4, GT16, LT4 }
3. **Transvaginal USG Uterus :**Transvaginal USG Uterus is represented by a term set = { Small, Normal, Bulky }
4. **USG Pelvis Ovarian Cyst :** USG Pelvis Ovarian Cyst is represented by a term set = { Absent, Small, Medium, Large}
5. **USG Pelvis Uterus :** USG Pelvis Uterus is represented by a term set = { Small, Normal, Bulky}
6. **USG Pelvis Fibroid:** USG Pelvis Fibroid Mass is represented by a term set = { Absent, Small, Medium, Large}
7. **USG Pelvis Ovaries :** USG Pelvis Ovaries is represented by a term set = { Normal, Enlarged}
8. **CA 125 :** CA 125 is represented by a term set = { Normal, Above Normal}
9. **CBC HCT :** CBC HB is represented by a term set = { Low, Normal, High }

10. **CBC WBC count** : CBC WBC count is represented by a term set = { Normal, Increased, Lowered}

11. **PhyExam:** PhyExam is represented by term set = {Absent, Stage 1, Stage 2, Stage 3, Stage 4}

5.5.3 Fuzzy Sets for *Test* Parameter

Upon defining the term sets, for each of the term set the membership functions (Table 5.24) are defined by consulting the experts. Some of the term sets are as shown below.

Table 5.24: Membership functions defined for each term set

TransVaginal USG Blueberry Cyst	
Present	1
Absent	0
TransVaginal USG ET	
GT4	3-15
GT 16	15 onwards
LT 4	0-4
Transvaginal USG Uterus	
Small	8-112 cm
Normal	96-180 cm
Bulky	270 cm onwards
USG Pelvis Ovarian Cyst	
Absent	0 cm
Small	0-3 cm
Medium	2-6 cm
Large	5-10 cm
USG Pelvis Uterus	
Small	8-112 cm
Normal	96-180 cm
Bulky	270 cm onwards

USG Pelvis Fibroid	
Absent	0
Small	1-4 cm
Medium	2-7 cm
Large	6-10 cm
USG Pelvis Ovaries	
Normal	5-15 cc
Enlarged	13 -30 cc
Decreased	0-55 ng/ml
Normal	50-210 ng/ml
Increased	200 ng/ml onwards
CA 125	
Normal	0-36
Above_Normal	35 onwards
CBC HCT	
Low	0-37
Normal	35-50
High	47 onwards
WBC Count	
Lowered	0-3500 cells/mcL
Normal	3400-11500 cells/mcL
Increased	10500 cells/mcL onwards
Platelet Count	
Lowered	0-50000mL
Normal	150000-400000 mL

5.5.4 Fuzzy Rules for *Test* Parameter

From the above 74 fuzzy sets and 1020 fuzzy rules are defined. The rules which do not produce a diagnosis are ignored for obvious reason. Some of the rules used in the case studies are shown below.

Rule 1 If (*TVUSG_BBRCyst* is *Present* OR *PVLAP_BBR* is *Present* OR *PVLAP_PGLS* is *Present*) Then *Endometriosis Present*

Rule 2 If (*TVUSG_BBRCyst* is Present OR *PVLAP_BBR* is *Present* OR *PVLAP_PGLS* is *Absent*) Then *Endometriosis Present*

Rule 3 If (*TVUSG_BBRCyst* is *Present* OR *PVLAP_BBR* is *Absent* OR *PVLAP_PGLS* is *Present*) Then *Endometriosis Present*

Rule 7 If (TVUSG_BBRCyst is Absent OR PVLAP_BBR is Absent OR PVLAP_PGLS is Present) Then Endometriosis Present

Rule 8 If (TVUSG_BBRCyst is Absent OR PVLAP_BBR is Absent OR PVLAP_PGLS is Absent) Then Endometriosis Absent

Rule 9 If (VYI_KOH_Fungus is Present) Then Vaginal Yeast Infection Present

Rule 10 If (VYI_KOH_Fungus is Absent) Then Vaginal Yeast Infection Absent

Rule 21 If (USGPV_OVC is Small AND USGPV_UT is Bulky AND USGPV_TOMass Present) Then PID Present

Rule 22 If (USGPV_OVC is Medium AND USGPV_UT is Normal) Then Ovarian Cyst Present

Rule 23 If (USGPV_OVC is Medium AND USGPV_UT is Normal AND CA125 is Normal) Then Ovarian Cyst Present

Rule 24 If (USGPV_OVC is Medium AND USGPV_UT is Normal) Then Ovarian Cyst Present

Rule 25 If (USGPV_OVC is Medium AND USGPV_UT is Normal AND CA125 is Above_Normal) Then Ovarian Cancer Present

Rule 28 If (USGPV_OVC is Medium AND USGPV_UT is Bulky AND USGPV_TOMass Present) Then PID Present

Rule 29 If (USGPV_OVC is Large AND USGPV_UT is Normal) Then Ovarian Cyst Present

Rule 30 If (USGPV_OVC is Large AND USGPV_UT is Normal AND CA125 is Normal) Then Ovarian Cyst Present

Rule 31 If (USGPV_OVC is Large AND USGPV_UT is Normal) Then Ovarian Cyst Present

Rule 32 If (USGPV_OVC is Large AND USGPV_UT is Normal AND CA125 is Above_Normal) Then Ovarian Cancer Present

Rule 33 If (USGPV_OVC is Large AND USGPV_UT is Small) Then Ovarian Cyst Absent

Rule 34 If (USGPV_OVC is Large AND USGPV_UT is Bulky) Then Ovarian Cyst Absent

Rule 35 If (USGPV_OVC is Large AND USGPV_UT is Bulky AND USGPV_TOMass Present) Then PID Present

Rule 52 If (CTS_CLS is Small OR CA125is Above_normal) Then Ovarian Cancer Present

Rule 59 If (USGPV_OVC is Medium OR CA125is Above_normal) Then Ovarian Cancer Present

Rule 60 If (USGPV_OVC is Large OR CA125is Above_normal) Then Ovarian Cancer Present

Rule 85 If (VC_Biopsy_SQCellCx is Present OR CTS_PVLMPF is Enlarged OR CTS_Tumor is Present) Then Vulval Cancer Present

Rule 86 If (PAP_SM_SQCellCx is Absent OR CYSCO_MLS is Absent OR PROSCO_MLS is Absent) Then Vulval Cancer Absent

Rule 87 If (PAP_SM_SQCellCx is Absent OR CYSCO_MLS is Absent OR PROSCO_MLS is Present) Then Vulval Cancer Present

Rule 88 If (PAP_SM_SQCellCx is Absent OR CYSCO_MLS is Present OR PROSCO_MLS is Absent) Then Vulval Cancer Present

Rule 134 If (USG_PV_UT is Bulky AND USG_PV_TOMass is Present AND CTS_Tubes is Inflamed AND CTS_OV is Inflamed AND LAPTO_TOMass is Present AND WBC_Count is Raised AND CBC_NutPh is Present AND CBC_Lympct is Present) Then Pelvic Inflammatory Disease Present

Rule 135 If (USG_PV_TOMass is Present OR LAPTO_TOMass is Present) Then Pelvic Inflammatory Disease Present

Rule 136 If (USG_PV_UT is Bulky AND USG_PV_TOMass is Present) Then Pelvic Inflammatory Disease Present

Rule 137 If (USG_PV_UT is Bulky AND USG_PV_TOMass is Present AND WBC_Count is Raised) Then Pelvic Inflammatory Disease Present

Rule 146 If (PAPSM_MagCell is Present OR PAPSM_DyspCell is Present) Then Cervical Cancer Stage I Present

Rule 147 If (ECC_MagCell is Present OR ECC_DyspCell is Present) Then Cervical Cancer Stage I Present

Rule 148 If (Biopsy_Mag_Cell is Present OR Biopsy_SQCellCx is Present) Then Cervical Cancer Stage I Present

Rule 149 If (PAPSM_MagCell is Present AND Biopsy_Mag_Cell is Present) Then Cervical Cancer Stage I Present

Rule 150 If (PAPSM_MagCell is Present AND Biopsy_SQCellCx is Present) Then Cervical Cancer Stage I Present

Rule 151 If (PAPSM_DyspCell is Present AND Biopsy_Mag_Cell is Present) Then Cervical Cancer Stage I Present

Rule 165 If (Proj_LVL is Decreased AND BCP_ProthTime is Increased AND BCP_ProthTime is Decreased) Then Dysfunctional Uterine Bleeding Present

Rule 166 If (Endo_Biopsy_SecOrProChg is Present AND BCP_ProthTime is Increased AND BCP_ProthTime is Decreased) Then Dysfunctional Uterine Bleeding Present

Rule 167 If (Endo_Biopsy_SecOrProChg is Absent AND BCP_ProthTime is Increased AND BCP_ProthTime is Decreased) Then Dysfunctional Uterine Bleeding Present

Rule 172 If (HYST_UTTissue is Present AND USGTV_UT is Bulky AND USGPV_MyoMCyst is Small) Then Adenomyosis Present

Rule 173 If (HYST_UTTissue is Present AND USGTV_UT is Normal AND USGPV_MyoMCyst is Small) Then Adenomyosis Absent

Rule 174 If (HYST_UTTissue is Absent AND USGTV_UT is Bulky AND USGPV_MyoMCyst is small) Then Adenomyosis Absent

Rule 175 If (USGTV_UT is Bulky AND USGPV_MyoMCyst is small) Then Adenomyosis Present

Rule 189 If (USGPV_Fibroid is Large OR MRI_Fiborod is Small) Then Uterine Fibroid Present

Rule 190 If (USGPV_Fibroid is Large OR MRI_Fiborod is Medium) Then Uterine Fibroid Present

Rule 191 If (USGPV_Fibroid is Large OR MRI_Fiborod is Large) Then Uterine Fibroid Present

Rule 195 If (MRI_Fiborod is Small AND CBC_HB is Low AND CBC_HCT is Low) Then Uterine Fibroid Present

Rule 196 If (MRI_Fiborod is Medium AND CBC_HB is Low AND CBC_HCT is Low) Then Uterine Fibroid Present

Rule 204 If (USG_PV_UT is Bulky OR MRI_UT Bulky OR USG_PV_UT is Medium OR MRI_UT is Medium) Then Endometritis Present

Rule 205 If (USG_PV_UT is Bulky AND USG_PV_UTCOND is Het) Then Endometritis Present

Rule 206 If (USG_PV_UT is Medium AND USG_PV_UTCOND is Het) Then Endometritis Present

Rule 219 If (USG_PV_OV is Bulky AND USG_PV_OVC is Small) Then Polycystic Ovarian Syndrome Present

Rule 220 If (USG_PV_OV is Normal AND USG_PV_OVC is Small) Then Polycystic Ovarian Syndrome Present

Rule 223 If (USG_PV_OV is Bulky AND USG_PV_OVC is Absent) Then Polycystic Ovarian Syndrome Present

Rule 231 If (UPT_HCG is Positive) Then UPT to be done Present

Rule 232 If (UPT_HCG is Negative) Then UPT to be done Absent

Rule 234 If (PrPhyExam is Stage 1 OR PrPhyExam is Stage 2 OR PrPhyExam is Stage 3 OR PrPhyExam is Stage 4) Then Uterine Prolapse is Present

5.5.5 Algorithm for Stage III

1. Get input from Initial Screening (Stage I) model and History Rule Base (Stage II) model (Patient having multiple disease diagnosed).
2. Accept *Test* parameter values from the patient.
3. Calculate membership value for each fuzzy set and every term set defined under *Test* parameter which is accepted in linguistic form.

   Use fuzzy sets defined, identify the type of the fuzzy set, find the values of α, β, γ and δ. Use the following formulae for the respective fuzzy set type.

   All the fuzzy sets are Trapezoidal fuzzy sets so we use Equation 4.13 calculate membership value.
4. Use Mamdani type Fuzzy Inference System using center of gravity as a defuzzification method.
5. Display the result.
6. Stop.

5.5.6 Stage III Case study

From the output of Stage I and Stage II, we could observe that the *Test* parameter could be applied to 153 patients. The following tables demonstrate application of *Test* parameter Rulebase to some of these 153 patients.

1. Patient 29

Stage I and Stage II diagnosis: {*Endometriosis*, *Pelvic Inflammatory Disease (PID)*, *Adenomyosis*}

Tests Suggested and test results received are as in Table 5.25 for the patient P_{29}.

Table 5.25: Tests suggested and test results received for patient P_{29}

Disease Name	**Test Suggested**	**Test Results**
Endometriosis	Transvaginal USG Blueberry Cyst	Blueberry Cyst Absent
Pelvic Inflammatory Disease	CBC WBC Count	5704 cells/mcL
	Pelvic USG T.O. Mass	Uterus Bulky, No T.O. Mass Present

Adenomyosis	Transvaginal US Uterus	Uterus Bulky, multiple cysts in myometrium small in size

Table 5.26 : Fuzzy Rules fired for Patient P_{29}

Antecedent	**Rule applied**	**Min(Max)**	**Result of min (max)**	**Max (min) of all**	**Consequent**
(TVUSG_BBRCyst is *Absent* OR PVLAP_BBR is *Present* OR PVLAP_PGLS is Present)	(TVUSG_BBRCyst is 0 OR PVLAP_BBR is 0 OR PVLAP_PGLS is 0)	Max (0,0,0)	0	Min(0,0,0,0) = 0	Endometriosis is Absent
(TVUSG_BBRCyst is *Absent* OR PVLAP_BBR is *Present* OR PVLAP_PGLS is *Absent*)	(TVUSG_BBRCyst is 0 OR PVLAP_BBR is 0 OR PVLAP_PGLS is 0)	Max (0,0,0)	0		
If (TVUSG_BBRCyst is *Absent* OR PVLAP_BBR is *Absent* OR PVLAP_PGLS is *Present*)	(TVUSG_BBRCyst is 0 OR PVLAP_BBR is 0 OR PVLAP_PGLS is 0)	Max (0,0,0)	0		
(TVUSG_BBRCyst is *Absent* OR PVLAP_BBR is *Absent* OR PVLAP_PGLS is *Absent*)	(TVUSG_BBRCyst is 0 OR PVLAP_BBR is 0 OR PVLAP_PGLS is 0)	Max (0,0,0)	0		

(USG_PV_UT is *Bulky* AND USG_PV_TOMass is *Present*)	(USG_PV_UT is 1 AND USG_PV_TOMass is 0)	Min (1,0)	0	Max(0,0)=0	Pelvic Inflammatory Disease Present with Possibility 0
(USG_PV_UT is *Bulky* AND USG_PV_TOMass is *Present* AND AND WBC_Count is *Raised*)	(USG_PV_UT is 1 AND USG_PV_TOMass is 0 AND AND WBC_Count is 0)	Min (1,0,0)	0		
(USGTV_UT is *Bulky* AND USGPV_MyoMCyst is *Small*)	(USGTV_UT is 1 AND USGPV_MyoMCyst is 1)	Min(1,1)	1	Max (1,0,0,0) =1	Adenomyosis Present with Possibility 1
(USGTV_UT is *Bulky* AND USGPV_MyoMCyst is *Medium*)	(USGTV_UT is 1 AND USGPV_MyoMCyst is 0)	Min (1,0)	0		
(USGTV_UT is *Normal* AND USGPV_MyoMCyst is *Absent*)	(USGTV_UT is 0 AND USGPV_MyoMCyst is 0)	Min(0,0)	0		
(USGTV_UT is *Bulky* AND USGPV_MyoMCyst is *Absent*)	(USGTV_UT is 1 AND USGPV_MyoMCyst is 0)	Min(1,0)	0		

Similar is the case for patients: P_{41}, P_{44}, P_{115} and P_{119} to get the diagnosis as *Adenomyosis*.

2. Patient 37

Stage I and Stage II diagnosis :{ *Vaginal Yeast Infection, Pelvic Inflammatory Disease (PID), Cervical Cancer (stage I)}*

Tests Suggested and test results received are as in Table 5.27 for the patient P_{37}.

Table 5.27: Tests suggested and test results received for patient P_{37}

Disease Name	**Test Suggested**	**Test Results**
Vaginal Yeast Infection	KOH Test	Fungus Absent
Pelvic Inflammatory Disease	CBC WBC Count	7660 cells/mcL
	Pelvic USG T.O. Mass	Uterus Bulky, No T.O. Mass Present
Cervical Cancer	Pap Smear	Malignant cells present and dysplastic cells present
	Biopsy Cervix	Squamous Cell Carcinoma Present

Table 5.28: Fuzzy Rules fired for Patient P_{37}

Antecedent	**Rule applied**	**Min(Max)**	**Result of min(max)**	**Max (min) of all**	**Consequent**
If (VYI_KOH_Fungus is Present)	If (VYI_KOH_Fungus is 0)	Min(0)	0	0	Vaginal Yeast Infection is Present with Possibility **0**
(USG_PV_UT is *Bulky* AND USG_PV_TOMass is *Present*)	(USG_PV_UT is 1 AND USG_PV_TOMass is 0)	Min(1,0)	0	Max(0,0)=0	Pelvic Inflammatory Disease Present with Possibility **0**
(USG_PV_UT is *Bulky* AND USG_PV_TOMass is *Present* AND AND WBC_Count is *Raised*)	(USG_PV_UT is 1 AND USG_PV_TOMass is 0 AND AND WBC_Count is 0)	Min(1,0,0)	0		
If (PAPSM_MagCell is Present OR PAPSM_DyspCell is Present)	If (PAPSM_MagCell is 1 OR PAPSM_DyspCell is 0)	Max(1,0)	1	Min(1,1,1,1) =1	Cervical Cancer Present with Possibility **1**
If	If	Max(0,1)	1		

Antecedent	**Rule applied**	**Min(Max)**	**Result of min(max)**	**Max (min) of all**	**Consequent**
(Biopsy_Mag_Cell is Present OR Biopsy_SQCellCx is Present)	(Biopsy_Mag_Cell is 0 OR Biopsy_SQCellCx is 1)				
If (PAPSM_MagCell is Present AND Biopsy_Mag_Cell is Present)	If (PAPSM_MagCell is 1 AND Biopsy_Mag_Cell is 0)	Max(1,0)	1		
If (PAPSM_MagCell is Present AND Biopsy_SQCellCx is Present)	If (PAPSM_MagCell is 1 AND Biopsy_SQCellCx is 0)	Max(1,1)	1		

Similar is the case for patients: P_{66} and P_{85} to get the diagnosis as *Cervical Cancer*.

3. Patient 17

Stage I and Stage II diagnosis :{ *Dysfunctional Uterine Bleeding (DUB), Uterine Fibroid, Adenomyosis}*

Tests Suggested and test results received are as follows for the patient P_{17}.

Table 5.29: Tests suggested and test results received for patient P_{17}

Disease Name	**Test Suggested**	**Test Results**
Dysfunctional Uterine Bleeding	Transvaginal USG Uterus	Uterus Normal in size
	Harmon Progesterone level	45 ng/ml (decreased)
	Endometrial Biopsy	Secretary changes noticed
Uterine Fibroid	USG Pelvis Fibroid	No Fibroid found
Adenomyosis	Transvaginal US Uterus	Uterus Normal, No cysts found

Table 5.30: Fuzzy Rules fired for Patient P_{17}

Antecedent	**Rule applied**	**Min(Max)**	**Result of min(max)**	**Max (min) of all**	**Consequent**
If (Endo_Biopsy_ SecOrProChg is Present AND Proj_LVL is Decreased)	If (Endo_Biopsy_ SecOrProChg is 1 AND Proj_LVL is 1)	Min(1,1)	1	Max(1,0,1) =1	Dysfunctional Uterine Bleeding is Present with Possibility **1**
If (USGTV_UT is Bulky AND Endo_Biopsy_ SecOrProChg is Present)	If (USGTV_UT is 0 AND Endo_Biopsy_ SecOrProChg is 1)	Min(0,1)	0		
If (USGTV_UT is Normal AND Endo_Biopsy_ SecOrProChg is Present)	If (USGTV_UT is 1 AND Endo_Biopsy_ SecOrProChg is 1)	Min(1,1)	1		
If (Endo_Biopsy_ SecOrProChg is Present OR Proj_LVL is Decreased OR USGTV_UT is Bulky)	If (Endo_Biopsy_ SecOrProChg is 1 OR Proj_LVL is 1 OR USGTV_UT is 0)	Max(1,1, 0)	1	Min(1) =1	Dysfunctional Uterine Bleeding is Present with Possibility **1**
If (USGPV_Fibroid is Absent OR MRI_Fiborod is Absent)	If (USGPV_Fibroid is 1 OR MRI_Fiborod is 1)	Max(1, 1)	1	Min (1) =1	Uterine Fibroid Absent with Possibility 1
If (USGTV_UT is Bulky AND USGPV_MyoMCyst	If (USGTV_UT is 0 AND USGPV_MyoMCyst	Min(0,0)	0	Max(0,0, 0,0) = 0	Adenomyosis Present with Possibility **0**

Antecedent	**Rule applied**	**Min(Max)**	**Result of min(max)**	**Max (min) of all**	**Consequent**
is small)	is 0)				
If (USGTV_UT is Bulky AND USGPV_MyoMCyst is Medium)	If (USGTV_UT is 0 AND USGPV_MyoMCyst is 0)	Min(0,0)	0		
If (USGTV_UT is Normal AND USGPV_MyoMCyst is small)	If (USGTV_UT is 1 AND USGPV_MyoMCyst is 0)	Min(1,0)	0		
If (USGTV_UT is Normal AND USGPV_MyoMCyst is Medium)	If (USGTV_UT is 1 AND USGPV_MyoMCyst is 0)	Min(1,0)	0		

Similar is the case for patients: P_{19}, P_{25}, P_{28}, P_{96}, P_{104}, P_{125}, P_{129}, P_{130}, P_{156}, P_{161}, P_{162}, P_{172}, P_{180}, P_{186} and $P_{188}$to get the diagnosis as *Dysfunctional Uterine Bleeding (DUB)*.

4. Patient 11

Stage I and Stage II diagnosis: {*Dysfunctional Uterine Bleeding (DUB), Uterine Fibroid, Adenomyosis*}

Tests Suggested and test results received are as follows for the patient P_{11}.

Table 5.31: Tests suggested and test results received for patient P_{11}

Disease Name	**Test Suggested**	**Test Results**
Adenomyosis	Transvaginal US Uterus	Uterus Normal, No cysts found
Uterine Fibroid	USG Pelvis Fibroid	Fibroid found of size 8.9 cm
	CBC HB	8.2 Low HB
Dysfunctional Uterine Bleeding	Transvaginal USG Uterus	Uterus Normal in size
	Harmon Progesterone level	68 ng/ml (Normal)

Table 5.32 : Fuzzy Rules fired for Patient P_{11}

Antecedent	**Rule applied**	**Min(Max)**	**Result of min(max)**	**Max (min) of all**	**Consequent**
If (USGTV_UT is Bulky AND USGPV_MyoMCyst is small)	If (USGTV_UT is 0 AND USGPV_MyoMCyst is 0)	Min(0,0)	0	Max(0,0, 0,0) = 0	Adenomyosis Present with Possibility **0**
If (USGTV_UT is Bulky AND USGPV_MyoMCyst is Medium)	If (USGTV_UT is 0 AND USGPV_MyoMCyst is 0)	Min(0,0)	0		
If (USGTV_UT is Normal AND USGPV_MyoMCyst is small)	If (USGTV_UT is 1 AND USGPV_MyoMCyst is 0)	Min(1,0)	0		
If (USGTV_UT is Normal AND USGPV_MyoMCyst is Medium)	If (USGTV_UT is 1 AND USGPV_MyoMCyst is 0)	Min(1,0)	0		
If (Endo_Biopsy_ SecOrProChg is Present OR Proj_LVL is Decreased OR USGTV_UT is Bulky)	If (Endo_Biopsy_ SecOrProChg is 0 OR Proj_LVL is 0 OR USGTV_UT is 0)	Max(0,0, 0)	0	0	Dysfunctional Uterine Bleeding Present with Possibility **0**
If (USGTV_UT is Normal AND Proj_LVL is Decreased)	If (USGTV_UT is 1 AND Proj_LVL is 0)	Min(1,0)	0	Max(0,0) =0	Dysfunctional Uterine Bleeding Present with Possibility **0**
If (USGTV_UT is Bulky AND Proj_LVL is	If (USGTV_UT is 0 AND Proj_LVL is 0)	Min(0,0)	0		

Antecedent	**Rule applied**	**Min(Max)**	**Result of min(max)**	**Max (min) of all**	**Consequent**
Decreased)					
If (USGPV_Fibroid is Large OR MRI_Fiborod is Small)	If (USGPV_Fibroid is 1 OR MRI_Fiborod is 0)	Min(1,0)	0	Max(0,0, 0, 0, 0, 1)=1	Uterine Fibroid Present with Possibility 1
(USGPV_Fibroid is Large OR MRI_Fiborod is Medium)	(USGPV_Fibroid is 1 OR MRI_Fiborod is 0)	Min(1,0)	0		
If (USGPV_Fibroid is Large OR MRI_Fiborod is Large)	If (USGPV_Fibroid is 1OR MRI_Fiborod is 0)	Min(1,0)	0		
If (USGPV_Fibroid is Small AND CBC_HB is Low)	If (USGPV_Fibroid is 0 AND CBC_HB is 1)	Min(0,1)	0		
If (USGPV_Fibroid is Medium AND CBC_HB is Low)	If (USGPV_Fibroid is 0AND CBC_HB is 1)	Min(0,1)	0		
If (USGPV_Fibroid is Large AND CBC_HB is Low)	If (USGPV_Fibroid is 1 AND CBC_HB is 1)	Min(1,1)	1		

Similar is the case for patients: P_{21}, P_{31}, P_{36}, P_{57}, P_{58}, P_{63}, P_{73}, P_{101}, P_{145}, P_{121}, P_{183}, P_{185}, P_{208}, P_{219}, P_{221} and P_{222} to get the diagnosis as *Uterine Fibroid*.

5. Patient 207

Stage I and Stage II diagnosis :{ *Pelvic Inflammatory Disease (PID), Vaginal Yeast Infection, Dysfunctional Uterine Bleeding, Uterine Fibroid, Adenomyosis, Leucorrhoea*}

Tests Suggested and test results received are as follows for the patient P_{207}.

Table 5.33: Tests suggested and test results received for patient P_{207}

Disease Name	**Test Suggested**	**Test Results**
Pelvic Inflammatory Disease	CBC WBC Count	11542 cells/mcL
	Pelvic USG T.O. Mass	Uterus bulky in size, T.O. Mass Present
Vaginal Yeast Infection	KOH test	No fungus found
Endometriosis	Transvaginal USG Blueberry Cyst	Blueberry Cyst Absent
Adenomyosis	Transvaginal USG Uterus	Uterus Bulky, No cysts found
Uterine Fibroid	USG Pelvis Fibroid	Fibroid found of size 8.2 cm
Dysfunctional Uterine Bleeding	Transvaginal USG Uterus	Uterus Bulky in size
	Harmon Progesterone level	60 ng/ml (Normal)

Table 5.34 : Fuzzy Rules fired for Patient P_{207}

Antecedent	**Rule applied**	**Min(Max)**	**Result of min(max)**	**Max (min) of all**	**Consequent**
(USG_PV_UT is *Bulky* AND USG_PV_TOMass is *Present*)	(USG_PV_UT is 1 AND USG_PV_TOMass is 1)	Min(1,1)	1	Max(1,1)=0	Pelvic Inflammatory Disease Present with Possibility **1**
(USG_PV_UT is *Bulky* AND USG_PV_TOMass is *Present* AND AND WBC_Count is *Raised*)	(USG_PV_UT is 1 AND USG_PV_TOMass is 1 AND AND WBC_Count is 1)	Min(1,1,1)	1		
If (USGTV_UT is Normal AND Proj_LVL is Decreased)	If (USGTV_UT is 0 AND Proj_LVL is 0)	Min(0,0)	0	Max(0,0) =0	Dysfunctional Uterine Bleeding Present with Possibility **0**
If (USGTV_UT is	If (USGTV_UT is 1	Min(1,0)	0		

Antecedent	**Rule applied**	**Min(Max)**	**Result of min(max)**	**Max (min) of all**	**Consequent**
Bulky AND Proj_LVL is Decreased)	AND Proj_LVL is 0)				
If (VYI_KOH_Fungus is Present)	If (VYI_KOH_Fungus is 0)	Min(0)	0	0	Vaginal Yeast Infection is Present with Possibility **0**
If (USGTV_UT is Bulky AND USGPV_MyoMCyst is small)	If (USGTV_UT is 1 AND USGPV_MyoMCyst is 0)	Min(1,0)	0	Max(0,0, 0,0) = 0	Adenomyosis Present with Possibility **0**
If (USGTV_UT is Bulky AND USGPV_MyoMCyst is Medium)	If (USGTV_UT is 1 AND USGPV_MyoMCyst is 0)	Min(1,0)	0		
If (USGTV_UT is Normal AND USGPV_MyoMCyst is small)	If (USGTV_UT is 0 AND USGPV_MyoMCyst is 0)	Min(0,0)	0		
If (USGTV_UT is Normal AND USGPV_MyoMCyst is Medium)	If (USGTV_UT is 0 AND USGPV_MyoMCyst is 0)	Min(0,0)	0		
If (TVUSG_BBRCyst is 0 OR PVLAP_BBR is 0 OR PVLAP_PGLS is 0)	If (TVUSG_BBRCyst is 0 OR PVLAP_BBR is 0 OR PVLAP_PGLS is 0)	Max(0,0,0)	**0**	Min (0,1,1,1) =0	Endometriosis Present with Possibility **0**
If (TVUSG_BBRCyst is 0 OR	If (TVUSG_BBRCyst is 0 OR	Max(0,0,1)	1		

Antecedent	**Rule applied**	**Min(Max)**	**Result of min(max)**	**Max (min) of all**	**Consequent**
PVLAP_BBR is 0 OR PVLAP_PGLS is 1)	PVLAP_BBR is 0 OR PVLAP_PGLS is 1)				
If (TVUSG_BBRCyst is 0 OR PVLAP_BBR is 1 OR PVLAP_PGLS is 0)	If (TVUSG_BBRCyst is 0 OR PVLAP_BBR is 1 OR PVLAP_PGLS is 0)	Max(0,1,0)	1		
If (TVUSG_BBRCyst is 0 OR PVLAP_BBR is 1 OR PVLAP_PGLS is 1)	If (TVUSG_BBRCyst is 0 OR PVLAP_BBR is 1 OR PVLAP_PGLS is 1)	Max(0,1,1)	1		

Similar is the case for patients: P_{30}, P_{33}, P_{39}, P_{45}, P_{50}, P_{72}, P_{81}, P_{88}, P_{94}, P_{105}, P_{111}, P_{114}, P_{120}, P_{124}, P_{133}, P_{139}, P_{141}, P_{142}, P_{146}, P_{170}, P_{177}, P_{181}, P_{182}, P_{190}, P_{201}, P_{204}, P_{209}, P_{214} and P_{217} to get the diagnosis as *Pelvic Inflammatory Disease*.

6. Patient 224

Stage I and Stage II diagnosis: {*Pubertal Menorrhagia, Endometriosis, Dysfunctional Uterine Bleeding (DUB), Uterine Fibroid, Adenomyosis*}

Normally, no special test is suggested for *Pubertal Menorrhagia*. In this case, the diagnosis is based on the fact that rule out the other diseases and arrive at correct diagnosis.

Tests Suggested and Test Results received are as follows for the patient P_{224}.

Table 5.35: Tests suggested and test results received for patient P_{224}

Disease Name	**Test Suggested**	**Test Results**
Endometriosis	Transvaginal USG Blueberry	Blueberry Cyst not seen

Disease Name	**Test Suggested**	**Test Results**
	Cyst	
Uterine Fibroid	USG Pelvis Fibroid	No fibroid seen
Dysfunctional Uterine Bleeding (DUB)	Transvaginal USG Uterus	Uterus Normal in size
	Harmon Progesterone level	68 ng/ml (Normal)
Adenomyosis	MRI	No thickened junction zone marked

Table 5.36: Fuzzy Rules fired for Patient P_{224}

Antecedent	**Rule applied**	**Min(Max)**	**Result of min(max)**	**Max (min) of all**	**Consequent**
If (USGTV_UT is Bulky AND USGPV_MyoMCyst is small)	If (USGTV_UT is 0 AND USGPV_MyoMCyst is 0)	Min(0,0)	0	Max(0,0, 0,0) = 0	Adenomyosis Present with Possibility **0**
If (USGTV_UT is Bulky AND USGPV_MyoMCyst is Medium)	If (USGTV_UT is 0 AND USGPV_MyoMCyst is 0)	Min(0,0)	0		
If (USGTV_UT is Normal AND USGPV_MyoMCyst is small)	If (USGTV_UT is 1 AND USGPV_MyoMCyst is 0)	Min(1,0)	0		
If (USGTV_UT is Normal AND USGPV_MyoMCyst is Medium)	If (USGTV_UT is 1 AND USGPV_MyoMCyst is 0)	Min(1,0)	0		
If (USGPV_Fibroid is Absent OR MRI_Fiborod is Absent)	If (USGPV_Fibroid is 1 OR MRI_Fiborod is 1)	Max(1, 1)	1	Min (1) =1	Uterine Fibroid Absent with Possibility 1
If (TVUSG_ BBRCyst is Present	If (TVUSG_BBRCyst	Max(0,0,0)	0	Min(0,0,0,0) =0	Endometriosis Present with

Antecedent	**Rule applied**	**Min(Max)**	**Result of min(max)**	**Max (min) of all**	**Consequent**
OR PVLAP_BBR is Present OR PVLAP_PGLS is Present)	is 0 OR PVLAP_BBR is 0 OR PVLAP_PGLS is 0)				Possibility **0**
If (TVUSG_BBRCyst is Present OR PVLAP_BBR is Present OR PVLAP_PGLS is Absent)	If (TVUSG_BBRCyst is 0 OR PVLAP_BBR is 0 OR PVLAP_PGLS is 1)	Max(0,0,1)	0		
If (TVUSG_BBRCyst is Present OR PVLAP_BBR is Absent OR PVLAP_PGLS is Present)	If (TVUSG_BBRCyst is 0 OR PVLAP_BBR is 1 OR PVLAP_PGLS is 0)	Max(0,1,0)	0		
If (USGTV_UT is Normal AND Proj_LVL is Decreased)	If (USGTV_UT is 0 AND Proj_LVL is 0)	Min(0,0)	0	Max(0,0) =0	Dysfunctional Uterine Bleeding Present with Possibility **0**
If (USGTV_UT is Bulky AND Proj_LVL is Decreased)	If (USGTV_UT is 1 AND Proj_LVL is 0)	Min(1,0)	0		

All the other diseases are ruled out in the process of differential diagnosis so the diagnosis is Pubertal Menorrhagia.

7. Patient 123

Stage I and Stage II diagnosis: {*Pubertal Menorrhagia, Endometriosis, Uterine Fibroid, Adenomyosis*}

Normally, no special test is suggested for *Pubertal Menorrhagia*. In this case, the diagnosis is based on the fact that rule out the other diseases and arrive at correct diagnosis.

Tests Suggested and Test Results received are as follows for the patient P_{123}.

Table 5.37: Tests suggested and test results received for patient P_{123}

Disease Name	**Test Suggested**	**Test Results**
Endometriosis	Transvaginal USG Blueberry Cyst	Blueberry Cyst not seen
Uterine Fibroid	USG Pelvis Fibroid	No fibroid seen
Adenomyosis	MRI	No thickened junction zone marked

Table 5.38: Fuzzy Rules fired for Patient P_{123}

Antecedent	**Rule applied**	**Min(Max)**	**Result of min(max)**	**Max (min) of all**	**Consequent**
If (USGTV_UT is Bulky AND USGPV_MyoMCyst is small)	If (USGTV_UT is 0 AND USGPV_MyoMCyst is 0)	Min(0,0)	0	Max(0,0, 0,0) = 0	Adenomyosis Present with Possibility **0**
If (USGTV_UT is Bulky AND USGPV_MyoMCyst is Medium)	If (USGTV_UT is 0 AND USGPV_MyoMCyst is 0)	Min(0,0)	0		
If (USGTV_UT is Normal AND USGPV_MyoMCyst is small)	If (USGTV_UT is 1 AND USGPV_MyoMCyst is 0)	Min(1,0)	0		
If (USGTV_UT is Normal AND USGPV_MyoMCyst is Medium)	If (USGTV_UT is 1 AND USGPV_MyoMCyst is 0)	Min(1,0)	0		

Antecedent	**Rule applied**	**Min(Max)**	**Result of min(max)**	**Max (min) of all**	**Consequent**
If (USGPV_Fibroid is Absent OR MRI_Fiborod is Absent)	If (USGPV_Fibroid is 1 OR MRI_Fiborod is 1)	Max(1, 1)	1	Min (1) =1	Uterine Fibroid Absent with Possibility 1
If (TVUSG_BBRCyst is Present OR PVLAP_BBR is Present OR PVLAP_PGLS is Present)	If (TVUSG_BBRCyst is 0 OR PVLAP_BBR is 0 OR PVLAP_PGLS is 0)	Max(0,0,0)	0	Min(0,1,1) =0	Endometriosis Present with Possibility **0**
If (TVUSG_BBRCyst is Present OR PVLAP_BBR is Present OR PVLAP_PGLS is Present)	If (TVUSG_BBRCyst is 0 OR PVLAP_BBR is 0 OR PVLAP_PGLS is 1)	Max(0,0,1)	1		
If (TVUSG_BBRCyst is Present OR PVLAP_BBR is Present OR PVLAP_PGLS is Present)	If (TVUSG_BBRCyst is 0 OR PVLAP_BBR is 1 OR PVLAP_PGLS is 0)	Max(0,1,0)	1		

All the other diseases are ruled out in the process of differential diagnosis so the diagnosis is Pubertal Menorrhagia. But it is incorrect diagnosis as the patient's age is 39 years which is not a pubertal age.

8. Patient 38

Stage I and Stage II diagnosis: {*Vaginal Yeast Infection, Uterine Prolapse*}

Uterine Prolapse is generally diagnosed using physical/clinical examinations; no separate tests are suggested for Uterine Prolapse.

Tests Suggested and Test Results received are as follows for the patient P_{38}.

Table 5.39: Tests suggested and test results received for patient P_{29}

Disease Name	**Test Suggested**	**Test Results**
Vaginal Yeast Infection	KOH test	No impression of Fungus
Uterine Prolapse	Physical Examination	Leading edge of Prolapse extends from around 2 cm beyond the hymenal ring.

Table 5.40 : Fuzzy Rules fired for Patient P_{38}

Antecedent	**Rule applied**	**Min(Max)**	**Result of min(max)**	**Max (min) of all**	**Consequent**
If (VYI_KOH_Fungus is Present)	If (VYI_KOH_Fungus is 0)	Min(0)	0	0	Vaginal Yeast Infection is Present with Possibility **0**
If (PrPhyExam is Stage 1 OR PrPhyExam is Stage 2 OR PrPhyExam is Stage 3 OR PrPhyExam is Stage 4)	If (PrPhyExam is 0 OR PrPhyExam is Stage 0 OR PrPhyExam is 1 OR PrPhyExam is 0)	Max(0,0,1,0)	1	1	Uterine Prolapse is Present with possibility 1

In this case, as Vaginal Yeast Infection is ruled out, Uterine Prolapse is the diagnosis. Similar is the case for the patients P_{49}, P_{174}, P_{213}.

5.6 Classification of Patients

The Gynaecology symptoms are broadly classified as symptoms related to menstrual cycles, menstrual flow, tumors, vaginal infections, carcinoma, infertility etc. Patients

suffering from same symptoms generally are diagnosed by similar diseases. This similarity varies by the severity of the symptoms and the history of the patient. As the narration of symptoms by patients contain huge amount of vagueness, it is necessary to model this vagueness and classify the patients accordingly.

We have used different approaches to classify the patients depending upon the symptoms they possess viz. Fuzzy Similarity Measures, Bi-variate Statistical Measure and Fuzzy C-Means method.

5.6.1. Fuzzy Classification

The classification is done using the fuzzy classification methods viz. Fuzzy Similarity Measures (Cosine Amplitude and Max-Min method) and Fuzzy C-Means.

A. Fuzzy Similarity Measures

Fuzzy Similarity Measures used for patients' classification uses expert's knowledgebase and the supervised clustering method which gives strength and stability to the model. The patient's data related to symptoms and scanned by the experts was used. The detailed algorithm is as follows.

Algorithm: Patients' Classification

1. Get Patients' data in the form of symptoms/ complaints narrated by patients in tabular form s x p. (Table 5.16). Assign membership grades for the linguistic hedges used in the perceptions recorded for symptoms.
2. Apply similarity measures Cosine Amplitude method and Max-Min methods using following formula on the above-mentioned s x p table to generate a tolerance relation (R).

   For Cosine Amplitude method

   $r_{ij} = \frac{|\sum_{k=1}^{m} x_{ik} x_{jk}|}{\sqrt{(\sum_{k=1}^{m} x^2{}_{ik})(\sum_{k=1}^{m} x^2{}_{jk})}}$, Where $0 \leq r_{ij} \leq 1$

   For Max-Min method

   $r_{ij} = \frac{\sum_{k=1}^{m} \min(x_{ik}, x_{jk})}{\sum_{k=1}^{m} \max(x_{ik}, x_{jk})}$

3. Check if the relation R is equivalence (Equation 4.11):

The relation R is *Reflexive*, if $\mu_R (x_i, x_i) = 1 \; \forall \; x_i$.

The relation is *Symmetric*, if $\mu_R (x_i, x_j) = \mu_R (x_j, x_i) \; \forall \; i, j$.

To check if the relation R is *Transitive* i.e. $\mu_R (x_i, x_j) = \lambda_1$ and $\mu_R (x_j, x_k) = \lambda_2 \rightarrow \mu_R (x_i, x_k) = \lambda$ Where $\lambda \geq \min [\lambda_1, \lambda_2]$

4. If not an equivalence relation then perform $R^2 = R \text{ o } R$ (Equation 4.10) and go to step 3 otherwise go to step 5.
5. Apply α-cuts to the obtained equivalence relation and classify the patients.
6. Stop.

Case Study Example

The patient's data of 226 patients was initially scanned by the experts and are recorded in the table of the form s x p. In this table, the patient's symptoms are recorded linguistically as High severity (1), Moderate severity (0.5), Low severity (0.25) and No Symptom present (0).A sample set of 9 patients is considered for computational demonstration (Table 5.41).

Table 5.41: Patient Symptom Relation (Case Study Example)

	P_1	**P_2**	**P_3**	**P_4**	**P_5**	**P_6**	**P_7**	**P_8**	**P_9**
S_1	0	0	0	1	1	0	0	0	1
S_2	0	0	0	0	0.75	0	0	0	0
S_3	0	0	0	1	0.5625	0	0	0	1
S_4	1	0	1	0.5625	0	0	0	0	0
S_5	0.5625	0.5625	0	0	0	0	0	0	0
S_6	0	0	0	0	0	0	1	0	0
S_7	1	1	0	0	0	1	0	1	0
S_8	0	0	0	0	0	1	1	1	0

i. Cosine Amplitude method

After application of the Cosine Amplitude method (Equation 4.5), relation R is obtained which is fuzzy tolerance relation (Algorithm : Patient's Classification) which then is converted to fuzzy equivalence relation (Equation 4.11) and the resultant matrix of size 9 x 9 which is shown in Table 5.42.

Table 5.42: Fuzzy equivalence relation obtained using Cosine Amplitude method
(9 patients, 8 symptoms)

	P_1	P_2	P_3	P_4	P_5	P_6	P_7	P_8	P_9
P_1	1	0.754	0.657	0.37	0.37	0.616	0.5	0.616	0.37
P_2	0.754	1	0.657	0.37	0.37	0.616	0.5	0.616	0.37
P_3	0.657	0.657	1	0.37	0.37	0.616	0.5	0.616	0.929
P_4	0.37	0.37	0.37	1	0.806	0.37	0.37	0.37	0.806
P_5	0.37	0.37	0.37	0.806	1	0.37	0.37	0.37	0.37
P_6	0.616	0.616	0.616	0.37	0.37	1	0.5	1	0.37
P_7	0.5	0.5	0.5	0.37	0.37	0.5	1	0.5	0.37
P_8	0.616	0.616	0.616	0.37	0.37	1	0.5	1	0.37
P_9	0.37	0.37	0.929	0.806	0.37	0.37	0.37	0.37	1

ii. Max-Min method

After application of the Max-Min method (Equation 4.6) we get relation R which is fuzzy tolerance relation (Algorithm : Patient's Classification) which is converted to fuzzy equivalence relation (Equation 4.11) and the resultant matrix of size 9 x 9 which is shown in Table 5.43.

Table 5.43: Fuzzy equivalence relation obtained using Max-Min method
(9 patients, 8 symptoms)

	P_1	P_2	P_3	P_4	P_5	P_6	P_7	P_8	P_9
P_1	1	0.61	0.39	0.188	0.188	0.39	0.333	0.39	0.188
P_2	0.61	1	0.39	0.188	0.188	0.39	0.333	0.39	0.188
P_3	0.39	0.39	1	0.188	0.188	0.39	0.333	0.39	0.188
P_4	0.188	0.188	0.188	1	0.806	0.188	0.188	0.188	0.78
P_5	0.188	0.188	0.188	0.568	1	0.188	0.188	0.188	0.568
P_6	0.39	0.39	0.39	0.188	0.188	1	0.333	1	0.188
P_7	0.333	0.333	0.333	0.188	0.188	0.333	1	0.333	0.188
P_8	0.39	0.39	0.39	0.188	0.188	1	0.333	1	0.188

	P_1	P_2	P_3	P_4	P_5	P_6	P_7	P_8	P_9
P_9	0.188	0.188	0.188	0.78	0.568	0.188	0.188	0.188	1

The above mentioned two methods are applied to all 226 patients and related 123 symptoms to get the resultant fuzzy equivalence relation to classify 226 patients.

B. Fuzzy C-Means

Fuzzy clustering is an unsupervised method for data analysis, which is quite powerful. The objects which are on boundaries are allowed to belong to more than one class with some degree of membership value, indicating partial membership among the clusters. Fuzzy C-Means is most widely used algorithm which is more natural than hard clustering in many cases (Suganya & Shanthi, 2012).

The FCM algorithm implements the clustering task for a data set by minimizing an objective-function subject to the probabilistic constraint that the summation of all the membership degrees of every data point to all clusters must be one. This constraint results in the problem of this membership assignment, that noises are treated the same as points which are close to the cluster centers. However, in reality, these points should be assigned very low or even zero membership in either clusters (Yinghua Lu, *et. al*., 2013).

The performance of FCM, depends on weighting factor m`. The value of m` is to be chosen which best suits the application area.

Algorithm: Fuzzy C-Means

An effective algorithm for fuzzy classification, called iterative optimization, was proposed by Bezdek (1981).

The steps in this algorithm are as follows:

1. Fix *c (*$2 \leq c < n$*)* and select a value for parameter m'. Initialize the partition matrix, $\underset{\sim}{U}^{(0)}$ Each step in this algorithm will be labeled r, where r = 0, 1, 2,. . ..
2. Calculate the *c* centers $\{v_i^{(r)}\}$ for each step (Equation 4.19).
3. Update the partition matrix for the r^{th} step, $\underset{\sim}{U}^{(r)}$ as follows(Equation 4.21):

$$\mu_{ik}^{(r+1)} = \left[\sum_{j=1}^{c} \left(\frac{d_{ik}^{(r)}}{d_{jk}^{(r)}} \right)^{2/(m'-1)} \right]^{-1} \text{ for } I_k = \phi$$

Or

$\mu_{ik}^{(r+1)} = 0$ for all classes i where $i \in \underset{\sim}{I}_k$

Where $I_k = \{i \mid 2 \le c < n; d_{ik}^{(r)} = 0\}$ And $\underset{\sim}{I}_k = \{1, 2, \ldots, c\} - I_k$

And $\sum_{i \in I_k} \mu_{ik}^{(r+1)} = 1$

4. If $\|\underset{\sim}{U}^{r+1} - \underset{\sim}{U}^{(r)}\| \le \varepsilon$, stop; otherwise set r = r + 1 and return to step 2.

Here 'n' is the number of objects and 'c' is the number of clusters, Where μ_{ik} is the degree of membership that the object x_{kj} pertains to the cluster centre v_i, $U = \{\mu_{ik} \mid i=1, 2,\ldots.c, k = 1,2,\ldots..n\}$ which is the membership matrix that has to satisfy the constraints step 3. $V = \{v_i \mid i =1, 2\ldots.c\}$ is the cluster prototype matrix and v_i is the prototype of the centre of cluster i.

*See Annexure 5.5 for Fuzzy C-Means Program Screenshot.

Case Study Example:

The input to this model is the output of Initial Screening Stage i.e., number of patients diagnosed as correct single disease are considered for the classification. There are such 65 patients out of 226 and those patients have 47 related symptoms which forms 65 x 47 sized data set.

The number of clusters (c = 14) indicate the number of diseases patients get classified into. In the present investigation, after many re-runs, the value of m' was finalized to be two, Ɛ being a threshold of termination condition is chosen as 0.01.

To explain the computational procedure of Fuzzy C-Means, out of 65 patients and 123 features (symptom), a sample set of 8 (n = 8) patients (data points) and 13 (m = 13) related features are considered.

The number of clusters considered here are 5 (c = 5) for the probable diseases which are *Uterine Prolapse, Abortion, Pelvic Inflammatory Disease, Viginal Yeast Infection,*

Urinary Track Infection. The assumption here is that the patients get clustered into different clusters depending on the symptom they possess.

In our study, to initialize U^0 matrix, we used the concept of reference group. FCM being an unsupervised learning algorithm, we considered the first cluster as reference cluster and remaining rows of the U^0 matrix are initialized randomly as shown in Table 5.44.

Table 5.44: U^0 matrix

	P_1	**P_2**	**P_5**	**P_6**	**P_{16}**	**P_{18}**	**P_{24}**	**P_{71}**
C_1	1	0	0	0	1	0	1	0
C_2	0	1	0	1	0	0	0	1
C_3	0	0	1	0	1	1	0	1
C_4	0	1	0	0	1	0	0	0
C_5	1	0	0	1	0	1	1	0

As stated earlier, the diagnosis of all the patients is already done by using Computational Rule of Inference which gives pretty correct output. Considering this as a reference point, the patients suffering from disease '*Uterine Prolapse*' (Cluster 1) are initialized to value 1 in the U^0 matrix and remaining patients to value 0.

Initially as suggested by Dunn, the weighting factor m` is taken as 2. The same algorithm is rerun for varying the values of m` in the range 1.80 to 2.3 by the interval 0.01 and also in the range 2 to 5 by the interval 0.5.

The Euclidian distance (Ɛ) as suggested by Bezdek is assumed as 0.01.

By using FCM algorithm, Cluster center calculated in final iteration is as in Table 5.45.

Table 5.45: Final Cluster Centre

C_1	0.078	0.025	0.025	0.025	0.062	0.019	0.025	0.019	0.002	0.044	0.025	0.051	0.025
C_2	0.074	0.025	0.025	0.025	0.063	0.019	0.025	0.019	0.002	0.044	0.025	0.05	0.025
C_3	0.074	0.025	0.025	0.026	0.064	0.019	0.025	0.019	0.002	0.043	0.025	0.049	0.025
C_4	0.074	0.025	0.025	0.025	0.062	0.019	0.025	0.019	0.002	0.044	0.025	0.05	0.025
C_5	0.075	0.025	0.025	0.025	0.062	0.019	0.025	0.019	0.002	0.044	0.025	0.050	0.025

5.6.2 Crisp Classification (Crisp Similarity Measures)

The classification is based on the comparison between measurable and non measurable parameters.

A. Gower's Coefficient

This is one of the similarity measures used in multivariate data analysis. Gower's Coefficient method estimates the similarity between elements (patients) when the variables are binary i.e. measurable and non-measurable. However, the non-measurable variables are dichotomous (yes/no) are not based on partial belief.

Algorithm: Patients' Classification using Gower's Coefficient

1. Get Patients' data in the form of symptoms/ complaints including some measurable variables narrated by patients in tabular form s x p (Table 5.46). Assign membership grades for the linguistic hedges used in the perceptions recorded for symptoms.
2. Apply Gower's Coefficient method using following formula on the above mentioned s x p table, to generate a tolerance relation (R).

   $S_{ij} = \frac{\sum_{k=1}^{p} w_{ijk} S_{ijk}}{\sum_{k=1}^{p} w_{ijk}}$ where $S_{ijk} = 1 - ([x_{ik} - x_{jk}] / R_k)$
3. Check if the relation R is equivalence (Equation 4.11):

   The relation R is *Reflexive*, if $\mu_R (x_i, x_i) = 1 \; \forall \; x_i$.

   The relation is *Symmetric*, if $\mu_R (x_i, x_j) = \mu_R (x_j, x_i) \; \forall$ i, j.

   To check if the relation R is *Transitive* i.e. $\mu_R (x_i, x_j) = \lambda_1$ and $\mu_R (x_j, x_k) = \lambda_2 \rightarrow \mu_R (x_i, x_k) = \lambda$ Where $\lambda \geq \min [\lambda_1, \lambda_2]$
4. If not an equivalence relation then perform $R^2 = R \circ R$ (Equation 4.10) and go to step 3 otherwise go to step 5.
5. Apply α-cuts to the obtained equivalence relation and classify the patients.
6. Stop.

Case Study Example

The P x S table contains all the non-measurable values i.e. symptoms narrated by patients. Gower's Coefficient method works on multivariate variables including

measurable and non-measurable variables. In Gynaecology, 'Age' is the most important factor which has major impact on disease diagnosis and which is measurable variable. So we include 'age' as additional symptom in the initial list of symptoms (Sardesai, Kharat, Deshpande & Sambarey, 2015).

To explain the computational procedure of fuzzy Gower's Coefficient, out of 226 patients and 123 related symptoms, a sample set of 9 patients and 8 related symptoms are considered. In addition to the 8 symptoms, one measurable parameter, 'Age' of the patient is considered as symptom (Table 5.46).

Table 5.46: Patient-Symptom relation with measurable parameter 'Age'
(9 patients, 9 symptoms)

	S_1	S_2	S_3	S_4	S_5	S_6	S_7	S_8	S_9
P_1	46	N	N	N	A	VO	N	A	N
P_2	22	N	N	N	N	VO	N	A	N
P_3	21	N	N	N	A	N	N	N	N
P_4	55	A	N	A	VO	N	N	N	N
P_5	73	A	O	VO	N	N	N	N	N
P_6	53	N	N	N	N	N	N	A	N
P_7	17	N	N	N	N	N	A	N	A
P_8	31	N	N	N	N	N	N	A	A
P_9	55	A	N	A	N	N	N	N	N

Application of fuzzy Gower's Coefficient for P_{ij} (Equation 4.18) is as follows.

$P_{12} = (w_{121}s_{121} + w_{122}s_{122} + w_{123}s_{123} + w_{124}s_{124} + w_{125}s_{125} + w_{126}s_{126} + w_{127}s_{127} + w_{128}s_{128} + w_{129}s_{129}) / (w_{121} + w_{122} + w_{123} + w_{124} + w_{125} + w_{126} + w_{127} + w_{128} + w_{129})$

$S_{121} = 1 - ((x_{11}-x_{21}) / R_1) = 1-((46-22)/56) = 1-(24/56) = 1- 0.42857 = 0.57143$

$P_{12} = (1 * 0.57143 + 0*1+0*1+0*1+1*0+0*1+0*1+0*1+0*1) / (1 + 0+0+0+1+0+0+0+0)$

$P_{12} = 0.57143 / 2 = 0.28571$

After application of binary similarity measures termed as Gower's Coefficient, to all p_{ij}, we get relation R which is fuzzy tolerance relation which is converted to fuzzy equivalence relation (Equation 4.11) and the resultant matrix of size 9 x 9 which is shown in Table 5.47.

Table 5.47: Fuzzy equivalence relation obtained using Gower's Coefficient method (9 patients, 9 symptoms)

	P_1	**P_2**	**P_3**	**P_4**	**P_5**	**P_6**	**P_7**	**P_8**	**P_9**
S_1	1	0.2857	0.2455	0.1697	0.1929	0.2798	0.25	0.2798	0.1929
S_2	0.2857	1	0.2455	0.1607	0.1929	0.2798	0.25	0.2798	0.1929
S_3	0.2455	0.2455	1	0.1607	0.1929	0.2322	0.2322	0.2455	0.1929
S_4	0.1697	0.1607	0.1607	1	0.1697	0.1697	0.1697	0.1697	0.1697
S_5	0.1929	0.1929	0.1929	0.1697	1	0.1929	0.1929	0.1929	0.2262
S_6	0.2798	0.2798	0.2455	0.1697	0.1929	1	0.25	0.6071	0.1929
S_7	0.25	0.25	0.2322	0.1697	0.1929	0.25	1	0.25	0.1929
S_8	0.2798	0.2798	0.2455	0.1697	0.1929	0.6071	0.25	1	0.1929
S_9	0.1929	0.1929	0.1929	0.1697	0.2262	0.1929	0.1929	0.1929	1

Same method is applied to all 226 patients and 124 symptoms to get the resultant fuzzy equivalence relation to classify all 226 patients.

❐❐❐

Chapter 6

Results and Discussion

The detailed exposition of the results and discussion, after the application of various techniques, is listed below:

6.1 Experts' Classification

6.2 Inter-Rater Reliability

6.3 Stage I : Initial Screening

6.4 Stage II : *History* Inference System with Fuzzy Rule base

6.5 Stage III : *Tests* Inference System with Rule base

6.6 Three Stage Model : An Analysis

6.6.1. Input-Output Model

1. Singleton System
2. Serial System
3. Serial-Parallel System

6.6.2. Venn Diagram

6.7. Classification of Patients: An Analysis

6.7.1. Fuzzy Similarity Measures and Gower's Coefficient

6.7.2. Fuzzy Similarity Measures Initial Screening Model

6.7.3. Fuzzy C-Mean

6.7.4 Fuzzy C-Mean, Cosine Amplitude method and Initial Screening Model

This section discusses the results of all the methods that were implemented, and analyses the output of the implementation of every algorithm. In the implementation of the simulation process, it is necessary to check the experts' perceptions that were obtained earlier and are expressed as their agreement rate. All the work that has been done in the research is related to the state of patients so it becomes obvious that the patients are classified on the basis of their symptoms. Some of the implemented classification methods are based on supervised learning algorithms while others fall in the category of unsupervised learning. To arrive at the better classification model, especially in case of Gynaecology patients, comparative evaluation was carried out.

6.1 Experts' Classification

The first part of the chapter refers to the application of similarity measures (Cosine Amplitude and Max-Min) to the perceptions received from different domain experts. These methods fall into category of supervised learning. The classification results and classification diagrams for both the methods are shown in Table 6.1 and figure 6.1 respectively. It is observed that experts E_4 and E_6 are in one group in their agreement with possibility of 0.981 using fuzzy similarity measures - Cosine Amplitude method, while the agreement with possibility of 0.95 is obtained using fuzzy similarity measure; Max-Min method. The degree of possibility to arrive at same result in Cosine Amplitude method, in this particular case, is better than that of Max-Min method, so the results of Cosine Amplitude method are considered for further analysis.

It can also be inferred that in this method, the experts get classified in three groups $\{E_1\}$, $\{E_8\}$ & $\{E_2, E_3, E_4, E_5, E_6, E_7\}$ while for the possibility value of 0.937, the same groups get classified in Max-Min method. It can be stated that the experts $\{E_2, E_3, E_4, E_5, E_6, E_7\}$ agree with one another in their diagnostic labels. Therefore, their perceptions in linguistic terms are considered in further analysis. The reason the two experts, E_1 and E_8 are not in the classification because their perceptions vary significantly while the perceptions of remaining six experts are very close to each other.

The authors cross-verified the diagnosis, given by the model based on perceptions shared by the experts, with the actual diagnosis given by respective experts for every patient. We observed that the diagnosis is similar by the experts who have been classified

in one group. This indicates that the classification of the experts done by using the mathematical formalism is in complete agreement with the actual diagnostic process.

Table 6.1: Classification of Experts: Classification result and Classification Diagram using Cosine Amplitude and Max-Min methods (8 experts, 226 patients)

	Cosine Amplitude Method		**Max-Min Method**
α_1	{ E_1, E_2, E_3, E_4, E_5, E_6, E_7, E_8}	α_1	{ E_1, E_2, E_3, E_4, E_5, E_6, E_7, E_8}
$\alpha_{0.981}$	{(E_4, E_6), E_1, E_2, E_3, E_5, E_7, E_8}	$\alpha_{0.95}$	{(E_4, E_6), E_1, E_2, E_3, E_5,E_7,E_8}
$\alpha_{0.976}$	{(E_4, E_5, E_6), E_1, E_2, E_3, E_7,E_8}	$\alpha_{0.938}$	{(E_4, E_5, E_6, E_7), E_1, E_2, E_3, E_8}
$\alpha_{0.975}$	{(E_2, E_3, E_4, E_5, E_6), E_1, E_7, E_8}	$\alpha_{0.937}$	**{(E_2, E_3, E_4, E_5, E_6, E_7), E_1, E_8}**
$\alpha_{0.973}$	**{(E_2, E_3, E_4, E_5, E_6, E_7), E_1, E_8}**	$\alpha_{0.795}$	{(E_1, E_8, E_2, E_3, E_4, E_5, E_6, E_7)}
$\alpha_{0.935}$	{(E_1, E_8, E_2, E_3, E_4, E_5, E_6, E_7)}		

The classification diagram using Cosine Amplitude method and Max-Min Method for the experts is as follows.

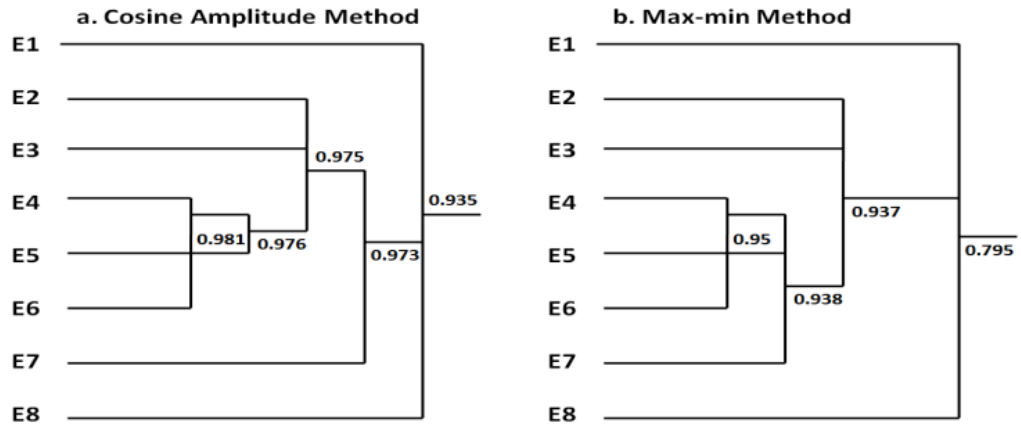


Figure 6.1: Classification of Experts: Dendogram

6.2 Inter-Rater reliability

Fleiss Kappa Coefficient is one of the well-known techniques used in inter-reliability computations. So, it was used in Inter-rater reliability estimation of multiple experts. The agreement among experts, for individual patient that was diagnosed, is presented in Table 6.2 using Fleiss Kappa Coefficient method.

Table 6.2: Agreement between experts for individual patient

Patient	**(κ)**	**Remarks**	**Patient**	**(κ)**	**Remarks**	**Patient**	**(κ)**	**Remarks**
P1	0.57	Moderate	P83	0.75	Substantial	P160	0.75	Substantial
P2	0.75	Substantial	P84	0.54	Moderate	P163	0.57	Moderate
P5	0.54	Moderate	P87	0.75	Substantial	P164	0.54	Moderate
P6	0.75	Substantial	P92	0.75	Substantial	P165	0.75	Substantial
P9	0.75	Substantial	P97	0.75	Substantial	P168	0.54	Moderate
P13	0.75	Substantial	P102	0.75	Substantial	P175	0.75	Substantial
P16	0.57	Moderate	P106	0.75	Substantial	P178	0.75	Substantial
P18	0.75	Substantial	P107	0.75	Substantial	P179	0.57	Moderate
P22	0.75	Substantial	P111	0.54	Moderate	P181	0.25	Fair
P23	0.75	Substantial	P117	0.54	Moderate	P184	0.75	Substantial
P24	0.57	Moderate	P126	0.75	Substantial	P189	0.75	Substantial
P26	1.00	Perfectly Agreement	P128	0.75	Substantial	P193	0.75	Substantial
P35	0.75	Substantial	P134	0.75	Substantial	P194	0.75	Substantial
P42	0.57	Moderate	P135	0.75	Substantial	P197	0.54	Moderate
P43	0.75	Substantial	P136	0.75	Substantial	P198	0.54	Moderate
P50	0.54	Moderate	P143	0.75	Substantial	P204	0.54	Moderate
P56	0.54	Moderate	P144	0.57	Moderate	P205	0.57	Moderate
P67	0.75	Substantial	P148	0.54	Moderate	P206	0.54	Moderate
P71	0.54	Moderate	P149	0.75	Substantial	P211	0.57	Moderate
P74	0.75	Substantial	P151	0.75	Substantial	P215	0.75	Substantial
P76	0.75	Substantial	P154	0.54	Moderate	P220	0.54	Moderate
P77	0.75	Substantial	P155	0.54	Moderate	P225	0.75	Substantial
P80	1.00	Perfectly Agreement	P157	0.54	Moderate	P226	0.54	Moderate

From above table we can infer following result for 69 patients according to Fleiss guidelines to interpret the Kappa:

- All the experts agree perfectly with one another, for 2 patients.
- For 39 patients, the agreement among the experts is Substantial.
- For 28 patients, the agreement among the experts is Moderate.
- The agreement among the experts is *Fair* for one patient.

The agreement among all the experts for all the patients collectively, is calculated by successively calculating P_BAR, Pe and finally Kappa Coefficient as below.

P_BAR	0.667702
Pe	0.137550
Kappa Coefficient **(κ)**	**0.614705**

Fleiss Kappa Coefficient for all experts and all patients results into 0.61, indicating '**Substantial'** agreement among all eight experts according to Fleiss guidelines to interpret the Kappa. The case study infers that all the eight gynaecologists are almost similar in their opinions for expressing the membership values of all linguistic variables. All identified similar experts' knowledge-base can be aggregated in order to formulate multi-expert knowledge-base for diagnosing the patient. It is true that there will be variation in experts' opinion but it, invariably is within the statistical limits.

6.3 Stage I: Initial Screening

In stage I, fuzzy occurrence and fuzzy conformability indication relations are computed (Equation1 and 3). Table 6.3 and Table 6.4 represent the final fuzzy occurrence and fuzzy conformability indication relation matrices using max-min composition.

Table 6.3: Disease patient occurrence indication matrix (p xd) (case study example)

	P_1	P_2	P_3	P_4	P_5	P_6	P_7	P_8	P_9
D_1	0	1	0	1	0	1	0	0.0625	0
D_2	0.5625	1	1	0	0.5625	0	1	0.5	0.5625
D_3	1	0.75	0	0	1	0.75	1	0.75	1
D_4	1	0	0	0	1	1	1	0	0.75
D_5	0	0	0	0	0	0	1	0.75	0
D_6	0	1	0.5	1	0	1	0. 5	0.75	0
D_7	1	0	0	0	1	1	0	0	0.5625
D_8	1	1	1	0.5625	1	0.5625	0.75	0.5	1
D_9	0	1	0	1	0	1	0	0	0

Table 6.3 and Table 6.4 infer that disease D_2 occurs '*Always*' in patient P_2 and '*Always*' confirms the disease. So, we can state that patient P_2 is suffering from disease D_2. Similarly, patient $P_2$is also suffering from diseases D_2, D_6, D_8 and D_9.

Table 6.4 : Disease patient confirmability indication matrix (p x d) (case study example)

	P_1	**P_2**	**P_3**	**P_4**	**P_5**	**P_6**	**P_7**	**P_8**	**P_9**
D_1	0	1	0	1	0	1	0	0	0
D_2	0.75	1	1	0	0.75	0	0.75	0.5	0.75
D_3	1	0.75	0	0	1	0.75	1	0.75	0.75
D_4	1	0	0	0	1	0	1	0	0.75
D_5	0	0	0	0	0	0	1	0.75	0
D_6	0	1	0.5	1	0	1	0.75	0.5625	0
D_7	1	0	0	0	1	1	0	0	0.5625
D_8	1	1	1	0.5625	1	0.5625	0.75	0.5	1
D_9	0	1	0	1	0	1	0	0	0

Table 6.5: Diagnosis of patients in case study example (case study example)

Patient	**Possible diseases occurred in the patient**
P_1	Uterine Fibroid (D_3), Adenomyosis (D_4), Endometriosis (D_7), Pelvic Inflammatory Disease (D_8)
P_2	Vaginal Yeast Infection (D_1), Ovarian Cyst (D_2), Cervicitis (D_6), Pelvic Inflammatory Disease (D_8), Leucorrhoea (D_9)
P_3	Ovarian Cyst (D_2), Pelvic Inflammatory Disease (D_8)
P_4	Vaginal Yeast Infection (D_1), Cervicitis (D_6), Leucorrhoea (D_9)
P_5	Uterine Fibroid (D_3), Adenomyosis (D_4), Endometriosis (D_7), Pelvic Inflammatory Disease (D_8)
P_6	Vaginal Yeast Infection (D_1), Cervicitis (D_6), Endometriosis (D_7), Leucorrhoea (D_9)
P_7	Uterine Fibroid (D_3), Adenomyosis (D_4), Dysfunctional Uterine Bleeding (D_5)
P_8	Disease Unspecific
P_9	Pelvic Inflammatory Disease (D_8)

Table 6.5 shows that max-min composition does not result in to only single disease diagnosis but identifies more than one disease or multiple diagnoses in a patient which is

termed as Initial Screening by the physicians. The output of the model is same as the diagnosis by physician at this stage. For patient P_9 the model has diagnosed a single disease: Pelvic Inflammatory Disease (PID). For all other seven patients, the gynaecologist suggests further investigative tests to arrive at the single disease diagnosis. In patient P_8, the diagnosis given by model is '*Disease Unspecific*'. There are various reasons to receive output as '*Disease Unspecific*'. Some of these reasons could be as follows:

a. The symptoms narrated by the patient may not match with the symptoms of any of the currently selected 31 diseases.
b. The symptoms with specific severity narrated by the patients may not result in a possibility value which is decided as a α-cut value in the current model.
c. It is mostly observed in many patients that the patient with psychic history cannot be diagnosed correctly.

An overview of the diagnosis analysis for one expert using Initial Screening Stage is presented below.

- Total number of patients diagnosed by model =226.
- Number of patients with only 1 disease as diagnosed by model and confirmed by the expert = 50.

The correctly diagnosed patients are : P_1, P_2, P_5, P_6, P_9, P_{13}, P_{16}, P_{18}, P_{23}, P_{24}, P_{26}, P_{35}, P_{42}, P_{56}, P_{67}, P_{71}, P_{74}, P_{76}, P_{77}, P_{80}, P_{83}, P_{84}, P_{87}, P_{92}, P_{102}, P_{106}, P_{107}, P_{110}, P_{117}, P_{126}, P_{136}, P_{143}, P_{144}, P_{148}, P_{149}, P_{157}, P_{159}, P_{160}, P_{163}, P_{165}, P_{168}, P_{175}, P_{178}, P_{179}, P_{189}, P_{193}, P_{198}, P_{205}, P_{211}, P_{220}.

- Number of Patients with multiple diseases as diagnosed by model, all correct and confirmed by the expert = 50
- Number of Patients with multiple diseases as diagnosed by model, partial correct and confirmed by the expert = 107
- Diagnosis percentage with 100 % accuracy by the model (Only 1 disease is diagnosed by model) and confirmed by the expert = 22.12%.
- Diagnosis percentage of initial screening model diagnosis with 1 + multiple diseases confirmed by the expert = 87.17%.

- Failure percentage of initial screening model = 12.83%.

It is observed that the model gives 12.83% incorrect diagnosis. The possible reasons may be as follows.

i. There are certain diseases which are not considered in the scope of the study. So, the symptoms that are narrated by the patients, related to such diseases, could not be understood by the model. This results into no diagnosis and the model gives output as '*Disease Unspecific*'.

ii. The patient may have history / symptoms other than Gynaecology related symptoms and so the model fails to diagnose the relevant diseases. In such a case, patient is directed to other branch of medicine for the diagnosis.

iii. It is noted in many patients that the psychological imbalance causes changes in female hormones, namely estrogens and progesterone, and consequently causes disturbance in working of female reproductive system.

iv. The result of the max-min composition may not be received as 'Always' (1) in both, fuzzy occurrence and fuzzy confirmability relations. As we have taken α-cut 1 for the defuzzification, the symptoms which are weak in appearance are not projected during the diagnosis process.

In specific, the reason for inconsistency of the diagnosis of the model, in some of the patients, is justified / elaborated as follows:

Table 6.6 : Remarks on Inconsistancies of the diagnosis by model

	Diagnosis by model	**Diagnosis by Expert 1**	**Reason of failure**
P_{22}	*Secondary Amenorrhea*	*Pregnancy, DUB*	Menses absent for 3 months, further investigation is required
P_{34}	*Disease Unspecific*	*Prolapse , Cystocele*	Further Investigations required
P_{51}	*Disease Unspecific*	*Incomplete evacuation with septisis*	Disease not considered in the study
P_{60}	*Disease Unspecific*	*Oligomenorrhea*	Disease not considered in the study
P_{63}	*Pelvic Inflammatory Disease(PID), Dysfunctional Uterine Bleeding (DUB),*	*Ovarian mass*	Disease not considered in the study

	Diagnosis by model	**Diagnosis by Expert 1**	**Reason of failure**
	Uterine Fibroid, Adenomyosis		
P_{64}	*Endometriosis, Dysfunctional Uterine Bleeding (DUB), Uterine Fibroid, Adenomyosis*	*Bicornuate uterus*	Disease not considered in the study
P_{68}	*Endometriosis, Pelvic Inflammatory Disease (PID), Uterine Fibroid, Adenomyosis*	*Endometriosis*	Further investigation required
P_{70}	*Disease Unspecific*	Tuberculus Endometritis	Disease not considered in the study
P_{75}	*Urinary Track Infection, Pelvic Inflammatory Disease(PID)*	*Prolapse / Cystocele*	No direct symptom of *Prolapse*; it is overlapped with *Cystocele*
P_{82}	*Endometriosis, Pelvic Inflammatory Disease(PID), Uterine Fibroid, Adenomyosis*	*Tuberculus Endometritis*	Disease not considered in the study
P_{89}	*Disease Unspecific*	*PCOS*	If we take α-cut as 0.75, we get *PCOS* as diagnosis. But we have finalized 1 as α-cut value for health as high risk area.
P_{100}	*Disease Unspecific*	*Disease Unspecific*	Patient has a history/symptoms related to other branch of medicine. Can't be treated as Gynaecology patient.
P_{116}	*Vaginal Yeast Infection, Pelvic Inflammatory Disease(PID) , Lecuorrhoea*	*Candidiasis*	*Candidiasis* is a special case of *Vaginal Yeast Infection* which is not separately included in the study.
P_{123}	*Endometriosis, Uterine Fibroid, Adenomyosis, Pubertal Menorrhagia*	*PCOS*	Symptoms of *PCOS* and *Puberty* overlapping
P_{128}	*Pubertal Menorrhagia*	*PCOD, endometrial damage due to DnC*	Symptoms of *PCOS* and *Puberty* overlapping. To check endometrial damage, USG is required.
P_{129}	*Vaginal Yeast Infection, Pelvic*	*CaCx, Erosion,*	Further investigation is required

	Diagnosis by model	**Diagnosis by Expert 1**	**Reason of failure**
	Inflammatory Disease(PID), Dysfunctional Uterine Bleeding (DUB), Uterine Fibroid, Adenomyosis, Lecuorrhoea , Pubertal Menorrhagia	*Perimenopausal*	
P_{132}	*Disease Unspecific*	*Perimenopausal*	Condition of patient is due to Perimenopausal age. Not a disease
P_{135}	*Pubertal Menorrhagia*	*PCOS*	Symptoms of *PCOS* and *Puberty* overlapping.
P_{151}	*Vaginal Yeast Infection, Lecuorrhoea , Cervicitis*	*Cervicitis*	Symptoms of *Vaginal Yeast Infection* and *Cervicitis* overlapping. Further Investigations required.
P_{155}	*Pelvic Inflammatory Disease (PID)*	*Haemoperitoneum with haemorrhagic cyst of ovary (cyst ruptured on ovary)*	Further investigation is required
P_{158}	*Disease Unspecific*	*Unspecific, Calcium deficiency*	Not a Gynaecology patient
P_{166}	*Disease Unspecific*	*Disease Unspecific*	Not a Gynaecology patient
P_{181}	*Pelvic Inflammatory Disease (PID)*	*CaCx*	Symptoms overlapping. Further investigation is required
P_{196}	*Disease Unspecific*	*Psychic history*	Patient with a psychic history leads to Gynaecology problems
P_{200}	*Dysfunctional Uterine Bleeding (DUB), Secondary Amenorrhea*	*Dysmenorrhoea, Secondary Amenorrhea*	Further investigation required
P_{215}, P_{225}	*Secondary Amenorrhea*	*UPT to be done*	Further investigations required
P_{226}	*Dysfunctional Uterine Bleeding (DUB), Secondary Amenorrhea*	*Incomplete Abortion*	Further investigations required

In this study, perceptions of 8 domain experts are considered and the program is executed for each of the experts' perceptions data, keeping the patient's data same. The result is summarized in Table 6.7 which shows the detailed diagnosis analysis for 226 patients.

Table 6.7: Diagnosis analysis for 8 experts (8 experts, 226 patients)

Diagnosis Analysis	**Experts**							
	E_1	**E_2**	**E_3**	**E_4**	**E_5**	**E_6**	**E_7**	**E_8**
One Disease Correct	50	41	50	54	50	53	56	18
Multiple Diseases All correct	40	5	2	6	1	4	6	5
Multiple Diseases partial correct	107	50	61	59	64	57	54	61
Incorrect diagnosis	28	131	113	107	109	112	110	142
Accuracy Percentage (Single disease)	22.12	18.14	22.12	23.89	22.12	23.45	24.78	7.96
Overall Accuracy Percentage	87.16	42.48	50.00	51.77	50.88	50.44	51.33	37.17

In Table 6.7, Row 2 & Row 3 infers multiple disease diagnosis for some of the patients. Therefore, in the quest of arriving at a single disease, there was a need to look for an additional mathematical formalism.

It can be concluded that experts get classified in three groups viz. Group 1 consisting (E_2, E_3, E_4, E_5, E_6, E_7), Group 2 consisting (E_1) and Group 3 consisting of (E_8). From Table 6.7, we can observe that the overall accuracy percentage of the diagnosis for experts (E_2,E_3, E_4, E_5, E_6, E_7) fall in a near range where as accuracy percentage for E_1 is much greater than these experts and for E_8, it is very less. So, E_1 and E_8 can be classified as two separate groups and remaining all the experts can be grouped together. The result obtained using Initial Screening model supports the results of Expert's classification using Cosine Amplitude method. Out of 8 experts, 6 experts agree with each other. This confirms the result of Inter-rater reliability which shows that the agreement between the experts is '*Substantial*'.

It is observed that the result of Initial Screening Stage based on Experts' perceptions matches with the classification result. This indicates that the diagnosis of patients done by

the model is substantially similar to that done by experts (E_2, E_3, E_4, E_5, E_6, E_7) and is far away from that done by experts E_1 and E_2. With this we can claim that the Classification of experts using Fuzzy Similarity measures correlates with the Initial Screening model and the reliability of the model verifies with the computations of Kappa Coefficient.

6.4 Stage II: *History* Inference System with Fuzzy Rule Base

In the Stage I, 50 patients were diagnosed correctly. Out of remaining 176 patients, 30 patients were identified using Type 1 fuzzy inference system, for whom the '*history*' criteria (Stage II) are applicable to arrive at a single disease. We can state in no uncertain terms that 29 out of 30 patients are correctly diagnosed.

Table 6.8: Patients diagnosed using Stage II

Patient Id	**Diagnosis**
P_{164}	*Secondary Amenorrhea*
P_{22}, P_{103}, P_{215}	*UPT to be done*
P_{100}	**No Diagnosis**
P_{90}, P_{226}	*Incomplete Abortion*
P_{20}, P_{93}, P_{154}, P_{192}, P_{199}, P_{200}, P_{225}	*Secondary Amenorrhea(UPT to be done)*
P_{52}, P_{69},P_{218}	*Cervical Cancer*
P_{129}	*Cervical Cancer / DUB*
P_{79}	*Incomplete Abortion / DUB*
P_{187}	*Pubertal Menorrhagia*
P_{153},P_{191},P_{223}	*Endometriosis / Fibroid*
P_{54}, P_{65}, P_{138}	*DUB*
P_{132}, P_{137}, P_{202}	*Perimenopausal*
P_{14}	*Uterine Cancer*

The Table 6.8 shows patients P_{153}, P_{129}, P_{79}, P_{191} and P_{223} were not diagnosed for single disease so are passed to stage III for further diagnosis.

In stage II, only one patient (P_{100}) was incorrectly diagnosed. The reason for failure is narrated below:

The history of the patient is: *Age* = 25 years, fits in fuzzy set *Age - Fertile* (F=1), Marital Status: *Unmarried* (*M_Status* = U), *Amenorrhea* for 4 years which does not fit in any of the *LMP* fuzzy sets. In the fuzzy sets as defined, *Amenorrhea* is termed when no

menses are observed for more than 1.5 months to 4.5 months. Then, till 9 months the patient is considered as *Gravid*, and until about 1.5 years after the birth of child, it is termed as *Lactational Amenorrhea*. More than 4 years of Amenorrhea should be considered as *Menopause* however *Menopause* is not possible at early age such as 25 years in this case. So, none of the rules could get fired and the model gave no output. The gynaecologists invariably termed the disease as *Secondary Amenorrhea* for the symptoms: '*Age* 25 and *No menses* present'. As it is not a good practice to redefine the fuzzy set for every extreme case, we consider this case either as an exceptional case or an outlier. The initial screening model also diagnosed this patient as '*Disease Unspecific*', so the patient P_{100} is considered as an outlier.

The patients P_{79}, P_{153}, P_{191}, P_{129} and P_{224} are correctly diagnosed in Stage II however; they are diagnosed for multiple diseases. Hence, investigative tests were suggested for them and their test results were passed to Stage III for further diagnosis.

Table 6.9 shows the increased accuracy performance in the overall diagnosis by the model after application of rules to all 30 patients in Stage II.

Table 6.9: Diagnosis analysis for 8 experts after applying *History* rulebase (8 experts, 226 patients)

Diagnostic Analysis	**Experts**							
	E_1	**E_2**	**E_3**	**E_4**	**E_5**	**E_6**	**E_7**	**E_8**
One Disease Correct	64	50	58	65	60	63	69	37
Multiple Diseases All correct	45	12	9	13	8	11	13	13
Multiple Diseases Partial correct	93	48	55	53	58	52	52	59
Incorrect diagnosis	24	116	104	95	100	100	92	115
Accuracy Percentage (Single disease)	28.32	22.12	25.66	28.76	26.55	27.88	30.53	16.37
Overall Accuracy Percentage	89.38	48.67	53.92	57.96	55.75	55.75	59.29	48.23

6.5 Stage III: *Tests* Inference System with Fuzzy Rule Base

Out of 176 patients, 29 patients are correctly diagnosed in Stage II. Out of these 29 patients, 5 patients (P_{79}, P_{153}, P_{191}, P_{129}, and P_{224}) are required to be passed to Stage III as they have received multiple disease diagnosis. In short, 152 patients need assistance of Stage III. Depending upon the symptoms they possess and their diagnosis done by Initial Screening Stage, the investigative tests are suggested to these 152 patients. The

respective test results are given to the Stage III. Table 6.10 shows some of the cases along with the details of their diagnosis by Stage I and II and the final diagnosis by Stage III.

Table 6.10 Diagnosis of Stage III over the input from Stage I and Stage II diagnosis (Sample cases)

Patient Id	**Diagnosis by Model (Stage I and II)**	**Diagnosis by Model Stage III**
P_{46}	***Uterine Prolapse*** *, Urinary Track Infection*	*Uterine Prolapse*
P_{49}	***Uterine Prolapse*** *, Vaginal Yeast Infection*	*Uterine Prolapse*
P_{79}	*Dysfunctional Uterine Bleeding (DUB),* ***Abortion***	*Abortion*
P_{89}	*Disease Unspecific*	*Polycystic Ovarian Syndrome*
P_{123}	*Endometriosis , Uterine Fibroid , Adenomyosis ,* ***Pubertal menorrhagia***	*Pubertal Menorrhagia*
P_{129}	***Dysfunctional Uterine Bleeding (DUB)****, Cervical Cancer*	*Dysfunctional Uterine Bleeding*
P_{153}	***Endometriosis****, Uterine Fibroid*	*Endometriosis*
P_{191}	***Endometriosis****, Uterine Fibroid*	*Endometriosis*
P_{194}	*Secondary amenorrhea ,*	*Polycystic Ovarian Syndrome*
P_{223}	***Endometriosis****, Uterine Fibroid*	*Endometriosis*
P_{224}	*Endometriosis, Dysfunctional Uterine Bleeding(DUB), Uterine Fibroid, Adenomyosis,* ***Pubertal Menorrhagia***	*Pubertal Menorrhagia*

The diagnosis process of Stage III for some of the above cases is discussed as:

1. For patient P_{89}, Stage I and Stage II diagnosis was '*Disease Unspecific*'. The original version of the model did not evaluate this patient. In the revised version, the model is learned for such cases to diagnose the patient at Stage III. Here, the model re-runs Stage I, Initial Screening Stage, and takes the α-cut as 0.75 instead of 1 to arrive at common diseases from fuzzy occurrence indication relation and fuzzy confirmability indication relation. With this α-cut value, Stage I gives output as: {*Dysfunctional Uterine Bleeding (DUB), Ovarian Cancer, Polycystic Ovarian Syndrome*}. Stage II can't diagnose this patient so is passed to Stage III directly. The test that is suggested for *Polycystic Ovarian Syndrome* and *Ovarian Cancer* is *USG Pelvis Ovary*. This test shows no presence of ovarian mass but detects the appearance of small cysts in ovary

as well as enlarged ovaries. The test *CA125* shows normal results that rule out the chances of *Ovarian Cancer*. The test for *DUB* was also conducted showing normal level of *Progesterone* Hormone. *Transvaginal USG of Uterus* shows that the size of uterus is normal which means there is no chance of *DUB*. Presence of small cysts in ovary and enlarged ovaries confirm the disease *Polycystic Ovarian Syndrome*. Similar is the case for patient P_{194}.

2. For Patient P_{153}, Stage I output shows the diseases as {*Endometriosis, Pelvic Inflammatory Disease, Uterine Fibroid, Adenomyosis, Pubertal Menorrhagia*}. It is passed to Stage II for '*History*' parameter testing which gave diagnosis as {*Endometriosis, Uterine Fibroid}*. In Stage II, the age is checked which is found 20 years. This age is not Puberty age so *Pubertal Menorrhagia* is ruled out. *PMC_Status* is *Irregular*, *PMC_Flow* is *Scanty* and *Age* is *Early Fertile* which leads to confirmation of either *Endometriosis* or *Uterine Fibroid* with the other symptoms which are screened in Stage I. So, *Pelvic Inflammatory Disease* and *Adenomyosis* are also ruled out. Stage II still cannot give output as a single disease diagnosis so the output {*Endometriosis, Uterine Fibroid}* is passed to Stage III with investigative tests as *USG Pelvis*. The test result showed *blueberry cyst* present which confirmed the disease as *Endometriosis*.

3. Similar is the case for patients P_{191} and P_{223}.

4. Diagnosis of Patient P_{129} by Stage I is {*Vaginal Yeast Infection, Pelvic Inflammatory Disease, Dysfunctional Uterine Bleeding, Uterine Fibroid, Adenomyosis, Leucorrhoea, Pubertal Menorrhagia*}. It is identified by Stage II and is passed as input to Stage II which gives output as {*Dysfunctional Uterine Bleeding, Cervical Cancer*}. As Stage II does not arrive at single disease diagnosis, it is passed to Stage III and the patient is asked to perform tests to confirm the diagnosis for *Dysfunctional Uterine Bleeding* and *Cervical Cancer*. For *Cervical Cancer, Pap Smear* is suggested which gave result as 'no malignant cells or dysplastic present'. So, *Cervical Cancer* is ruled out. *Transvaginal USG* and *Progesterone Hormone Level* tests are suggested which show bulky uterus and decreased Progesterone Hormone Level, confirming the disease as *Dysfunctional Uterine Bleeding*.

5. {*Dysfunctional Uterine Bleeding, Abortion*} is the diagnosis shown by Stage I for patient P_{79}. As it is not single disease diagnosis, it is passed to Stage II to identify the symptoms of '*History*' parameters: *Age* as *Fertile*, *Low Parity*, *Normal Marital Status* and *LMP* as 60 days. The Stage II gave output as {*Dysfunctional Uterine Bleeding and Abortion*} so it is passed to Stage III for single Disease Diagnosis. Tests suggested for *Dysfunctional Uterine Bleeding* i.e. *Transvaginal USG* shows *Bulky Uterus* and decreased level of *Progesterone Hormone*. This result ruled out *Abortion* and confirmed the disease *Dysfunctional Uterine Bleeding*.

6. For patient P_{123}, the diagnosis by Stage I is {Endometriosis, Uterine Fibroid, Adenomyosis, Pubertal Menorrhagia}. Tests suggested for '*Endometriosis*' are *Trans-vaginal USG Blueberry Cyst* and for '*Uterine Fibroid*' the test is *USG Pelvis Fibroid.* The USG result shows no endometrial tissue growth or growth of cyst which rules out '*Endometriosis*' and '*Uterine Fibroid*'. '*Adenomyosis*' is normally confirmed by the test MRI with the appearance of *thickened junction Zone*, which is not seen in this patient. The result shows no abnormalities found inside the uterus and hence, '*Adenomyosis*' is also ruled out. So, the output by model is '*Pubertal Menorrhagia*'. But in this case the output is incorrect as age of the patient is 39 which is not a pubertal age.

7. Similar is the case for patient P_{224}. Although this patient is also diagnosed as "*Pubertal menorrhagia*" like patient P_{123}, it is the correct diagnosis as her age is 12 years.

   The final diagnosis of 153 patients is as shown below:

Table 6.11: Diagnosis of Stage III over the input from Stage I and Stage II diagnosis

Patient Id	**Diagnosis**
P_{79}	*Abortion*
P_{29}, P_{41}, P_{44}, P_{115}, P_{119}	*Adenomyosis*
P_{37}, P_{66}, P_{85}	*Cervical Cancer*
P_{17}, P_{19}, P_{25}, P_{28}, P_{96}, P_{104}, P_{125}, P_{129}, P_{130}, P_{156}, P_{161}, P_{162}, P_{172}, P_{180}, P_{186}, P_{188}	*Dysfunctional Uterine Bleeding*

Patient Id	**Diagnosis**
P_{10}, P_{40}, P_{48}, P_{62}, P_{68}, P_{112}, P_{153}, P_{191},P_{203}, P_{223}	*Endometriosis*
P_3, P_8, P_{78}	*Endometritis*
P_{11}, P_{21}, P_{31}, P_{36}, P_{57}, P_{58}, P_{63}, P_{73}, $P_{101}P_{145}$, P_{121}, P_{183}, P_{185}, P_{208}, P_{219}, P_{221}, P_{222}	*Uterine Fibroid*
P_{51}, P_{60}, P_{64}, P_{70}, P_{82}, P_{128}, P_{140}, P_{151}, P_{155}, P_{158}, P_{166}, P_{196}	*Unspecific Disease (Incorrect Diagnosis)*
P_{116}, P_{127}	*Leucorrhoea*
P_{27} , P_{140}	*Ovarian Cyst*
P_{89}, P_{122}, P_{135}, P_{194}	*Polycystic Ovarian Syndrome*
P_{12}, P_{30}, P_{33}, P_{39}, P_{45}, P_{50}, P_{72}, P_{81}, P_{88}, P_{94}, P_{105}, P_{111}, P_{113}, P_{114}, P_{120}, P_{124}, P_{133}, P_{139}, P_{141}, P_{142}, P_{146}, P_{170}, P_{177}, P_{181}, P_{182}, P_{190}, P_{201}, P_{204}, P_{207}, P_{209}, P_{214}, P_{217}	*Pelvic Inflammatory Disease*
P_{34}, P_{38}, P_{46}, P_{49}, P_{55}, P_{91}, P_{118}, P_{150}, P_{152}, P_{171}, P_{174}, P_{212}, P_{213}	*Uterine Prolapse*
P_{224}	*Pubertal Menorrhagia*
P_{215}	*Secondary Amenorrhoea*
P_{197}	*UPT to be done*
P_{75}, P_{108}, P_{134}, P_{167}, P_{206}, P_{216}	*Urinary Track Infection*
P_4, P_7, P_{15}, P_{32}, P_{43}, P_{47}, P_{53}, P_{59}, P_{61}, P_{86}, P_{95}, P_{97}, P_{98}, P_{99}, P_{131}, P_{147}, P_{169}, P_{173}, P_{176}, P_{184}, P_{195}, P_{210}	*Vaginal Yeast Infection*
P_{151}	*Cervicitis*

It is observed from the above table that the model could not diagnose 11 patients correctly. The reason for inconsistency of the diagnosis by the model in some of the patients is justified / elaborated as in Table 6.12.

Table 6.12 : Remarks on Inconsistancies of the diagnosis by model

Patient Id	**Diagnosis by model**	**Diagnosis by Expert 1**	**Reason of failure**
P_{51}	*Unspecific Disease*	Incomplete evacuation with septisis	Disease is not considered in the study
P_{60}	*Unspecific Disease*	*Oligomenorrhea*	Disease is not considered in the study
P_{64}	*Endometriosis, Dysfunctional Uterine Bleeding (DUB), Uterine Fibroid, Adenomyosis*	*Bicornuate Uterus*	USG shows *Bicornuate Uterus* for which the model does not contain solution.
P_{70}	*Unspecific Disease*	*Tuberculus Endometritis*	Disease is not considered in the study
P_{82}	*Endometriosis, Pelvic Inflammatory Disease(PID), Uterine Fibroid, Adenomyosis*	*Tuberculus Endometritis*	Disease is not considered in the study
P_{123}	*Endometriosis, Uterine Fibroid, Adenomyosis, Pubertal menorrhagia*	*Polycystic Ovarian Syndrome*	Reason as explained above.
P_{128}	*Pubertal menorrhagia*	*PCOS*, endometrial damage due to D&C	The model gives the diagnosis as *Pubertal Menorrhagia* due to symptoms and age of the patient. But the USG report shows endometrial damage.
P_{155}	*Pelvic Inflammatory Disease (PID)*	Haemoperitoneum with haemorrhagic cyst of ovary (cyst ruptured on ovary)	USG shows cyst ruptured on ovary. The model does not contain solution for the problem.
P_{158}	*Unspecific Disease*	Unspecific, Calcium deficiency	Not a Gynaecology patient
P_{166}	*Unspecific Disease*	*Unspecific Disease*	Not a Gynaecology patient
P_{196}	*Unspecific Disease*	Psychic history	Patient with a psychic history leads to Gynaecology problems

The summary of the overall diagnosis process for three stages is as given in Table 6.13.

Table 6.13: Output of differential diagnosis process

	Stage I	**Stage II**	**Stage III**
Number of patients Input to Stage	226	30	152
Number of patients correctly diagnosed as single disease	50	24	141
Number of patients incorrectly diagnosed	29	1	11
Accuracy Percentage	22.12%	80.00%	92.81%
Overall Accuracy of the model	**95.13%**		

6.6 Three Stage Model: A Review

The model developed is three stage Input-Output model in which the output of stage I is given as input to stage II whose output in turn is input to stage III.

6.6.1 Input-Output Model

Following are the factual related to above mentioned Input-Output model.

i. Sometimes, we get final output at Stage II and we stop the serial process at Stage II itself. In many situations, signs of a patient are not applicable to Stage II, so it is directly passed to Stage III to arrive at final diagnosis. In these two cases it is considered as *Serial System*.

ii. In some cases, we get the final output at the stage I where Stage II and Stage III are not in picture, we claim this as *Singleton System*.

iii. Another type of system which is observed in some cases is *Serial-Parallel System*, in which, the output of Stage I is given to either Stage II or Stage III at which we get final output.

1. **Singleton System:** In the Gynaecology disease diagnosis process, some of the diseases are directly diagnosed from the symptoms narrated by the patient. In the proposed Three Stage model, the first stage, Initial Screening Stage deals with the Symptoms of patient. It accepts symptoms as input and gives a single or multiple

diseases diagnosed as output. The singleton system can be expressed by the output as the correct single disease diagnosis output at Stage I.

Input: Symptoms of patient

Process: max-min composition

Output: Correct Single disease diagnosed at Stage I.

It can be graphically represented as:

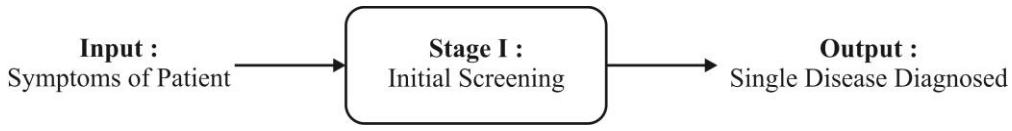


Figure 6.2. Singleton System

Total number of patients diagnosed by this system: 50 (using perceptions of Expert 1)

The patients are : P_1, P_2, P_5, P_6, P_9, P_{13}, P_{16}, P_{18}, P_{23}, P_{24}, P_{26}, P_{35}, P_{42}, P_{56}, P_{67}, P_{71}, P_{74}, P_{76}, P_{77}, P_{80}, P_{83}, P_{84}, P_{87}, P_{92}, P_{102}, P_{106}, P_{107}, P_{110}, P_{117}, P_{126}, P_{136}, P_{143}, P_{144}, P_{148}, P_{149}, P_{157}, P_{159}, P_{160}, P_{163}, P_{165}, P_{168}, P_{175}, P_{178}, P_{179}, P_{189}, P_{193}, P_{198}, P_{205}, P_{211} and P_{220}.

Case Study :

Consider the patient P_{74}. The symptoms are:

Age: 23 years. Marital Status: Married, Menarche: 14 years, LMP: 20 days back, PMC: 4D/30days/RMPL

C/O passing stool and air through vagina since 15 days, vaginal itching

The entries in patient-symptom table are as shown in Table 6.14. Table 6.15 shows the D x S table for Occurrence and Confirmability relation values.

Table 6.14: Symptom-Patient entries for Patient P_{74}

Symptoms	**Severity**
Passing of air and stool through vagina	1
Vaginal itching, burning	1
White discharge	0
Burning Micturition	0

Table 6.15: Occurrence and Confirmability values of Rectovaginal Fistula

Rectovaginal Fistula	Passing of air and stool through vagina	Vaginal itching, burning	White discharge	Burning Micturition
Occurrence Rel.	1	0.5	0.25	0.25
Confirmability Rel.	1	0.75	0.5	0.25

The sample computations of max-min composition for Occurrence Indication relation and Confirmability Indication relation are shown below.

Occurrence Indication Relation:

(X_{23}, Z_{74}) = Max (min (1, 1), min (0.5, 1), min (0.25, 0), min (0.25, 0))

= Max (1, 0.5, 0, 0)

= 1

Confirmability Indication Relation:

(X_{23}, Z_{74}) = Max (min (1, 1), min (0.75, 1), min (0.5, 0), min (0.25, 0))

= Max (1, 0.75, 0, 0)

= 1

As the Occurrence and Confirmability indication relation yields '1' and we are considering the α-cut value as 1, the diagnosis is: the patient P_{74} is suffering from the disease "Rectovaginal Fistula". In this case, as we have received a single disease, the process of differential diagnosis is stopped.

2. **Serial System:** In the process of differential diagnosis, the disease may not get diagnosed by only symptoms. In Gynaecology diseases, the *History* Parameter as well as the *Tests* that are conducted plays a vital role. In the Three Stage model, Stage II deals with the *History* Parameter and Stage III with *Tests* conducted. Depending upon the involvement of the *History* parameter or *Tests* Conducted, the Serial System takes following forms:

a. **Initial Screening – History parameter:** The History parameter cannot be applied to all the diseases. Certain diseases require the application of parameters like *Age, LMP, PMC_Flow, Marital Status, Parity* etc. Stage II works on the diseases diagnosed as

multiple diseases by Stage I and the *History* parameter values in order to give output as the single disease diagnosis.

Initial Screening:

Input: Symptoms of patient

Process: max-min composition

Output: Multiple diseases diagnosed.

History Parameter:

Input : Multiple diseases diagnosed by Stage I + fuzzified Value of *History* parameter

Process : Type 1 Fuzzy Inference System

Output: Single disease diagnosed.

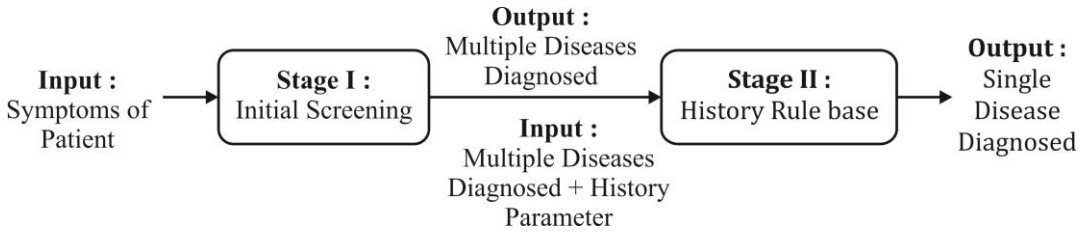


Figure 6.3. Serial System (Stage I-Stage II)

Total number of patients diagnosed by this system: 24

The patients are: P_{164}, P_{22}, P_{103}, P_{215}, P_{90}, P_{226}, P_{20}, P_{93}, P_{154}, P_{192}, P_{199}, P_{225}, P_{52}, P_{69}, P_{218}, P_{200}, P_{187}, P_{54}, P_{65}, P_{138}, P_{132}, P_{137}, P_{202} and P_{14}.

Case Study:

Consider the patient P_{65}. The diagnosis by Stage I is {*Pelvic Inflammatory Disease (PID), Dysfunctional Uterine Bleeding (DUB), Uterine Fibroid, Adenomyosis*}, which is a partial diagnosis so is passed to Stage II.

The *History* parameters applied are as below.

Age: 40 (F = 1), *LMP*: 60 days (MMC =1, PMC = 0.047619) and *PMC Flow:* Continuous (C).

Tests Suggested and test results received for this patient are as shown in Table 6.16.

Table 6.16: Implementation of History Parameter Rules for patient P_{65}

Antecedent	**Rule applied**	**Min**	**Result of min**	**Max of all**	**Consequent**
If (Age is PM AND PMC_Status is IRR AND PMC_Flow is E AND LMP is MMC)	If (Age =0 AND PMC_Status =1 AND PMC_Flow = 1 AND LMP =1)	Min (0, 1, 1, 1)	0	Max (0,0,0,0, 1, 0.047619, 0, 0)	DUB Present with possibility =1
If (Age is PM AND PMC_Status is IRR AND PMC_Flow is E AND LMP is PMC)	If (Age =0 AND PMC_Status =1 AND PMC_Flow =0 AND LMP =0.047619)	Min (0, 1, 0, 0.047619)	0		
If (Age is PM AND PMC_Status is IRR AND PMC_Flow is C AND LMP is MMC)	If (Age =0 AND PMC_Status =1 AND PMC_Flow =1 AND LMP =1)	Min (0, 1, 1, 1)	0		
If (Age is PM AND PMC_Status is IRR AND PMC_Flow is C AND LMP is PMC)	If (Age =0 AND PMC_Status =1 AND PMC_Flow =1 AND LMP =0.047619)	Min (0, 1, 0, 0.047619)	0		
If (Age is F AND PMC_Status is IRR AND PMC_Flow is C AND LMP is MMC)	If (Age =1 AND PMC_Status =1 AND PMC_Flow =1 AND LMP =1)	Min (1, 1,1, 1)	1		
If (Age is F AND PMC_Status is IRR AND PMC_Flow is C AND LMP is PMC)	If (Age =1 AND PMC_Status =1 AND PMC_Flow =1 AND LMP =0.047619)	Min (1, 1, 1, 0.047619)	0.047619		
If (Age is F AND PMC_Status is IRR AND PMC_Flow is E AND LMP is MMC)	If (Age =1 AND PMC_Status =1 AND PMC_Flow =0 AND LMP =1)	Min (1, 1, 0, 1)	0		
If (Age is F AND PMC_Status is IRR AND PMC_Flow is E AND LMP is PMC)	If (Age =1 AND PMC_Status =1 AND PMC_Flow =0 AND LMP =0.047619)	Min (1, 1, 0, 0.047619)	0		
If (PMC_Status is IRR AND PMC_Flow is S AND Age is F)	If (PMC_Status =1 AND PMC_Flow =0 AND Age =1)	Min (1, 0, 1)	0	Max(0,0) = 0	DUB Present with possibility 0
If (PMC_Status is IRR AND PMC_Flow is S AND Age is EF)	If (PMC_Status =1 AND PMC_Flow =0 AND Age =0)	Min (1, 0, 0)	0		

Here, as the patient does not have *PMC_Flow* Scanty, the last two rules as shown in the Table 6.16 cannot diagnose the disease due to lack of input information for the rule, although are fired. So the final diagnosis in this case is: the patient is suffering from the disease *Dysfunctional Uterine Bleeding*. The diagnosis process stops with this single disease diagnosis.

b. Initial Screening – Tests conducted: The diseases for which the *History* parameter cannot be applied are directly passed to Stage III. The input to Stage III is multiple diseases diagnosed and the results of tests conducted. Stage III works on the diseases output by Stage I and the result of Tests conducted to give output as the single disease diagnosis.

Initial Screening:

Input: Symptoms of patient

Process: max-min composition

Output: Multiple diseases diagnosed.

Tests Conducted:

Input: Multiple diseases diagnosed by Stage I + Values of results of tests conducted

Process: Type 1 Fuzzy Inference System

Output: Single disease diagnosed.

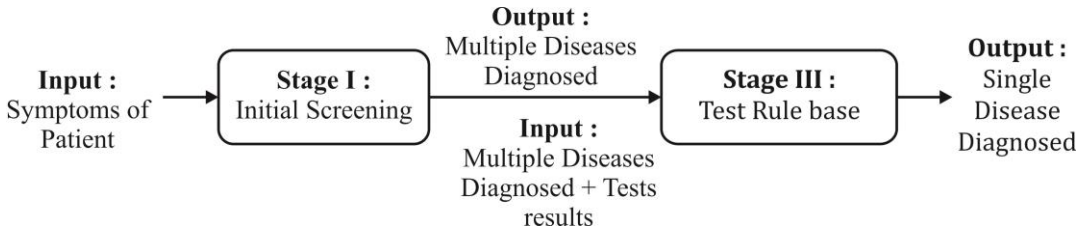


Figure 6.4.Serial System (Stage I – Stage III)

Total number of patients diagnosed by this system: 137

The patients are : P_{29}, P_{41}, P_{44}, P_{115}, P_{119}, P_{37}, P_{66}, P_{85}, P_{17}, P_{19}, P_{25}, P_{28}, P_{96}, P_{104}, P_{125}, P_{130}, P_{156}, P_{161}, P_{162}, P_{172}, P_{180}, P_{186}, P_{188}, P_{10}, P_{40}, P_{48}, P_{62}, P_{68}, P_{112}, P_{203}, P_3, P_8, P_{78}, P_{11}, P_{21}, P_{31}, P_{36}, P_{57}, P_{58}, P_{63}, P_{73}, P_{101}, P_{145}, P_{121}, P_{183}, P_{185}, P_{208}, P_{219}, P_{221}, P_{222}, P_{140}, P_{151}, P_{158}, P_{116}, P_{127}, P_{27}, P_{140}, P_{89}, P_{122}, P_{135}, P_{194}, P_{12}, P_{30}, P_{33}, P_{39}, P_{45}, P_{50}, P_{72}, P_{81}, P_{88}, P_{94},

P_{105}, P_{111}, P_{113}, P_{114}, P_{120}, P_{124}, P_{133}, P_{139}, P_{141}, P_{142}, P_{146}, P_{170}, P_{177}, P_{181}, P_{182}, P_{190}, P_{201}, P_{204}, P_{207}, P_{209}, P_{214}, P_{217}, P_{38}, P_{46}, P_{49}, P_{55}, P_{91}, P_{118}, P_{150}, P_{152}, P_{171}, P_{174}, P_{212}, P_{213}, P_{224}, P_{215}, P_{197}, P_{75}, P_{108}, P_{134}, P_{167}, P_{206}, P_{216}, P_4, P_7, P_{15}, P_{32}, P_{43}, P_{47}, P_{53}, P_{59}, P_{61}, P_{86}, P_{95}, P_{97}, P_{98}, P_{99}, P_{131}, P_{147}, P_{169}, P_{173}, P_{176}, P_{184}, P_{195}, P_{210} and P_{151}

Case Study:

Consider the patient P_{108} for whom Stage I diagnosis is: {*Urinary Track Infection, Cervical Cancer (Stage I), Dysfunctional Uterine Bleeding (DUB), Uterine Fibroid, Adenomyosis*}

Tests Suggested and test results received for this patient are as shown in table 6.17 and Table 6.18 shows the implementation of rules for *Tests* conducted.

Table 6.17: Tests Suggested and results recorded for patient P_{108}

Disease Name	**Test Suggested**	**Test Results**
Urinary Track Infection	Urine Culture	Pathogen Growth is seen
	Urinalysis G3	Pus cells present in sample
Uterine Fibroid	USG Pelvis Fibroid	No Fibroid found
Adenomyosis	Transvaginal US Uterus	Uterus Normal, No appearance of cysts

Table 6.18: Implementation of Tests Conducted Rules for patient P_{108}

Antecedent	**Rule applied**	**Min(Max)**	**Result of min(max)**	**Max (min) of all**	**Consequent**
If (URANA_PusCells is Present OR UC_PathoGrowth is Absent OR CBC_CRPR is Normal)	If (URANA_PusCells is 1 OR UC_PathoGrowth is 1 OR CBC_CRPR is 0)	Max(1,1,0)	1	Min (1,1,1,1) = 1	Urinary Track Infection Present with Possibility **1**
If	If	Max(1,1,0)	1		

Antecedent	**Rule applied**	**Min(Max)**	**Result of min(max)**	**Max (min) of all**	**Consequent**
(URANA_PusCells is Present OR UC_PathoGrowth is Absent OR CBC_CRPR is Positive)	(URANA_PusCells is 1 OR UC_PathoGrowth is 1 OR CBC_CRPR is 0)				
If (URANA_PusCells is Present OR UC_PathoGrowth is Present OR CBC_CRPR is Normal)	If (URANA_PusCells is 1 OR UC_PathoGrowth is 1 OR CBC_CRPR is 0)	Max(1,1,0)	1		
(URANA_PusCells is Present OR UC_PathoGrowth is Present OR CBC_CRPR is Positive)	If (URANA_PusCells is 1 OR UC_PathoGrowth is 1 OR CBC_CRPR is 0)	Max(1,1,0)	1		
If (USGTV_UT is Bulky AND USGPV_MyoMCyst is small)	If (USGTV_UT is 0 AND USGPV_MyoMCyst is 0)	Min(0,0)	0	Max(0,0, 0,0) = 0	Adenomyosis Present with Possibility **0**
If (USGTV_UT is Bulky AND USGPV_MyoMCyst is Medium)	If (USGTV_UT is 0 AND USGPV_MyoMCyst is 0)	Min(0,0)	0		
If (USGTV_UT is Normal AND USGPV_MyoMCyst is small)	If (USGTV_UT is 1 AND USGPV_MyoMCyst is 0)	Min(1,0)	0		
If (USGTV_UT is	If (USGTV_UT is 1	Min(1,0)	0		

Antecedent	**Rule applied**	**Min(Max)**	**Result of min(max)**	**Max (min) of all**	**Consequent**
Normal AND USGPV_MyoMCyst is Medium)	AND USGPV_MyoMCyst is 0)				
If (USGPV_Fibroid is Absent OR MRI_Fiborod is Absent)	If (USGPV_Fibroid is 1 OR MRI_Fiborod is 1)	Max(1, 1)	1	Min (1) =1	Uterine Fibroid **Absent** with Possibility **1**

Here, as Stage I gives multiple diseases as output. *History* parameter is not applicable for this patient so is directed to Stage III. In Stage III, the tests for *Urinary Track Infection, Uterine Fibroid* and *Adenomyosis* are carried out. The results are input to Stage III, respective rules are fired. *Uterine Fibroid* and *Adenomyosis* are ruled out to give the single disease diagnosis as *Urinary Track Infection*.

c. **Initial Screening – History parameter – Tests conducted:** There are some cases where the *History* parameter is applicable on the output of Stage I. This helps to rule out some of the diseases but still we cannot arrive at single disease diagnosis. So the output of Stage II is passed to Stage III which gives single disease diagnosis.

Initial Screening:

Input: Symptoms of patient

Process: max-min composition

Output: Multiple diseases diagnosed.

History Parameter:

Input: Multiple diseases diagnosed by Stage I + Value of History parameter

Process: Type 1 Fuzzy Inference System

Output: Multiple diseases diagnosed.

Tests Conducted:

Input: Multiple diseases diagnosed by Stage II + Values of results of Tests conducted

Process: Type 1 Fuzzy Inference System

Output: Single disease diagnosed.

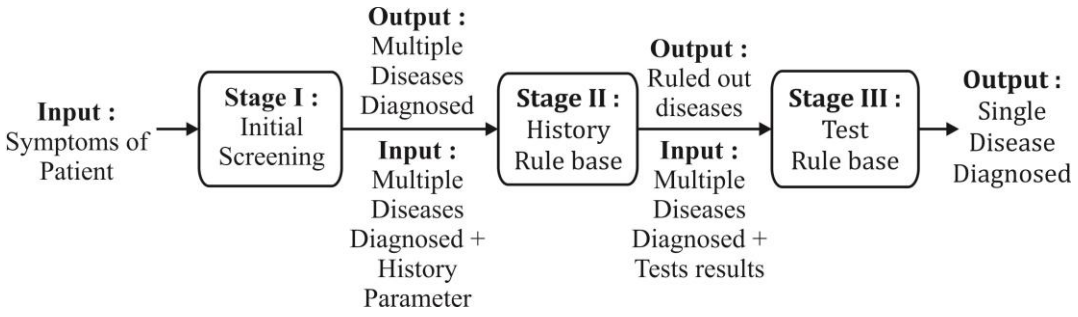


Figure 6.5.Serial System (Stage I – Stage II – Stage III)

Total number of patients diagnosed by this system: 5

The patients are: P_{129}, P_{79}, P_{153}, P_{191}, and P223.

Case Study:

Consider the Patient P_{223}. Stage I gives output as {*Endometriosis, Cervical Cancer (Stage I), Dysfunctional Uterine Bleeding (DUB), Uterine Fibroid, Adenomyosis, Pubertal menorrhagia*}

Considering the *Age* and *PMC_nature* of the patient, the output of Stage I is given to Stage II for *History* Parameter checking. The parameters applicable are as below:

Age = 30 (F = 1), *PMC_nature* = Painful (PF)

Table 6.19: Implementation of *History* Parameter Rules for patient P_{223}

Antecedent	**Rule applied**	**Min**	**Result of min**	**Max of all**	**Consequent**
If (PMC_Status is IRR AND Age is EF and PMC_nature = PF)	If (PMC_Status =1 AND Age =0 and PMC_nature = 1)	Min (1,0 1)	0	Max (0, 1)	Endometrios is or Fibroid present with possibility 1
If (PMC_Status is IRR AND Age is F and PMC_nature = PF)	If (PMC_Status =1 AND Age =1 and PMC_nature = 1)	Min (1,1 1)	1		

The diagnosis by Stage II is {Endometriosis, Uterine Fibroid}, which is not a single disease diagnosis yet. The inclusion of Stage II has ruled out the diseases {*Cervical*

Cancer (stage I), Dysfunctional Uterine Bleeding (DUB), Adenomyosis, Pubertal Menorrhagia} and thereby eliminated stress for the patient to undergo the unnecessary tests for the ruled out diseases.

The patient is asked to undergo Tests and is passed to Stage III for final diagnosis. Tests Suggested and test results received are as presented in Table 6.20 and Table 6.21 shows the implementation of rules for *Tests* conducted.

Table 6.20: Tests Suggested and results recorded for patient P_{223}

Disease Name	**Test Suggested**	**Test Results**
Endometriosis	Transvaginal USG Blueberry Cyst	Blueberry Cyst Present
Uterine Fibroid	USG Pelvis Fibroid	No Fibroid found

Table 6.21: Implementation of Tests conducted Rules for patient P_{65}

Antecedent	**Rule applied**	**Min(Max)**	**Result of min(max)**	**Max (min) of all**	**Consequent**
If (TVUSG_BBRCyst is Present OR PVLAP_BBR is Present OR PVLAP_PGLS is Present)	If (TVUSG_BBRCyst is 1 OR PVLAP_BBR is 0 OR PVLAP_PGLS is 0)	Max(1,0,0)	1	Min (1,1,1,1) =1	Endometriosis Present with Possibility **1**
If (TVUSG_BBRCyst is Present OR PVLAP_BBR is Present OR PVLAP_PGLS is Absent)	If (TVUSG_BBRCyst is 1 OR PVLAP_BBR is 0 OR PVLAP_PGLS is 1)	Max(1,0,1)	1		
If (TVUSG_BBRCyst	If (TVUSG_BBRCyst	Max(1,1,0)	1		

Antecedent	**Rule applied**	**Min(Max)**	**Result of min(max)**	**Max (min) of all**	**Consequent**
is Present OR PVLAP_BBR is Absent OR PVLAP_PGLS is Present)	is 1 OR PVLAP_BBR is 1 OR PVLAP_PGLS is 0)				
If (TVUSG_BBRCyst is Present OR PVLAP_BBR is Absent OR PVLAP_PGLS is Absent)	If (TVUSG_BBRCyst is 1 OR PVLAP_BBR is 1 OR PVLAP_PGLS is 1)	Max(1,1,1)	1		
If (USGPV_Fibroid is Absent OR MRI_Fiborod is Absent)	If (USGPV_Fibroid is 1 OR MRI_Fiborod is 1)	Max(1, 1)	1	Min (1) =1	Uterine Fibroid Absent with Possibility 1

The output by Stage III is '*Endometriosis* is present' thus eliminating *Uterine Fibroid*.

3. **Serial-Parallel Systems:** This system is a combination of two serial Systems viz. Initial screening – History parameter (section 2-a) and Initial Screening – Tests conducted (section 2-b). The output of stage I is given to either Stage II or Stage III to arrive at single disease diagnosis but never given to both the stages at the same time.

Total number of patients diagnosed by this system=

Number of patients diagnosed by Stage I + Number of patients diagnosed by Stage II

= 24 + 137 = 161

Using path I (Stage I → Stage II), the patients diagnosed are : P_{164}, P_{22}, P_{103}, P_{215}, P_{90}, $_{226}$, P_{20}, P_{93}, P_{154}, P_{192}, P_{199}, P_{225}, P_{52}, P_{69}, P_{218}, P_{187}, P_{54}, P_{65}, P_{138}, P_{132}, P_{137}, P_{202}, P_{14} and P_{200}.

Using path II (Stage I → Stage III), the patients diagnosed are : P_{29}, P_{41}, P_{44}, P_{115}, P_{119}, P_{37},P_{66}, P_{85}, P_{17}, P_{19}, P_{25}, P_{28}, P_{96}, P_{104}, P_{125}, P_{130}, P_{156}, P_{161}, P_{162}, P_{172}, P_{180}, P_{186}, P_{188}, P_{10}, P_{40}, P_{48}, P_{62}, P_{68}, P_{112}, P_{203}, P_3, P_8, P_{78}, P_{11}, P_{21}, P_{31}, P_{36}, P_{57}, P_{58}, P_{63}, P_{73}, P_{101}, P_{145}, P_{121}, P_{183}, P_{185}, P_{208}, P_{219}, P_{221}, P_{222}, P_{140}, P_{151}, P_{158}, P_{116}, P_{127}, P_{27}, P_{140}, P_{89}, P_{122}, P_{135}, P_{194}, P_{12}, P_{30}, P_{33}, P_{39}, P_{45}, P_{50}, P_{72}, P_{81}, P_{88}, P_{94}, P_{105}, P_{111}, P_{113}, P_{114}, P_{120}, P_{124}, P_{133}, P_{139}, P_{141}, P_{142}, P_{146}, P_{170}, P_{177}, P_{181}, P_{182}, P_{190}, P_{201}, P_{204}, P_{207}, P_{209}, P_{214}, P_{217},P_{38}, P_{46}, P_{49}, P_{55}, P_{91}, P_{118}, P_{150}, P_{152}, P_{171}, P_{174}, P_{212}, P_{213}, P_{224}, P_{215}, P_{197}, P_{75}, P_{108}, P_{134}, P_{167}, P_{206}, P_{216}, P_4, P_7, P_{15}, P_{32}, P_{43}, P_{47}, P_{53}, P_{59}, P_{61}, P_{86}, P_{95}, P_{97}, P_{98}, P_{99}, P_{131}, P_{147}, P_{169}, P_{173}, P_{176}, P_{184}, P_{195}, P_{210} and P_{151}.

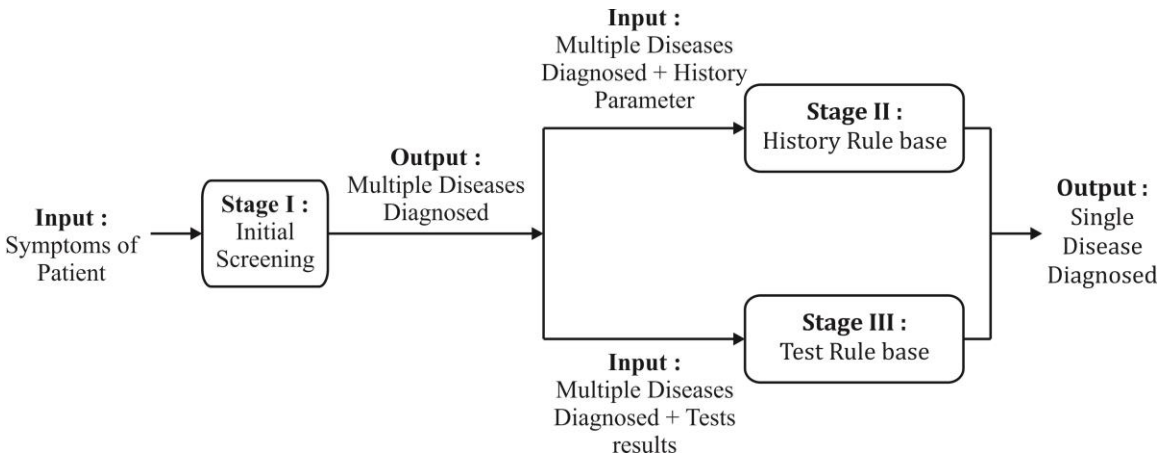


Figure 6.6. Serial-Parallel System

The serial-parallel system may not yield to final stage with correct output every time. As an example, if the patient is getting single disease output at Stage I itself then also this system has to follow either path1 or path 2, which is an additional burden on the model. Secondly, if the patient is passed from Stage I to Stage II for diagnosis and Stage II is not able to diagnose a single disease then the patient should be passed to Stage III. But in this system, there is no path which directs the patient to Stage III. The system directly expects the Single disease output after Stage II.

So, we can say that the developed model does not fit in the serial-parallel system, but is either a Singleton System or a Serial System.

6.6.2 Venn Diagram

From the output of 3-stage model, we can draw the concept diagram showing the relationship, interconnection and dependency among the defined three stages. The Stage I, Stage II and Stage III represent the Symptoms, *History* Parameter and results of *Tests* Conducted respectively.

The study is conducted on 226 patients who pass through different stages and in a way, receive confirmed single disease diagnosis or non-confirmed single disease diagnosis.

This divides the set X containing all 226 patients in two sets

A = {Patients who have confirmed single disease diagnosis}

B = {Patients who have for whom single disease diagnosis is not confirmed}

So $X = A \cup B$

Set A and Set B are further represented as

$A = A1 \cup A2 \cup A3 \cup A4$

$B = B1 \cup B2$

Where,

A1 = Patients received single disease diagnosis at Stage I

A2 = Patients diagnosed by Stage I, not received confirmed single disease diagnosis so are passed to Stage II.

$\therefore$ A2 = Stage I $\cap$ Stage II

A3 = Patients diagnosed by Stage I, not received confirmed single disease diagnosis so are passed to Stage II and are further passed to Stage III due to non-confirmed single disease diagnosis received at Stage II.

$\therefore$ A3 = Stage I $\cap$ Stage II $\cap$ Stage III

A4 = Patients diagnosed by Stage I, for whom Stage II is not applicable so are directly passed to Stage III.

$\therefore$ A4 = Stage I $\cap$ Stage III

Set B1 = Patients who are passed through Stage I, Stage II and Stage III and have received non-confirmed Single Disease Diagnosis.

$\therefore$ B1 = Stage I $\cap$ Stage II $\cap$ Stage III

B2 = Patients who are passed through Stage I and Stage III and have received non-confirmed Single Disease Diagnosis.

∴ B1 = Stage I ∩ Stage III

The Venn diagram for the above sets is as shown in figure 6.7.

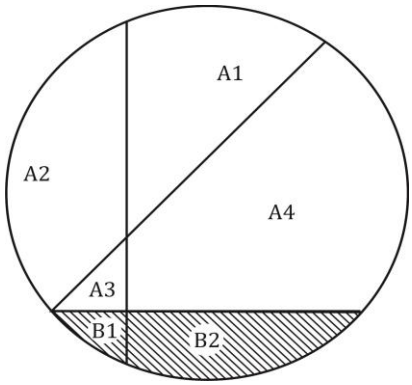


Figure 6.7 Venn diagram for output of Three Stage model

6.7 Classification of Patients: An Analysis

The second part the research study focuses on the classification of patients using various methods like fuzzy similarity measures, Gower's Coefficient and Fuzzy C-Means. This section analyses the results obtained using these classification methods.

6.7.1 Fuzzy Similarity Measures and Gower's Coefficient

The second part of the research relates to the application of fuzzy similarity measures method (Cosine Amplitude and Max-Min) and Gower's Coefficient method to classify patients which shows confirmation of classification of different patients after application of the three methods (Figure 6.8).Table 6.22 shows the result of three methods; Cosine Amplitude, Max-Min and Gower's Coefficient method, applied to all 226 patients and 123 symptoms (124 symptoms for Gower's Coefficient). The patients those are not listed in the Table 6.22 do not get classified into any group so are not listed. They are singleton sets.

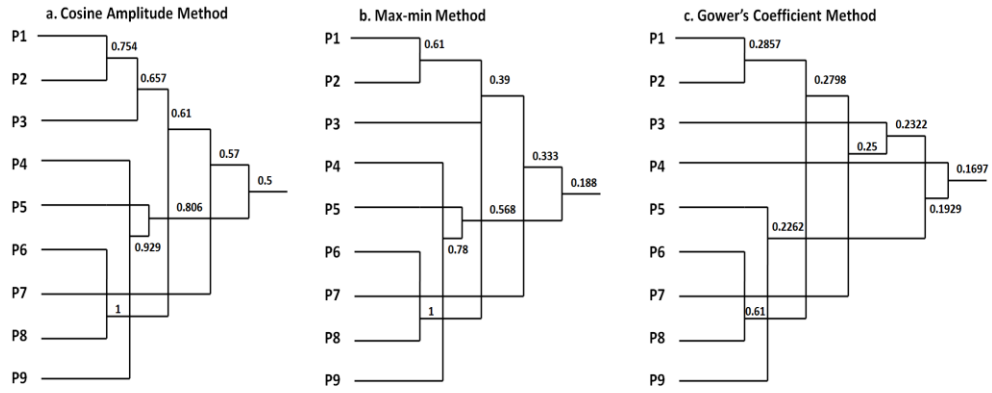


Figure 6.8: Classification of Patients: Classification diagram using Cosine Amplitude, Max-Min method and Gower's Coefficient method (Case Study: 9 patients, 9 symptoms)

Table 6.22: Classification of Patients: using Cosine Amplitude, Max-Min method, Gower's Coefficient method (226 Patients)

α-cut	**Cosine Amplitude Method**	**Max-Min Method**	**Gower's Coefficient Method**
α = 1	(157,198,220),(5,50),(1,42,144),(9,102),(19,162),(22,215,225),(28,44),(35,51,165),(60,89),(117,148,155),(119,172,222),(143,149),(189,205),(223,224)	(157,198,220),(5,50),(1,42,144),(9,102),(19,162),(22,215,225),(28,44),(35,151,165),(60,89),(117,148,155),(119,172,222),(143,149),(189,205),(223,224)	(198, 220)
α = 0.88	(35,151,165,97,159),(110,209),(190, 203,223,224,119,222,172),(130,186,188),(47,105),(3,10,45),(5,50,56),(19,125,162),(17,104,94),(18,160),(25,138),(1,42,144),(9,102),(22,215,225),(28,44),(57,198,220),(60,89),(117,148,155),(143,149),(189, 205)	(17,94,104),(25,138),(97,159),(18,160),(5,50),(9,102),(19,162),(22,215,225),(28,44),(35,151,165), (1,42,144),(28,43) (60,89),(117,148,155), (119,172,222),(143,149),(157,198,220),(189,205), (223, 224),	(148,155),(143,149),(19,162),(44,28),(215,225), (222,172), (5,50),(9,102),(157,198,220),(1,42), (151, 165),

The patients are classified into various groups for various α-cut values, which infer the possibility of their similarity:

- Patients P_{157}, P_{198} and P_{220} get classified into one group using fuzzy similarity measures methods with degree of confidence 1.This indicates that the symptoms for these three patients exactly match with each other.

- Patient P_{157} is not classified with P_{198} and P_{220} using Gower's Coefficient method. The measureable parameter 'Age' is used in this method which is not considered in other two fuzzy set theoretic based similarity measures. More importantly, partial belief is the strength of fuzzy set theory approaches while in Gower's Coefficient method; the symptoms described linguistically are in dichotomous terms (Yes/No). These could be the possible reasons why the output using statistical and fuzzy set theory methods are different. For example: Age of P_{57} is 30 years and that of P_{198} and P_{220} is 32 years so, P_{57} does not get classified in the group using Gower's Coefficient.
- Similar is the case for P_5 and P_{50} and other groups.
- The other α-cut value which matches all three methods is 0.88 which classifies some more patients in different groups. This indicates that the patients, who get classified at this cut-off value, also have same symptoms.
- The classification is based on the symptom of a patient, we decided the cut-off at degree of confidence value 1 (i.e. α-cut =1) so as to match the symptoms with high degree of confidence.

It is observed that the specific symptom occurs more frequently in many patients. Example for patients P_{157}, P_{198} symptoms is–'pain in abdomen'. This information can be helpful for health experts to find the cause of the disease related to these symptoms in specific area. We can infer that the symptoms of the patients classified into one group and found exactly same at α-cut level 1, indicate that the patients get classified correctly using the fuzzy similarity measures and two-valued binary logic based crisp similarity measure, Gower's Coefficient. In certain Gynaecological diseases, the diagnosis heavily depends upon the parameter 'Age'. For such diseases, the Gower's Coefficient method is more efficient.

6.7.2 Fuzzy Similarity Measures and Initial Screening Model

The first part of the case study, i.e. in initial screening part, Fuzzy Occurrence and Fuzzy Confirmability indication relations are processed using Equation 4.3. Table 6.23 shows the result of classification of all 226 patients at possibility value 1. The patients that are not shown in the Table 6.23 have not got classified yet in any class at defined possibility value 1.

Table 6.23: Patient classes using Cosine Amplitude and Max-Min method

(All 226 patients)

Cosine Amplitude Method	**Max-Min Method**
(1, 42, 144), (5, 50), (9, 102), (19, 162), (22, 215, 225), (28, 44), (35, 151,165), (57, 198, 220), (60, 89), (117, 148, 155), (119, 172, 222), (143, 149), (189, 205), (223, 224)	(5, 50), (9, 102), (19, 162), (22, 215, 225), (28,44), (35, 151, 165), (1, 42, 144), (28, 43) (60, 89), (117, 148, 155), (119, 172,222), (143, 149), (157, 198, 220), (189, 205), (223, 224)

Table 6.24: Analysis of Initial Screening model and Classification model

(Sample Display of patients)

Class	**Patient Id**	**Disease suffering from**
(P_1, P_{42}, P_{144})	P_1	*Uterine Prolapse* ,
	P_{42}	*Uterine Prolapse*
	P_{144}	*Uterine Prolapse*
(P_5, P_{50})	P_5	*PID*
	P_{50}	*PID*
(P_9,P_{102})	P_9	*Abortion*
	P_{102}	*Abortion*
(P_{19}, P_{162})	P_{19}	*Dysfunctional Uterine Bleeding (DUB) , Uterine Fibroid , Adenomyosis*
	P_{162}	*Dysfunctional Uterine Bleeding (DUB) , Uterine Fibroid , Adenomyosis*

Table 6.24 shows, patients P_1, P_{42} and P_{144} get classified into one class, patients P_5 and P_{50} in another class and so on. Table 6.24 shows the actual analysis of diagnosis of patients for some of the classes, which is exactly same, indicating that the classification of patients correctly matches with the diagnosis of the patient using Initial screening. It can be observed that the patients P_1, P_{42} and P_{144} get classified into one class using fuzzy

similarity measures techniques and the Initial Screening model gives the same diagnosis as '*Uterine Prolapse*'. Similar is the case with remaining patients.

6.7.3 Fuzzy C-Means

In this algorithm the membership is assigned to each data point corresponding to each cluster center. This assignment is based on distance between the cluster center and the data point. The membership towards the particular cluster center is increased if the data is closer to the cluster center. Clearly, summation of membership of each data point should be equal to one.

The FCM takes 6 iterations to obtain the final U* matrix as shown in Table 6.25.

Table 6.25: Final U* matrix (Sample data: 8 patients, 13 symptoms)

	P_1	**P_2**	**P_5**	**P_6**	**P_{16}**	**P_{18}**	**P_{24}**	**P_{71}**
C_1	**0.2012**	0.1998	0.1996	**0.2003**	**0.2007**	0.1998	**0.2008**	0.1997
C_2	0.1997	0.2	0.2001	0.1999	0.1998	**0.2001**	0.1998	0.2001
C_3	0.1995	0.2	**0.2005**	0.1998	0.1998	0.2	0.1996	**0.2004**
C_4	0.1996	**0.2001**	0.1999	0.1999	0.1997	**0.2001**	0.1997	0.1999
C_5	0.2	0.2	0.1999	0.2001	0.2	0.2	0.2001	0.1999

As the U* matrix gives the membership/belongingness of particular patient in each class, patient having maximum membership in particular class gets clustered in that class. The membership value indicates the belongingness with definite possibility value in the particular class. For example, for patient P_1, it belongs to all the five classes but the maximum membership is 0.2012 for class C_1, so it gets classified into class C_1. Similarly, patients P_4, P_5, P_7 get clustered in class C_1.

In this case, it is observed that the patients possessing similar symptoms get classified into one cluster. In most of the cases, it is seen that the symptoms possessed by patients lead to one disease so we claim that the clusters resemble the diseases.

Exceptionally, in some cases, the patient belongs to multiple clusters with same possibility value. Detailed analysis of such patient reveals a single disease which may manifest itself quite differently, depending on the patient, and with different intensities. A

single symptom may correspond to different diseases. On the other hand, several diseases present in a patient may interact and interfere with the usual description of any of the diseases.

E.g. Patient P_6 belongs to cluster C_2 and C_4 with possibility value. In our case, a patient has some symptoms which exactly match with the symptom set of two or more clusters so they belong to two or more clusters. More accurately, the clusters are formed based on the symptoms that a patient possesses which in many cases relates to specific disease also. Table 6.26 shows the clusters formed from Table 6.25.

Table 6.26: FCM result (8 patients, 13 symptoms)

Class	**Result of FCM**
C1	{ P1, P6, P16, P24}
C2	{P18}
C3	{ P5, P71}
C4	{P2, P18}
C5	{ϕ}

6.7.4 Fuzzy C-Mean, Cosine Amplitude method and Initial Screening Model

In our research study, the stage I (initial screening model) of diagnosis model uses fuzzy compositional rule of inference for the diagnosis, in which expert knowledge-base is used. *Disease x Symptom* relation is obtained from different experts for Occurrence and Confirmability values. The composition operator is used to find the relation between *Patient x Disease*. The result is obtained by max-min composition and this result is verified by experts' opinion. This gives more strength to the output of the model (Sardesai, Kharat, Deshpande & Sambarey, 2015). That is the reason, output of initial screening model is considered as reference point for the comparison of three methods. Table 6.27 shows the result of max-min composition (Initial Screening Stage: Stage I), Cosine Amplitude method and Fuzzy C-Means.

From table 6.27 below, it can be observed that clusters/classes obtained by using Cosine Amplitude method are closer to classes obtained from initial screening model as

compared to that of FCM. The result of Cosine Amplitude method gets improved further if we decrease the α-cut to next possibility value.

Table 6.27: Patient Classification comparison (8 patients, 13 symptoms)

Initial Screening Model	**Cosine Amplitude**	**FCM**
(P_1, P_{16}, P_{24}), **(P_5, P_{71})**, (P_6), (P_2), (P_{18})	(P_1, P_{16}), (P_2), **(P_5, P_{71})**, (P_{16}), (P_{18}), (P_{24})	(P_1, P_6, P_{16}, P_{24}), (P_{18}), **(P_5, P_{71})**, (P_2, P_{18}), (ϕ)

E.g. For α-cut 0.577, the classes obtained are (P_1, P_{16}, P_{24}), (P_2), (P_5, P_{71}), (P_6), (P_{18}) which match exactly with the classes obtained by initial screening model. On the contrary, FCM being unsupervised clustering method gives less performance.

From Table 6.27, it can be further observed that performance of Cosine Amplitude is better than that of FCM. Table 6.28 gives the comparison result for the three methods for all 65 patients which were obtained as single diagnosis during Initial Screenings Stage.

From the different values of α-cut Cosine Amplitude result is further improved with decreased possibility value. In case of FCM, the controlling factor is value of m` which we have chosen as 2 after varying it from 1.85 to 5. It is observed that best possible results are obtained for the value m` = 2.

It is observed that the classification of patients is best achieved by using max-min composition than Cosine Amplitude method and FCM due to following reasons:

- In max-min composition, experts' knowledge-base is used which gives strength and stability to the model. Cosine Amplitude method and FCM do not use knowledge-base.
- Max-min composition uses physical chain analogy in which the strength of all the symptoms severity governs the diagnosis process. No physical analogy is used in Cosine Amplitude method.
- Max-min composition is supervised learning method as it is under the control of expert's experience. Cosine Amplitude and FCM are unsupervised learning methods.
- The performance of FCM depends on weighing factor m`. The right value of m` should be chosen to suit the application area. Performance of max-min composition in

our research depends on the experts' knowledge-base. Performance of Cosine Amplitude depends on the α-cut / possibility value we choose.

In comparison with FCM, Cosine Amplitude gives better performance but the stability of the model is achieved using max-min composition. In other words, max-min composition is superior to other two methods.

Table 6.28: Patient Classification comparison (All 65 patients)

Result of Initial Screening Model	**Result of Cosine Amplitude**	**Result of FCM**
(P_1, P_{16}, P_{24}, P_{42}, P_{144}, P_{163}, P_{179}, P_{189}, P_{205}, P_{211}), (P_2, P_{13}), (P_5, P_{50}, P_{56}, P_{71}, P_{84}, P_{117}, P_{148}, P_{157}, P_{168}, P_{181}, P_{198}, P_{220}), (P_6, P_9, P_{35}, P_{43}, P_{92}, P_{97}, P_{102}, P_{110}, P_{149}, P_{165}, P_{193}), (P_{18}, P_{160}, P_{178}), (P_{23}), (P_{26}, P_{80}), (P_{67}), (P_{74}), (P_{76}), (P_{77}, P_{87}), (P_{83}), (P_{106}), (P_{107}, P_{126}), (P_{194})	(P_1, P_{42}, P_{144}),(P_5, P_{50}, P_{56}, P_{148}, P_{155}), (P_9, P_{102}), (P_{35}, P_{97}, P_{151}, P_{165}), (P_{143}, P_{149}), (P_{215}, P_{225}), (P_{18}, P_{160}), (P_{26}, P_{80}), (P_{178}, P_{179}, P_{181})	(P_1, P_9, P_{16}, P_{24}, P_{42}, P_{102}, P_{144}, P_{163}, P_{198}, P_{205}, P_{211}), (P_5, P_{16}, P_{50}, P_{56}, P_{71}, P_{117}, P_{148}, P_{155}, P_{194}), (P_6, P_9, P_{16}, P_{35}, P_{43}, P_{77}, P_{92}, P_{97}, P_{102}, P_{143}, P_{149}, P_{151}, P_{159}, P_{165}), (P_{18}, P_{102}, P_{134}, P_{160}), (P_{84}, P_{111}, P_{194}), (P_9, P_{102}), (P_9, P_{77}, P_{102}), (P_2, P_{13}, P_{22}, P_{23}, P_{26}, P_{67}, P_{76}, P_{80}, P_{83}, P_{107}, P_{110}, P_{111}, P_{126}, P_{128}, P_{135}, P_{157}, P_{168}, P_{175}, P_{178}, P_{179}, P_{179}, P_{181}, P_{189}, P_{193}, P_{194}, P_{204}, P_{215}, P_{220}, P_{225}), (P_{24}, P_{76}, P_{26}, P_{84}, P_{106}),

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Chapter 7

Concluding Remarks and Scope for Further Research

Dealing with the uncertainty has been one of the major objectives of scientific research. The success of probability theory has high visibility in achieving some of the objectives of decision making in a research. However, such successes mask a fundamental limitation; the inability to operate on what may be called perception based / imprecise or more concretely fuzzy information. This chapter presents a set of Concluding Remarks based on results and discussion of the case study as well as the Scope for Future Research.

7.1 Concluding Remarks

- The results obtained more or less conclusively demonstrate application of fuzzy set theoretic operations and Fuzzy Logic in the diagnosis of gynecological diseases. Therefore, it is likely that the ongoing dialogue for and against Fuzzy Set Theory (FST) by Professor Lotfi Zadeh has reached a steady state.
- The development of Medical Decision Support System (MDSS) addresses perception based diagnosis of patients for gynecological diseases. This method might be suitable for other MDSS as well, with suitable modifications.

- Many a times, domain experts do not agree with one another is the general comment made and at least by some of the critics. The FST based approach, coupled with a defined statistical method, should be used in final expert selection before embarking on application of fuzzy sets and Fuzzy Logic system.
- To initiate efforts on Fuzzy MDDS, initial screening method using fuzzy relational calculus should be used. This will help the patients, at least to some extent, to avoid all other investigating tests to be conducted directly at initial stage itself.
- The study reemphasises the need of computer aided clinical decision support to manage medical knowledge in MDSS and also states that the same can be used in other disease diagnoses as well.

7.2 Scope for Further Research

- In order to enhance credibility of the findings that have been reported in the present work, similar attempts can be made with respect to other women related diseases. Disease diagnosis-treatment-prognosis-diagnosis is a relatively new area for the application of soft computing techniques. Efforts should be made in this direction.
- Use of Type 1 Fuzzy Relational Calculus and Fuzzy Inference System (FIS) is appropriate, and the possibility of additional Bio-inspired computing methods, that include Type 2 Fuzzy Inference System (T2FIS), can be explored.
- It is generally expected that the applied nature of research, as reported in this Thesis, should ultimately result in the development of user friendly software. For the stress testing of the software, a need for many more case studies has been recognized. A β-version of the software is required to be generated and distributed among multiple gynaecologists for β-testing to record the real time diagnosis results. More refinements can be made in the software depending on the test results.

The exhaustive contents presented in this thesis end on a philosophical quote of Sir Winston Churchill *"This is not the end. Not even beginning of the RnD. May be, perhaps an end of the beginning!"*

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Annexure

Annexure 3.1

Other Gynaecological Disorders

1. Pelvic infections

The infection of one pelvic organ usually spreads to the other more frequently. There is direct communication of the peritoneal cavity to the exterior through the vagina. In spite of these, the frequency and intensity of pelvic infection is kept lowered by the defense mechanism. Some of the common pelvic infections are:

a. Pelvic Inflammatory Disease
b. Infections following delivery and abortion
c. Infections following Gynaecological procedures
d. Infections following IUD
e. Infections secondary to other infections - appendicitis

2. Sexually transmitted infections

Sexually transmitted infections include infections that are predominantly transmitted through sexual contact from an infected partner. Modes of transmission include sexual contact, placental (HIV, syphilis), by blood transfusion or infected needles (HIV, hepatitis B or syphilis) or by inoculation on to the birth canal (gonococcal, chlamydial or herpes). Gynaecological morbidities associated with sexually transmitted diseases (STDs) are high. Chronic pelvic infection, Pan, infertility, ectopic pregnancy, vulval and cervical neoplasia are long term squeal. Sexually transmitted diseases are as follows.

a. Diseases in which bacterial agent is involved:

Gonorrhoea, Non-gonococcal urethritis, Syphilis, Lymphogranuloma venereum, Chancroid, Granuloma inguinale, Non-specific Vaginitis, Mycoplasma infection

b. Diseases in which viral agent is involved:

AIDS, Genital herpes, Condyloma acuminate, Molluscum contagiosum, Viral hepatitis, CIN

c. **Diseases in which protozoal agent is involved:**
   Bacterial vaginosis (BV), Trichomonas vaginitis
d. **Diseases in which fungal agent is involved:**
   Monilial vaginitis
e. **Diseases in which ectoparasites agent is involved:**
   Cabbies, Pediculosis pubis

3. **Infections of individual pelvic organs**

The vulval and perineal skin is usually resistant to common infection. However, the defense is lost following constant irritation by the vaginal discharge or urinary incontinence. The vulval infection may be affected secondarily; the primary site may be elsewhere in the adjacent structures.

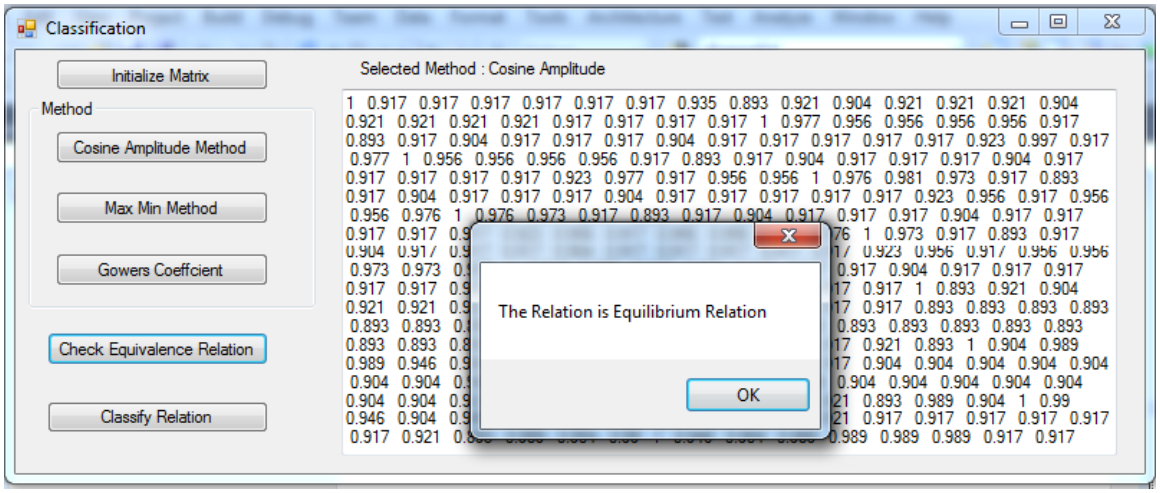
It is difficult to classify the vulval infection but the following aetiological classification is of help:

4. **Disorders of menstrual cycles** are categorized as Dysmenorrhoea, Primary Dysmenorrhoea (Spasmodic), Secondary Dysmenorrhoea (Congestive), Premenstrual Syndrome (PMS)
5. **Abnormal Menstrual Bleeding** is defined by Menorrhagia (Hypermenorrhoea), Polymenorrhoea (Epimenorrhoea), Metrorrhagia, Oligomenorrhoea and Dysfunctional Uterine Bleeding (DUB).
6. **Displacement of Uterus** is of two types Retroversion or Pelvic Organ Prolapse (POP) which included Vaginal Prolapse or Uterine Prolapse.
7. **Benign lesions of vulva and vagina** are Vulval Epithelial Disorders, Vulval Ulcers, Miscellaneous swellings, Vaginal Cysts, Vulval Pain Syndrome.
8. **Benign Lesions of the Cervix** is usually Cervical Ectopy (Erosion), Eversion (Ectropion), Cervical Tear, Cervical Cysts or Elongation of the Cervix.
9. **Benign Lesions of the Uterus** are of following types: Fibroid, body or corporeal fibroid, Cervical Fibroid, Fibroid Prolyp, Placental Prolyp, Malignant Prolyp
10. **Benign Lesions of the Ovary** are Ovarian Enlargement, Borderline Epithelial tumours of the ovary and Parovarian Cyst

11. **Endometriosis and Adenomyosis**
12. **Premalignant lesions** are of two types viz. Premalignant Vulval Lesions (Vulval intraepithelial neoplasia (VIN), Paget's disease, Lichen sclerosus, Squamous cell hyperplasia, Cindyloma accuminata) and Premalignant Endometrial Lesion
13. **Genital malignancy is of following types** Vulval Carcinoma, Vaginal Carcinoma, Carcinoma cervix, Endometrial carcinoma, Sarcoma Uterus, Sarcoma Botryoides (embryonal rhabdomyosarcoma), Carcinoma Fallopian Tube, Malignant Ovarian tumour (Ovarian Cancer)
14. **Urinary problems in Gynaecology** include Urinary Incontinence, Genuine Stress Incontinence (GSI), Urge Incontinence, Overactive Bladder, Painful Bladder Syndrome (PBS), Overflow Incontinence, Reflex Incontinence, Voiding Disorder, Urinary Track Infections, Dysuria, , Frequency of Urination, Urethral Caruncle
15. **Genital fistulae:** They are of 3 types: Genitourinary Fistula, Urethrovaginal Fistula, Rectovaginal Fistula
16. **Genital track injuries** are Old complete perineal tear (CPT), Coital injuries, Rape victims
17. **Amenorrhoea:** It is of the types Primary Amenorrhoea, Secondary Amenorrhoea, Polycystic Ovarian Syndrome (PCOS), Premature Ovarian Failure.
18. **Special disorders:** They include Abnormal Vaginal Discharge, Pruritus Vulve, Pelvic pain, Acute Pelvic pain, Chronic Pelvic pain, Trappedn (Residual) Ovarian Syndrome, Ovarian Remnant Syndrome, Postmenopausal Bleeding, Low Backache, Breast in Gynaecology, Brest Carcinoma, Psychosexual Problems, Vaginismus, Dyspareunia, Abdominopelvic lump, Adnexal Mass, Hirsutism, Galactorrhoea.

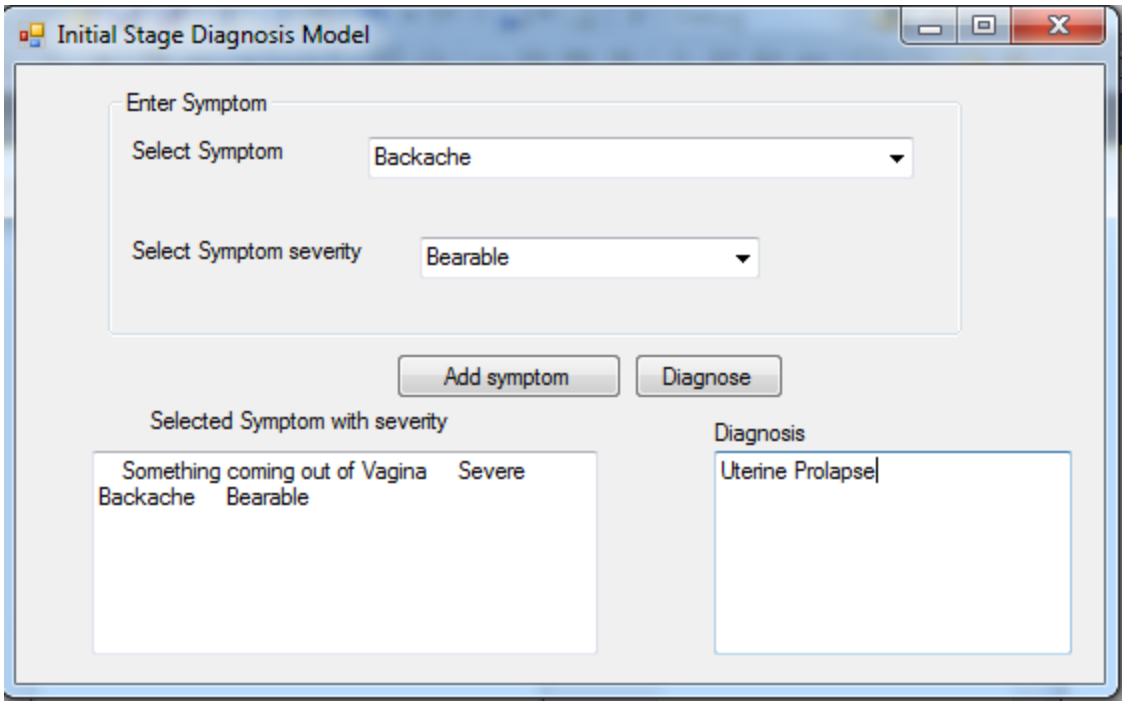
Annexure 5.1

Classification Program Screenshot



Annexure 5.2(a)

Initial Screening Stage Program Screenshot



Annexure 5.2(b)

Initial Screening Stage Program Code Snippet

Code snippet for the click of button diagnose is as presented below.

```
private void btn_diagnose_Click(object sender, EventArgs e)
{
string result, patient;
int index = cb_Patnames.SelectedIndex;
textBox1.Text = "";
patient = "P" + Convert.ToString(index + 1);
string memberval;
result = "";
double[,] ConfirmedDis = new double[100, 100];
int n = 0, m = 0, I, j;
double jmin = 0;
j = 0;
for (i = 0; i < SPCol; i++)
  for (j = 0; j < DSORow; j++)
  {
   if (index == i)
   {
   if (((Occur_PD_Rel[j, i] == 1) && (Confir_PD_Rel[j, i] == 1)))
   {
   ConfirmedDis[n, 0] = j;
   ConfirmedDis[n, 1] = Confir_PD_Rel[j, i];
   n++;
   }}}
  if (n != 0)
  {   for (int a = 0; a < n; a++)
  {
   memberval = ChkMemGrade(ConfirmedDis[a, 1]);
   result = result + DiseaseList[Convert.ToInt16(ConfirmedDis[a, 0])] + " , ";
  } }
 if (n == 0)
  result = "Disease Unspecific: cannot be diagnosed, requires further investigation";
  textBox1.Text = result;
}
```

Annexure 5.3

Disease names and symptoms related to Table 5.4 and 5.5

Diseases		Related Symptoms	
D1	Vaginal Yeast Infection	**S1**	Backache
D2	Ovarian Cyst	**S2**	Increased frequency of Micturition
D3	Uterine Fibroid	**S3**	Pain In Lower Abdomen
D4	Adenomyosis	**S4**	Painful Menstruation
D5	Dysfunctional Uterine Bleeding	**S5**	Irregular Menses
D6	Cervicitis	**S6**	Heavy Bleeding between periods
D7	Endometriosis	**S7**	Vaginal bleeding between periods
D8	Pelvic Inflammatory Disease	**S8**	passage of clots
D9	Leucorrhoea	**S9**	painful intercourse
		S10	Weakness
		S11	White Discharge
		S12	Vaginal itching
		S13	Burning Micturition
		S14	Abdominal swelling
		S15	Bowl Bladder Complaints
		S16	Abdominal Pain
		S17	No Menses

Annexure 5.4

Fuzzy Sets for *History* Paramerer

1. Fuzzy Set for 'Age'

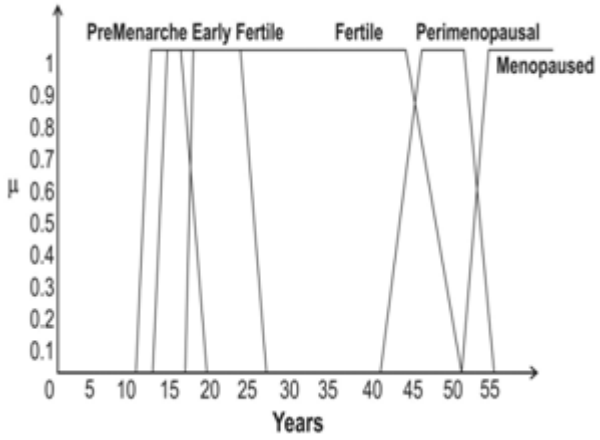


Figure A.1: Fuzzy Set for '*Age*'

Table A.1: Fuzzy Set for '*Age*'

	PreMenarche	Early Fertile	Fertile	Perimenopausal	Menopaused
α	10	13	16	40	50
β	12	15	18	42	52
γ	15	24	48	53	98
δ	17	26	50	55	100

2. Fuzzy Set for 'PMC_Flow'

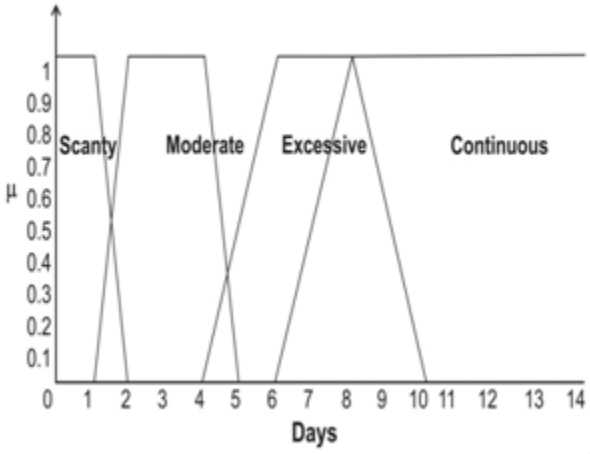


Figure A.2 Fuzzy Set for '*PMC_Flow*'

Table A.2: Fuzzy Set for Age

	Scanty	Moderate	Excessive	Continuous
α	0	1	4	6
β	0	2	5	7
γ	1	4	9	15
δ	2	5	10	20

3. Fuzzy Set for 'Marital Status

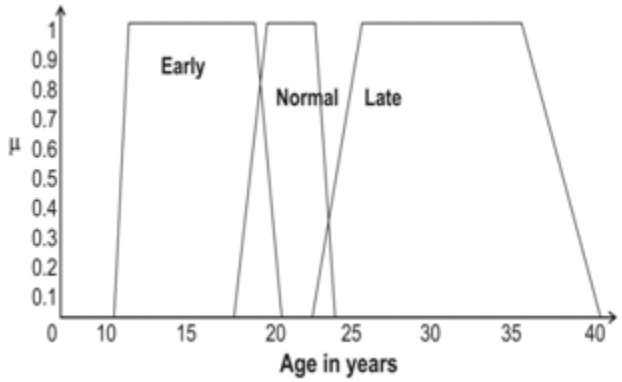


Figure A.3 Fuzzy Set for '*Marital Status*'

	Unmarried	Early	Normal	Late
α	0	10	18	23
β	0	11	19	24
γ	0	19	24	39
δ	0	20	25	40

4. Fuzzy Set for 'Parity'

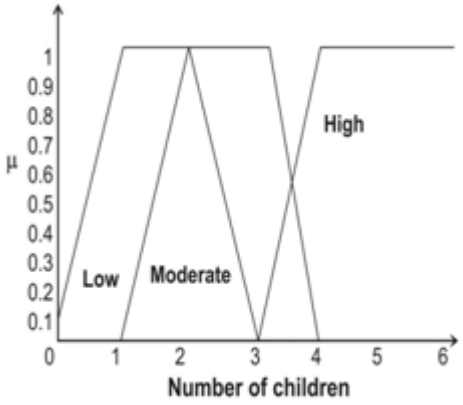


Figure A.4 Fuzzy Set for '*Parity*'

Table A.4: Fuzzy Set for '*Parity*'

	Nil	Low	Moderate	High
α	0	0	1	3
β	0	1	2	4
γ	0	2	3	8
δ	0	3	4	10

5. Fuzzy Set for LMP

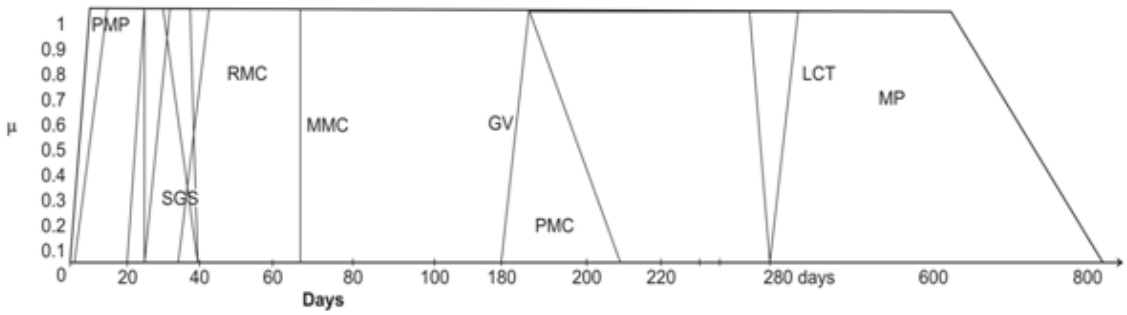


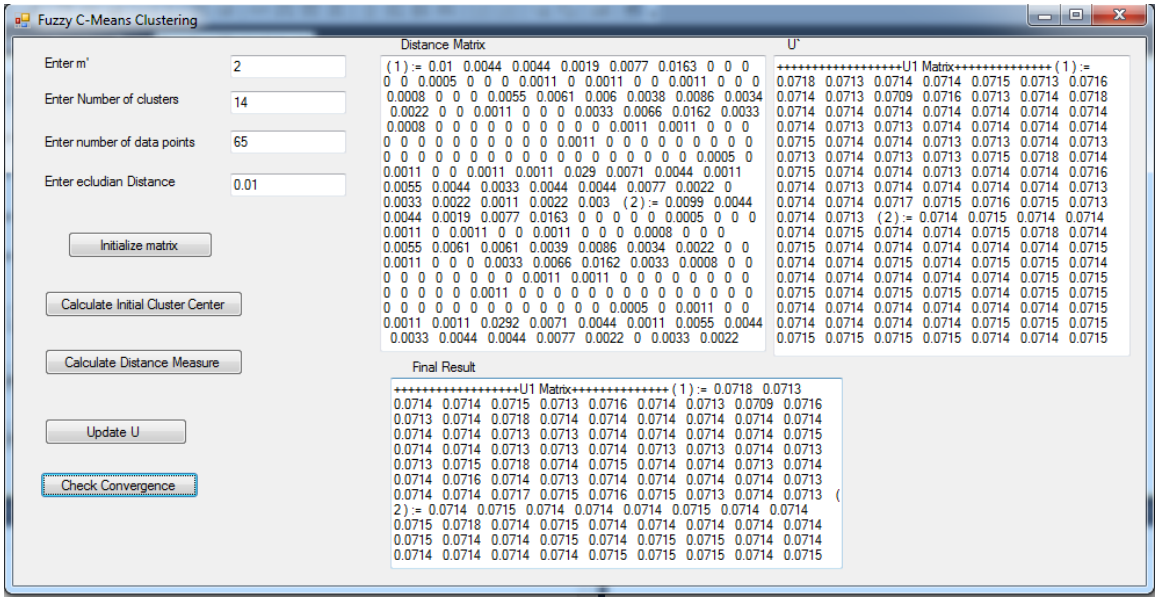
Figure A.5 Fuzzy Set for '*LMP*'

Table A.5: Fuzzy Set for '*LMP*'

	PMP	SGC	RMC	MMC	PMC	LCT	GV	MP
α	1	10	20	28	55	280	0	150
β	7	12	21	32	60	300	0	155
γ	22	18	28	70	200	500	270	800
δ	30	20	30	90	210	500	280	800

Annexure 5.5

Screen shot: Fuzzy C-Means Clustering



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