Republic of Iraq
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Department of Software

Naive Bayes and Fuzzy Logic to Toulmin's Argumentation model for Conflicted Medical Remedy Problems

A DISSERTATION
SUBMITTED TO THE COUNCIL OF THE COLLEGE OF INFORMATION TECHNOLOGY FOR POSTGRADUATE STUDIES OF UNIVERSITY OF BABYLON IN PARTIAL FULFILLMENT OF THE REQUIREMENTS FOR THE DEGREE OF DOCTOR OF PHILOSOPHY IN INFORMATION TECHNOLOGY-SOFTWARE

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بِسْمِ ٱللَّهِ ٱلرَّحْمَٰنِ ٱلرَّحِيمِ

وَ قُلْ رَبِّ زِدْنِي عِلْماً

صدق الله العلي العظيم

سورة طـه **الآية** ١١٤

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Dedication

In The Name of Allah Most Gracious Most Merciful

Praise be to God who gave me the strength, inspiration and courage to complete this work.

Gratitude is not enough...

to my father who

He always encouraged me to complete my studies and stood by me every moment of my life for his spirit of mercy and forgiveness.

For my mother without her prayers and satisfaction. I can't succeed. I pray to God to protect her.

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Abstract

Argumentation is a relatively new topic of artificial intelligence that has a wide range of applications in various fields like management, law, political science, medicine, mathematics, and others. The goal of using argumentation is to increase the computer's ability to prove and debate opinions, sentiments, and theorems. Argumentation is a term that is used almost every day, when there is in a conflict and disagreement among individuals. Argumentation can be useful in explaining a decision that has already been made.

Toulmin's classic model has been applied to solve conflict remedy problems, three methods have been used to improve the performance of Toulmin's argument model, namely Naive Bayes , Fuzzy Logic and then both of them are used together. The symptoms and medical history of the patient were used and remedy characteristics were extracted, then the weight of the supporting and contrarian argument was calculated for each remedy, so that the medical decision supported was calculated for each remedy.

For evaluating the performance of the proposed methods, the data sets were annotated by a team of human experts in medicine .The samples are distributed by model and show the patient characteristics such as symptoms, signs, patient history, and suggested remedies for these patients. Next, the team's opinions about the drugs for these patients were proposed. These suggested opinions are matched with the results of the proposed model using a confusion matrix. The confusion matrix is used in evaluating

the performance of a rating model through the calculation of performance metrics like recall , precision and F-measure .

Several experiments were conducted for two diseases hypertension and angina pectoris. The results obtained using a medical patients dataset for hypertension disease were 90% for F-measure using the classical Toulmin's model, 92% for F-measure using the improved Toulmin's model by naïve Bayes , 94% for F-measure using the improved Toulmin's model by fuzzy logic, 95% for F-measure using the improved Toulmin's model by naïve Bayes and fuzzy logic. The results obtained for angina pectoris disease were 92% for F-measure using the classical Toulmin's model, 95% for F-measure using Toulmin's model with naïve Bayes, 96% for F-measure using the improved Toulmin's model by fuzzy logic , and 98% for F-measure using Toulmin's model with naïve Bayes and fuzzy logic.

These results depict the outperformance of the proposed algorithms compared with the classical Toulmin's model. In addition, experimental results showed that the proposed methods for enhancing performance of Toulmin's model are effective .

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List of Abbreviations

Abbreviation	Description
AT	Argumentation Theory
ACTA	Argumentative Clinical Trial Analysis
ADM	Argumentation Decision Making
BDI	Belief-Desire-Intention
BV	Blurred Vision
CA	Computational Argumentation
CAPSULE	Computer Aided Prescribing Using Logic Engineering
CTM	Classical Toulmin’s Model
ECG	Electrocardiography
ESR	Erythrocyte Sedimentation Rate
FL	Fuzzy Logic
FP	False Positives
FMPD	Fuzzy Medical Patients Dataset
FN	False Negatives
FOL	First Order Logic
HBP	High Blood Pressure
HBR	Heart Boats Rate
LBP	Low Blood Pressure
MPD	Medical Patients Dataset
MF	Membership Function
MAP	Maximum A Posterior
NB	Naive Bayes
NSAIDS	Non-Steroidal Anti-Inflammatory Drugs
NVR	Number of Valid Rebuttal
NVW	Number of Valid Warrants

RE	Recall
RCT	Randomized Controlled Trial
SOB	Shortness of Breath
SWR	Sum Weight of Rebuttal
SWW	Sum Weight of Warrant
TAM	Toulmin’s Argumentation Model(TAM)
TM	Toulmin’s Model
TMA	Toulmin’s Model Argumentation
TMF	Toulmin’s Model with Fuzzy logic
TMFNB	Toulmin’s Model with Fuzzy logic and Naive Bayes
TMNB	Toulmin’s Model with Naive Bayes
TN	True Negatives
TP	True Positives
TMNB	Toulmin’s Model with Naive Bayes

CHAPTER ONE

GENERAL INTRODUCTION

1.1 Overview

Argumentation is a relatively novel area of Artificial Intelligence with numerous applications in disciplines such as law, management, mathematics, political science, and medicine[1].By leveraging argumentation, computers can be empowered to support and debate concepts, viewpoints, and opinions more effectively. This cutting-edge technology has the potential to revolutionize the way we approach problem-solving in these fields, allowing us to explore new possibilities and uncover innovative solutions[2].

Argumentation is a concept that is encountered in everyday life, often in the form of debates and disagreements between individuals. This has led to a long history of argumentation, with the study of the form of arguments by various scholars giving rise to the theory of rhetoric and argumentation [3]. Additionally, similar models have been used to address problems with information representation, judicial logic, and negotiation.

Argumentation is the process of demonstrating or refuting a claim, and is used to establish facts, introduce new ideas, or combat misconceptions in the minds of others. It is a specific problem that results from thinking [4,5].

To facilitate discussions of problem solutions in a variety of disciplines, scholars have suggested a wide variety of reasoning models. Argument mining is the process of identifying argumentative elements in documents written in common language [6]. This helps writers craft convincing arguments and viewers organize their ideas. The claim, statement, and memoranda fundamental elements described in Toulmin's

(1958) Argument Model are frequently used to build arguments. Ultimately, understanding the elements of an argument can help individuals make informed decisions and come to a consensus[7].

The study of argumentation theory (AT) focuses on how premises can, regardless of whether they have been chosen, lead to conclusions through logical reasoning. AT examines logic, reasoning, and formal laws in both natural and man-made settings. Argumentation involves negotiation and discussion, both of which are essential components of the collaborative decision-making process[8].

In artificial intelligence and related fields, a discussion framework is a method for addressing contested information and deriving inferences from it using formal reasoning. A collection of theory defenses constitutes the basic knowledge, and a collection of reasons can be encoded by using binary communication to avoid conflicts between the arguments[9].

The subfield of philosophical logic known as AT has recently gained significant attention in the field of logic-based artificial intelligence. Dialectic theory has become increasingly important with the development of formal models that resemble human thought[10].

According to argumentative theory, a choice must be made regarding which reasons are acceptable given a collection of arguments, some of which may be in opposition to others. To determine whether an argument is acceptable, it is not enough to simply consider its obstacles; one must also consider whether the opportunity seekers are at odds with one another. Argumentation can be helpful in justifying a choice that has already been made[11].

Depending on the decision criteria encoded, a decision-making model can provide an ordering on a collection of choices that may be complete or partial. This research offers a pro and con strategy for premises, which reflect patient complaints and drug use, and conclusions (claims), which are represented by suggested drugs[12].

Stephen Toulmin's method of argumentation is a useful tool for interpreting reasoning. His structural model calls for the identification and separation of the different elements of reasoning into a recognizable order and structure, allowing for a thorough examination of the argumentation. To better understand how this model is used in medicine, it is important to understand the components of the model and how they are connected.

In order to persuade others of the truth of an argument, Stephen Toulmin's method of argumentation requires the use of rational reasoning. In an essay, the author uses the claim of the argument to persuade the reader to agree or deny the claim, because condition, justifications, agreements, endorsements, refutations, and qualifications[13]. This entails using Toulmin's justification, which allows for argumentation across premises, proving opposing arguments and determining the strength of the proof to decide the victor.

Stephen Toulmin's model of argumentation was introduced as an alternative to the traditional model, with the main purpose of analyzing the structure of argumentation. This model consists of six components when constructing the argumentation: data, which are facts and evidence used to prove an argument; warrants, which are general statements that link the claim and the data; qualifiers, which are words that show the strength of the argumentation; rebuttals, which are counter-arguments when the general argument is not true; backing, which are statements used to support the argument and claims ,which are represent conclusions of argumentation[14] .

In this dissertation, the Toulmin Argument Model (TAM) will be employed to evaluate the pros and cons of a recommended medicine for patients, and based on the strength of the evidence, patients will be able to make an informed decision about whether or not to take the medicine. Finally, fuzzy logic and the Naive Bayes method will be combined with the Toulmin model to provide a more reliable medical recommendation for suggested drugs. To maximize the performance of the Toulmin model, fuzzy logic will be used first, followed by the Naive Bayes method as a qualifier.

1.2 Related Works

Several works focus on the frameworks of reasoning, utilizing Toulmin's model of argumentation to draw conclusions from conflicted problem in different fields and others focus some works in using Toulmin's model in medical domain .

1.2.1 Preview Works of Toulmin's Model in the Conflicting Problem

Stephan Toulmin's argumentative strategy provides a useful framework to persuade others of the validity of a point in a debate. His model uses clauses, reasons, justifications, recommendations, refutations, and qualifiers to challenge or support the argument through premises, allowing the author to convince the audience to accept or reject the argument through claims [15]. These often clash with the locations of attacks and the support structures, and the credibility of the proof will ultimately decide the winner. Toulmin's model has a logical framework that makes it invaluable for resolving conflicts and issues.

Toulmin's approach is employed in a number of contexts to resolve disputes. It is used in the creation of academic papers in the area of education, illustrating the fundamental steps in article writing (facts, conclusion) [16]. If used as a legal interpreter, the Toulmin model could help to clear up a multitude of complex issues. It has also been applied in medicine in a number of contexts, including the development of clinical and healthcare standards and the resolution of clinical conflict for patients based on their desires and conditions. The conflict and problem-solving paradigm proposed by Toulmin is used in the subsequent parts of earlier research [17], making it a powerful tool for resolving disputes.

Kristijonas et al.[17] developed a novel logic formalism to reason with conflicting clinical standards, patient preferences, and personal data. This formalism combined rational decisions based on goals and hypotheses, with the aim of achieving the general objective of patient well-being. To settle conflicts between suggestions, the patient's preferences and conditions were taken into account, and patient-centered objectives were emphasized to produce non-conflicting results. Furthermore, the authors advocated elevating objectives in terms of tastes.

Paul Reisert et al.[18]further explored the application and format of the Toulmin(TM) paradigm for policy talks. This paradigm can be used to address regular conflicts, and a computer model was developed to autonomously assemble Toulmin's case from the internet. The semantic connection between phrases was used to determine which aspect of outsourcing Toulmin instantiation is the most difficult [18].

Cynthia R. Collins [19] proposed that a convincing case or claim can be evaluated based on the premises that support it and the quality of the evidence basis. To this end, they employed Toulmin's model of reasoning to develop analytical answers to complex issues, providing researchers with a practical, hands-on learning experience in understanding the scope and difficulties of constructing clinical cases [19].

Gabriel Vagner et al.[20],sought to provide elements that bolster belief reasoning by presenting a case based on the BDI (belief-desire-intention) proxies inference model. Utilizing Toulmin's reasoning model, they demonstrated argument development based on the BDI agents inference structure, which can be used by the agent to form new opinions based on fresh information and to support those beliefs .This approach allows for the assignment of weight to arguments, making verification easier. This method can be applied to a variety of fields as it enables the implementation of numerous qualified functions. Utilizing the generated approach has the benefit of enabling standard case analysis and impartial evaluation of each component of the framework [20].

Hong and Abdul Talib.[21] recommended Toulmin's reasoning model as a way to enhance scientific discourse in chemistry instruction. Utilizing Toulmin's model is open to support development to get around its restrictions based on the structure of its implementation in scientific education and the nature of chemistry [21].

Admoko et al.[22],evaluated the accuracy of the information, employed Toulmin's reasoning framework, and identified an infodemic in the COVID-19 pandemic era. They used alternative methods to gain a better understanding of the situation. This pattern of argumentation identified three fundamental components as well as three additional components of the field of argumentation . Table 1.1 lists the sample works that addressed conflicting issues using Toulmin's model reasoning.

Table 1.1 Preview Works of Toulmin's Model in Conflicting Problems

Reference & year	Approach	Advantages	Limitations
Paul Reisert Et al 2015	They employed Toulmin's model to analyze political discussions, and developed an algorithm for automating the construction process..	It can be employed in everyday conflicts that are pertinent to a particular region.	Semantic connections between argumentative statements
Cynthia R Collins 2016	They selected the beginning of an insightful study issue statement using Toulmin's logical argument model as a guide. The Toulmin type was utilized to assess complex or pressing issues and devise solutions.	It facilitates the utilization of logical instruments to cultivate interdisciplinary expertise in nursing and the health sciences to address a variety of issues.	Determine the argument's reach and the potential effect of rebuttals.
Vagner Gabriel Et al 2018	They explore how reasoning is generated using Toulmin's model for argument formation, which is based on the inference structure of BDI agents.	It facilitates a granular analysis of an argument, examining each component of the structure independently.	It must calculate the weights of each opinion.
Hong & Abdul Talib, 2018	They conducted an analysis to identify the rhetorical and language patterns present in the students' writings using	They developed Toulmin's model argumentation.	It cannot be used in the rebuttal stage.

	Toulmin's model.		
Kristijonas et al 2019	a new organized logic formalism for debating opposing clinical recommendations, personal opinions, and patient-specific information was suggested.	Clinicians employ argumentation to resolve conflicts in clinical guidelines.	
Admoko et al 2021	By utilizing the Toulmin's reasoning pattern to evaluate false information, they were able to identify the infodemic that has been rampant during the COVID-19 pandemic.	They offered a different method for identifying and judging the reliability of material.	It necessitates three additional components from a related field of discourse.

1.2.2 Preview Works of Toulmin’s Model in the Medicine

There are numerous works that deduce medical knowledge using argumentation, as well as numerous resources to support their theories. Several works focus on the frameworks of reasoning, utilizing Toulmin's model of argumentation to draw conclusions from medical knowledge. This model provides a comprehensive structure for analyzing and evaluating arguments, allowing for a more thorough understanding of the evidence and its implications.

Francisco and Elizabeth.[23] make a concerted effort to provide components for the study and evaluation of the chosen methods, as well as their contribution to the development of argumentative skills that enhance the potential for interaction between the participants. Their research serves as a primes example of how patients, doctors, and healthcare staff can effectively communicate. Theory of Argumentation and medical decision making is used to assess the dependability of clinical arguments, and is a pioneering implementation of argument theory in the medical field [23].

Wilk et al.[24],offer guidelines for practical application in their publication, taking into account the needs of providing recommendations, both the patient and their individual medical circumstances. They provided patient conditions and opinions, which were then converted into first order logic (FOL) principles using FOL operators.

Gupta et al.[25] employed dependency and grammatical form parsers to extract comparative forms from biological literature. To evaluate the quantity of contentious data in their dataset, they developed syntax-based tree kernels to support their decision. Randomized controlled trials (RCTs) are a popular method of assembling data to back clinical judgments, with the results typically ranging from 0 to 1, with 1 indicating readily interpretable arguments and 0 otherwise [25].

Tobias Mayer et al. [26], further advanced this research by creating a novel annotated collection focused on four diseases—diabetes, glaucoma, hypertension, and hepatitis B—to assess the adaptability of the methods to different medical specialties. Their research might be the first to autonomously extract claims and supporting data from clinical studies using reasoning tools [26], thus providing a more efficient and reliable way to derive dialectical information from clinical data.

Computational Arguments (CA), a logic-based technique that offers a systematic approach to reasoning with evidence by demonstrating assertions for and against specific findings, were utilized by Kokciyan et al.

[27]to illustrate how information about patients and their various preferences is gathered. They proposed a design for the CONSULT system, which utilizes principles and facts to construct logical arguments that are then examined to resolve conflicts between various therapy choices and patient/physician preferences [27].

Tobias Mayer et al.[28],presented the Controversial Clinical Trials Analysis (ACTA), an instrument designed to assist doctors in the study of clinical trials. ACTA analyzes clinical trial summary textual evaluations submitted by users, pinpointing the connections between various argumentative elements. This research provides a first-order logic technique for the automatic analysis of clinical trial papers from an argumentation standpoint [28].

Tobias Mayer et al[29]. proposed a comprehensive argument structure that enabled the identification of the arguments evidence and claims as well as the prediction of the relationship—whether it was an attack or a support—between the two. By labeling 500 RCT papers from the MEDLINE database, they also compiled a collection containing information on diabetes, glaucoma, hepatitis, and other diseases, achieving a global F1-measure of 0.68.

The most closet work of proposed study ,which was by Kokciyan for the CONSULT system. These efforts of related works are summarized in table 1.2.

Table 1.2. Previous Works of Toulmin's Model in the Medicine

Reference &year	Approach	Advantages	Limitations
Francisco and Elizabeth 2015	They serve as a prime example of how medical staff, patients, and physicians effectively collaborate and communicate.	Utilizing Toulmin's paradigm, they discovered a novel application in the area of medicine.	
S. Gupta et al. 2017	They used dependency and syntactic form parsers to accomplish their objective of obtaining a comparative form for tree kernel-based biological texts.	Arguments are expressed on a scale from 0 to 1, with 1 indicating a clearly understandable input.	Every decision in the dataset must be supported, which takes a lot of effort to analyze.
Wilk et al. 2017	They proposed a therapeutic strategy based on established guidelines. First-order logic principles were employed, and a graph was then utilized to generate recommendations.	It is a cutting-edge technique that draws on patient choices.	Due to the utilization of the graph, the symbolic representatio n of FOLs (First-Order Logic) restrictions prevents any non-

			monotonic modifications.
Kokciyan et al 2018	In order to express recommendations clearly and precisely using first-order logic, argumentation is employed to reason with patient preferences.	Inconsistencies between treatment choices and patient desires can be resolved by carefully analyzing the arguments presented.	The reasons for our conclusions have been gathered from a variety of sources.
Tobias Mayer et al. 2018	They proposed utilizing an automated approach to extract persuasive evidence from clinical data.	New automated techniques for extracting claims and associated data from clinical studies have revolutionized the way research is conducted.	There is a scarcity of information regarding illnesses in the collection.
Tobias Mayer et al. 2019	To assist physicians in clinical trial analysis, researchers have unveiled the Argumentation Clinical Trial Analysis (ACTA) instrument.	They created instruments to help doctors perform study for clinical trials.	They discovered the connections between the various reasoning elements.
Tobi Mayer et al 2020	They predicted the correlation between	They made choices based on the chance	Finding the connections

	aggression and assistance and proposed a structure for classifying argumentative components into assertions and evidence.	theory.	between arguing elements is challenging.

1.3 Problem Statement

- As the thousands of lives lost worldwide due to medication errors and adverse effects of medications, medication conflict issues are among the most challenging in the medical field[30]. For example, Americans take more than 34 billion ibuprofen pills every day, thought to be safe non-steroidal anti-inflammatory medicines (NSAIDS) such as Paracetamol, aspirin, and ibuprofen. However, these medications are a major contributor to renal disease and are responsible for more than 200,000 cases of gastrointestinal bleeding. In adolescents, they can lead to Reyes syndrome, toxic migraines, and stomach ulcers.
- The elderly are particularly vulnerable to adverse drug reactions, as they are more likely to have multiple pre-existing medical conditions and impaired liver and renal function, which can affect drug metabolism and elimination [31,32]. On average, elderly citizens in the United States spend over $3 billion annually on prescription drugs, with an average of 13 prescriptions written for each patient each year.
- A subset of philosophical logic known as Argumentation Theory (AT) has evolved far beyond its original purpose, becoming a major area of research for logic-based Artificial Intelligence (AI). Argumentation

theory has become increasingly important with the development of formal models that emulate human-like reasoning [1,4].

- In this research, premises - represented by a patient's symptoms and medical history and conclusions (represented by suggested medications) are inferred using an argumentative inference structure. The strength of the evidence will be used to decide the victor of Stephen Toulmin's alternative argumentation form, which is used to validate an argument through the evidence that is currently available or to disprove an argument's opposition through the premises. As Toulmin's model has a logical structure for this purpose, it will be employed to resolve conflicts [15].

1.4 Study Aims

1- Build efficient system of argumentation .

2- Solve the remedy conflict problems of patients.

3- Build an advanced system to help doctors of diagnosing which is the best treatment of patients based on many features of drugs and the patients.

4- Build an advanced medical system in the supported decision-making process, which based on size of the support and the attack to make this decision.

1.5 Motivations

This work is motivated by the need to :

- Support the medicine domain to robust systems for making supported medical decisions .

- Advance systems that use a tool to help doctors of choosing the optimal treatment of the patients focuses on patients history .
- Improveperformance of Toulmin’s argumentation model .

1.6 Contributions

The purpose of this dissertation is to contribute knowledge in the filed through the following:

1- Using the Toulmin’s model argumentation to solve conflicting problems related to remedies.

2- Using Naïve Bayes as qualifier in Toulmin's argumentation model to improve the performance of this model .

3- Using fuzzy logic approach in Toulmin's argumentation model to improve the performance of this model .

4- Using fuzzy logic approach with Naïve Bayes technique together to improve the performance of the Toulmin’s model argumentation.

5- Building a new medical datasets from Iraqi hospitals and creating labels of it from human experts for evaluation.

1.7 The limitations

There are many limitations faced this study. The can by summarized by the nations of :

1-Obtaining the optimal medical dataset, which is considered one of the biggest challenges in this field.

٢- Labeling a dataset from human experts in the field of medicine is a difficult task that takes a long time, which is needed in evaluating the results of the proposed system.

1.8 Dissertation Structure

The first chapter , includes the introduction ,related works, problem statement , study objectives ,motivations ,contribution , limitations and structure of the dissertation. The rest of this dissertation is:

-Chapter Two: This chapter provides the introduction of the argumentation theory and it applications . It also provides the introduction of the Toulmin's argumentation model , the focus is on using this model in resolving the conflict problems in the medicine domain. Then, the chapter gives brief coverage of naïve Bayes technique especially the way of using this algorithm for improving the Toulmin's model argumentation. The fuzzy logic technique is also presented in details in addition to the evaluation metrics used in the proposed system.

-Chapter Three: It focuses on the proposed system design in details and the algorithms used in the system.

-Chapter Four: It discusses the experimental results of the proposed system in details.

-Chapter Five: It presents discusses the conclusions and the suggested future works.

CHAPTER TWO

THEORETICAL FOUNDATION

2.1 Introduction

The intention of this chapter intends to provide an introduction to argumentation theory. Argumentation theory and many methods of argumentation support and argumentation attack are mentioned in details . Toulmin’s model argumentation will be discuss in details . Also, we will cover Naïve Bayes theory and fuzzy logic technique that are used to improve the performance of the Toulmin’s model argumentation. Lastly, presented the evaluation metrics used to evaluate the performance of the suggested model will be presented.

2.2 Argumentation Theory

Argumentation theory (AT), or argumentation, is the interdisciplinary study of how logical reasoning can lead to conclusions; data based on premises, whether they have been voted on or not. They include civil debate, discourse, and persuasion as arts and sciences[33]. It examines reasoning, logic, and procedural rules in both natural and artificial environments. Argumentation entails deliberation and bargaining, both of which are central to the rule of collaborative decision-making. An argumentation framework is a mechanism for dealing with disputed material and drawing conclusions from it using formal arguments in artificial intelligence and related fields[٨,34].

Input-level information in the abstract discussion method is a set of abstract arguments. It can be represented by applying binary connections to a set of arguments, since conflicts between arguments can be avoided. The attack relation can be represented by arrows, and the argument framework can be represented graphically as arguments as node[34,4]. Several modifications have been discovered in Dung's framework, such as logic-based discussion methods and value-based discussion methods.

Controversy is a sub-branch of philosophical logic that, outside of its primary context, has grown to become a major topic of logic-based artificial intelligence in the last decade [35]. Due to the development of formal models, which are represented by human-like thinking, dialectic theory has gained importance over time.

Abstract argumentation methods are shown to be useful in modeling and examining defensible reasoning processes [3,36]. Argumentation begins with the use of a knowledge base and the formalization of arguments. The second level entails explaining several defeat relationships. Argument and defeat relationships are grouped under an argumentation for evaluation. The use of acceptance semantics for computing is a step after defining the state of justification and rational acceptance of it [37].

Argumentation theory states that for given a set of arguments, some of which are antagonistic to others, a decision must be made as to which arguments are acceptable. It is not sufficient to look at the argument's detractors to assess its acceptability status. It is also necessary to determine whether the opportunists are opposed to each other [38]. The discussion consists of one or more premises to justify the conclusion as shown in Figure 2.1.

$$\begin{array}{l} \textit{Premise } 1 \\ \textit{Premise } 2 \\ \quad\vdots \\ \textit{Premise } \mathrm{n} \\ \hline \therefore \textit{Conclusion} \end{array}$$

OR

$$\textit{Premise } 1, \textit{Premise } 2, \ldots, \textit{Premise } 2 \mapsto \textit{Conclusion}$$

$$P_1, P_2, \ldots, P_n \Rightarrow C$$

Fig 2.1 The Argumentation Components

Remember that an argument consists of "a set of statements that attempt to justify a claim by supporting it with reasons, or by defending it from things, or both". Depending on what is considered an objection to a claim, the argument defined may thus include description[39]. Here's why If the 'objection' to a claim is merely a request for its justification, or an express doubt about it or its disapproval of it, is not accompanied by any reason, then the defense of the claim against such objections consists simply of trying to justify the claim by supporting it with reasons.

This is a ground level argument. However, if the "objection" is an argument against the claim, then the defense of the claim involves in attempt to justify the rejection of that argument by supporting the rejection with reasons [40]. An argument is a way of thinking. It consists of various statements or propositions (logicians call them premises or reasons) from which we draw some statement or conclusion.

They are supported and/or justified by propositions that lead us to something new, or another statement or outcome stemming from our discussion process[41]. In other words, an argument is a continuum of statements or reasons intended to establish a situation that leads to another statement as a conclusion. An argument is a vehicle for our medical reasoning.

An argumentation is itself is a discussion between two or more people in which at least one person presents an argument[42]. This means submitting proposals by one or more proponents and merging them to arrive at a mutually acceptable solution.

In this light, the physician's discussion with his patient(s), the exchange of ideas between physicians, the research and publication of results, and the proposal of decisions in the field of medical care and prevention are part of the broader field of medical arguments [23]. For the best results and the maximum benefit for patients, we want our argument to be as flawless as possible: medicine based on flawless arguments[43].

An argument falls within the realm of reasoning, that is, as a tool of forming inferences, judgments, or conclusions from facts or premises. It is a systematic use or presentation of arguments. Proper arguing with ourselves and with other interested parties is one important way to deal with a particular health problem, disease, medical care, and medical error too[1,44].

Argumentation can also be seen as a study of the principles by which beliefs and actions are evaluated and related to each other. It enables us to discover beliefs and actions that are reasonable in any social context and which are concerned with the selection and organization of ideas to justify certain situations[6,13].

2.2.1 Argumentation Basics

In its simplest form, an argument consists of two assumptions: a premise and a conclusion supported by that premises as the structure is shown in figure 2.2a. The conclusion of the argument is supported by several premises that can only be expressed as a continuum structure if taken collectively, according to Freeman's terms. None of the relevant buildings premises can sustain the conclusion on their own as shown in the diagram. The linked support is shown in figure 2.2b through the connection of the buildings before they are attached to the score.

An argumentation is a structure that occurs when a number of arguments are linked to one another and form a nation of greater complexity. The manner in which arguments related to larger complexes can be described as attacking or supporting arguments and circle represent support and square represent the attack[42]. Each of them can be described as follows:

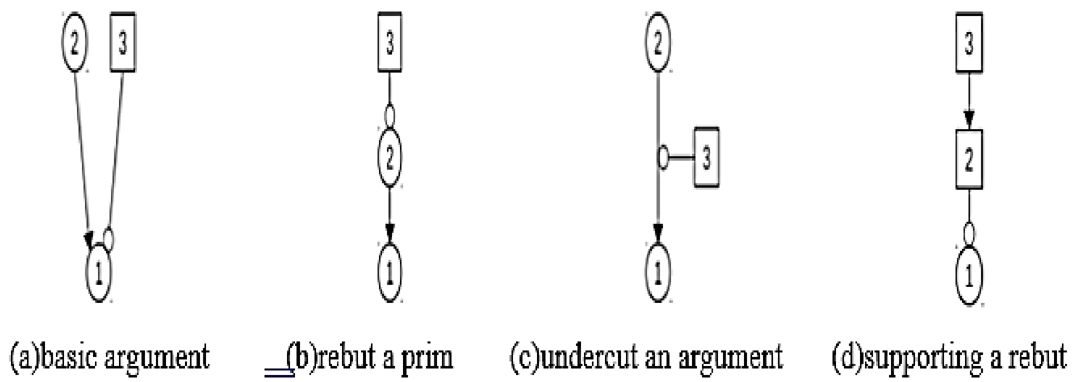


Fig 2.2 Basic Relation and Complex Formation

2.2.2 Argumentation Support(AS)

There are a variety of methods that can be used to support the conclusion of an argument. The first method is to collect as many arguments as possible of the same result; The second way is to expand on the already obtained argument. All arguments are self-contained, and can present one over the other. To avoid confusion with convergent Freeman structure, this structure is called multi-support [42].

As shown in figure 2.3c, the new argument is linked forward to the same conclusion is represented by a graph with different arrows to connect the new argument to the common conclusion, utilizing the premises[2,40]. Another option to provide more support for the conclusion is to continue building the argument by supporting either argument's premise. A new argument can be presented by one author in order to persuade another of the validity of a premise [42]. It indirectly supports the conclusion by explicitly supporting the premise.

The supported text passage has two functions: one serves as an introduction in the original argument, and the other serves as a conclusion of the subsequent argument [8]. Following Freeman's terminology, the resulting structure can be referred to as serial. As shown in figure 2.3d, such a hierarchical structure can be simply displayed in a diagrammatic argument by relating the premises of the new argument to its conclusion, being one of the premises of the original argument[41].

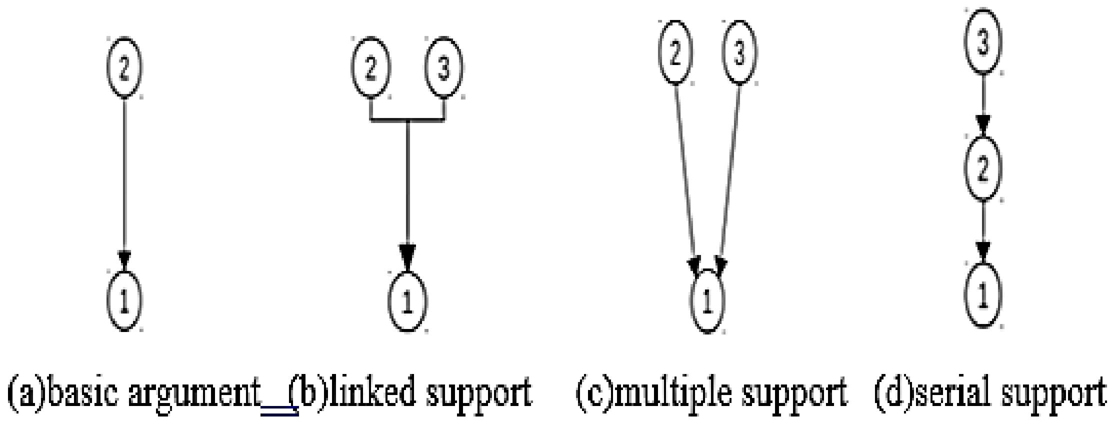


Fig 2.3 Types of the Support

2.2.3 Argumentation Attack

There are many ways to present evidence in favor of an argument; However you will focus on these ways of providing evidence against an argument. The first is to present an argument against it by presenting a conclusion that contradicts the endorsement of it; The second is to attack the argument presented by attacking the building or using force to weaken its support [43]. Solid arrows are preferred over round arrowhead strikes in the argument scheme.

There is frequently a refutation of the conclusion supported by the building premises. This type of counterargument is known as a refutation of the conclusion. Being able to tell them apart depends on the attacker's dedication to the end result. The conclusion that involves the denial by the attackers' claims in practice is preferable to the principle of the attack[44].

As a result, some exceptions do not state the claim that the negation of a conclusion is valid nor is the claim that the negation of a conclusion valid. For many inferences to draw from the premises, you may present possible arguments in favor of refusing the conclusion or possible exceptions [45].

An appeal will unlikely to be affected, while an exception without a reference note is questionable. Depending on the level of the text, this means that the author has the opportunity not only to present an argument against his conclusion or an expected exception to his argument, but also to strengthen it by explaining why it is important to consider this objection. Figure 2.4 shows the types of attacks on controversy.

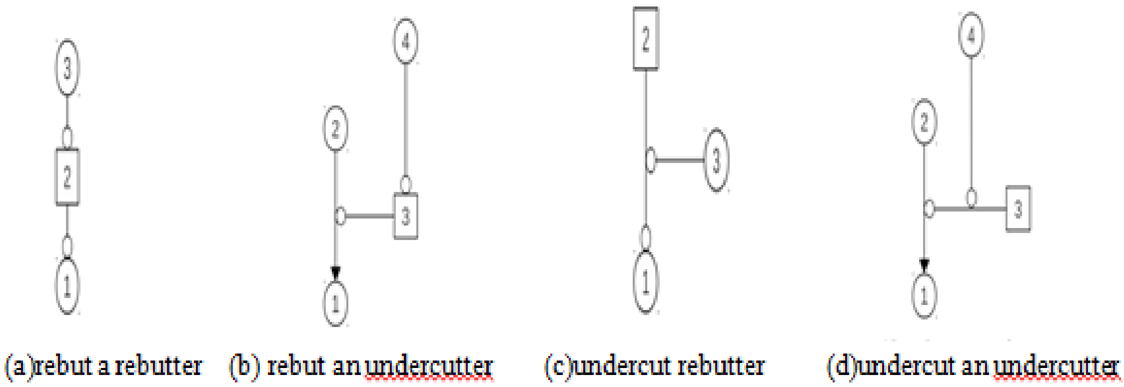


Fig. 2.4 Types of Attack

2.3 Argumentation In Decision Making (ADM)

In order to make a decision using argument, we will use argument to construct arguments for and against each decision, with the goal of determining the best decision. The best decision is the one that satisfies most goals. However, this should not be the only criterion for decision selection: any formal method of decision making is based on a model, a formal representation of the problem[46].

The quality of the model affects the quality of the decision. Two factors determine the quality of the model: the quality of the information on which the model is built, and the quality (correctness) of the model itself. Given these two inherent risk factors, we argue that any formal DM method must not only identify the best decision but also provide a justification for the outcome, such that the impact on decision-making from potential defects in the model can be traced [47].

Formal methods of argumentation are suitable for this purpose. They made both a claim and a description of how the information available was used to arrive at that claim, and how any counterarguments would be addressed. Our decision-making framework uses logical arguments about the possible outcomes of decisions[48]. Indeed, in everyday life, the decision is often based on arguments and counter-arguments. An argumentation can also be useful in explaining a choice that has already been made. In the following, we will develop this argument-based model for decision making .

For a long time, decision making, which is generally seen as a kind of thinking towards action, has piqued the curiosity of many scientists, including computer scientists. Each decision problem entails choosing the best possible action from a set of options, based on a wealth of knowledge about the current state of the world and possible actions as a result [49]. There may be insufficient or ambiguous information available. Economists mostly created classic decision theory, which focuses on defining what constitutes a rational decision maker. They prepared a list of guidelines to compare a variety of options [50].

In the present state, partial information is mixed with complete information about a given state of the world, generating a set of possible actions as input. Next, the function evaluates the value of the results of the obtained actions [51]. Because of its explanatory power, an argument is the most appropriate tool for defense. The argument has been introduced by several scholars only recently in the analysis of decision making.

Practically, decisions are made according to arguments and counter-arguments in daily life. An argumentation can be useful for explaining decisions that have already been made. The decision-making model displays a demand for a number of options, which may be partially or entirely based on the encoded decision criteria as shown in Figure 2.5.

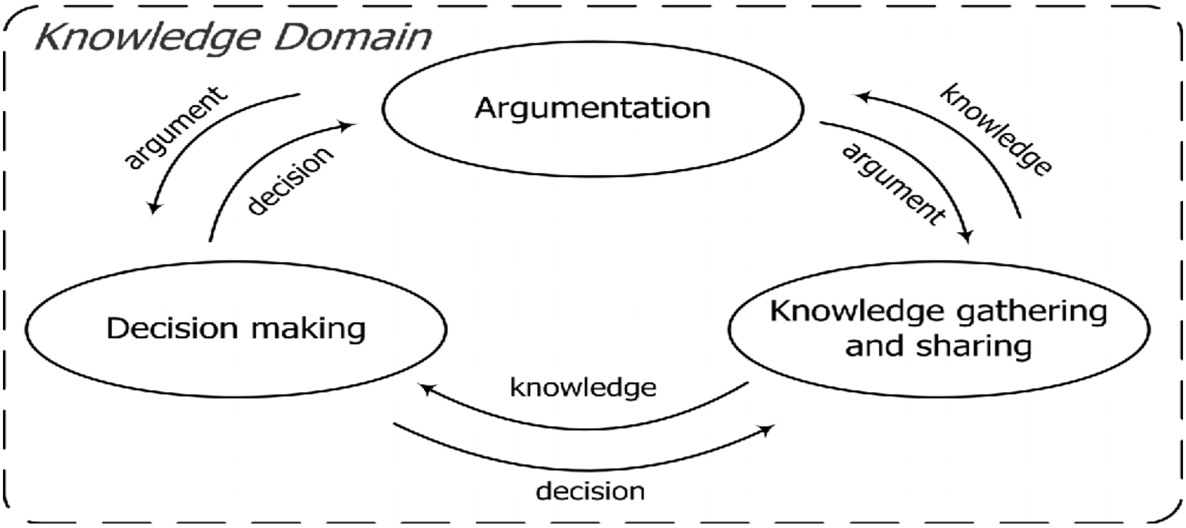


Fig 2.5 The Argumentation and Decision Making

In this study, Toulmin's argumentation model will be used to compute argumentation support and argumentation against for suggested drugs. Then, decision are to be made regarding whether or not this drug should be taken based on the higher value computed by means of a qualifying function.

2.4 Argumentation Methods

The many major types of arguments are :

- Deductive Arguments

  A deductive argument is based on a strong premise of conclusion. It is a top-down approach where you arrive at a conclusion based on a hypothesis that is assumed to be true.

- Inductive Arguments

  An inductive argument is the opposite of a deductive argument. It is a bottom-up approach that allows you to reach conclusions based on his observations. Of these two types of arguments, inductive arguments go from the specific to the general.

- Toulmin Argument

Toulmin's argumentation is another argument-building tool developed by British philosopher Stephen Toulmin. The most important questions in Toulmin's argument are the claim or statement of opinion, and the reasons or statements for which the reasons are related to the claim. Arguing with the strongest evidence claims success[15]. Their argument is true and sound in theory. In the following sections, this method is explained in detail.

- Rogerian Argument

Rogerian's argument comes into play when you have to find the best possible solution. It is basically a negotiation strategy in which you define a common goal and try to establish common ground. Many of us are familiar with Rogerian arguments and have used them in our lives, without even knowing.

2.5 Toulmin's Model Argumentation(TMA)

In the 1950s, British philosopher Stephen Toulmin proposed a new paradigm of argument [15,52] in hope that it would better fit our ways of thinking today and the questions and problems of modern life. It exists, and is being applied and used in a growing number of fields in the arts and sciences, including medicine. Compared to earlier paradigms, reflection often reflects backwards from the conclusion (the claim) to all the elements (the building blocks of the argument) that contributed to its support and value[53].

However, we anticipate the uses of this kind of argument when developing and implementing a research project or when we admit or see a patient for the first time and develop the “case” from initial “impression” to clinical planning and execution or community care with all the decisions these plans carry and implement [16]. Let's look at the modern debate from a more formal and philosophical point of view first and then in terms of its applications in medicine. Toulmin provided an original example of the argument [52] which is redrawn here in the form of figure 2.6. Toulmin's model contains six elements, or building blocks, with connectors between them:

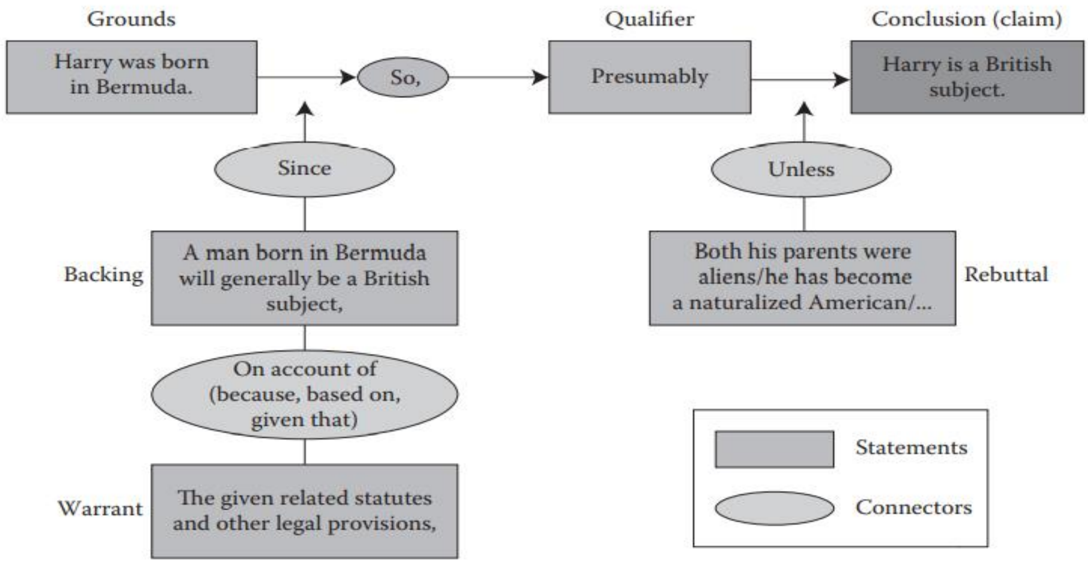


Fig 2.6 Original Example of a Modern Argument.

Let's consider again the example of sore throat/antibiotics to illustrate Toulmin's method of medical argument: "I will prescribe you antibiotics for a bacterial throat infection (claim, conclusion of the argument) because looking at your red throat, patchy tonsils and fever, positive rapid lab test results (underpinnings), Treatment with penicillin may be the best option in your case[54].

All our past experience and clinical studies show that we must do this to spare you serious complications from such infections (support), so let's definitely go this way (qualifier), if you agree, and unless you are allergic to penicillin (rebuttal), in which case we should opt for another type of treatment." A new claim supported by alternative premises or statements that applies to a different condition. Figure 2.7 represents a graphical structure of this kind of modern argument.

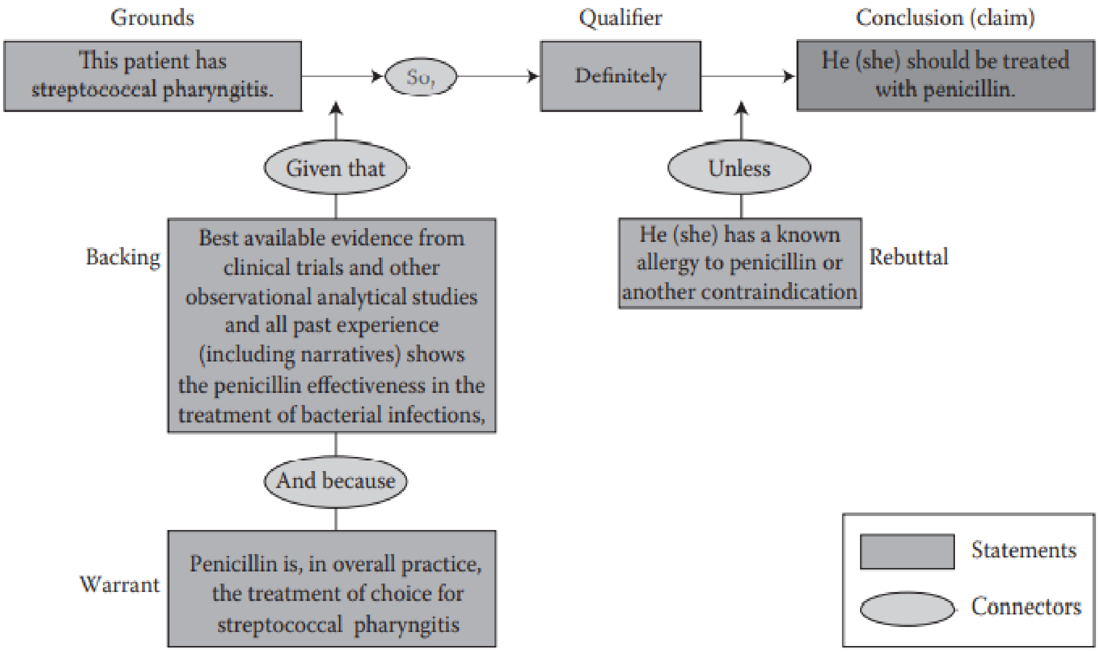


Fig 2.7 Toulmin's Modern Argument Model in a Medical Example.

The more in-depth examination of argument structure and representation presented in this work is based on Stephen Toulmin's approach to uses of argument. Toulmin's goal was to find out why formal logic in philosophy provided a brief overview of the human mind, and to devise a new structure for the logical nation based on an analysis of practical reasoning.

Toulmin has offered a method for evaluating the logical microstructure of ordinary arguments, based on analysis in the philosophy of syllogisms [55,56], and based on the idea that argument is a "primary locus of practical human reasoning". Toulmin's goal is to construct a variety of "practical arguments", also known as important arguments, that usually lack practical significance.

On the other hand, Toulmin's practical argument aims to reconcile the justifying function of an argument against the deductive function of theoretical arguments [57]. Practical arguments first obtain a claim of utility, and then provide an explanation for it, and at the same time, theoretical arguments provide conclusions according to a number of principles in order to arrive at a claim.

Toulmin believes reasoning is less active than reasoning including exploration of new ideas, but more active including testing and filtering already established concepts. This is a goal that can be achieved through the justification task. Toulmin believes that a good justification for a claim is essential to the success of a strong argument [57]. Figure 2.8 shows the relationship between the components of Toulmin's model .

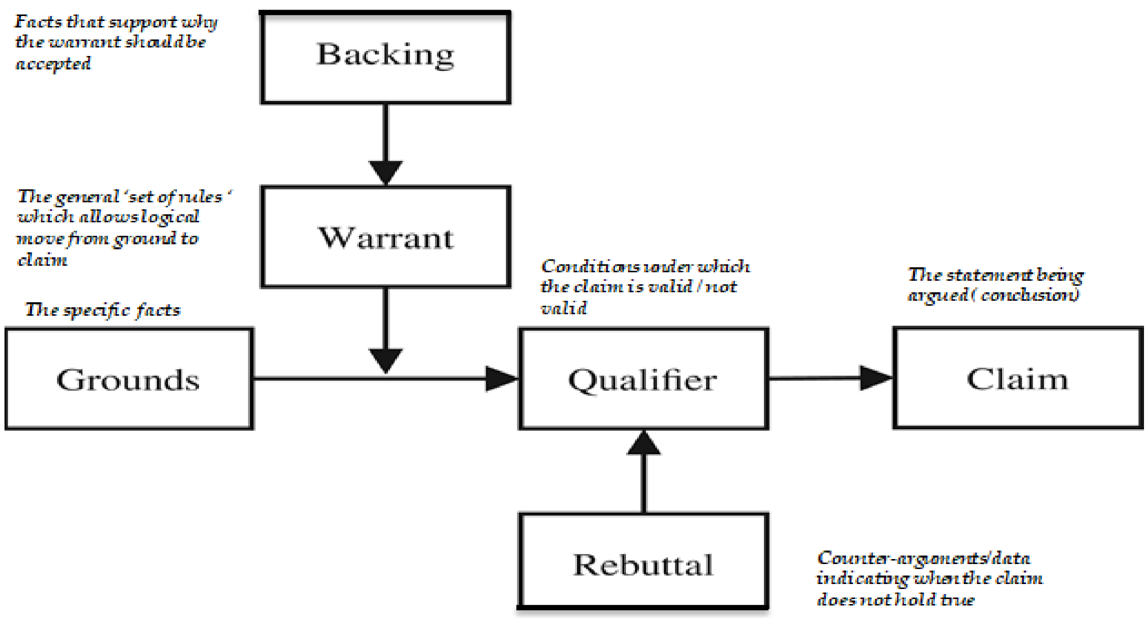


Fig ٢.8 The Toulmin's Model Components

Toulmin proposed a structure for assessing arguments in uses of argument (1958), which includes six connected components:

•Ground

Information that can be used as the basis for a claim. The basis consists of certain facts that support the claim, and the next component of the argument is the grounds on which the claim is based. If we want to consider an argument as well-founded and convincing, we need to ask whether the basis for its claim is reliable. A claim about reasons is a claim about the starting point of an argument. If we want to feel the power of a claim someone is making, we need to be willing and able to place ourselves at or near the starting point[56].

If someone claims that exposure to strong magnetic fields relieves depression or that patients who arrive have better health care outcomes, some smart people might dismiss the implied reasons, not because they have carefully weighed the evidence and reached such a conclusion but simply because they suspect that reasons like these claims can be consistent with the natural laws underlying science and medicine [57].

Others may find these reasons reasonable and positively enticing. All kinds of reasons are possible. This may include common sense, general knowledge, personal experience, logical inferences, empirical findings, and even simple appeals to authority. No matter how clear and well formulated a claim is, its persuasiveness can never override the grounds on which it is based [55,14].The ground "Harry was born in Bermuda" in the example explained in figure 2.6.

- Premises

The premises or statements made in arguments are either perceptual, reflecting the nature of things, or value judgments, reflecting the worthiness of something, such as goodness, righteousness, significance, or moral acceptability. The various premises and post conclusions to be used in the argumentative process are descriptive, predictive, or evaluative statements, or propositions of facts or values that affirm the existence or value of something: "This patient has a fever." As policy proposals, they provide statements emphasizing the actions to be taken and the desired change: "We must know the cause and treat it accordingly." Those who advocate change must provide sufficient evidence and arguments to overcome the presumption (an inherent feature of opposition to change) of existing beliefs and policies [56].

- Claim

A conclusion must be reached. A conclusion is a claim, and the data that supports the conclusion are also claims. The first component of an argument is its claim—a conclusion or way of looking at the problem or issue toward which the argument is trying to lead us. Examples of claims include: Physicians should not use CT scans to detect lung cancer, radiation doses delivered to the US population by diagnostic medical imaging pose an unacceptable level of risk, Diagnostic radiology is a great profession of choice and should be cared for patient is always the primary concern in making medical decisions [58]. In each case, the argument makes a claim that we may either reject or accept, although the claims made are of very different kinds and are subject to very different kinds of 'proof'. In some cases, claims are about means, whereas in others they are about ends.

In fact, being clear about claims is one of the best persuasion tools because it makes the argument more convincing. More important than just the claim itself is what we are being asked to agree to do. A person who claims that members of a group are undercompensated may not only be making a claim about pay levels but expect colleagues to take some action about it [59]. In this study, the claim is made of prognostic drugs for a patient based on the patient's features.
The claim in example mentioned in figure 2.4 was : “Harry is a British subject.”

- Warrant

Warrant is a declaration of intent to proceed from the ground to the claim. When the warrant is insufficient for the readers or listeners, more support must be provided. The warrant is an inference license according to which the data support the claim, while the backing provides in turn support for the warrant. Warrants are both similar to grounds and different in a crucial respect[26,27].Grounds simply refer to the kind of backing that accompanies a claim, whereas warrants ask whether these particular grounds actually support the claim in question.

In principle, it may be possible to justify a claim based on its financial impact. This may call for empirical study, including a trial, real or hypothetical, of the proposed strategy to determine its true effects. In some cases, such a trial may show that the grounds do not provide a good warrant for the claim. The warrant “a man born in Bermuda will generally be a British subject” in the example explained in figure 2.6 .

Modus Ponens technique in AI consider one common inference rules in AI systems. They are defined as systems with the ability to capture expert knowledge, facts and reasoning techniques to help care providers in routine work by applying inference methods to help in decision support and manage data to come up with reasoned conclusions[29].The science and engineering of making smart machines is what makes them important. With the simulation of human intelligence, the operations performed by machines that are special computer systems that learn the acquisition of information, the rules of its use .

The reasoning uses rules to reach approximate or definite conclusions and to self-correct. These techniques are used to diagnose the appropriate medications for patients because they are more accurate in making a decision. In the medical applications of AI, there is a wide range of applications. Doctors assess patients and their health risks with the help of automated AI[45].

Inference in Fuzzy Logic (FL) In any logic or thought process, inference is the formal process of deriving a C proposition (a result or conclusion) from a set of P premises on the basis of evidence and inference. The stated rules of inference govern the process by which such deductions are lawfully made within that logic or thought process. Classical calculus most often uses two sets of rules to control inference [60]. The rules of inference that govern inference in the forward direction

(inference) are called modus ponens.
If P, the premises, imply C, and if the premises P are declared to be valid or true, therefore, then C must be true.

The Modus Ponens example as:

<u>Premises :</u>

P1: X have A.
P2: B used for all’s A .
C : If X have A, then B.

<u>Conclusion :</u> B

The facts (p1,p2) are premises and (C) will represent claim . The warrants of use the C based on these many premises. In this study C(claim) represents suggestion drugs and the premises represent the patient’s symptoms and history (patient’s features) .

- Backing

The next important element of arguments distinguished by Toulmin is that of the backing of warrants. Backings provide support for warrants. They become relevant when a warrant is challenged. According to Toulmin, the occurrence of a backing presupposes the occurrence of data and claim . Toulmin also emphasizes the difference between backing and warrant, backings can be categorical statements of fact just like data, while warrants always are general bridge-like statements. A central point in Toulmin’s book is that different kinds of backings occur in different fields of argument[16,53].

Among Toulmin’s examples of backings are statutes and acts of Parliament, statistical reports, appeals to the results of experiments and references to taxonomical systems. All may provide the backing that warrant the arguments as they are acceptable in particular fields. The Backing determines how well founded warrants are[15,52]. The warrant is a rule, law, principle, intuition, or commonsense observation on which an argument relies. Backing is less about any particular fact than about a whole domain of knowledge.

The claim and the warrant are believed to be the most important in practical arguments, but backing, qualifier, and rebuttal may not be necessary in other cases. Figure 2.8 shows the interrelationships of Toulmin’s components of argument. TMA has been utilized for solving the drug conflict problems, which is considered one of the most challenge in this the medicine domain. Many drugs features were considered in this study to make decision about using/not using the drug. Each warrant has a weight, which ranges from 0 to 1. This value increases according to the level of confidence that the claim will have based on the data.

$$\mathrm{SWW}=\sum_{i=1}^{nvw} WWi \qquad (2.1)$$

SWW(sum weight of warrant)

In equation 2.1, nvw stands for the number of valid warrants and (WWi) is the weight of each valid warrant (valid here means that it matches the data). Subsequent to the computing of the sums, the values are normalized.

- Rebuttals

Rebuttals are conditions or circumstances under which our claim does not apply. They undermine the force of supporting grounds and other building blocks of the argument[26,29]. As exclusion criteria in a clinical sense, they must be depend on the best evidence is available and otherwise justified. In Harry example, “both his parents were Aliens/he has become a naturalized American” is a rebuttal.

Rebuttal statements are notes that can be used to refute a claim. R provides the exception conditions of the argument, while R finds in the argument a way to directly attack its conclusion, for example by claiming the opposite of the conclusion, or by showing that it is impossible or incorrect. Little real interest in medicine is certain[55]. Most of what is interesting about what we know and do involves some level of uncertainty—uncertainty caused by some imperfect evidence or simple human limitation. We never know everything, and in some circumstances we don't know the crucial things.

For example, doctors often perform treatment before a patient's prognosis is known for sure. In this study, many current pharmacological properties will be used to refute potential drug side effects, drug interaction properties, and drug contraindications, and then calculate the combination weights for each of them[45]. R is the information that reduces confidence in the claim.

Each rebuttal also has a weight, which ranges from 0 to 1 and increases according to the level of certainty that the data will discredit the claim. Equation (2.1) does the same as equation (2.2), but summing over the data matching the list of rebuttals. In equation 2, nvr stands for the number of valid rebuttals and WRi is the weight of each valid rebuttal[29].

$$\text{SWR}=\sum_{i=1}^{nvr} WRi \qquad (2.2)$$

SWR (sum weights of rebuttal)

- Qualifier

The qualifier is an expression, often a number or a single word , somehow quantifying our certainty about our claim in light of the preceding argument blocks and connections between them: The high incidence of cancers is “definitely,” “probably,” and “more certainly than uncertainly” due to the air pollution, “80%” of cancer cases are due to the carcinogens in the air, “we are 90% sure that this health problem is an environmental problem,” and so on. In this example, “presumably” is a qualifier.

Qualifier are Words or phrases that come to mind are probably, possible, impossible, certainly, presumably and necessarily. Qualifier can express a degree of force that the data give to the claim by the warrant. Not all conclusions enjoy the same level of certainty or confidence. In some cases, a claim may be truly certain[26,27,29].

In Qualifier A weight that quantifies the support that a claim has .The qualify function q aims to receive data, warrant, and rebuttal facts, and with those facts generate a confidence value for the claim. This qualify function can be implemented according to the needs of the user, adapting to various domains[26].

The qualifier is computed subtracting $SWR_{normalized}$ from $SWW_{normalized}$ generating a value as shown in Equation (2.3).

$$q = SWW\ normalized\ -\ SWR\ normalized \qquad (2.3)$$

After calculating Equation 3, qFinal is computed using equation 4, which is the final confidence level of the claim.

$$\text{q Final}=\begin{cases} |q| & if\ SWW\ >\ SWR \\ 1-|q| & if\ SWW\ <\ SWR \end{cases} \qquad (2.4)$$

It is a value between 0 and 1, which is transformed into a symbolic qualifier according to the following rules:

Table 2.1 Claim Confidence Level

Range	Claim confidence level
[0,0.2)	Not Certainly
[0.2,0.4)	Hardly
[0.4,0.6)	Maybe
[0.6,0.8)	Presumably
[0.8,1.0)	Certainly

2.6 Naïve Bayes Theory(NB)

NB is a simple technique for constructing classifiers: models that assign class labels to problem instances, represented as vectors of feature values, where the class labels are drawn from some finite set based on a common principle: all naive Bayes classifiers assume that the value of a particular feature is independent of the value of any other feature, given the class variable[61]. The NB classifier considers each of these features to contribute independently to the class probability, regardless of any possible correlations between these features[62].

For some types of probabilistic models, NB classifiers can be trained very efficiently in a supervised learning environment. In many practical applications, parameter estimation of naive Bayesian models uses the maximum method; In other words, one can work with a naive Bayes model without accepting Bayes probability or using any Bayes methods [63].

Despite their simple design and seemingly simplistic assumptions, naive Bayes classifiers have worked well in many complex real-world situations. Analysis of the Bayesian classification problem showed that there are sound theoretical reasons for the apparently unreasonable effectiveness of naive Bayes classifiers. However, a comprehensive comparison with other classification algorithms showed that Bayes classification is outperformed by other methods, such as boost trees or random forests [64].

The advantage of Naive Bayes is that it requires only a small number of training data to estimate the parameters needed for classification. Easy to implement, Fast, If independence is assumed, It works more efficiently than other algorithms, It is highly scalable, capable of making probability predictions, and of handling both continuous and discrete data, Insensitive to irrelevant features, can work easily with missing values and easy to update when new data arrives [65, 66].

Here are the probability calculations based on the Bayes theorem, can be seen in the formula :

$$P(y|x1, \dots, xn) = \frac{P(x1|y)P(x2|y)\dots.P(xn|y)P(y)}{P(x1)p(x2)\dots\dots.P(xn)} \qquad (2.6)$$

P(y|x) is the posterior probability of class (y, target) given predictor (x, attributes).

P(y) is the prior probability of y class.

P(x|y) is the likelihood which is the probability of predictor given class.

P($x_١$,…, x_n) is vector of features.

The mathematical function argmax is widely used in machine learning applications. It is an operation that finds the argument that gives the maximum value from a target function. It's also the most popular method for identifying the class with the highest expected probability in machine learning[67]**.** Argmax is a function that takes as input a vector z of n real numbers and returns the index of the maximum values of a vector as equation (2.٧)

$$\textbf{NB}\text{result} = argmax(z) \qquad (2.٧)$$

Where z represents a vector, the NB result is the index of high value in a vector.

When predicting a class, the model calculates the posterior probability for all classes and selects the largest posterior probability as the predicted class. This value is referred to as the Maximum A Posterior (MAP).

Using the above function, we can obtain the class, given the predictors. For each drug , the features used were drug interaction ,drug contraindication ,drug cost ,drug side effect and drug efficiency compute these features for support and attack condition and then choose maximum probability . In this work naive Bayes will be used as qualifier in Toulmin 's model argumentation .

For each item with the features $P(x_1, x_2, \dots, x_n | y)$ represents a conditional probability from multiplying the item features that appears in y condition, or it can be called a probability of item in y condition that have features $(x_1, \dots, x_n)$. Then P(y) is the prior probability of an item in y class . The prior probability calculations can be seen in the formula :

$$P(y) = N(y) / Ntotal \qquad (2.8)$$

$N(y)$ is the number of appearance of an item in a y category, while N is the total number of appearance of an item in all categories, then the decision is made by comparison between probability of items in each class then they are classified depending on which is greater. In this dissertation the decision making about this drug should be given to the patient or not .The most contributions in this study using naïve Bayes theorem as qualifier in Toulmin's argumentation model for improving Toulmin's model performance .

The most disadvantage of using the naïve Bayes technique in the previous probability is the zero probability ; a problem can be solved by Laplace, which is used a technique used to solve such kinds of problems. This technique uses prior probability and conditional probability to smooth categorical data. Laplace smoothing (LS) is generally used to solve zero problems [68].

$$P(y) = \frac{Ny + 1}{N+1} \tag{2.9}$$

$P(y)$ is the probability of occurrence of the item representing y class.

Ny represents the number of item occurrences of y class.

N is the total number of occurrences of this item.

The other disadvantages of naïve Bayes are :The strong assumption about the features to be independent is hardly true in real-life applications, data scarcity and chances of loss of accuracy.

2.7 Fuzzy Logic(FL)

Fuzzy logic works well with other techniques. In particular, it provides accurate responses to ambiguous, inaccurate, or ambiguous data. Because FL allows ideas to be expressed in linguistic terms, it provides a formal mathematical system for representing problems using familiar words. As a result, fuzzy logic has proven to be a powerful and effective tool for modeling systems with uncertainties in their inputs or outputs or for use when exact models of the system are either unknown or very complex [69].

FL, like any other tool, must be used correctly and carefully. Fuzzy logic has been found to give excellent results in many general areas. The most common use today is in systems for which complete or appropriate models are difficult to define or develop and in systems or tasks that use human observations as inputs, control rules, or decision rules [70]. Fuzzy logic simplifies the task of acting on and operating with often vague, imprecise, or ambiguous information that is common to human speech, ideas, or reasoning. It provides a way to solve a set of problems that would have been difficult or impossible to solve using traditional methods [71, 72].

2.7.1 Fuzzy Subsets

In relation to crisp sets, as we noted, fuzzy sets are supersets (of crisp sets) whose members consist of collections of objects that satisfy imprecise properties to varying degrees. Zadeh suggests that F is a fuzzy subset of the set of real numbers and suggests that it can be represented by a membership function (MF).

The MF value is the extent or degree of membership of each real number (r) in the subset of numbers [70]. With such a construction, it turns out that fuzzy subsets correspond to continuous value logic and that any element can have different degrees of subset membership. In the fuzzy world, we define or define a domain as the discourse universe. However, values within and equal to the two extremes are considered to be members of [72].

2.7.2 Fuzzy Membership Function

To formulate a membership function of the fuzzy concept one might hypothesize several desirable properties. These might include the following properties:

- Normality

  It is desirable that the value of the membership function (grade of membership). We are working with membership values 0 or 1. Normalize of membership degree for each variable can be computed by equation(2.1٠) as:

$$M_F(x)=\begin{cases} 0 & x <= a \\ (x-a)/(b-a) & b > x > a \\ 1 & x >= b \end{cases} \qquad (2.10)$$

a ,b boundary of linguistic variables

x is variable

- Monotonicity

The membership function should be monotonic. The μF(r) should be to 1.0 and vice versa. We are working with membership values in the range [0–1].

- Symmetry

The membership function should be one such that numbers equally distant to the left and right of equal membership values. We are working with membership values in the range [0–1]. It is important that one realize that these criteria are relevant only to the fuzzy property and that other such concepts will have appropriate criteria for designing their membership functions[٧٣].

2.7.3 Fuzzy Logic with Argumentation

The knowledge base is fuzzy to allow the experts to express their expertise (premises and rules) associated with the scores of interest in the unit period. The arguments are attached to a grouping of importance expressed in premises and grammar [7٤]. Then the extensions are calculated and the strength of each can also be obtained based on their strong arguments. Strengths are used to rank fuzzy extensions from strongest to weakest, on the basis of which decisions can be made [7٥].

In the fuzzy an attack relation is defined to express the strength of the attacks between arguments. This approach is also different from ours since we use explicit attacks [7٦]. The strength of the attacks depends on both the set of fuzzy arguments supporting the attacker and the strength of the attack. It presents an approach to discussion based on the logic of fuzzy description[7٧]. Arguments are a mixture of fuzzy linguistic variables and existential knowledge, and are involved in fuzzy attack and support relations [7٨].

2.8 Argumentation Systems Evaluation Method

One of argumentation systems evaluation method is external validation, which consists of comparing the results of a proposed model to an externally known result, such as externally provided dataset labels. It measures the extent to which labels match externally supplied labels[67].

In general, the evaluation measures are defined from a matrix with number of examples correctly and incorrectly classified for each category, this matrix named confusion matrix of classification and matching matrix for experts opinions . The matching matrix for two classes is shown in table 2.2.

A confusion matrix, also known as an error matrix, is a summarized table used to assess the performance of a classification model. The number of correct and incorrect predictions are summarized with count values and broken down by each class.

A confusion matrix is an N x N matrix used for evaluating the performance of a classification model, where N is the number of target classes. The matrix compares the actual target values with those predicted by proposed model. This gives us a holistic view of how well our classification model is performing and what kinds of errors it is making[7٩]. For a binary classification problem, we would have a 2 x 2 matrix as shown in table 2.2 with 4 values:

Table 2.2: The Confusion Matrix

		True Class	
		Positive	Negative
Predicted Class	Positive	TP	FP
	Negative	FN	TN

The confusion matrix consists of four basic characteristics (numbers) that are used to define the measurement metrics of the classifier.

The following are descriptions of the TP, FP, FN, and TN concepts:

1- True Positive (TP) examples are those that are correctly predicted to belong to the positive class.

2- False Positive (FP): examples that are predicted to be positive but are actually negative.

3- False Negative (FN): examples that are predicted to be negative but are actually positive.

4- True Negative (TN) : instances correctly predicted as belong to the negative class.

Performance metrics of an algorithm are accuracy, precision, recall, and F1 score, which are calculated on the basis of the TP, TN, FP, and FN.

Accuracy of an algorithm is represented as the ratio of correctly classified (TP+TN) to the total number (TP+TN+FP+FN).

$$\text{Accuracy} = \frac{TP+TN}{(TP+TN+FP+FN)} \qquad (2.11)$$

The fraction of recovered instances that are relevant to the search is known as precision. The Precision(P) refers to the model's accuracy. It's also known as the positive prediction value. [٨٠,8١]. The typical precision equation is provided in equation 2.13.

$$\text{Precision}= \frac{TP}{TP+FP}$$ (2.١2)

The Recall (R) is the percentage of relevant examples recovered out of all relevant examples [78,79]. The typical recall equation is as follows:

$$\text{Recall} = \frac{TP}{TP+FN}$$ (2.١3)

Recall is also called as sensitivity.

F1- score is also known as the F- Measure. The F-measure is a precision-to-recall trade-off. It is the harmonic mean value of both precision and recall [67,7١]. The conventional F-measure equation is as follows:

$$\text{F1-score} = \frac{2*presision*recall}{presision+recall}$$ (2.١4)

CHAPTER 3

PROPOSED SYSTEM

3.1 INTRODUCTION

The proposed systems and its stages are described in this chapter. Our proposed system falls into three systems first one is the classical Toulmin’s argumentation model , the second system uses naïve Bayes for improving Toulmin’s argumentation and third one uses the fuzzy logic with naïve Bayes for enhancing Toulmin’s model. A detailed definition of the first suggested model and function is given in section 3.2. Section 3.3 presents the second proposed model which uses naïve Bayes technique as qualifier(decision stage) inside Toulmin’s structure for enhancing performance of Toulmin’s model in details.

The third proposed model explained in section 3.4 Naive Bayes and fuzzy logic techniques were used to improve performance of Toulmin’s argumentation model for choosing optimal remedies for the patients based on the several features of drugs and patients. The last section presents system evaluation and algorithm .The first proposed approach, algorithms are designed to all primary processing stages. For two remain improvements approaches a design will focus only on the processing stages which differ from first processing stage.

3.2 The First Proposed System

First one is the classical Toulmin’s model is the first proposed method which inputs the patients’ symptoms and history which represent premises in Toulmin’s model ,then the suitable remedy is chosen based on patients’ symptoms and drug use .Linking between patients symptoms and drug use is considered as warrant in the Toulmin’s model . After diagnosis, the suitable remedy for patient and drug features were extracted and patients history was inputted ,then the support features of the drugs and attack features(rebuttal part in Toulmin's model)were computed , then support premises competed with attack premises by qualify functions , The winner will be determined by the strength of the evidence. Based on this result the decision will be made about whether a drug should be take or not as shown in algorithm (3.1) . Figure 3.1 shows all stages of the first proposed model .

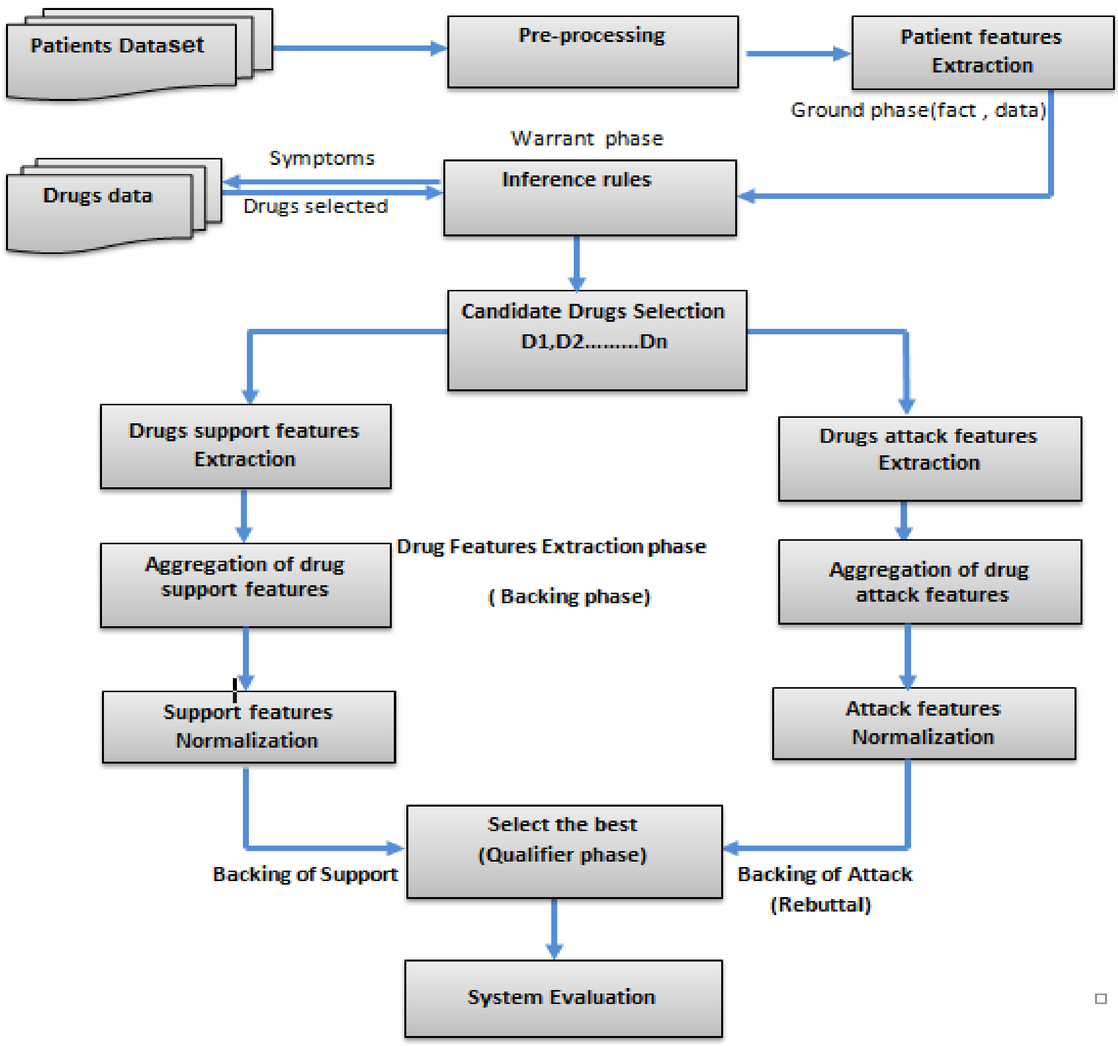


Fig 3.1. The Architecture of the First Proposed Model

Algorithm (3.1) : classical Toulmin's Algorithm. Input :patient dictionary(pd), suggestion drugs list(sdl) , support features

list(suplis), attack features list(attlis) .

Output : list of decisions(sddl) , list of confident level values of decisions(conll) .

% Variables Definition

pd: dictionary % dictionary of patients

suplis: list %list of support values of drugs

attlis :list %list of attack values of drugs

sup: float % support normalize value

att: float % attack normalize value

sddl: list% list of decisions

conll: list % list of confident level of decision

q:float %value of qualifier function

conf: string

```
  Begin
    1-  For each patient  in patients dictionary :
    2-      For I in range (0,length(sdl)) :
    3-          For each item in support features list:
    4-              Sup=∑ support normalize features
    5-          End for
    6-          For each item in attack  features list:
    7-              att=∑ attack  normalize features
    8-          End for
    9-          Compute qualify function by
                    q=sup-att
    10-         If sup ≥ att then
    11-             make decision of use drug='should'
    12-             Add decision to list of suggestion drug decision (sddl)
```

13- Sddl[i]= ’should’

14- Compute confident level of decision by

conf= absolute value of q

15- Add conf to confident level list (conll)

Conll[i]=conf

16- Else

17- Make decision of use drug= ‘should not’

18- Compute confident level of decision by

conf= 1-absolute value of (q)

19- Add decision to list of suggestion drug decisions

Sddl[i]= ‘should not’

20- Add conf to confident level list

21- Conll[i]=conf

22- End if

23- End for

End Algorithm

3.2.1 Patients Datasets

This phase describes the two datasets used in all proposed models. The first one centered on five diseases: hypertension, Angina pectoris, myocardial Infarction, atrial fibrillation and heart failure, with 2000 patients sample, 200 samples of hypertension patients, 330 samples of angina pectoris patients, 470 samples of myocardial Infarction, 500 samples of atrial fibrillation, and 500 samples of heart failure . The second one is fuzzy medical patients dataset(FMPD) consist of 200 samples (100 sample of hypertension and 100 sample of angina pectoris diseases) ,which are used for third proposed system .These datasets are real cases got from education hospitals in different cities in Iraq. Some files are also got from the websites https://www.drugs.com and https://go.drugbank.com/.com ,which content drug database online . The dataset consist of patients symptoms and signs, patient’s history and remedies use. The form of dataset is UTF-8 text file was used in this study.

3.2.2 Pre-processing Phase

In many tasks, it is necessary to clean or pre-process the data, which is as important as building the model itself. Regarding unstructured data like text, this process is essential in reducing the processing time and increasing its accuracy. As for the model used in this work, the pre-processing steps include: punctuation removal, space line removal, in-line removal, transfer all fact to under casing letter , and frequency data removal. Python programing language and PyCharm editor were used to implementation these models. The steps of pre-processing stage are shown in algorithm (3.2):

```
Algorithm (3.2) :  pre-processing Algorithm

Input   :  sam1, hiss1 .   % for two Medical datasets PMD,FPMD.
Output : Cleaned sam ,hiss . % lists of symptoms and histories of patients.
% Variables Definition
   a,a_file ,fo,foo: text files
Begin
    a_file = open("d:\\new data\\1\\sam1.txt", "r") % loading file of
patients symptoms
    fo = open("d:\\new data\\1\\sam.txt", "w")
    foo = open("d:\\new data\\1\\hiss.txt", "w")
```

```
    a= open("d:\\new data\\1\\hiss1.txt", "r") % loading file of patients histories
1-  for line in a_file: % loop for symptoms of patients
2 -      if not line.isspace(): % remove empty line
3-                 line=line. lower() % translate text to small letter
4-       stripped_line = line. strip()% remove space in beginning and end of line and remove special characters
5-       line = stripped_line. split() % separate words in each line based on white space
         fo.write('%s\n' % line)
   End for
6-  for line in a : % loop for history of patients
7-       if not line. isspace(): % if not empty line
8-                 line=line. lower() %
9-       stripped_line = line. Strip()%
10-      line = stripped_line. split() % list of patient history .
       foo.write('%s\n' % line)
   End for
End Algorithm
```

3.2.3 Patient Features Extraction

In this phase after inputting data for the proposed model and then prepressing each text file including patient symptoms , signs and patient history , these facts will represent patient features. Clinical patient features are fever, gender , high blood pleasure(HBP), low blood pleasure (LBP),chest pain , blurred vision, ESR ,testing Blood routine ,total white blood cell (WBC) and test total cholesterol ,which the row represent patient and columns represent symptoms of patient as shown in figure 3.2.

HT	Pulse	Cholesterol	ESR	chestpain	Shortnessofbreath	Blurredvision		
1	0	1	0	1	1	0	1	0
1	1	1	1	1	1	0	1	0
1	0	1	0	1	1	1	1	0
1	1	1	0	1	1	1	1	1
1	0	1	0	1	1	0	1	0
1	1	1	0	1	1	1	0	1
1	1	1	1	1	1	0	1	0
1	0	1	0	1	1	1	1	1
1	0	1	0	1	1	0	1	0
1	0	1	0	1	0	0	1	0
1	1	1	0	1	1	1	0	1
1	0	1	0	1	0	0	1	0
1	1	1	1	1	1	0	1	0
1	0	1	0	0	1	0	1	0
1	1	1	0	0	1	1	1	1
1	0	1	0	1	1	0	1	0
1	1	0	1	1	1	0	1	0
1	1	1	1	1	1	0	1	0
1	1	1	0	1	1	1	1	1
1	1	0	1	1	1	0	1	0
1	0	1	1	1	1	0	1	0
1	1	1	1	0	1	0	1	0
1	1	1	0	1	1	1	1	1
1	1	1	0	1	0	0	1	0
1	1	1	1	1	1	0	1	0
1	1	1	1	0	1	0	1	0
1	1	1	0	1	0	1	1	1
1	1	1	1	1	1	0	1	0
1	0	1	1	1	1	0	1	0
1	1	1	1	1	1	0	1	0
1	1	1	0	1	0	0	1	0
1	0	1	1	1	1	0	1	0
1	0	1	1	1	1	0	1	0
1	1	0	1	0	1	0	1	0
1	1	0	1	1	0	0	1	0

Fig 3.2 Samples of Patients of PMD

Patient history features are considered the important features detected for suggesting drugs for patients. These features include liver problems , kidney problems , age , blood urine problems(BU) , blood sugar problems(BS) and chronic diseases such as asthma. All these features(facts) are considered premises for argumentation support decisions are made in light of their values as shown in figure 3.3 .

Age	Smoke	FimalyHx	Kidney	heartfailure	BS	liver
0	0	0	0	1	1	1
1	0	1	1	1	0	0
0	0	0	0	1	1	1
1	1	1	0	0	1	1
0	0	0	0	1	1	1
1	0	1	1	1	0	0
1	0	1	1	1	0	0
0	0	0	0	1	1	1
0	0	0	0	1	1	1
1	0	1	1	1	0	0
0	0	0	0	1	1	1
1	0	0	1	1	1	0
1	0	1	1	1	0	0
0	0	0	0	1	1	1
1	0	1	1	1	0	0
1	1	0	1	1	0	1
1	0	0	1	1	0	0
1	0	1	1	1	0	0
1	0	0	0	1	0	0
1	0	1	1	1	0	0
1	0	1	1	1	0	0
1	1	0	0	0	1	1
1	1	1	0	0	1	1
1	0	0	1	1	0	0
1	0	0	1	1	0	1
1	0	0	1	1	0	1
1	0	1	1	1	0	0
1	0	0	1	1	0	0
1	0	1	1	1	0	0
1	0	0	1	1	0	0
1	0	1	1	1	0	0
1	1	0	0	0	1	1
1	1	0	0	0	1	1
1	1	1	0	1	0	1
1	1	0	0	1	0	1

Fig.3.3 Samples Patients History

To create patients features for medical patients dataset(MPD) , read the facts and history of patient as premises and then use the special criteria for translating these facts to features values (1 or 0) . The value (1) mean this patient has this feature and (0) means this patient does not have .

Each patient symptoms and patients history represented by dictionary data structure consist of patient name as key in dictionary and two lists one for patient symptoms and the second list used for the patient history as shown in algorithm (3.3).

Algorithm (3.3) : Patients Features Extraction Algorithm

Input : lis, hiss % text files

Output : dictionary of patients features(pf) % dictionary have patients names and patient symptoms list , patient histories list

% Variables Definition
Pf: {}% dictionary

```
lis : array of patients symptoms lists
hiss : array of patients histories lists
sa,hs :text files
Begin
1- sa = open("d:\\new data\\1\\sam.txt", "r") % load file of patients symptoms
2- hs= open("d:\\new data\\1\\his.txt", "r") % load file of patients histories
   lis = []
   hiss=[]
3-For each line in sa do
4-   line = stripped_line. split() % separate words in each line based on white space
5-   pf ← patient id %add patient id to dictionary
6-   lis=lis.append(line) %  add patient symptoms list in array of patients lists
7-   pf← [lis] %add list of symptoms to dictionary
8-   line = stripped_line. split() %list of patient history
9-   hiss ← hiss.append(line)% array of lists of patient histories
10-  pf← [hiss] %add list of patient history to dictionary
End for
End Algorithm
```

3.2.4 Candidate Drugs Selection

Detecting the patient's symptom and patient's history is followed by linking between patient symptom and drugs use for drugs diagnosis. This is known as the warrant stage as shown in algorithm (3.4). The Modus

Ponens technique was used at this stage as a conclusion base to link the symptoms and signs of the patient with the use of drugs to diagnose candidate drugs, and then through the application of inference methods, which help in supportive decision-making and data management to reach logical conclusions, which is the diagnosis of the suggested drugs for patients .

Algorithm (3.4) : Warrant Algorithm

Input : patients symptoms list(lis) , drugs dictionary(drg) .

Output : patients dictionary contained suggested drugs % pd

% Variables Definition

Lis: list

drgs:list

Drg: dictionary of drugs

Sym: string %patient symptom or sign

Dr: string % drug item

pd_dru: list % list of suggested drugs

Begin

1- For i in range(0,length(lis)):
2- Using inference rule for matching drug use with patient symptom (lis[i]) for extracting candidate drugs list([drgs]) % output of algorithm (3.5) Modus Ponens technique(lis[i],drg, [drgs]) .
3- pd_dru[i] ← [drgs] % Add drug list ([drgs]) to suggestion drugs family in patients dictionary (pd_dru)
4- Choose minimum side effect as suggestion drug(sugdr) from suggestion drugs family(pd_dru) from results of algorithm (3.8)
5- End for

End Algorithm

Algorithm (3.5) : Modus Ponens Algorithm(inference technique)

Input : patient symptom (sym) , drugs dictionary(drg)

Output : drugs list (drgs)

% Variables Definition
Drg: dictionary

Drgs: list % list of suggestion drugs

Begin

1- Drgs ← [] % assign empty list for drgs list

2-For i in range (0,length(drg)) do % loop for each suggestion drugs

3- if (drg[i].use == 'sym') then %check for matching between drug use and patient symptom

4- Drgs ←drgs. extend(drug[i]) % add drg[i].name to drugs list

5- End if

6- End for

End Algorithm

3.2.5 Drug Features Extraction

After candidate drugs extraction based on patients features , features of each drug in suggestion drugs will be extracted as shown in algorithm (3.6).

Algorithm (3.6) : Drug Features Extraction Algorithm

Input : suggestion drug (sugdr) .

Output : support features of suggested drug list(suplis) and attack features list(attlis) .

% Variables Definition

suplis: list

attlis: list

sugdr: string % drug item

Begin

Suplis=[]

Attlis=[]

1- For each item in suggestion drugs do% loop for build support features and attack features lists

2- Assign drug efficiency feature value for support list

suplis.extend(efficiency[sugdr]) % to get drug efficiency from output of algorithm(3.6)

3- Assign drug side effects feature value for attack list

attlis. extend(sideef[sugdr])% to get drug side effects from output algorithm(3.6)

4- Assign drug interaction feature value of support and attack lists

suplis. extend (1- inter[sugdr]) % to get drug interaction from output of algorithm(3.6)

attlis. extend (inter[sugdr])% to get drug interaction for attack

5- Assign drug contraindication feature value of support and attack lists

suplis. extend (1- cont[sugdr]) % to get drug contraindication of support list from output of algorithm(3.6)

attlis. extend (cont[sugdr])% to get drug contraindication feature of attack list

6- Assign drug cost feature value of support and attack lists.

suplis. extend (1- cost[sugdr]) % to get drug cost for support list.

attlis. extend (cost[sugdr]) % to get drug cost of attack list.

7- Assign drug availability feature value of support and attack lists.

suplis. extend(available [sugdr]) % to get drug availability features of support lists.

attlis. extend(1- available [sugdr])% to get drug availability features of attack list.

End for

End Algorithm

These features are :

3.2.5.1 Drug Efficiency

A medical treatment or a drug have to be used when it is beneficiary for the patients. The concept of benefit involves the drug's efficiency in getting the desired outcome. The most efficacious treatment, based on the best evidence this can be computed manually from rate patient's response. This feature is used as support feature for the drug as shown in equation (3.1). Algorithm (3.7) a shows this feature as :

$$Drug\ efficiency\ feature\ (Deff) = \frac{number\ of\ positive\ responses}{totol\ number\ of\ responses} \quad (٣.١)$$

Algorithm (3.7) : Compute Drug Efficiency Feature Algorithm

Input : suggested drug name (dr_name) .

Output : drug efficiency (dr_eff) . % drug efficiency as real value

% Variables Definition

de: dictionary %dictionary of drugs efficiency

dr_name: string

dr_eff: float

```
Begin
   1- Load drug efficiency text file
   2- Create drugs efficiency dictionary (de)
   3- For i in range (0,lenght(de)) do   % loop for length drugs efficiency
      dictionary
   4-      If de[i].name=='dr_name' then     % check  drug name with
      key in drugs efficiency dictionary
   5-           Compute dr_eff according to equation (3.1)
   6-             dreff←de[i].eff % Assign drug item value in de to dr_eff
                  variable to get  drug efficiency value
   7-       End if
   7-End for
End Algorithm
```

3.2.5.2 Drug side effects

Unpredicted events or undesirable reactions to drugs are known as adverse or side effects. These effects can be either minor ones as the case of runny nose to ones that threat life due to their increasing level of danger like the heart attack; for example. In this phase, this feature will be computed from more than 60 side effects such as itching, bleeding, tiredness, dizziness, rash, face redness and upper chest redness and this feature is considered as an attack for the drug . This feature is calculated by summing these effects divided by the number of these effects as shown in equation (3.2) .

$$side\ effects\ rate(ser) = count(f1, f2, \ldots\ldots, fn)/n \qquad (3.2)$$

Such f_1 ,f_2....f_n represent adverse effects of drugs , n is the number of side effects as shown in figure 3.

Almitrine	0	0	0	0	1	1	0	0	0	0	0	0	0	0	0	0	0	0	0
Ammoniumbicarbonate		0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0
Dimenhydrinate	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Cinnarizine	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0
Diphenidol	0	0	0	0	1	0	0	0	0	1	0	0	0	0	0	0	0	0	0
Levosulpiride	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Meclizine	0	1	0	0	1	0	0	0	0	1	0	0	0	0	1	0	0	0	0
Pyridoxine	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0
Trimetazidine	0	0	0	0	1	0	0	0	0	1	0	0	0	0	0	0	0	0	0
Epinephrine	0	0	1	1	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Reproterol	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0
Amlodipine	0	0	0	0	0	0	0	0	0	0	1	1	0	1	0	0	0	0	0
Atorvastatin	0	0	0	0	0	1	1	0	1	0	0	0	0	0	0	0	0	1	0
Diltiazem	0	1	1	0	1	1	1	0	0	0	0	1	0	0	0	1	1	1	1
Teicoplanin	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0
Valproatebismuth		0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0
aspirin	0	0	0	0	0	0	0	0	1	1	0	0	0	0	0	0	0	0	0
Atenolol	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Benidipine	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Celiprolol	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Isosorbide	0	0	0	1	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0
Isosorbidedinitrate		0	0	0	1	0	0	0	0	1	0	0	0	0	0	0	0	0	0
Metoprolol	0	0	1	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Molsidomine	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Nadolol	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Nicorandil	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Nitroglycerin	0	1	0	0	1	1	0	0	0	0	1	1	0	0	0	0	0	0	0
Pindolol	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Propranolol	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Atorvastatin	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	1	0	0	0
Lovastatin	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0
Pravastatin	0	0	0	0	1	0	0	1	0	1	0	0	0	0	0	0	0	0	0
Rosuvastatin	0	0	0	0	1	0	0	1	0	0	0	0	0	0	0	0	0	0	0
Simvastatin	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0
TocopherylNicotinate		0	0	0	0	1	0	0	0	0	1	0	0	0	0	0	0	0	0

Fig 3.4 Side Effects of Drugs

Algorithm (3.7) shows how to compute drug side effects for all drugs .

Algorithm (3.7) : Compute Drug Side Effects Feature Algorithm .

Input : suggestion drug(sugdr). % drug name

Output : drug side effects average (sid). % real value .

% Variables Definition
Sum: integer number

ser : float number

Sid: dictionary % dictionary of drug side effects

Begin

1- Sum=0, N=60

2- Create drug side effects dictionary (sid)

- For i in range(0,length(sid)) do % loop for length drug side effects dictionary sid
- For j in range (0,length(line)): % line has N features loop for each Colum in drug side effects .
- Sum=Sum + int(j)
- End for
- ser[i]=Sum/N
- Add drug name as key in sid and average as real value
  Sid[i] ={dr_name: drugs[i], av: ser[i]}
- End for

3- Check suggestion drug with side effect dictionary for get side effect average of drug

4- For k in range (0,length(sid)) do

5- If (sugdr==sid[k].name) then
   Sid[k].av

6- Break % Exit out of loop

7- End for

End Algorithm

After diagnosing the drug list for each patient symptom (drug family) and calculating the side-effect rate for each drug in this list, we need to choose the treatment with the minimum side-effect rate for each family, as shown in algorithm (3.8). This feature is very important to the patient and the weight of this feature has a great influence in deciding whether or not to use this drug for patients. For each drug family used vectors of side effect rate (ser) as shown in equation (3.3) .

side effects rate = [$ser(dr_1)$, $ser(dr_2)$, … $ser(dr_n)$[

$$Drug\ side\ effect(Dsdef) = min[side\ effects\ rate] \tag{3.3}$$

Algorithm (3.8) show how compute minimum side effects for all drugs

Algorithm (3.8) : compute minimum drug side effects feature Algorithm .

Input : dictionary of drug side effect (sid) . % the dictionary have drug name and side effect rate

Output : drug name of minimum drug side effects rate (drgnam).

% Variables Definition

Drname: string % name of candidate drug based on minimum side effect

sid :dictionary %dictionary of drugs side effects

min: float number

name: string

Begin

1- For k in range (0,length(sid)-1): % loop for length of side effect dictionary , k counter.
2- Min=side effect rate value of first item in side effect .
3- Name=name of first item in drug side effect dictionary
4- For I in range(k+1 ، length(sid)) do % I counter
5- If sid [i].side < min then
6- min= sid[i].side
7- Name= sid[i].name
8- End if
9- End for
10- sid[k].name=name % this filed represent drug name
11- sid[k].side= min % this filed represent drug side effect

12- Drgnam $\leftarrow$ sid[k].name

13- End for

End Algorithm

3.2.5.3 Drug Interaction

A drug interaction is a change in the effect or side effects of a drug resulting from its being taken concomitantly with another drug in the list of suggested treatments. This feature can be used to support or attack a drug, which specifies the value (0) when the drug does not interact with another item in the drug list and the value (1) when there is a significant interaction, while the value (0.5) means that this drug interacts, but only slightly. The value (0) can be used as a supporting aspect of the drug as shown in equation (3.3). Algorithm (3.9) show how to compute drugs interaction feature .

$$Drug_{interaction}\ (Dint)=\begin{cases} 0 & if\ drug\ item\ not\ interacted \\ 0.5 & if\ drug\ has\ miner\ interacted \\ 1 & if\ drug\ has\ major\ interacted \end{cases} \qquad (3.4)$$

Algorithm (3.9) : Compute Drug Interaction Feature Algorithm .

Input : drug item . % sugdrg

Output : drug interaction value(intf).

% Variables Definition

Sugdrg: string% represent drug name

Intf: float

Maj :list % list of drug major interaction

mine : list % list of drug minor interaction

Begin

1- Create list of drugs major interacted with this drug % maj list

2- Create list of drugs minor interacted with this drug % mine list

3- If (sugdrg not in maj and sugdrg not in mine) then % check whether suggestion item not have interacted

4- intf=0

5- Else

6- If (sugdrg in maj) then % check whether suggestion item have major interacted

intf=1

7- Else

8- If (sugdrg (in mine then %check if drug item have miner interact

intf=0.5

9- End if

10- End if

End Algorithm

3.2.5.4 Drug Contraindications

A contraindication is a specific situation in which a drug, procedure, or surgery should not be used because it may be harmful to the person based on patient history. A procedure or medicine that falls under this category must be avoided. This feature can be used to attack the suggested drug used ,which assigns value (1) when a drug has contraindications with the patient history . The (0) value can be used to support this drug. The algorithm (3.10) shows how to compute drug contraindications.This feature is computed as :

$$drug_{contrf}(Dcont)=\begin{cases} 1 & if\ \ drug\ item\ prevent\ for\ patient \\ 0 & Otherwise \end{cases} \quad (3.5)$$

Algorithm (3.10) : Compute Drug Contraindications Feature Algorithm .

Input : the suggestion drug(sd), patient history list(his) . % suggestion drug and history list

Output : drugs contraindications feature value for each drug. % contf

% Variables Definition

Sd: drug suggestion

his: list% list of patient history

Conf: integer

Cont :list % list of drug contraindication with patient history

Begin

1- For each history item of patient (his list)% loop for patient history

2- Create list of drugs Contraindications with this history% cont list

3- Cont ← Cont. append(list) % add new list end of cont list

4- Check suggestion drug item whether found in cont list

If sugdrg in cont then

contf=1

5- Else

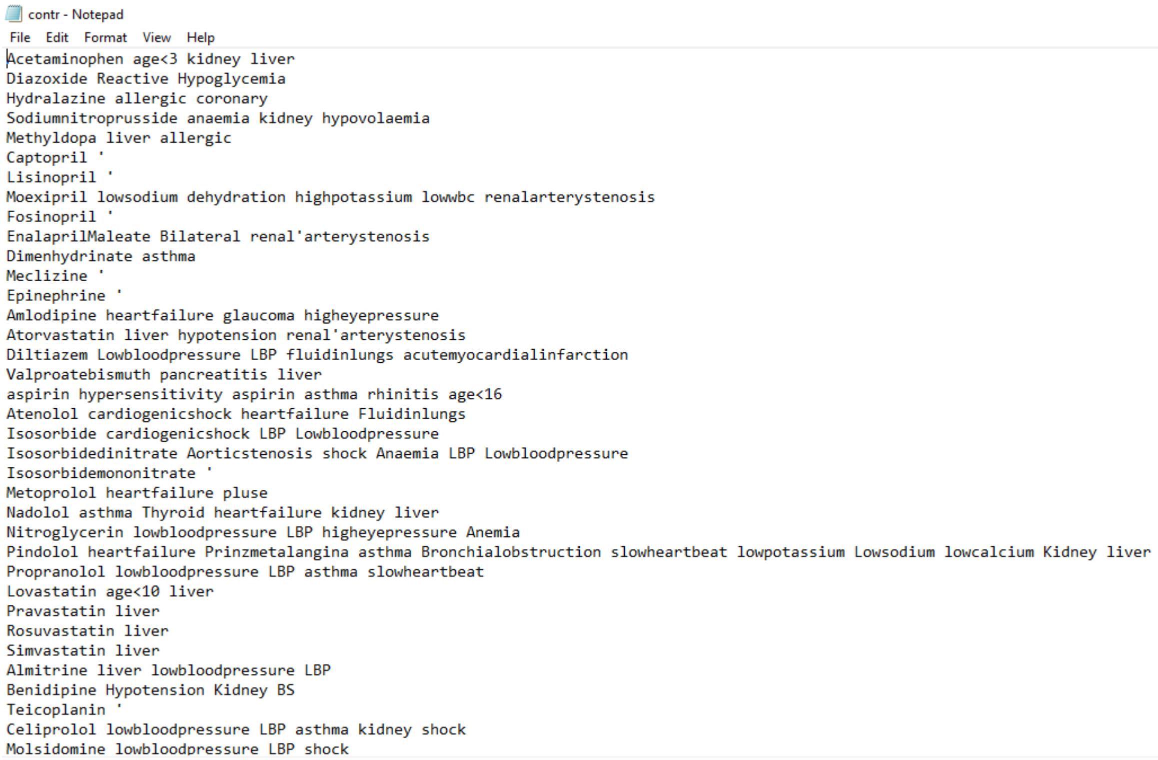
contf=0

6- End if

7- End for

End Algorithm

The figure 3.5 Show the drug name in first Colum and others columns represent the histories of patients contraindicated with this drugs



```
contr - Notepad
File Edit Format View Help
Acetaminophen age<3 kidney liver
Diazoxide Reactive Hypoglycemia
Hydralazine allergic coronary
Sodiumnitroprusside anaemia kidney hypovolaemia
Methyldopa liver allergic
Captopril '
Lisinopril '
Moexipril lowsodium dehydration highpotassium lowwbc renalarterystenosis
Fosinopril '
EnalaprilMaleate Bilateral renal'arterystenosis
Dimenhydrinate asthma
Meclizine '
Epinephrine '
Amlodipine heartfailure glaucoma higheyepressure
Atorvastatin liver hypotension renal'arterystenosis
Diltiazem Lowbloodpressure LBP fluidinlungs acutemyocardialinfarction
Valproatebismuth pancreatitis liver
aspirin hypersensitivity aspirin asthma rhinitis age<16
Atenolol cardiogenicshock heartfailure Fluidinlungs
Isosorbide cardiogenicshock LBP Lowbloodpressure
Isosorbidedinitrate Aorticstenosis shock Anaemia LBP Lowbloodpressure
Isosorbidemononitrate '
Metoprolol heartfailure pluse
Nadolol asthma Thyroid heartfailure kidney liver
Nitroglycerin lowbloodpressure LBP higheyepressure Anemia
Pindolol heartfailure Prinzmetalangina asthma Bronchialobstruction slowheartbeat lowpotassium Lowsodium lowcalcium Kidney liver
Propranolol lowbloodpressure LBP asthma slowheartbeat
Lovastatin age<10 liver
Pravastatin liver
Rosuvastatin liver
Simvastatin liver
Almitrine liver lowbloodpressure LBP
Benidipine Hypotension Kidney BS
Teicoplanin '
Celiprolol lowbloodpressure LBP asthma kidney shock
Molsidomine lowbloodpressure LBP shock
```

Fig.3.5 The Contraindication Drugs

3.2.5.5 Drug cost

The cost of each property will be calculated in this feature. The cost of purchasing a medicine will be compared with other medicines. In this study, the cost of the drug is used to support or attack, when the cost of the drug is low, which leads to an increase in the value of the collateral to support this drug, otherwise the collateral to cancel this drug will increase. The value of this attribute depends on the financial ability of the patient. This feature takes (0), (0.5), or (1) based on the price of the drug. This feature is calculated as shown in equation (3.5). Algorithm (3.11) shows how to calculate the drug cost feature.

$$Drug_{cost}(Dco)=\begin{cases} 1 & if\ prices <= 10000 \\ 0.5 & if\ 10000 < prices <= 30000 \\ 0 & Otherwise \end{cases} \quad (3.5)$$

Algorithm (3.11) : Compute Drug Cost Feature Algorithm .

```
Input   :  suggestion drug(sdr)   ,drugs prices text file . % drgprice list
Output : value of  drug cost  . % drcost
% Variables Definition
drco: dictionary  % dictionary of drug cost
sdr: string % suggestion drug name
drcost :float % represent cost of suggestion of drug
drgprice: text file
  Begin
   1- Create dictionary of drug cost from  drugs prices file(drco) % drug
      cost.
   2- For I in range (0,length(drco)) :%loop for length of  drug cost
      dictionary
   3-    Check suggestion drug with drug cost dictionary % check to get
      suggestion drug price
   4-    If (suggestion drco[i]. price > 30000)  then
            drcost=1                % test for suggestion drug cost .
         Else
   5-       If (suggestion drco[i]. price < =10000)  then
                  drcost = 0
   6-       Else
                  drcost = 0.5
   7-       End if
   8-     End if
   9- End for
  End Algorithm
```

3.2.5.6 Drug availability

This feature will be used for each suggestion drug to support drug if the drug was available in pharmacies this feature takes value(1) that will increase the support side of the drug item ,otherwise the feature will takes the (0) value. This feature will be computed as first feature because it tests whether the drug item is available or not ,if not found this will increase the attack side of this drug from suggestion drugs list .This feature is used for competing drug item with other items in same family. This feature compute as shown in equation (3.6). Algorithm (3.12) explains how to compute this feature .

$$Drug_{\,available}\,(Dava)=\begin{cases} 1 & if\ drug\ available \\ 0 & Otherwise \end{cases} \tag{3.6}$$

Algorithm (3.12) : Compute Drug Availability Feature Algorithm .

Input : suggestion drug(sugdr) ,drugs list available. % dr_aval list

Output : drug availability feature value .% av_value

% Variables Definition

Sugdr: string % represent drug name

dr_aval :list % list of drug available

av_value : integer

Begin

1- av_value =0
2- For i in range (0,length(dr_aval)): % loop to length of list of available drugs I counter
3- If sugdr == dr_aval[i] then %Check the suggestion drug

available or not

4- av_value =1

5- Exit % break to exit from the loop

6- End if

7- End for

End Algorithm

3.2.6 Normalization Phase

In this phase normalization is used to scale the data of an attribute so that it falls in a smaller range . Each warrant and rebuttal have a weight ranging from 0.0 to 1.0. The value of the warrant increases according to the level of confidence in the claim, whereas rebuttal is the facts that lowers the confidence of the claim. The normalization brings all the attributes on the same scale. Subsequent to the computing of the sums, the values are normalized. In this study the features are normalized by dividing summation of features weights on the number of features as shown in equation (3.7) . The normalization of the warrant and the rebuttal of each drug is shown in algorithm (3.13)

$$Drugfeatures_{normalize}(NORM)= \frac{summation\ of\ all\ drug\ features\ weights}{number\ of\ drug\ features} \quad (3.7)$$

Algorithm (3.13) : Features Normalization Algorithm .

Input : dictionary of patients(pd) . % the dictionary have patient id ,drug feature weights list .

Output : support normalize value(sunor), attack normalize value ((attnor

% Variables Definition

Pd: dictionary % dictionary of patients

Sunor :float value % support normalize features

Attnor :float value % attack normalize features

Susumva :float value

Atsumva :float value

Begin

1- For each patient in dictionary of patient(pd) do
2- For each drug in suggestion drugs list in dictionary of patients do
3- Aggregation support features value % backing for warrant feature(susumva)
4- Aggregation attack features value % backing for rebuttal feature (atsumva)
5- End for
6- Divided summation of support features on number of features

   Apply $supportDrugfeatures_{normalize} = \frac{\boldsymbol{ssumv}}{\boldsymbol{number\ of\ drug\ features}}$
7- Sunor= $supportDrugfeatures_{normalize}$ % assign this value to support normalize.
8- End for
9- Divided feature value on summation of attack features on number of features by

   Apply $attackDrugfeatures_{normalize} = \frac{\boldsymbol{atsumv}}{\boldsymbol{number\ of\ drug\ features}}$
10- attnor = $attackDrugfeatures_{normalize}$ % assign this value to attack normalize

End Algorithm

3.2.7 Qualifier Phase

At this point, the decision is made by competition between the claim and the rebuttal and the winner is determined based on the strength of the evidence by using the ‘qualify function’ ,which computed by subtracting $SWR_{normalized}$ from $SWW_{normalized}$ for generating a value of each suggestion drug as mentioned in chapter two in equation (2.3) .After calculating qualify function, the qFinal is calculated by using equation (2.4), which represents the confidence level of the claim or the rebuttal . Figure (3.1) shows how the qualifier phase is used in the overall architecture of first proposed system.

3.3 The Second Proposed Model with Naïve Bayes

In this system naïve Bayes technique is used for each suggestion drugs based on support feature and attack feature as class condition ,these features and posterior probability of each class of suggestion drug are computed as shown in algorithm(3.14) . Prior probability of each class were computed from the classical Toulmin’s model results. When making a prediction for a class, it calculates the posterior probability of all classes ,then the highest value of posterior probability is chosen as the predicted category. This value is known to as the Maximum A Posterior (MAP) as mention in equation(2.6). The same dataset was used in first proposed model.

We can obtain the class is the predictors are given . For each drug the features used were drug interaction ,drug contraindication ,drug cost ,drug side effect and drug efficiency. We compute these features for support and attack condition and then choose maximum probability. In this work naive Bayes will be used as a qualifier in Toulmin's model argumentation.

For each drug with $P(f1, f2, \ldots, fn \mid X)$ represents a conditional probability from multiplying the drug features that appear in X condition, or it can be called a probability of drug in X condition that has features $(f_1, \ldots, f_n)$. Then P(X) is the prior probability of drug class X . The prior probability calculations can be computed based on the results of the classical Toulmin's model. After that the decision is made by comparing between the probability of drugs for each classes, then classifying them depend on which is greater the other . Then the decision making about this drug will be given to patient or not .

The most important contribution in this study is the use of naïve Bayes theorem as qualifier in Toulmin's argumentation model for improving Toulmin's model performance as show in figure (3.5). Algorithm (3.14) illustrates the use of naïve Bayes theory to enhance performance of Toulmin's model.

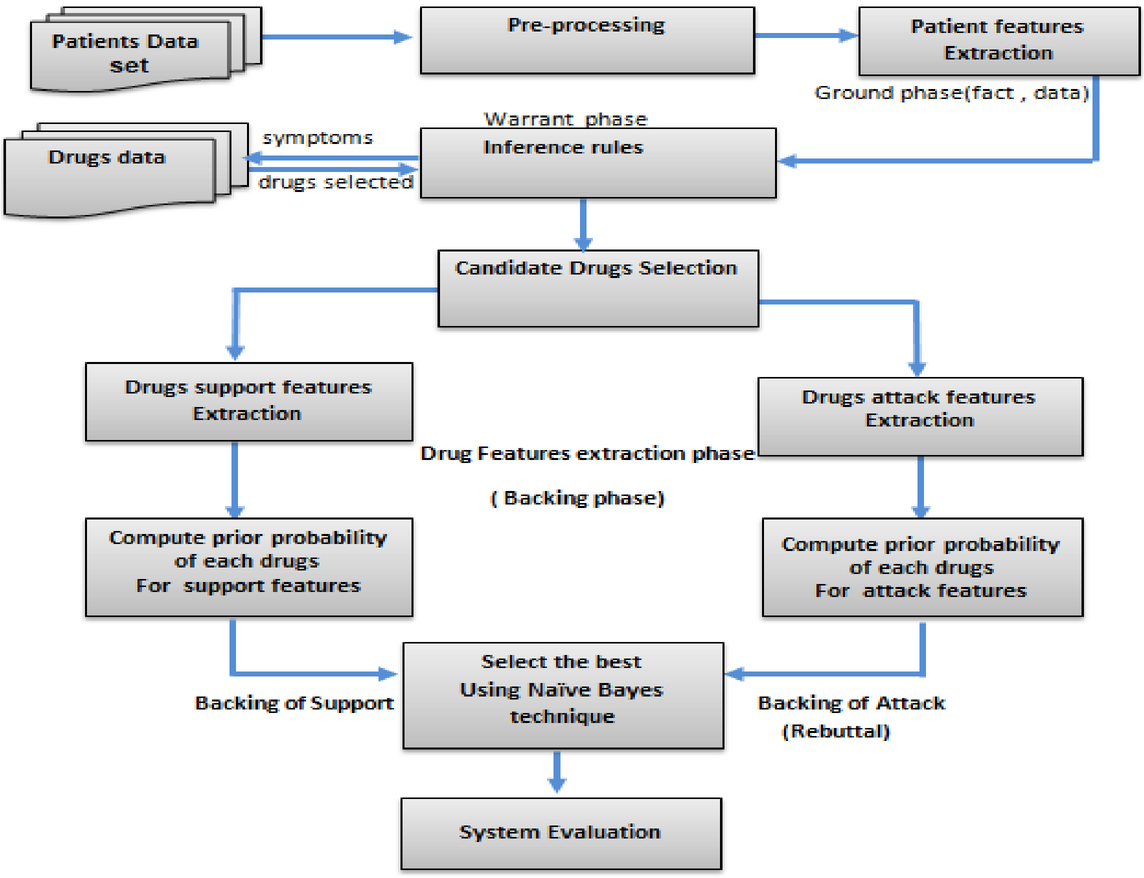


Fig 3.6 The Architecture of the Second Proposed Model

Algorithm (3.14) : Improved Toulmin's Model using Naïve Bayes Algorithm .

Input : dictionary of patients(pd). % the dictionary have patient id , suggestion drugs list(sdl) ,drug support features list, drug attack features list.

Output : list of decisions of suggestion drugs ,list of confident level values of decisions(conll) .

% Variables Definition

Pd: dictionary

Propatt: float % probability of attack features

Propsup: float % probability of support features

Prisu: list % probability priority for support drugs item

Priat: list % probability priority for attack drugs item

Props: list % list of support probabilities of suggestion drugs

Propa: list % list of support probabilities of suggestion drugs

Conll: list % list of confident level value of decisions

Sd: list % list of suggestion drug decisions

Sdl: list % list of suggestion drugs

Conf: string

Conpr1,Conpr1:float numbers % values of support and attack of drug

Begin

1- Create priority probability of support(prisu)list and priority probability of attack for suggestion drugs(priat)list .% compute priority probability of two classes from results of classical toulmin's model
2- For each patient in dictionary of patients do
3- For i in range(0,length(sdl)) do% loop for each suggestion drugs
4- For each item in support features list do % loop of create probability list
5- Create probability list props(item) % probability list of all support items
6- End for
7- For each item in attack features list do % loop of create probability list
8- Create probability list propa(item) % probability list of all attack items
9- End for
10- propsup=1,propatt=1
11- For each item in support probability list
12- If (props(item)==0)then props(item)= 0.0001 % avoid 0 probability
13- propsup=propsup*props(item) %compute probability of support features

```
14-    End for
15-    For each item in attack probability  list
16-       If (propa(item)==0) then  propa(item)= 0.0001 % avoid zero probability
17-       propatt=propatt*propa(item)% compute probability of attack features
18-    End for
19-    Conpr1=(propsup*prisu[i])/(propsup+propatt)
20-    Conpr2=(propat* priat[i])/(propsup+propatt)
21-     na=max(Conpr1, Conpr2) % compute maximum value
22-     q= Conpr1- Conpr2
23-     If (na==Conpr1) then
24-         make decision of "should use this  drug item"
25-         conf= absolute value of  (q) %Compute confident level of decision
26-         sd[i]='should' % Add decision to list of drug decisions
27-         conf=conll[i] %Add conf to confident level list
28-     Else
29-        make decision of "should not use this  drug item"
30-       conf= 1-absolute value of (q)% Compute confident level of decision
31-        sd[i]= 'not should' %Add decision to list of drug decisions
32-       conf[i]=conf% Add conf to confident level list
33-     End if
34-  End for %end loop of all drug items  i counter %
35- End for
End Algorithm
```

3.4 The Third Proposed System with Naïve Bayes and Fuzzy Logic

The dataset used in this approach is fuzzy medical patients dataset(FMPD), many membership functions are used to create linguistic variables (low, medium, high) for each symptom of the patient symptoms to achieve more accuracy in diagnosing the appropriate treatments(claim) for symptom of the family of those treatments. The improvement that occurred in this model is due to the selection of the accurate and optimal treatment for the patient's symptoms through the use of membership functions in the fuzzy logic technique as show in figure (3.3) .

As for this data set(FMPD)uses fuzzy logic technique with naïve Bayes theory to improve the results, since the nature of this data is a numerical data of the symptoms as shown in figure 3. , and then these symptoms are extracted using the many crisp rules, through which the patient's features are determined through linguistic variables, and this leads to the accuracy of suggesting the appropriate treatment for the patients.

HT	Pulse	Cholesterol	ESR	chestpain	Shortnessofbreath	
14	70	240	7	1	85	0
17	110	220	15	1	87	0
15	80	210	6	1	80	1
14	40	200	5	1	82	1
16	89	250	7	1	78	0
18	45	230	9	1	73	1
13	112	222	16	1	76	0
15	113	223	5	1	77	1
17	90	250	6	1	72	0
14	85	260	12	1	95	0
18	120	235	10	1	70	1
15	65	270	4	1	95	0
17	45	250	15	1	80	0
16	90	230	4	0	83	0
15	130	225	6	0	74	1
14	80	260	9	1	78	0
20	40	180	14	1	82	0
19	120	280	17	1	75	0
22	130	300	8	1	79	1
20	43	170	16	1	69	0
19	70	260	15	1	76	0
17	140	330	18	0	87	0
15	120	320	5	1	75	1
17	47	300	9	1	95	0
14	42	280	14	1	80	0
18	125	260	17	0	71	0
19	40	340	9	1	98	1
13	49	279	16	1	74	0
16	70	268	18	1	82	0
18	50	222	17	1	86	0
20	120	230	8	1	98	0
17	90	205	16	1	81	0
13	95	250	17	1	79	0
19	120	180	18	0	70	0

Fig 3.7 Patient Symptoms of FMPD

In this phase when the use of fuzzy medical patients dataset(FMPD) will create many rules in fuzzification stage to get linguistic variables for each patients symptoms of patients features for more accurately in suggestion drugs diagnose . The rules for Cholesterol as example :

Symptoms	linguistic variables
200 and below	Normal
201 - 220	Low
221 - 240	Medium
241 and above	High

The membership degree for each linguistic variables is computed as mentioned in chapter two in equation (2.10) . Other membership functions were created for clotting , heart rate , hypertension ,oxygen rate and temperature degree . Algorithm (3.15)shows the overall steps of Toulmin's model argumentation using naïve Bayes and fuzzy logic.

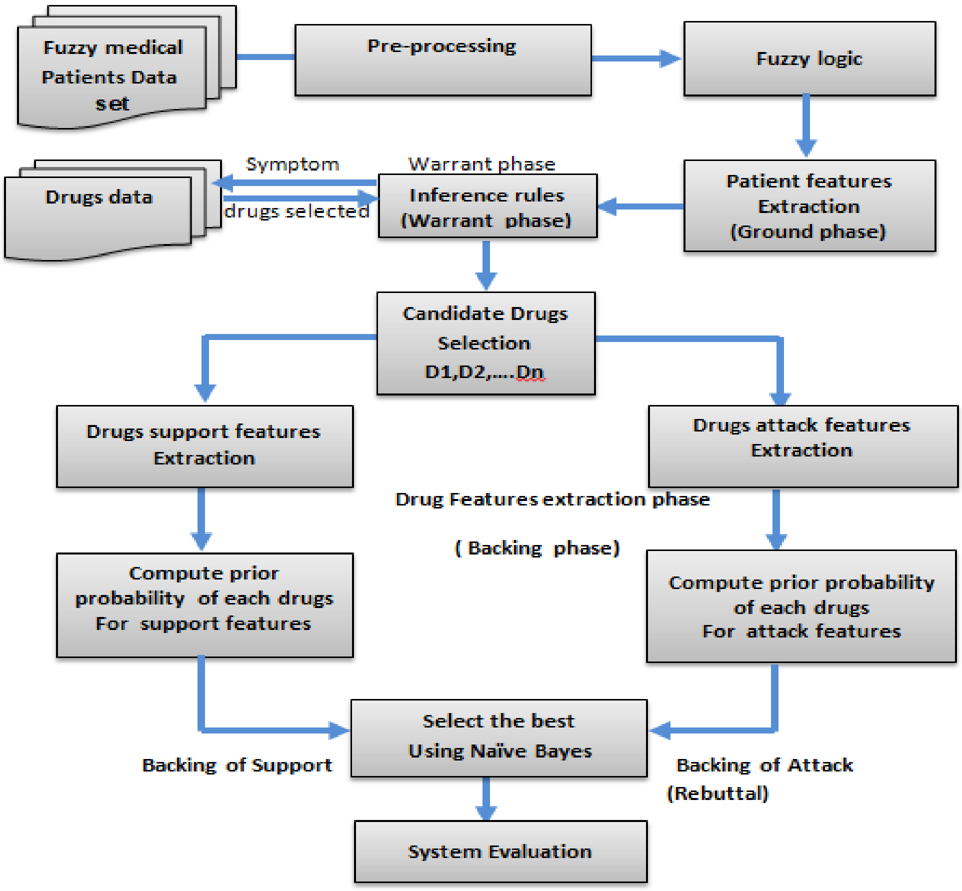


Fig 3.8 The Architecture of the Third Proposed Model

Algorithm (3.15) Overall steps of Toulmin's Model Argumentation using Naïve Bayes and Fuzzy logic .

Input: fuzzy patients datasets(FMPD) ,drugs dataset .

Output: patients dictionary(pd)% dictionary contain list of suggestion drugs and list of decisions of drugs.%

% Variables Definition

Pd: {}% dictionary

Sam,hiss: list %lists of patients

Begin

1- Pre-processing : pre-processing steps for cleaned dataset % sam ,hiss as output of call algorithm 3.2.

2- For each symptom of patient do% loop for patient symptoms

3- Create membership functions for get linguistic variables .% used fuzzy logic rules .

3- Patients features extraction(premise) based on outputs of membership functions % call algorithm 3.3

4- Warrant algorithm for linking between claims(suggested drugs) and premises(patient features) % output of algorithm 3.3

5- Candidate drugs extraction algorithm(Claim) % output of call algorithm 3.4.

6- Drugs features extraction (Backing) % output of call algorithm 3.5.

- Detect and compute support features .
- Detect and compute attack features (rebuttal) .

10- Using naive Bayes theory for making decision based on output of drugs features % qualifier phase in toulmin’s model .

11- End for

End algorithm

3.5 System Evaluation

In this phase, the confusion matrix will be used for evaluating the proposed models. At this point, the data set was annotated by a team of human experts in medicine .The samples are distributed by model and they show the patient characteristics such as symptoms, signs, patient history, and suggested medications for these patients(see samples in appendix). Next, the team's opinions about the drugs for these patients were proposed. These suggested opinions are matched to the results of the proposed models using a confusion matrix. The confusion matrix is used in evaluating the performance of a rating model through the calculation of performance metrics like accuracy, recall , precision and F-measure as mention in equations in chapter 2 (section 2.8).

CHAPTER FOURE

RESULTS &DISSICUSION

4.1 Overview

In this chapter, the methodology used to assess the proposed system is introduced. In this assessment several experiments were conducted to evaluate the performance of the proposed system. Due this system, labeled objects could be used to assess the proposed model by comparing the experts opinions about it and getting more meaningful results.

The approaches used in this study are classical Toulmin’s model(CTM) , improved Toulmin’s model using Naïve Bayes (TMNB) , improved Toulmin’s model using fuzzy logic(TMF) and improve Toulmin’s model using naïve Bayes and fuzzy logic approach(TMFNB). The results of the classical Toulmin’s model compared with the result of the improved Toulmin’s model using naïve Bayes and fuzzy logic is an optimum example of the development of Toulmin‘s model.

The proposed algorithms and evaluation measurements were programmed under Python code and evaluated using recall, precision and F-measure metrics.

4.2 System Requirement

The proposed model is implemented on a laptop with the following properties:

- ‘Hardware’: Ram 4 GB, Processor Intel® Core ™ i5.
- Operating System: Windows 10, 64-bit.
- Programing Language: Python (3.9)
- Supported Platform: PyCharm editor

4.3 Experimental Datasets

Two datasets are used to demonstrate and assess the proposed algorithms. First one is medical patient dataset(MPD). The data of patients were 0 and 1 saved in texts files form(txt) . The MPD contains more than 2000 patient samples of five cardiac diseases .These datasets were collected from educational hospitals in different city in Iraq, annotated by a team of experts working in the medical field.

For testing proposed system annotated 200 samples of hypertension disease and 330 samples of angina pectoris disease. Second dataset is fuzzy medical dataset(FMPD)which consists of the same diseases in first dataset , but differs in form of data . The data of patients were numerical data saved in texts files. To test the proposed system we annotated 100 samples of hypertension disease and 100 samples of angina pectoris disease. The drugs dataset consists of drug use and drugs interactions were gathered from sourced from online www.drugs.com , www.drugbank.com.

4.4 Preparing Data

In many tasks, it is necessary to clean or pre-process the data, which is as important as building the model itself. This process is essential in reducing the processing time and increasing its accuracy. As for the model used in this work, the pre-processing steps include: transfer all fact to under casing letter, punctuation removal, space line removal, in-line removal, and frequency data removal. After conduct pre-processing of datasets, lists of patients were built, now each patient have record of symptoms and record of history .

Also built lists of warrants for support and attack for justification of any decision will be made .Then built lists of decisions for all suggested drugs . The experts opinions was collected from physicians team working in medicine filed and built lists of these opinion for matching between experts opinion and model results .

This dissertation claims that using concepts as the basis of toulmin to improve effectiveness. Therefore we will employed the two datasets medical patient dataset(MPD), and fuzzy medical dataset(FMPD). After converted to numerical data, and presents this data as input . The overall steps for the proposed system illustrates in general algorithm (3.1).

4.5 Experimental Results of Medical Patients Dataset (MPD)

In this chapter, we have conducted the medical system experiments on the medical patients datasets ,which were collected from educational hospitals from different regions in Iraq. Several experiments were performed to show the effectiveness of the suggested system.

Patients' information is explained in table 4.1 where each column represents symptom ,which is itself a feature used as premise in Toulmin's model argumentation .Also the patient history is shown in table 4.2 represents premises in Toulmin's model argumentation. All experiments were conducted twice for each disease, once with four features , and the other used the same patients data with six features.

The symptoms of patients are represented by (0) or (1) which means that means this patient in case 0 does not hold this symptom and in case 1 this patient holds the symptom . The number of patients were 200 patients (samples) of hypertension disease and 330 of angina pectoris disease .

Table 4.1 Samples of Patients Symptoms and Signs

Patient Id	Symptoms & signs								
	HBP	LBP	Heart boats Rate (HBR)	Cholesterol	chest pain	Shortness of breath (SOB)	Blurred vision	Dizziness	Headache
P1	1	١	٠	١	٠	١	0	1	0
. . .									
Pn	1	٠	٠	١	١	١	1	0	1

Table 4.2 Sample of History of Patients

Patient id	Patients history						
	Age	Smoke	Chronic asthma	Kidney diseases	Heart failure	debit	Liver Diseases
P1	44	1	0	1	0	1	0
. . .							
Pn	60	0	0	0	1	0	1

4.5.1 First Experiment

The first experiment in this model was with the patients of hypertension disease. The number of patients was 200 patients (samples) for computing recall ,precision and f-measure metrics .These consider the standard assessments were applied to evaluate performance. Table 4.3 will show the metrics of recall ,precision, and f-measure according to equations (2.12, 2.١3, and 2.١4) for hypertension patients for four features and six features.

Table 4.3: Results of the Classical Toulmin's Model of Hypertension Disease

Disease name	No. of features	Recall (%)	Precision (%)	F-measure (%)
Hypertension	4	84	97	90
	٦	٧4	90	81

The results in this experiment in hypertension precision was 97% ,recall was 84% and F-measures was 90% for four features ,whereas for six features the precision was 90%,recall was 74% and F-measure was 81%.

4.5.2 Second Experiment

The second experiment in this model was with patients of angina pectoris disease. The total number of patients was 330 patients (samples) . Table 4.4 shows the results of patients of angina pectoris disease for four features and six features.

Table 4.4: Results of the Classical Toulmin's Model of Angina Pectoris Disease

Disease name	No. of features	Recall (%)	Precision (%)	F-measure (%)
Angina pectoris	4	87	97	92
	6	75	92	8٣

The results from this experiment in hypertension for four features can be summarized as follow: The precision was 97% ,recall was 87% and F-measures was 92% ,whereas in six features ,the precision was 75%,recall was 92% and F-measure was 83%.

4.5.3 Third Experiment

It applied the proposed model on the same patients data in the MPD dataset. Using the matching matrix, the results were compared to the patients cases that had been manually annotated. The third experiment used another approach to improve Toulmin's model argumentation which used naïve Bayes theory. Same samples were used in first and second experiments .

Prior probability was computed for each remedies item from results of the classical Toulmin's model and then posterior probability is computed for supported features and attack features of all suggested drugs and then which will be wining is computed . Table 4.5 explain the results achieved in this experiment in hypertension for four features ,the precision was 97% ,recall was 89 and F-measures was 93%,whereas in six features the precision was 92%,recall was 76% and F-measure was 83%.

Table 4.5 :Results of the Improved Toulmin's using Naïve Bayes of Hypertension Disease

Disease name	No. of features	Recall (%)	Precision (%)	F-measure (%)
Hypertension	4	89	97	93
	6	76	92	83

4.5.4 Fourth Experiment

The fourth experiment in this model was conducted with patients of angina pectoris disease using improved Toulmin's model using naïve

Bayes technique . The total number of patients was 330 patients (samples) .Table 4.6 explains the results of this experiment , the recall was 92% , precision was 97% and F-measures was 95% for four features ,whereas in six features the results achieved as precision was 92%,the recall was 83% and F-measure was 87%.

Table 4.6: Results of Improved Toulmin’s Model of Angina Pectoris Disease

Disease name	**No. of Features**	**Recall (%)**	**Precision (%)**	**F-measure (%)**
Angina pectoris	4	92	97	95
	6	٨3	9٢	٨7

According to the results that achieved in four experiments for medical patients dataset(MPD) .Table 4.7 summarizes the results of all experiments in this dataset.

Table 4.7: Overall Accuracy of All Experiments of MPD

Disease name	**Approach**	**No. of features**	**Recall (%)**	**Precision (%)**	**F-measure (%)**
Hypertension	**CTM**	**4**	**84**	**97**	**90**
		٦	**٧٤**	**90**	**81**
	TMNB	**4**	**88**	**98**	**93**
		6	**76**	**92**	**83**
Angina pectoris	**CTM**	**4**	**86**	**98**	**92**
		6	**75**	**92**	**8٣**
	TMNB	**4**	**92**	**97**	**95**
		6	**٨3**	**9٢**	**٨7**

We noted that the results in the improved Toulmin's using naïve Bayes technique were higher than results in classical Toulmin's model for two diseases hypertension and angina pectoris as shown in figures 4.1 and 4.2 .

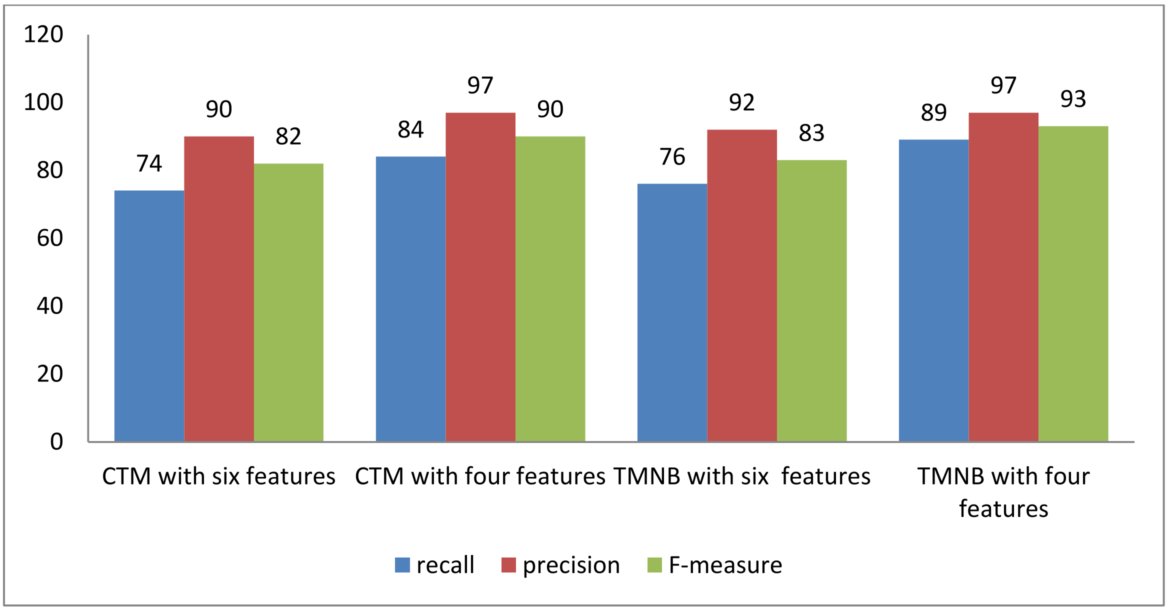


Fig 4.1 Results of in Hypertension Diseases for MPD

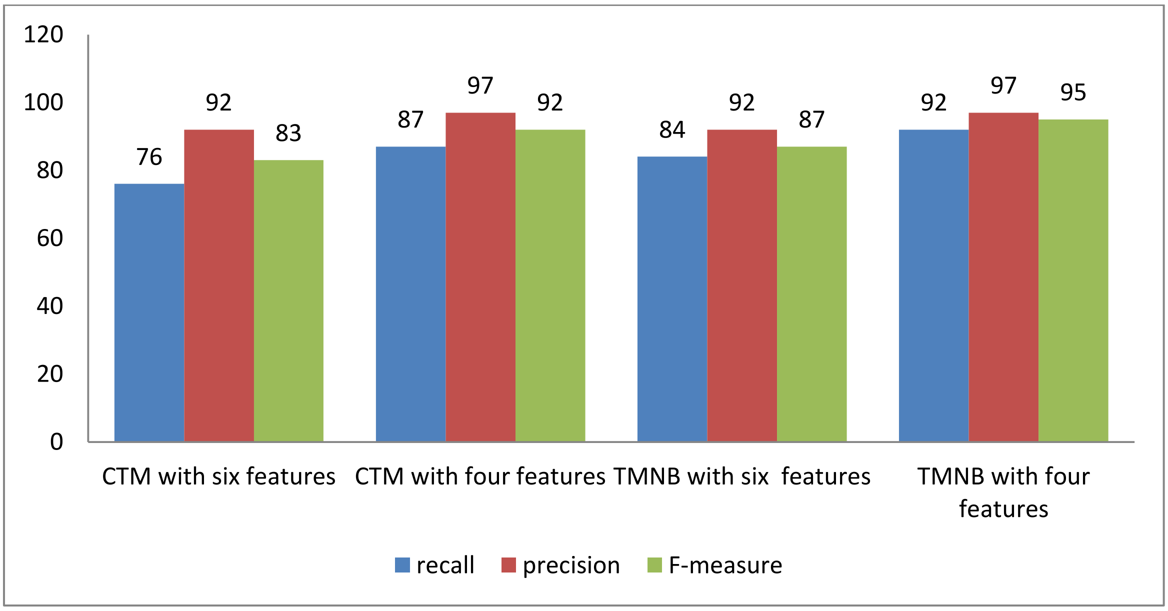


Fig 4.٢ : Results of Angina Pectoris Diseases for MPD

We noted the results of angina pectoris and hypertension diseases using four features are higher than the results gotten from using six features .

4.6 Experimental Results with Fuzzy Medical Patients Dataset (FMPD)

The number of patients were 200 patients (samples) ,100 of hypertension and 100 of angina pectoris disease. We used these samples for computing recall ,precision and f-measure. In this dataset(FMPD) the symptoms were represented in digital numbers and we used the membership functions in fuzzy logic to extract optimal features for the patient to get optimal drug of the patients.

For example when the patient has cholesterol more than 200 that mean this patient has this feature, this feature was extracted by membership functions as mentation in equation (2.10) .These features according membership function may be as (normal , low ,moderate ,high) for each grade in drugs family we choose the optimal drugs for the patient from each drugs family. After that we identify support and against features for each drug was suggested for the patient to make decision about whether the patient drug can use this drug or not.

Four experiments were conducted for two diseases(hypertension and angina pectoris) in FMPD. Table 4.8 shows the samples of patients in second dataset .

Table 4.8 Samples of Patients Symptoms and Signs of FMPD

Patient id	Symptoms & Signs								
	HBP	LBP	Heart boats Rate (HBR)	Cholesterol	chest pain	Shortness of breath(SOB)	Blurred vision (BV)	Dizziness	Head ache
P1	14	9	70	240	1	85	0	1	0
. . .									
Pn	19	12	135	400	0	75	1	0	1

4.6.1 Fifth Experiment

In this experiment fuzzy logic approach was used for improving performance of Toulmin‘s model(TMF) for diagnosing suitable remedy , then qualify function is used to compute the maximum value between the support and attack for making decision about using or not using this drug . Table 4.9 shows the precision ,recall and F-measure were achieved in this approach of hypertension diseases by considering four and six features in this approach .

Table 4.9: Results of the Improved Toulmin's using Fuzzy Logic of Hypertension Disease

Disease name	**No. of Features**	**Recall (%)**	**Precision (%)**	**F-measure (%)**
Hypertension	**4**	**89**	**97**	**93**
	6	**٧6**	**9٢**	**٨3**

The results in this experiment in hypertension of four features can be summarized as follows : the precision was 97% ,recall was 89 and F-measures was 93% ,whereas for six features the precision was ٧6%,recall was 92% and F-measure was 83%.

4.6.2 Sixth Experiment

In this experiment fuzzy logic approach was used with Toulmin‘s model for angina pectoris disease . Table 4.10 shows the precision ,recall and F-measure of angina pectoris disease by considering four and six features .

Table 4.10: Results of the Improved Toulmin’s using Fuzzy of Angina Pectoris Disease

Disease name	**No. of Features**	**Recall (%)**	**Precision (%)**	**F-measure (%)**
Angina pectoris	**4**	**93**	**٩7**	**95**
	6	**٨4**	**92**	**88**

The results in this experiment where four features were used in angina pectoris disease are as follow : the precision was 93% ,recall was 97 and F-measures was 95% ,whereas with six features , the precision was 84%,recall was 92% and F-measure was 88%.

4.6.3 Seventh Experiment

In this experiment another approach was used for improving Toulmin’s model argumentation which is used fuzzy logic with naïve Bayes theory (TMFNB) . Same samples were used in the fifth and sixth experiments .The prior probability also was computed for each medication item in suggestion remedies using the classical Toulmin’s model and then the posterior probability was computed for supported features (vector of support values) and attack features(vector of attack values) and then a decision is made about which will be the winner .

Table 4.11 explains the results related to the hypertension disease for four features , where the precision was 97% ,recall was 93 and F-measures was 95%,whereas in case of six features the precision was 77%,recall was 95% and F-measure was 85%.

Table 4.11 :Results of the Improved Toulmin’s using Fuzzy with Naïve Bayes of Hypertension Disease in the

Disease name	No. of features	Recall (%)	Precision (%)	F-measure (%)
Hypertension	4	93	٩7	95
	6	77	95	85

4.6.4 Eighth Experiment

In this experiment naïve Bayes with fuzzy logic used for enhancing the performance of Toulmin’s argumentation model using the same samples that were used in thefourth and the sixth experiments in this dataset. Table 4.12 shows the precision ,recall and F-measure related to the angina pectoris diseases .

The results of the four features were as follows: the recall was 96% , the precision was 100% and F-measures was 98% ,whereas in the case of the six features , the recall was 82%, the precision was 97% and F-measure was 89%.

Table 4.12 : Results of the Improved Toulmin's using Fuzzy with Naïve Bayes of Angina Pectoris Disease

Disease name	**No. of features**	**Recall (%)**	**Precision (%)**	**F-measure (%)**
Angina pectoris	4	96	100	98
	6	٨2	٩7	89

Table 4.13 Shows the results for two diseases and four and six features in four experiments for fuzzy medical patients dataset(FMPD).

Table 4.13: Overall Accuracy for All Experiments of FMPD

Disease name	**Approach**	**No. of Features**	**Recall (%)**	**Precision (%)**	**F-measure (%)**
Hypertension	**TMF**	**4**	89	98	93
		6	٧٦	9٢	٨3
	TMFNB	**4**	93	97	95
		6	٧7	9٥	٨5
Angina pectoris	**TMF**	**4**	93	٩7	95
		6	٨4	92	88
	TMFNB	**4**	96	100	98
		6	٨2	٩7	89

According to results come up with from the four experiments of the fuzzy medical patients dataset(FMPD) we noted that the results of the improved Toulmin's model using naïve Bayes technique and fuzzy logic were higher than the classical Toulmin's model for the two diseases hypertension and angina pectoris as shown in figures 4.3 and 4.4 .

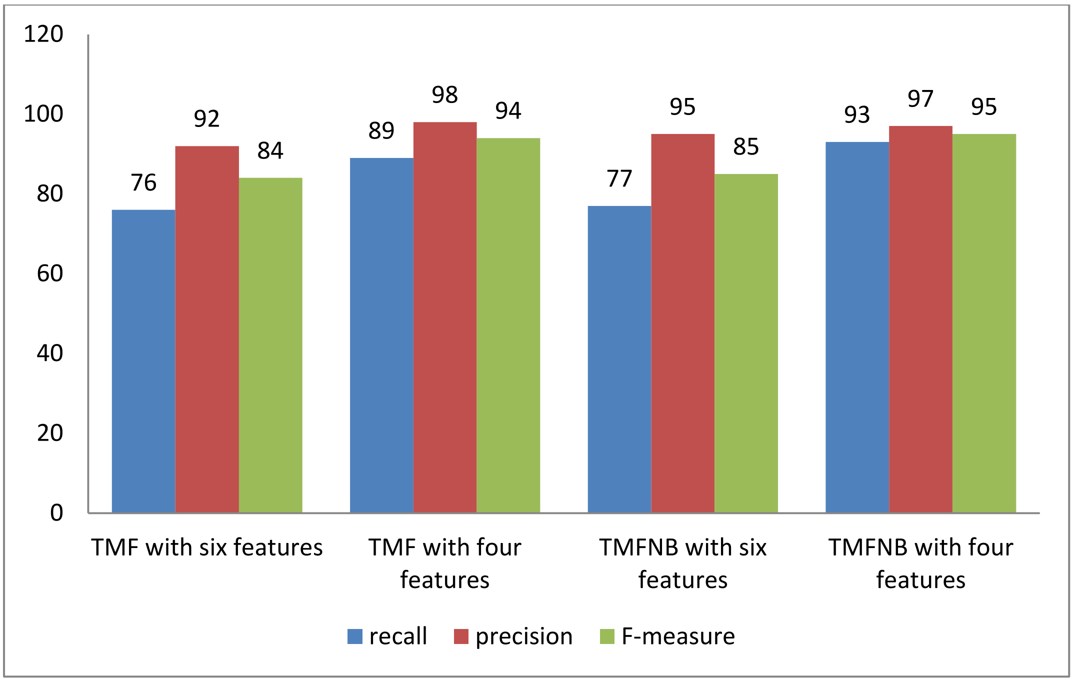


Fig 4.3 Results of Hypertension Disease for FMPD

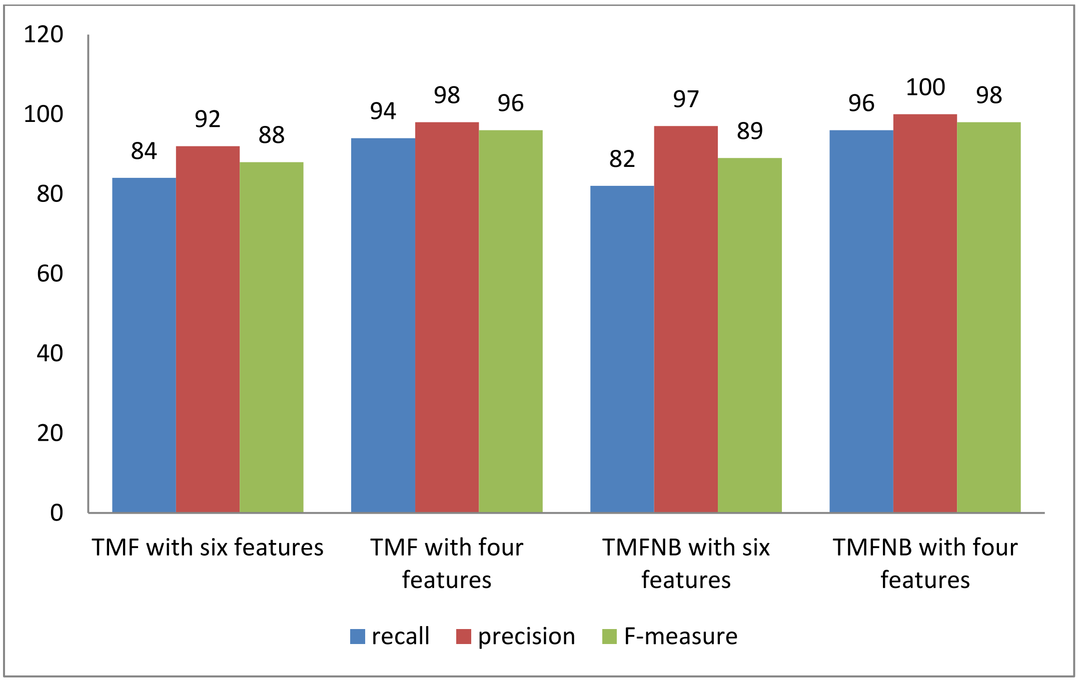


Fig 4.4 Results of Angina Pectoris Disease for FMPD

The results shown in figures 4.4 and 4.5 explain values of precision , recall, and F-measure that in two approaches of the used Toulmin's model argumentation ,the first represent the classical Toulmin's model and the others represents the enhancement of the performance of Toulmin's model by using fuzzy logic and naïve Bayes technique. We noted the results of angina pectoris were better than the results of hypertension disease .

4.7 Results Discussion

In this chapter, we analyzed the behavior of the proposed methods for improving Toulmin's model argumentation . We started by describing the corpus and then explaining the evaluation methods so that we can explain the results of the experiments. In general , several experiments are carried on two different types of corpora ,which are MPD and FMPD.

The experimental results show the proposed model for enhancing Toulmin's model using Naïve Bayes achieved good results for two corpora ,but we noted the results accomplished in using Toulmin's model with fuzzy logic and naïve Bayes in FMPD were it the highest .Table 4.14 shows a summary of the experimental datasets results and accuracy of algorithms with four and six features.

Table 4.14: Details of All Experiments

Disease name	Accuracy							
	CTM		TMNB		TMF		TMFNB	
	Four features %	Six features %	**Four features %**	Six features %	**Four features %**	**Six features %**	**Four features %**	Six features %
Hypertension	**90**	81	**93**	83	**94**	84	**95**	85
Angina pectoris	**92**	83	**95**	87	**96**	88	**98**	90

Figure 4.6 display the overall F-measure of all experiments. In first experiment of the patients of hypertension in first corpus called MPD, we noted the achieved f-measure in the classical Toulmin’s model was 90% for four features and 81% for take six features , then the third experiment is created on same samples for enhancing the classical Toulmin’s model using naïve Bayes technique. We noted little enhancement for example, the f-measure achieved in this approach was 93% using four features and 83% using six features ,whereas the enhancement that achieved in TMNB approach 95% for four features and 87% for six features .

In the third and fourth experiments where the naïve Bayes was applied to enhance the Toulmin’s model, noted improvement in the results, and this improvement is supported by a priori probability of each proposed medication in the patient's suggested treatments list, which we obtain from the results obtained from the use of the classic Toulmin’s model in first experiment, which is considered as a baseline for the data sets were used in this dissertation .Also we noted that the gotten results are better than results obtained from the others approaches .

Concerning the patients with angina pectoris, three experiments were conducted and the results were better than those related to patients of hypertension disease. We noted that the accuracy level in the second experiment with the use of the classic Toulmin’s model was 92% using four features, and then established in fourth experiment on the same samples to reinforce the classic Toulmin’s model using naïve Bayes was applied to improve the Toulmin’s model, the accuracy of which was 95%, and we also observed that the obtained results with six features using naïve Bayes are better than results accomplished through using classical Toulmin’s model .

In first experiment with the patients of hypertension in the second corpus ,which called fuzzy medical patients dataset (FMPD), we noted that the accuracy in the improved Toulmin's model by fuzzy logic was 94% , then other experiment applied on same samples using fuzzy with naïve Bayes technique we noted little enhancements in term accuracy which was 95%.

A for the patients with angina pectoris, four experiments were conducted and the results were better than the ones related to the patients of hypertension disease also . We noted that the accuracy achieved in the improved Toulmin's model by fuzzy was 95%, and then using fuzzy with Naïve Bayes was applied to improve the Toulmin's model, the achieved accuracy was 98%, we observed that this approach involve the highest results .

The experiments that were conducted for all cases of patients with hypertension and angina pectoris and the application of classical Toulmin's model approach and the proposed algorithms to develop Toulmin's model argument that the use of naïve Bayes with the Toulmin's model argumentation as clarified in figure (4.5) in addition to the results obtained from using the Naïve Bayes theory all show clearly the improvement in the results of MPD data set.

As for the second data set(FMPD)using fuzzy logic technique, a clear improvement is noted in the results, since the nature of this data is a numerical data of the symptoms, and then these symptoms are extracted using the membership functions, through which the patient's features are determined through linguistic variables, and this led to the accuracy of suggesting the appropriate treatment for the patient, which led to high accuracy in results, especially for patients with angina pectoris .

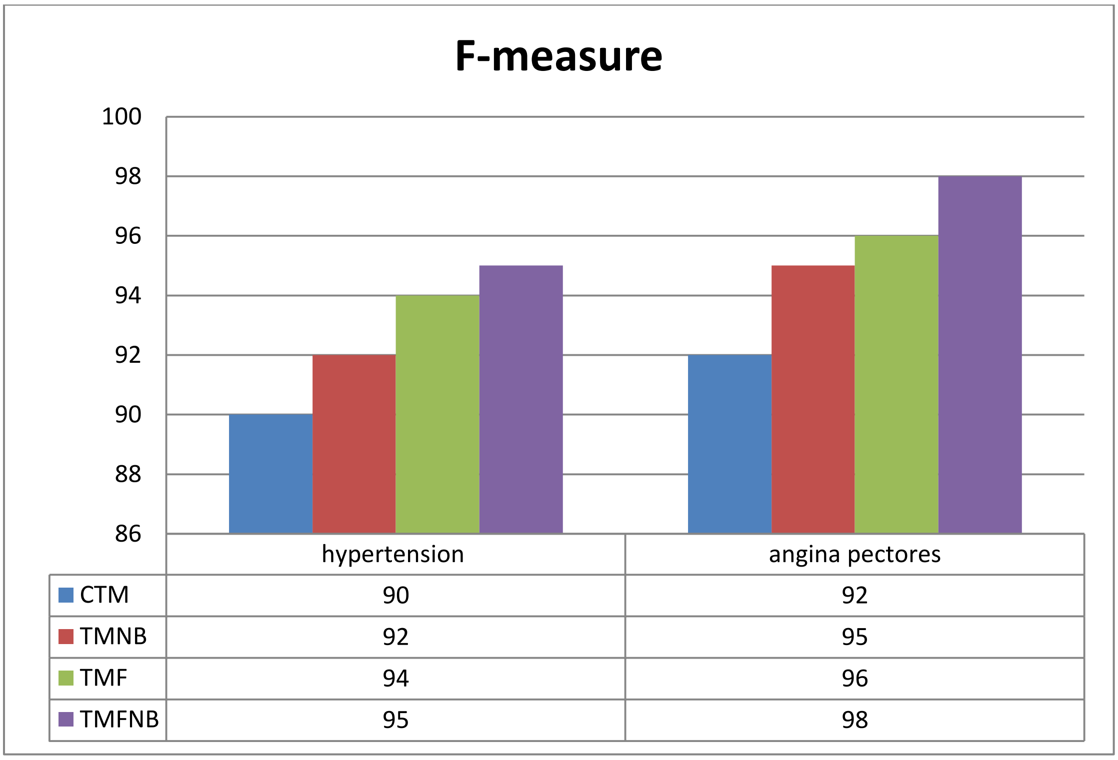


Figure 4.5: The Results of All Experiments with Four Features

Figure (4.6) shows the results obtained from all experiments for all proposed models for used six features for two datasets.

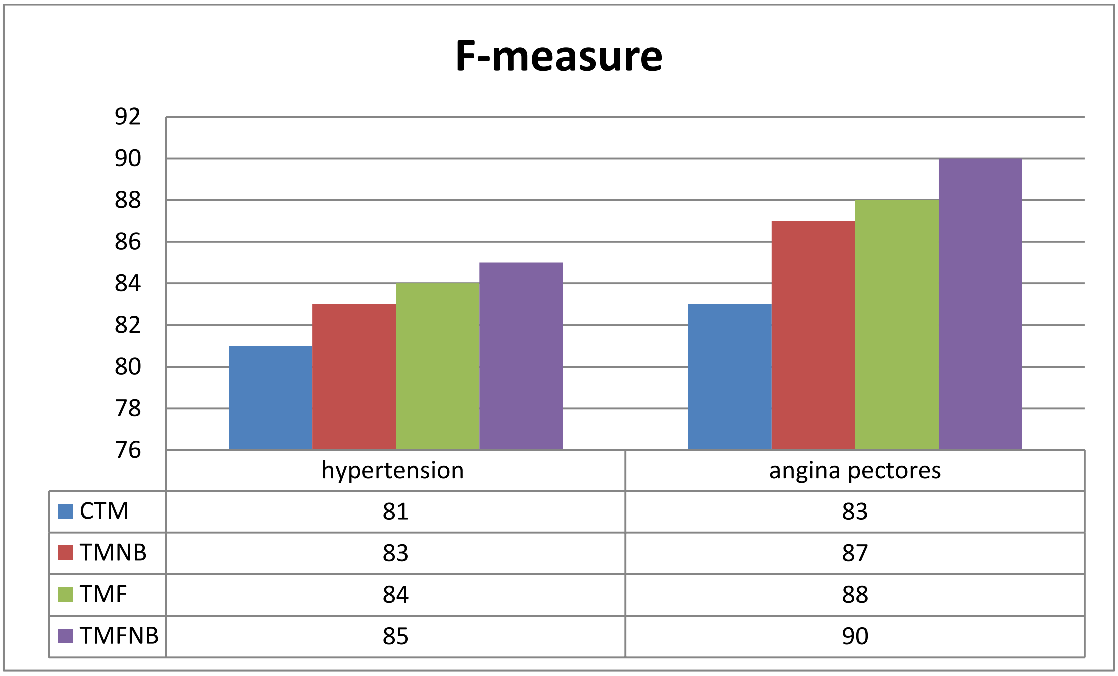


Figure 4.6: The Results of All Experiments with Six Features

It is noted from the results of all the conducted experiments and for all diseases that the results obtained from using four features are better than the ones obtained from using six features. All features have weights and through these weights the decision is made.

The cost features are related to the patient's limited physical capacity , which often leads to death due to the patient's inability to afford the treatment costs, and thus the patient is forced to take an alternative treatment, which may not result in a complete recovery.

As for the availability feature of treatment, it is also a feature that plays a big role for diagnosing the optimal treatment for the patient, but may its unavailability that will forces the doctor to replace the treatment because it is not available in the market and needs to be imported from other countries and need to long time.

Through all that mentioned earlier, we found that when using experiments with four features, the results obtained are more accurate than those results with the use of six features.

CHAPTER FIVE

CONCLUSIONS AND FUTURE WORKS

5.1 Conclusions

This dissertation presented three proposed algorithms for enhancing the performance of the classical Toulmin's model of argumentation . this work also used the classical Toulmin's model argumentation algorithm to compare the performance and to solve conflicting problems for suggesting the optimal remedy for patients. Several experiments are conducted and the results lead to the following conclusions

:

- The use of Toulmin's model argumentation for solving remedies conflict problems is beneficial in the medicine filed to make supported decisions .
- Created a new medical datasets from Iraqi educational hospitals and created labels of it.
- The improvement of results are recorded for the use of Naive Bayes with Toulmin's model which was 95% as compared to the results of the classic Toulmin's model which was 92% .
- The improvement of results of using the fuzzy logic with the Toulmin's model which was 96% as compared to the results of the classic Toulmin's model which was 92% .
- The use of the fuzzy logic with naïve Bayes was proposed to enhance the performance of the Toulmin's model argumentation . The result was 98% as compared to result of the classical Toulmin's model ,which was 92%, in terms of to some metrics as precision, recall and f-measure .

- Proving that two proposed fuzzy logic and Naïve Bayes algorithms are indeed appropriate methods for improving the performance of Toulmin’s model argumentation .
- Created labels of these medical datasets took big effort and long time.
- The use of Naive Bayes' theory and fuzzy logic approach with four features achieved better than results of use six features.

5.2 Suggested Future Works

There are several suggestions that can be handled in the future as follows :

1- Using the proposed algorithms of Toulmin’s model argumentation for diagnosing the best remedies for other diseases such as corona virus and acute anemia diseases.

2- Using Gaussian naïve Bayes type as the proposed algorithm for improving performance of Toulmin’s model argumentation by using continues values of features .

3- Trying to use other techniques to improve the performance of Toulmin's argument model such as decision tree algorithm and random forest algorithm .

4- Trying to get the optimal medical datasets which contain all things about patients such Electrocardiography (ECG) and all biological examinations of patients .

5- Applying the proposed online system as a guide to help patients know the features of remedies.

6- Trying to use deep neural network to improve the performance of Toulmin's argument model .

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جمهورية العراق

وزارة التعليم العالي والبحث العلمي

جامعة بابل

كلية تكنلوجيا المعلومات

قسم البرمجيات

النايف بيز والمنطق الضبابي لنموذج حجة تولمن لمشاكل العلاج الطبي المتضارب

اطروحة مقدمة

الى مجلس كلية تكنولوجيا المعلومات-جامعة بابل وهي جزء من متطلبات نيل درجة الدكتوراه فلسفة في تكنولوجيا المعلومات / برمجيات

من قبل

حمزة نوري فجر عبد الله

اشراف

ا.م.د.علي هادي حسن

١٤٤٤ هـ ٢٠٢٣ م

الخلاصة

الحجج هو موضوع جديد نسبيًا للذكاء الاصطناعي يحتوي على مجموعة واسعة من التطبيقات في مجالات متنوعة مثل الإدارة والقانون والعلوم السياسية والطب والرياضيات وغيرها. الهدف من استخدام الحجة هو زيادة قدرة الكمبيوتر على إثبات ومناقشة الآراء والمشاعر والنظريات. الحجة هو مصطلح يستخدم كل يوم تقريبًا ، ومع ذلك يتم استخدامه عندما يكونون في حالة وجود تعارض واختلاف بين الاشخاص. و يمكن أن تكون الحجة مفيدًا في شرح قرار تم اتخاذه بالفعل.

تم تطبيق نموذج تولمن تم تطبيق نموذج تولمين الكلاسيكي لحل مشاكل التناقض في العلاجات الطبية ، وقد تم استخدام ثلاث طرق لتحسين أداء نموذج حجة تولمن ، وهي نايف بيز و والمنطق الضبابي ثم استخدامهما معًا. حيث تم استخدام الأعراض والتاريخ الطبي للمريض واستخراج خصائص العلاج ، ثم حساب وزن الحجة الداعمة والمتناقضة لكل علاج ، و حساب القرار الطبي المدعوم لكل علاج.

لتقييم أداء الطرق المقترحة ، شرحت مجموعات البيانات من قبل فريق من الخبراء البشريين في الطب ، ووزعت العينات حسب النموذج ان تظهر خصائص المريض مثل الأعراض والعلامات وتاريخ المريض والأدوية المقترحة لهؤلاء المرضى. بعد ذلك ، تم اقتراح آراء الفريق حول الأدوية لهؤلاء المرضى. ثم مطابقة هذه الآراء المقترحة مع نتائج النموذج المقترح باستخدام مصفوفة الارتباك . تُستخدم هذة المصفوفة في تقييم أداء نموذج التصنيف من خلال حساب مقاييس الأداء مثل (الدقة ، الاستدعاء ، مقياس F).

تم إجراء العديد من التجارب على مرضى ارتفاع ضغط الدم والذبحة الصدرية ، وكانت النتائج التي تم الحصول عليها باستخدام مجموعة بيانات المرضى لمرض ارتفاع ضغط الدم ٩٠٪ باستخدام نموذج تولمين الكلاسيكي ، و ٩٢٪ باستخدام نموذج تولمين المحسن بواسطة نايف بيز ، ٩٤٪ باستخدام نموذج تولمين المحسن بواسطة المنطق الضبابي ، ٩٥٪ باستخدام نموذج تولمين المحسن بواسطة نايف بيز والمنطق الضبابي.

كانت النتائج التي تم الحصول عليها لمرض الذبحة الصدرية ٩٢٪ باستخدام نموذج تولمين الكلاسيكي ، ٩٥٪ باستخدام نموذج تولمين مع نايف بيز ، ٩٦٪ باستخدام نموذج تولمين المحسّن بواسطة المنطق

الضبابي ، و ٩٨٪ باستخدام نموذج تولمين مع نايف بيز والمنطق الضبابي. توضح هذه النتائج الأداء المتفوق للخوارزميات المقترحة مقارنة بنموذج تولمين الكلاسيكي. بالإضافة إلى ذلك ، أظهرت النتائج التجريبية أن الطرق المقترحة لتحسين أداء نموذج تولمين فعالة.

Appendix

15

symptoms

chest pain
Indigestion
Irregular heartbeats
Palpitation
headache
Vomiting
Angina Pectoris

history of patient

age>40
Cholesterol
BPL
kidney
BS

suggestion drug	Decision
Amlodipine	Should
CalciumCarbonate	Should
Amiodarone	Should
Procainamide	Should
Acetaminophen	not
Dimenhydrinate	not
Propranolol	not

16

symptoms

chest pain
Indigestion
Nausea
Irregular heartbeats
Palpitation
headache
fever
Angina Pectoris

history of patient

age>40
Cholesterol
BPL
BS
BU

suggestion drug	Decision
Amlodipine	Should
Calcium Carbonate	Should
Dimenhydrinate	not
Amiodarone	Should
Procainamide	Should
Acetaminophen	Should
Propranolol	Should

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symptoms

chest pain
Indigestion
Irregular heartbeats
Palpitation
headache
Angina Pectoris

history of patient

age>40
BPL
BS
BU

suggestion drug	Decision
Amlodipine	Should
Calcium Carbonate	Should
Amiodarone	Should
Procainamide	Should
Acetaminophen	not
Propranolol	Should

18

symptoms

chest pain
Irregular heartbeats
Palpitation
Vomiting
Angina Pectoris

history of patient

age>40
Cholesterol
BPL

suggestion drug	Decision
Amlodipine	Should
Amiodarone	Should
Procainamide	Should
Dimenhydrinate	not
Propranolol	Should

Angina Pectoris disease

105

symptoms

----

chest pain

Clotting

headache

Vomiting

fever

Sweating

history of patient

----

age<40

Cholesterol

asthma

kidney

BS

BU

Suggestion drugs Decision

Amlodipine ------------------------

aspirin ------------------------

Acetaminophen ------------------------

Dimenhydrinate ------------------------

Nicorandil ------------------------

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طبيب اختصاص باطنية

19

symptoms

---

chest pain

Shortness of breath

Indigestion

Irregular heartbeats

Palpitation

Sweating

Headache

Angina Pectoris

history of patient

---

age>40

BPL

BS

suggestion drug	Decision
Amlodipine	should
Epinephrine	not
Calcium Carbonate	should
Amiodarone	should
Procainamide	should
Aluminumchlorohydrate	not
Acetaminophen	not
Propranolol	not

20

symptoms

---

chest pain

Shortness of breath

Nausea

Irregular heartbeats

Palpitation

Sweating

Vomiting

Angina Pectoris

history of patient

---

age>40

Cholesterol

asthma

kidney

liver

BU

suggestion drug	Decision
Amlodipine	should
Epinephrine	not
Dimenhydrinate	not
Amiodarone	should
Procainamide	should
Aluminumchlorohydrate	not
Propranolol	not

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symptoms

---

chest pain

Shortness of breath

Indigestion

Irregular heartbeats

Palpitation

Sweating

Angina Pectoris

history of patient

---

age>40

asthma

BS

BU

suggestion drug	Decision
Amlodipine	should
Epinephrine	not
Calcium Carbonate	not
Amiodarone	should
Procainamide	should
Aluminumchlorohydrate	not
Propranolol	not

22

symptoms

Shortness of breath

Indigestion

Nausea

Irregular heartbeats

Palpitation

Vomiting

Angina Pectoris

history of patient

---

age>40

asthma

BPL

BS

BU

suggestion drug	Decision
Epinephrine	not
CalciumCarbonate	should
Dimenhydrinate	not
Amiodarone	should
Procainamide	should
Propranolol	not

23

symptoms

HT
Pulse
Cholesterol
chest pain
Shortness of breath
Blurred vision
Dizziness
headache

history of patient

---

age>40
Smoke
asthma
BS
liver

suggestion drug	Decision
Sodiumnitroprusside	Should
Propranolol	Should
Tocopherylnicotinate	not
Amlodipine	Should
Epinephrine	not
Almitrine	not
Dimenhydrinate	not

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symptoms

HT
Pulse
Cholesterol
chest pain
Shortness of breath
Dizziness

history of patient

---

age>40
Kidney
heart failure

suggestion drug	Decision
Sodiumnitroprusside	Should
Propranolol	not
Tocopherylnicotinate	not
Amlodipine	Should
Epinephrine	not
Dimenhydrinate	not

25

symptoms

HT
Pulse
Cholesterol
ESR
chest pain
Shortness of breath
Dizziness

history of patient

---

age>40
Kidney
heart failure
liver

suggestion drug	Decision
Sodiumnitroprusside	Should
Propranolol	not
Tocopherylnicotinate	not
Teicoplanin	not
Amlodipine	Should
Epinephrine	not
Dimenhydrinate	not

26

symptoms

HT
Pulse
Cholesterol
ESR
Shortness of breath
Dizziness

history of patient

---

age>40
Kidney
heart failure
liver

suggestion drug	Decision
Sodiumnitroprusside	Should
Propranolol	not
Tocopherylnicotinate	not
Teicoplanin	not
Epinephrine	not
Dimenhydrinate	Should

HT
Pulse
Cholesterol
chest pain
Shortness of breath
Blurred vision
Dizziness
headache
history of patient

age>40
asthma
Kidney
heart failure

suggestion drug	Decision
Sodiumnitroprusside	Should
Propranolol	not
Tocopherylnicotinate	not
Amlodipine	should
Epinephrine	not
Almitrine	not
Dimenhydrinate	not
Acetaminophen	not

HT
Pulse
Cholesterol
ESR
chest pain
Shortness of breath
Dizziness

history of patient

age>40
Kidney
heart failure

suggestion drug	Decision
Sodiumnitroprusside	Should
Propranolol	not
Tocopherylnicotinate	not
Teicoplanin	not
Amlodipine	Should
Epinephrine	not
Dimenhydrinate	not

29

symptoms

HT
Cholesterol
ESR
chest pain
Shortness of breath
Dizziness

history of patient

age>40
asthma
Kidney
heart failure

suggestion drug	Decision
Sodiumnitroprusside	Should
Tocopherylnicotinate	not
Teicoplanin	not
Amlodipine	should
Epinephrine	not
Dimenhydrinate	not

30

symptoms

HT
Pulse
Cholesterol
ESR
chest pain
Shortness of breath
Dizziness

history of patient

age>40
Kidney
Heart failure

suggestion drug	Decision
Sodiumnitroprusside	Should
Propranolol	not
Tocopherylnicotinate	not
Teicoplanin	not
Amlodipine	Should
Epinephrine	not
Dimenhydrinate	not

Hypertension disease

11

symptoms

HT
Pulse
Cholesterol
chest pain
Shortness of breath
Blurred vision
headache
history of patient

---

age<40
heart failure
BS
liver

suggestion drug	Decision
Sodiumnitroprusside	should
Propranolol	not
Tocopherylnicotinate	not
Amlodipine	should
Epinephrine	not
Almitrine	not
Acetaminophen	not

12

symptoms

HT
Cholesterol
chest pain
Shortness of breath
Dizziness
history of patient

---

age>40
Kidney
heart failure
BS

suggestion drug	Decision
Sodiumnitroprusside	should
Tocopherylnicotinate	not
Amlodipine	should
Epinephrine	not
Dimenhydrinate	not

13

symptoms

HT
Pulse
Cholesterol
ESR
chest pain
Shortness of breath
Dizziness
history of patient

---

ge>40
sthma
idney
eart failure

ggestion drug	Decision
diumnitroprusside	should
opranolol	not
copherylnicotinate	not
coplanin	not
lodipine	should
ephrine	not
nhydrinate	not

14

symptoms

HT
Cholesterol
Shortness of breath
Dizziness

history of patient

---

age<40
heart failure
BS
liver

suggestion drug

Sodiumnitroprusside should — should
Tocopherylnicotinate should — not
Epinephrine should — not
Dimenhydrinate should — not

Hypertension

120

symptoms

HBP

Pulse

Shortness of breath

Blurred vision

Dizziness

headache

History of patient

----

age>40

Smoke

asthma

heart failure

BS

liver

Suggestion drug	Decision
Sodiumnitroprusside	------------------------
Propranolol	------------------------
Nitroglycerin	------------------------
Almitrine	------------------------
Dimenhydrinate	------------------------
Acetaminophen	------------------------

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Hypertension

110

symptoms

HBP

Pulse

Shortness of breath

Blurred vision

Dizziness

headache

History of patient

----

age>40

Smoke

asthma

heart failure

BS

liver

Suggestion drug	Decision
Sodiumnitroprusside	------------------------
Propranolol	------------------------
Nitroglycerin	------------------------
Almitrine	------------------------
Dimenhydrinate	------------------------
Acetaminophen	------------------------

الدكتور
حامد عبيد الغانم
طبيب اختصاص ...

Hypertension

109

symptoms

HBP

Pulse

Cholesterol

ESR

chest pain

Shortness of breath

Dizziness

History of patient

----

age>40

Smoke

asthma

heart failure

BS

liver

Suggestion drug	Decision
Sodiumnitroprusside	----------------------
Propranolol	----------------------
Tocopherylnicotinate	----------------------
Teicoplanin	----------------------
Amlodipine	----------------------
Nitroglycerin	----------------------
Dimenhydrinate	----------------------

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ليث رزاق

الدكتور
حامد عبد الغا

Hypertension

115

symptoms

HBP

Pulse

ESR

Shortness of breath

Blurred vision

headache

History of patient

----

age<40

heart failure

Suggestion drug	Decision
Sodiumnitroprusside	------------------------
Propranolol	------------------------
Teicoplanin	------------------------
Nitroglycerin	------------------------
Almitrine	------------------------
Acetaminophen	------------------------

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حامد عبيد الغانمي
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Hypertension

116

symptoms

HBP

Pulse

Shortness of breath

Blurred vision

Dizziness

History of patient

----

age>40

Smoke

asthma

heart failure

BS

liver

Suggestion drug	Decision
Sodiumnitroprusside	------------------------
Propranolol	------------------------
Nitroglycerin	------------------------
Almitrine	------------------------
Dimenhydrinate	------------------------

Angina Pectoris disease

103

symptoms

----

chest pain

Indigestion

headache

Vomiting

fever

Sweating

history of patient

----

age>40

BPL

BS

Suggestion drugs Decision

Amlodipine ---------------------

CalciumCarbonate ---------------------

Acetaminophen ---------------------

Dimenhydrinate ---------------------

Nicorandil ---------------------

الدكتور
حامد عبيد الغانمي
طبيب اختصاص باطنية

Angina Pectoris disease

11

symptoms

chest pain

Shortness of breath

Indigestion

Irregular heartbeats

Palpitation

Sweating

fever

Angina Pectoris

history of patient

age>40

suggestion drug	Decision
Amlodipine	should
Epinephrine	not
Calcium Carbonate	not
Amiodarone	not
Procainamide	not
Aluminumchlorohydrate	not
Acetaminophen	not
Propranolol	should

12

symptoms

Shortness of breath

Indigestion

Nausea

Irregular heartbeats

Palpitation

Vomiting

fever

Angina Pectoris

history of patient

age>40

Cholesterol

asthma

BS

BU

suggestion drug	Decision
Epinephrine	not
CalciumCarbonate	not
Dimenhydrinate	not
Amiodarone	should
Procainamide	should
Acetaminophen	should
Propranolol	not

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symptoms

chest pain

Nausea

Irregular heartbeats

Palpitation

Vomiting

Angina Pectoris

istory of patient

ge>40

PL

ggestion drug	Decision
lodipine	should
enhydrinate	not
odarone	should
inamide	should
ranolol	should

14

symptoms

chest pain

Shortness of breath

Nausea

Irregular heartbeats

Palpitation

Sweating

headache

Angina Pectoris

history of patient

age>40

Cholesterol

BPL

liver

BU

suggestion drug	
Amlodipine	should
Epinephrine	not
Dimenhydrinate	not
Amiodarone	should
Procainamide	should
Aluminumchlorohydrate	not
Acetaminophen	not
Propranolol	should

101

symptoms

---

chest pain

Shortness of breath

Clotting

Irregular heartbeats

headache

Sweating

history of patient

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age>40

asthma

BS

BU

Suggestion drugs Decision

Amlodipine ---------------------

Nitroglycerin ---------------------

aspirin ---------------------

Amiodarone ---------------------

Acetaminophen ---------------------

Nicorandil ---------------------

الدكتور
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