Modified Toulmin's Argumentation Model Based on Prior Experiences

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Keywords

Argumentation; Toulmin's Model; Drugs Conflicting Problem; Naïve Bayes

RESEARCH PAPER

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Datasets are gathered from some educational hospitals in Iraq and they have been approved by experts from the medical sector. The samples used in the proposed system cover 325 cases with two kinds of diseases and the average percentages of accuracy with them were 93.03% (hypertension) and 95.125% (angina pectoris).

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1. Introduction

Argumentation is the branch of knowledge that deals with rationale reasoning which leads to a logical conclusion. It involves a statement and a set of premises that either support or deny that statement. The conclusion about that conclusion is actually a sort of decision making where deliberation and bargaining, which are components of argumentation, play an essential role. Frameworks of argumentation involve mechanisms that can act with conflicts so as to get conclusions [1].

Argumentation theory is an interdisciplinary field of logic and philosophy which has witnessed huge expansion that it turned to be a major topic in logic-based AI. Argumentation theory has become more important because of the development in its formal models that are similar to human thinking [2].

Argumentation theory proposed that when there are multiple antagonistic arguments a decision must be taken concerning the approval of these arguments [3].

The evaluation of a case acceptability does not involve the argument breakers. Actually, judging the contrarians as being opposed to each other or not is a must and arguments are thought to be beneficial in clarifying an already made [4].

The problems of remedies' conflict is a major challenge in the medical sector as huge numbers of patients lose their lives because of side effects of

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pharmacodynamic interactions and remedy errors [5]. The problem of pharmacodynamic interactions rises with the increase in the total number of the drugs used by the patient [6]. About (36%) of the American elders are recognized as being users of more than 5 kinds of drugs and supplement regularly, and 15% of those people are in danger of facing serious consequences of drug interactions [5].

Toulmin's argumentation model is considered one of the important argumentation models in artificial intelligence and has been used in several applications such as psychology [7], Advice analysis [8,9], decision-making [10−14], social studies [15], data analysis [14,16], STEM [16], analyzing argumentative essays [17,18].

Toulmin suggests a practical method to interpret arguments through recognizing and isolating the various elements of argumentation, thereby establishing perceivable structure for the securitization of arguments [19] where the elements of the model and their relation clarify the way of using this modeling as evidence-based medical study.

Toulmin's approach demands logical structures that allow persuading others of the validity of an argument [20]. The writer in an essay, for instance, intends to convince his readers of accepting or rejecting an argument or a claim by employing some clause structures, backing, qualifiers, warrant, etc as supportive evidence. Then, the competition between the support features and the attack features will be settled with regard to the strength of the available evidence. This means that Toulmin's model resolves disagreements by making use of logical structure of an argument.

Actually what distinguishes Toulmin's model from the traditional models is the structural analysis of arguments in terms of data, warrants, qualifiers, rebuttals, and backing. Data are the facts that prove arguments. Warrants represent the general assertions that connect claims and data [19]. Qualifiers show how the arguments premises are when the conditions are proposed to determine which argument premise is true. Rebuttals refer to the counter-argument or assertions which show the condition under which the arguments are no longer true. Backing, however, are supporters for warrant and it confirms that the warrants are true [19,20].

Also Toulmin's argument model is used to evaluate the correctness of information by designing and constructing an argumentation pattern that distinguishes three basic components and three additional components of a coherent argumentative discourse. Argument analysis of this pattern consists of three main components: claim, data, and warrant. Claims are determined by the availability of basic data. Data and claims form a logical reasoning bridge that act as a warrant. To construct a more complex pattern for analyzing arguments three additional components (backings, qualifiers, and rebuttals) can be added. Backings strengthen the warrant by providing additional evidence, while qualifiers provide strength by relating data to claims and rebuttals indicate circumstances where the warrant is no longer valid so that the claim can be rejected [21].

This study makes use of Toulmin's model, whose structure is shown in Fig. 1, in calculating the for and against arguments related to some particular drugs prescribed to patients in hospitals. The arguments that record highest values with regards to the qualified functions will be proved as the best claim; and hence the corresponding drug will be advised as the one that should be taken.

In our work the Naive Bayes technique is used as a qualifier to upgrade Toulmin's model and make it perform better in resolving conflicting issues in the medical sectors. This is done through the inference of the relation between the symptoms patients have and the medication they use, which results in a conclusion concerning (a claim) related to the diagnosis of a drug. Then, the fors -and- againsts approach is applied on every suggested drug to decide whether to use or disuse the proposed drug.

This study is framed as follows: literature review occurs in the second section, while material and methods comprise the third section. Finally, discussion of results and conclusions are presented in the fourth and fifth sections; respectively.

2. Literature review

A variety of applications in healthcare sectors utilizes the Toulmin model in sorting out problematic issues related to drugs and medications and to provide reliable guidelines for their use in light of

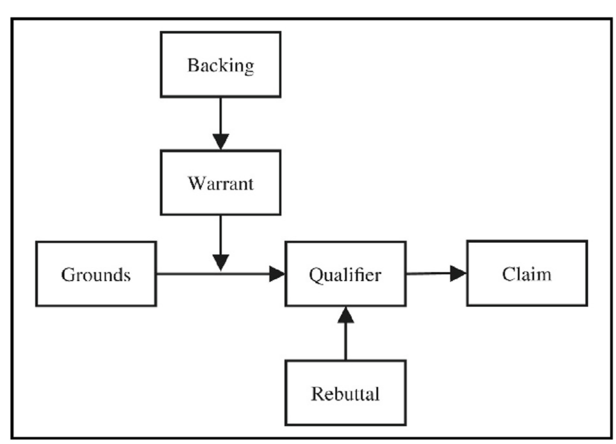

Fig. 1. Toulmin's model components.

the patients' conditions and the drugs' felicity to these conditions. This has brought about the use of the Toulmin model in combination with other structures to figure out medical data and find solutions to the debates that form an essential concern in the field.

Kristi Jonas et al. [22] developed a novel framework structure of argumentation to figure out the best claim by considering patient-focus goals that assume outcomes with no conflicts. His work focuses on resolving the potential conflicts through taking into account the patients' conditions and preferences.

Francisco and Elizabeth in Ref. [23] used the argument model to analyze the interaction between patients, healthcare staff and doctors to figure out to what extent the arguments in this context are valid.

Wilk et al. [24] employed a method to analyze patients' interactions to clinical directives presented in a form of graphs. The patients' responses to these directives were analyzed in terms of each individual's condition and preferences and they are mapped by a special operator into the first order logic rules (OLR).

Kokciyan et al. [25] used a logic-based methodology represented by computational argumentations that employ reasoning of claims which can be either for or against a particular conclusion. The authors initiated the consult system to collect data about patients' preferences from healthcare institutions. These data represented the arguments or claims that were analyzed to solve the inconsistency of the different medication choices and preferences.

Gabriel et al. [26] dealt with agents' argumentation with the aim of providing elements that support them. Toulmin's model is employed in developing the agents-based arguments and the way they proceed to BDI. Such a methodology helps utilize the implementation of a variety of functions in different domains.

Fejer et al. [27] surveyed the latest progress in strategies of argumentation that benefit from the Toulmin model in complicated issues in medical context.

Hamzah Noori Fejer and Ali Hadi Hasan in Ref. [28] used this model to address conflicting issues in the medical sector. They also used rules of inference, the symptoms a patient has and the medical record of treatments he has used thereby diagnosing the drug that can be recommended for the patient. Several treatment features compete to attack or support each treatment. A treatment item is accredited when it records the highest support value among other items.

Hamza Nouri Fajr and Ali Hadi Hassan in Ref. [29] upgrade Toulmin's model while handling conflicts in therapeutics. They worked on a number of competitive drug features which are then processed for decision-making, adding the Naïve Bayes technique as an improvement of the Toulmin model. They use the confusion matrix method in evaluating the outcomes of the model. They were able to achieve an accuracy achieved of 95% and 94% for two diseases (hypertension and angina) of a dataset of 200 patients.

Al-Fahum et al. [30] used PPG signals and feature selection-based classifiers to identify cardiorespiratory disorders based on time-domain feature extraction. They collected data from 360 healthy people and patients with cardiovascular disease for analysis and identification. Five types of cardiovascular disorders were considered using a two-stage classification process. In the first stage, they classified people's conditions to distinguish between healthy and unhealthy people. Then they entered the people who were found to be abnormal into a second-stage classifier that determined the type of disease. They used seven different classifiers to classify the data set. Based on the subset of features found by the classifier they found that the Naïve Bayes classifier had the best testing accuracy, with 94.44% for the first stage and 89.37% for the second stage. In light of the results of this study, the researchers explained the importance of the PPG signal, through which many parts of the time domain of the PPG signal can easily be extracted and analyzed to determine whether there are heart problems.

In this work, a modified Naïve Bayes-based Toulmin's argumentation model from prior experiments will be used to work out conflicts relevant to medication issues through the calculation of each medication item's fors- and- againsts arguments. Our work focuses on the prior knowledge to decrease the time consumption of argumentation processing as there will be no need to process the cases which are similar to those that had previously been processed and dealt with.

3. Materials and methods

The Toulmin model, the Naive Bayes technique and prior experiments are utilized in this work to figure out problematic issues in the medical sector by using symptoms on the patients' part and their medical treatment history as input premises in this system. These premises are input based on new cases patient symptoms and medical histories which are entered using friendly user interface, or based on the prior patients training datasets in the learning stage are used, patients suffering from hypertension and angina pectoris. The most reliable treatment is selected by considering the link between the disease's symptoms on the patients and their use of medications. That selection is followed by entering the extracted features of the recommended medication to the medical history of the patient. Then the Naive Bayes technique is used to compute all the medication's support and attack features and the competition between them to make a decision. A medication is accredited as the recommended one in light of value calculated by the Naive Bayes technique which is considered an improvement on the Toulmin model. Fig. 2 depicts the structure of the current study proposed system. Below are illustrations of the steps involved in this work:

3.1. Input data in user interface

In this part, a new patient case is introduced to the system, the new patient symptoms and medical histories are entered using friendly user interface to be stored in files records.

Clinical patient symptoms features are fever, gender, High Blood Pressure (HBP), Low Blood Pressure (LBP), chest pain, blurred vision, ESR, testing Blood routine, total white blood cell (WBC) and test total cholesterol. Patient history features are considered important for detecting the features of drugs suggested 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) consider premises for argumentation and then based on these values to make support decisions.

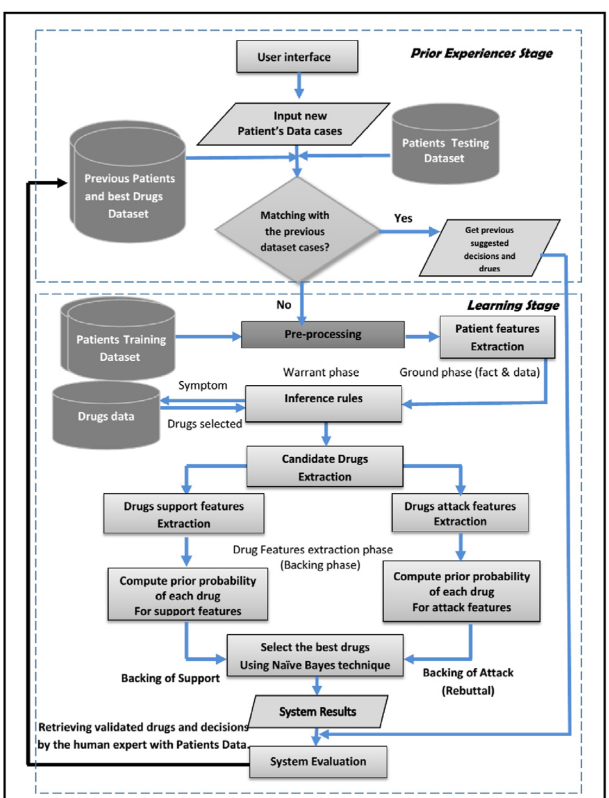

Fig. 2. Structure of the proposed system.

3.2. Input patients testing datasets

In this step of the study which depends on the medical patients testing datasets in the prior experiences stage, the datasets of patients suffering from hypertension and angina pectoris are used. Each patient has files for storing the records of symptoms and the records of medical history. Some cases of these testing patient files are similar to the files stored in the patient's training dataset in the learning stage.

3.3. Input patients training datasets

The other part of this study, based on the prior patients' training datasets in the learning stage used a dataset of patients suffering from hypertension and angina pectoris. Their relevant data are gathered from some Iraqi educational hospitals, commentated by medical experts and examiners. The dataset comprises symptoms, medical history, medication contradictions, and side effects on the patients' part.

3.4. Pre-processing data

In many tasks, it is necessary to clean or preprocess 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 of all facts to under casing letters, and frequency data removal.

3.5. Extraction of candidates' medications

Ponens Modes are the intelligent technology that has the ability to simulate human thinking and capture knowledge and the inference rules that can serve the healthcare staff in their work environment. This technology allows diagnosis of the most suitable remedy for patients by linking the symptoms that a patient has and the uses of the available medications. After extracting the features of medications and evaluating whether they are compatible to those symptoms and to the patients' medical record, a decision about including or excluding each treatment item is made.

3.6. Drug features extraction

In this phase features of each drug from suggestion drugs will be extracted to determine the appropriate drug as shown in algorithm (1).

Algorithm (1). : Drug Features Extraction Algorithm

```
Input:   suggestion drug (Sug_Drug).
Output: support features of suggested drug (Sup_List),
          attack features list (Att_List).

% Variables Definition
  Sup_List : list        % Support features of suggested drug
  Att_List : list        % Attack features list
  Sug_Drug : string    % drug item
  Begin
    1. Sup_List = empty list
    2. Att_List = empty list
    3. For each item in suggestion drugs do
    4.      Assign drug efficiency feature value for support list
    5.      Add (efficiency[Sug_Drug]) to Sup_List
    6.      Assign drug side effects feature value for attack list
    7.      Add (Side_Eff[Sug_Drug]) to Att_List
    8.      Assign drug interaction feature value for support and
            attack list
    9.      Add (1- inter[Sug_Drug]) to Sup_List
    10.         Add ( inter[Sug_Drug]) to Att_List
    11.     Assign drug contraindication feature value for sup-
            port and attack list
    12.         Add (1- cont[Sug_Drug]) to Sup_List
    13.         Add (cont[Sug_Drug]) to Att_List
    14.         Assign drug cost feature value for support and attack
         list
    15.         Add (1- cost[Sug_Drug]) to Sup_List
    16.         Add (cost[Sug_Drug]) to Att_List
    17.     Assign drug availability feature value for support and
            attack list
    18.         Add (available [Sug_Drug]) to Sup_List
    19.         Add (1- available [Sug_Drug]) to Att_List
    20.      End for
    21       End Algorithm
```

Drugs (or any medical treatment) should be used only when it will benefit a patient. The benefit takes into account the drug's ability to produce the desired result (efficiency). The most efficacious treatment bases on the best evidence that can rate a patient's response and this feature is considered a support feature for the drug.

Side effects, also known as adverse events, are unwanted or unexpected events or reactions to a drug. They can vary from minor problems like rhinorrhea to more serious problems that can threaten life, such as an increased risk of a heart attack. In this phase the side effects feature will compute more than 60 kinds of aftereffects such as dizziness, tiredness, itching, rash, face redness, bleeding and upper chest redness. The side effects feature is considered as attack for the drug. 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. This feature is very important to the patient and the weight of this feature has a great influence in deciding if this drug will or will not be used for patients.

A drug interaction refers to the change occurring in the drug's effect or its side effects resulting from it being taken concomitantly with another drug in the list of suggested treatments. This feature can be used to support or attack a drug. When the value is (0) it means that the drug does not interact with another item in the drug list while the value (1) indicates that there is a significant interaction, and the value (0.5) means that this drug interacts, but only slightly.

A contraindication is a specific situation in which a drug procedure, or a surgery should not be used because it may be harmful to the person based on the patient's history. Avoiding the procedure or medicine that falls under this category is a must. It is possible to use this feature for attacking the suggested drug that assigns value (1) when the drug has contraindications with the patient's history. The (0) value can be used to support this drug.

The cost of each drug will be calculated; the cost of purchasing the drug compared to other drugs will also be calculated. In this study, the cost of the drug is used to support or attack. When the cost of the drug is low, this 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 the values (0), (0.5), or (1) based on the price of the drug.

Drug availability feature will be used for each drug suggestion to support the drug if it is available in pharmacies, this feature takes value (1) that will increase the support side of a drug item, otherwise it will take the (0) value. This feature will be computed as first feature because this feature tests whether a drug item is available or not, if it is not found there will be an increase attack side for this drug in the suggestion drugs list. This feature is used for competing drug item with other items in the same family.

3.7. Qualifier phase

The ‘qualify’ function attempts to measure the degree of backing for an assertion by gathering data, justifying the assertion, making a confidence rating for it. This function can be used in various contexts and be tailored to the user's needs.

This system uses the Naïve Bayes technique for each suggestion drug based on support feature and attack feature as class condition, these features and probability of each class of suggestion drug computed by a qualifier method as shown in Fig. 3.

For each drug to have P (f_1, f_2, …, f_n |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 have features (f_1, …, f_n). Then P(X) is the prior probability of drug class X.

The prior probability calculations can be computed based on results of the classical Toulmin's model, after that the decision is made by comparison between probability of drugs for each class, and the classification then depends on which is greater. Finally, a decision is made on allowing or disallowing this drug to the patient.

When making a prediction for a class, it involves calculating the posterior probability of all classes and then choosing the highest value of posterior probability as the predicted category. This value is known as the Maximum A Posterior (MAP) as mentioned in equation (1).

$$\hat{y} = \underset{k\epsilon\{1,\ldots,k\}}{\operatorname{argmax}}\; p(C_k) \prod_{i=1}^{n} p(x_i|C_k) \quad (1)$$

Where

$\mathbf{x_i}$ represents drug feature.

$\mathbf{C_k}$ represents class k.

K is number of classes.

$\mathbf{P(C_k)}$ represents prior probability.

$\mathbf{P(x_i|C_k)}$ represents vector of conditional probability for C_k class features.

Given the predictors, we can obtain the class for each drug the features such as drug interaction, drug contraindication, drug cost, drug side effect and drug efficiency are computed to know whether they support or attack condition and to choose then the maximum probability as explicated in algorithm 2.

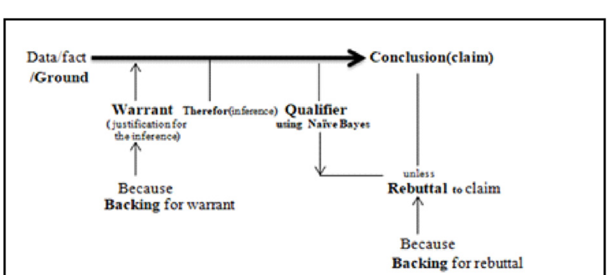

Fig. 3. Naive Bayes is used as a qualifier to upgrade Toulmin's model.

Algorithm (2). : Qualifier based on Toulmin with Naïve Bayes model.

Input: dictionary of patients.
suggestion drugs list (Sug_Drug), drug support features list (Sup_Feature), drug attack features list.
Output: list of decisions of suggestion drugs (Sug_Drug_Deci),
list of confident level values of decisions (Conf_Level).
% Variables Definition
Prob_Att *% probability of attack features*
Prob_Sup *% probability of support features*
Prio_Sup *% probability priority for support drugs item*
Prio_Att *% probability priority for attack drugs item*
Prob_Sug_Drug *% list of support probabilities of suggestion drugs*
Prob_Att_Drug *% list of support probabilities of attacks drugs*
Begin
1. Create priority probability of support (Prio_Sup) list, priority probability of attack (Prio_Att) list for each suggestion drugs.
% computes priority probability of two classes from results of classical toulmin's model.
2. For each patient in dictionary of patients do
3. For each Drug in Sug_Drug do
4. For each item in Sup_Feature list do
5. Create Prob_Sug_Drug (item)
6. End for
7. For each item in attack features list do
8. create Prob_Att_Drug (item)
9. End for
10. Prop_Sup =1, Prop_Att =1
11. For each item in support probability table
12. Prop_Sup = Prop_Sup * (Prop_Sup(item) + 0.0001)
13. End for
14. For each item in attack probability table
15. Prop_Att = Prop_Att * (Prop_Att(item) + 0.0001)
16. End for
17. Conpr1=(Prob_Sup*Prio_Sup[i])/(Prob_Sup+Prob_Att)
18. Conpr2=(Prob_Att*Prio_Att[i])/(Prob_Sup+Prob_Att)
19. q= Conpr1- Conpr2 *%Compute qualify function*
20. If Conpr1 ≥ Conpr2 then
21. Sug_Drug_Deci [i]= "should use this drug item"
22. Conf= absolute value of (q)
23. Else
24. Sug_Drug_Deci [i]= "should not use this drug item"
25. Conf = absolute value of (1- q)
26. End if
27. Conf_Level[i] = Conf
28. End for
29. End for
30. End Algorithm

3.8. System evaluation phase

In this phase, the results of the proposed system are evaluated in two directions. The first direction compared the input data (symptoms and medical histories) of new patients which are stored as new files with the previous data of old patients saved as historical datasets which contained the symptoms and medical histories, in addition to their output processing which are saved as the decisions of best Drugs. If the files records match, then print the previous suggested decisions and drugs and compute the time occupy to find it. Otherwise store in files the recorded patient's dataset to be processed by the improved Toulmin's argumentation model using Naïve Bayes and prior experiences to find results of drugs and the time occupy. These results are confirmed by the human experts as the best validated drugs and decisions with Patients Data then these results and data are retrieved to the Previous Patients and best Drugs Dataset.

In the second direction the evaluation of dataset of patients suffering from hypertension and angina pectoris will be done by using the confusion matrix. The prior patient's training datasets is processed by our suggested model and by considering the Prior Experiences in the learning stage. The confusion matrix is like a sort of table that summarizes the correct predictions and the incorrect ones, counts values and analyzes them in terms of each class. The performance metrics of the system involve precision, accuracy, recall as well as the F1 score which are got from TP, TN, FP, and FN. As shown in the following four equations.

$$\mathrm{Accuracy} = \frac{TP + TN}{(TP + TN + FP + FN)} \tag{2}$$

$$\mathrm{Precision} = \frac{TP}{TP + FP} \tag{3}$$

$$\mathrm{Recall} = \frac{TP}{TP + FN} \tag{4}$$

$$\mathrm{F-measure} = \frac{2{*}precision{*}Recall}{precision + Recall} \tag{5}$$

4. Results and discussion

In this section, the methodology used to assess the proposed system is introduced. In this assessment the experiments were conducted to evaluate the performance of the proposed system and the labelled objects could be used to assess the proposed system by comparing the experts' relevant opinions and get more meaningful results.

Two datasets are used to demonstrate and assess the proposed system. These datasets were collected from educational hospitals in different Iraqi cities. The first dataset is taken from the Medical Patient Training Dataset which contented 240 patient samples, 120 samples for each disease of hypertension and angina pectoris. While the second is Medical Patient Testing Dataset which contented 85 patient samples of hypertension and angina pectoris diseases. In these datasets each has two datasets the first one contains patient's information called medical patient dataset (MPD) in which each patient has a record of symptoms and a record of history.

Patient information is explained in Table 1, each column represents symptoms, which represent feature used as premise in improved Toulmin's model argumentation, also the patient history shown in Table 2 represents premises in improved Toulmin's model argumentation. The symptoms of patients are represented by (0) or (1), that mean this patient in case 0 does not hold this symptom and in case 1 this patient holds this symptom and these data are saved in texts files form (txt).

The second one is the drugs dataset consisting of drug used and drugs interactions. It was sourced from online: www.drugs.com, ww.drugbank.com

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

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

The experiments conducted to evaluate the performance of the proposed system are implemented into three parts.

4.1. Implement medical patient training dataset

The experiments are implemented on the medical patient training dataset in which each patient has a record of symptoms and record of history which are stored in files. These datasets contain files of 240 patients processed by improved Toulmin's argumentation model using Naïve Bayes [29] to find the drugs suggested for these patients in the learning

Table 1. Samples of patients symptoms and signs.

Patient Id	Symptoms and signs							
	HBP	LBP	Heart boats Rate (HBR)	Cholesterol	Chest pain	Shortness of breath (SOB)	Blurred vision	Dizziness	Headache
P_1	1	1	0	1	0	1	0	1	0
.									
.									
.									
P_n	1	0	0	1	1	1	1	0	1

Table 2. Sample of history of patients.

Patient Id	Patients history						
	Age	Smoke	Chronic asthma	Kidney diseases	Heart failure	debit	Liver Diseases
P_1	44	1	0	1	0	1	0
.							
.							
.							
P_n	60	0	0	0	1	0	1

stage. Getting the physicians' team's opinions about the drugs for these patients and then matching between these opinions and the results of the proposed model using a confusion matrix. The number of accurate and inaccurate predictions made by the classifier is summarized in a table called the confusion matrix. The effectiveness of this part of the system is computing performance indicators like Accuracy, Precision, Recall and F-measure, illustrated in Table 3.

Only when the doctors' view on the drugs match with predictions made by the system accurately, they are retrieved to be stored as files in the dataset of previous patients and best drugs.

4.2. Implement medical patient testing dataset

The experiments are implemented on the medical patient testing dataset in which each patient has a record of symptoms and record of history stored in files. These datasets contain files of 85 patients processed by improved Toulmin's argumentation model using Naïve Bayes and Prior Experiences to find the drugs suggestion. These files are stored as a record of symptoms and a record of history. Patient cases in the dataset to be compared with Previous Patients and best Drugs Dataset in the Prior Experiences Stage. If files records are matched we then get the previous suggested decisions and drugs immediately and compute the time occupied. Otherwise these files records are processed using the modified Naïve Bayes-based Toulmin's argumentation model from prior experiments in the learning stage.

The classifier predicts drugs for patients of hypertension and angina pectoris diseases then matches these results with the physicians' team's opinions to find the number of the accurate data and the inaccurate ones to summarize them in the confusion matrix table. The performance of this part of the system is evaluated using the metrics: Accuracy, Precision, Recall and F-measure to compute the effectiveness, as shown in Table 4.

There is also another important and effective measure for evaluating the performance of this part of the system, which is the time occupied to find the suggested drugs. The real addition to the proposed work is the benefit from similar priori experiment cases, as it will not require the processes of proving arguments, thus reducing time significantly. Fig. 4 shows the time it takes to implement experiments on 85 testing patient cases (some of which are similar) using the proposed system.

4.3. Implement input new patient's data cases

One of the efficient implementations of this system is the possibility of entering the new symptoms and medical histories of one patient case using friendly user interface to storing in records.

The system compares this input case with all previously processing files cases Dataset saved in Previous Patients and best Drugs dataset. If this new input case matches with one of the old cases, the same decisions and drugs that were suggested for the saved case in the old cases is displayed. Otherwise this case is processed using the modified Naïve Bayes-based Toulmin's argumentation model from prior experiments to find the results from the classifier, predict drugs for this patient case then match these results with the physicians' team's opinions to evaluate the suggesting drugs.

Table 3. Evaluation of the results of the training dataset processed by improving the Toulmin argument model using Naïve Bayes in the learning stage.

Disease name	Accuracy	Precision	Recall	F-measure
Hypertension	92%	91%	95%	94%
Angina pectoris	94%	93%	97%	95%

Table 4. Evaluation of the results of the testing dataset processed by improving Toulmin argument model using Naïve Bayes and Prior Experiences in all stages.

Disease name	Accuracy	Precision	Recall	F-measure
Hypertension	94.06%	94.7%	97.8%	96.2%
Angina pectoris	96.25%	96%	99.65%	97.8%

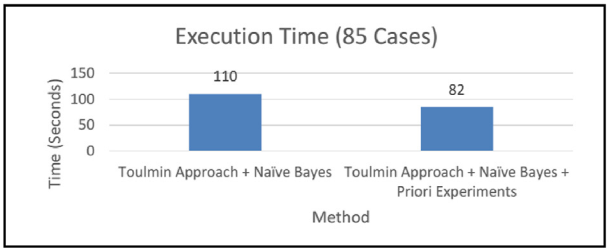

Fig. 4. Time Comparison between implementation of this part of the proposed system with Toulmin's and Naïve Bayes Model on same test patients' dataset.

The human expert permutated the inaccurate drugs with the accurate one to saving as validated drugs and decisions in dataset of Previous Patients and best Drugs.

4.4. Comparison of performance of the proposed system

This part of the research aims to compare the results of performance of the proposed system with the classical Toulmin's argumentation model on the same 85 samples of dataset for patients of hypertension and angina pectoris diseases. The results of the four experiments are evaluated using the metrics: Accuracy, Precision, Recall and F-measure. Table 5 compares the performance of the proposed system to that of the classical Toulmin's argumentation model [28].

4.5. The results discussion

According to the results attained in all experiments, we analyze the behavior of the proposed system to improve the argument of Toulmin's model [28]. We started by describing the Medical Patient Dataset (MPD) and then explaining the evaluation methods so that we could explain the results of the experiments. In general, experiments are performed on two types of datasets, namely the medical patient training dataset and the medical patient testing dataset, and on two types of patients: the ones suffering from hypertension and those suffering from angina pectoris. We also enter the new symptoms and the medical history for each patient suffering from any of the two diseases using friendly user interface.

The performance of improved Toulmin's argumentation model using Naïve Bayes [29] on Medical Patient Training Dataset shown in Table 3 and the proposed system "improved Toulmin's argumentation model using Naïve Bayes and Prior Experiences" on Medical Patient Testing Dataset shown in Table 4 for the two diseases are evaluated using the different metrics. In the second experiment, Hypertension disease got a very noticeable difference 94.06% in accuracy whereas the accuracy of the same disease in the first experiment was 92%. The Angina pectoris disease gained an accuracy of 96.25% in the second experiment, whereas the accuracy of the same disease in the first experiment was 94%. In addition to that when we compare the two experiments depending on the second metric represented by (Precision), we touch another decisive and clear difference. In the second experiment, Hypertension disease earned a Precision of 94.7%, whereas the Precision of the same disease in the first experiment was 91%. The Angina pectoris disease gained a Precision of 96% in the second experiment, whereas the Precision of the same disease in the first experiment was 93%.

In addition to the comparisons that have been made, if we compare the third metric (Recall) between the two experiments, we will see some difference in the performance between them. In the second experiment, Hypertension disease earned a Recall of 97.8%, whereas the Recall of the same disease in the first experiment was 95%. While, the Angina pectoris disease gained a Recall of 99.65% in the second experiment, the Recall of the same disease in the first experiment was 97%. Finally, if we compare in terms of the fourth metric (F-measure) between the two experiments, we touch a clear difference in the performance between them. In the second experiment, an F-measure of 96.2% was recorded for the Hypertension disease, while this measure was 94% for that disease in the first experiment. While the Angina pectoris disease gained an F-measure of 97.8% in the second experiment, it was 95% in the first one.

All the results of the experiments were based on six features and they gave an evaluation percentage

Table 5. Comparison the performance of the proposed system with classical Toulmin's argumentation model on same Dataset for hypertension and angina pectoris diseases.

Disease name	prediction types	Accuracy	Precision	Recall	F-measure
Hypertension	Toulmin argument model	77.5%	76.3%	91.6%	83.2%
	The proposed system	93.03%	92.85%	96.4%	95.1%
Angina pectoris	Toulmin argument model	86.7%	85.7%	97.5%	91.2%
	The proposed system	95.125%	94.5%	98.325%	96.4%

greater than 91, which is a very good percentage. The reasons that inhibit a higher percentage of the system's performance belong to two minor features represented by cost and availability of drugs. As for the cost of drugs, the presence of cases of patients whose income level was low prevented the system from supporting a group of high-cost medications that human experts insisted on when evaluating the correct and accurate drugs. Concerning availability, the unattainability of another group of medicines in local pharmacies reduced the percentages of matching with the correct and accurate choices of the human experts.

Also we observed that the results achieved in patients with angina pectoris compared with the results of those with hypertension disease were higher by all the evaluated metrics.

The percentages in Table 5 mirror a clear difference in all evaluation metrics, In the first metric (accuracy), we notice a clear superiority in the percentages, which were 93.03 compared to 77.5 for hypertension disease and 95.125 for angina pectoris disease compared to 86.7. In the second metric (Precision), we also notice clear superiority in the percentages, which were 92.85 compared to 76.3 for hypertension disease and 94.5 compared to 85.7 for angina pectoris disease. Also in the third metric (recall), we notice a relative difference in the percentages, as it was 96.4 versus 91.6 for hypertension disease, while for angina pectoris disease, it was 98.325 versus 97.5. In the last metric (F-measure), we notice a clear difference in the percentages, as it was 95.1 versus 83.2 for hypertension, while for angina pectoris disease, we find 96.4 versus 91.2.

The last observation is related to time consumption. The comparison, in terms of time, between our proposed system and the improved Toulmin's argumentation model using Naïve Bayes shows a reduction in the time occupied to find suggested drugs on the same testing patient cases for hypertension and angina pectoris diseases. The reduction was from 110 s to 82 s; this belongs to similarity between some tested patient cases which led to the dispense with the processes of proving arguments and there was only a comparison process of records of symptoms and records of history Patients cases in testing dataset with Previous Patients and best Drugs Dataset in the Prior Experiences Stage.

5. Conclusion

Argumentation plays a big role in several domains such as politics, economic, education etc. This paper presents a modified system on the Toulmin model for argumentation based on prior experiments to reduce the time and save the prior cases. The modified system depends on saving the prior knowledge of arguments with rebuttals and using this knowledge in similar next cases, this strategy is applied with Naive Bayes concept. Our system has been experimented on medical drugs conflict data. The results indicate that the modified model showed goods accuracy compared with the standard Toulmin model.

In order to enhance the performance of the Toulmin's model, this work utilizes a Naive Bayes as a qualifier as well as Prior Experiences with emphasis on therapeutic use applications in medicine to resolve drug conflict issues. In this study, a six number of drug features were taken into account when deciding whether or not to utilize this medical drug. A confusion matrix evaluation approach was used in this study. The dataset was annotated by a team of human experts in the field of medicine. For hypertension and angina pectoris diseases, the accuracy in this dataset was 93.03% and 95.125%, respectively. The performance of implement of improved Toulmin's argumentation model using Naïve Bayes and Prior Experiences was found to be superior to Toulmin's classical model [28], according to the results achieved by the experiments.

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Conflict of interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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