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A medical decision support system for disease diagnosis under uncertainty

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ABSTRACT

This paper presents a decision support system (DSS) modeled by a fuzzy expert system (FES) for medical diagnosis to help physicians make better decisions. The proposed system collects comprehensive information about a disease from a group of experts. To this aim, a cross-sectional study is conducted by asking physicians' expertise on all symptoms relevant to a disease. A fuzzy rule based system is then formed based on this information, which contains a set of significant symptoms relevant to the suspected disease. Linguistic fuzzy values are assigned to model each symptom. The input of the system is the severity level of each symptom reported by patients. The proposed FES considers two approaches to account for uncertain inputs from patients. Two case studies on kidney stone and kidney infection were conducted to demonstrate how the proposed method could be used. A group of patients were used to validate the effectiveness of the proposed expert system. The results show that the proposed fuzzy expert system is capable of diagnosing diseases with a high degree of accuracy and precision comparing to a couple of machine learning methods.

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1. Introduction

One of the most important areas in medical research is disease diagnosis, which is the first step to predict and prevent a possible outbreak of a disease. Accurate and early diagnosis would also prevent the progression of a chronic disease. A disease, however, may contain several similar symptoms to another disease, which could confuse even the most experienced physicians. Even worse, a patient may demonstrate a set of symptoms that can be attributable to several diseases, and these symptoms may not be readily quantifiable. When observing these symptoms, physicians with varying professional levels and clinical experience may differ in their diagnosis, resulting in misdiagnosis. In addition, patients may be unsure of their symptoms, which hinder diagnostic accuracy. The use of computers in medical diagnosis and prognosis has become necessary to provide consistent diagnostic results, especially with the increasing volume of medical data. To address these issues, a general structure of modeling a fuzzy expert system under uncertainty for a disease diagnosis is presented in this study. Various kinds of kidney disease diagnoses serve as a case study to demonstrate the proposed framework.

After introducing the fuzzy logic by Zadeh (1965), many applications of fuzzy systems emerged in different areas such as manufacturing, decision making and medicine. Applying fuzzy expert systems in medical science started in 1985 and the exponential growth of published papers shows the effectiveness of such a system (Sikchi, Sikchi, & Ali, 2013).

Adlassnig (1986) studied the use of fuzzy set theory in medical diagnosis in 1986. He stated that physicians, like others, could make a mistake and may not be correct or certain about the diagnosis they made. Later in 1995, Herrmann (1995) introduced a hybrid fuzzy-neural expert system for diagnosis to capture the user's knowledge by combining an expert system with a fuzzy-neural system. In this approach, a fuzzy neural network was used to make the fuzzy rules out of sample data. Bartolozzi et al. (2000) reviewed the application of various operation research techniques on medical diagnosis. Among all the techniques reviewed, they found that highly nonlinear dynamic systems with long lags were very promising in modeling natural systems. With the advent of data driven approaches, new data mining techniques were adopted in disease diagnosis. For example, Tsipouras et al. (2008) presented a fuzzy rule-based decision support system for diagnosing coronary artery disease that integrates data mining and fuzzy modeling. Bhatla and Kiran (2012) applied a similar combination of data mining and fuzzy modeling to help physicians better diagnose heart diseases. Akgundogdu, Kurt, Kilic, Ucan, and Akalin (2010) used an adaptive neural-fuzzy inference system to

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diagnose renal failure disease. In their models, they extracted the fuzzy rules by the subtractive clustering method and examined the model for a population of 112 patients. Uzoka, Osuji, and Obot (2011) utilized the decision support system for diagnosing malaria and compared the effectiveness of fuzzy and analytic hierarchy process (AHP) methodologies with their results. Using data from 30 patients, they showed that fuzzy and AHP methodologies can be employed successfully in the computer-based diagnostic models to assist non-expert physicians to diagnose malaria. They showed that the fuzzy logic method is slightly better than the AHP method based on the diagnostic outcomes.

Hasan et al. (2010) introduced an online diagnostic application that used fuzzy expert system. In their system, users could choose between diseases and symptoms. By answering the questions regarding their symptoms, the system could provide a relevant probability of disease. Their system, unlike many others, was not limited to a certain type of disease. Samuel, Omisore, and Ojokoh (2013) later introduced a web-based application diagnostic system. Their application was driven by fuzzy logic for diagnosing typhoid fever. Rustempasic and Can (2013) applied the fuzzy C-mean clustering method along with pattern recognition to diagnose Parkinson's disease. The patient's voice was used as one of the factors to diagnose whether the subject was suffering from the disease or not. The use of both the fuzzy clustering method and pattern recognition helped diagnose Parkinson's disease. Abushariah, Alqudah, Adwan, and Yousef (2014) adopted adaptive Neuro-fuzzy inference systems along with the artificial neural-network to diagnose heart disease. Biyouki, Turksen, and Fazel Zarandi (2015) used a fuzzy rule based expert system to diagnose thyroid disease. Maftouni, Turksen, Zarandi, and Roshani (2015) proposed a type-2 fuzzy rule-based expert system for Ankylosing Spondylitis diagnosis. They considered the vagueness of the problem and aimed to solve it using fuzzy logic. Saikia and Dutta (2016) applied fuzzy inference systems to predict Dengue disease. Dengue is a disease caused by mosquitos which, if not cured, may cause serious problems. Therefore, it is highly important to detect it early.

All of the work reviewed in the literature assumes that the inputs into the fuzzy system are certain. These fuzzy expert systems provide a framework to transfer a medical knowledge into mathematical models and overcome the vagueness in the behaviors in a system by applying linguistic values instead of using crisp values for system parameters. Inputs for a fuzzy system, however, are always deemed to be certain. This assumption may not always be true, especially for fuzzy systems for medical diagnostic purposes. Sometimes patients are not sure about the severity of their symptoms, for example, the severity of their pain.

This research addresses the issue of uncertainty by providing solutions discussed in details in the following sections. Section 2 describes the essence of the data used in the disease diagnosis procedure proposed. Section 3 proposes a heuristic method to deal with the uncertain nature of data collected from patients. This part identifies and categorizes each of the possible existing uncertainties inherited in the data collected. In Section 4, a case study with kidney diseases is used as an example to demonstrate the use of the proposed system. Section 5 provides the results obtained from the proposed system with uncertainty considerations and discusses the accuracy of the proposed method compared to those obtained by expert physicians. The final section includes contributions of the proposed method and suggestions for future research.

2. A medical heuristic fuzzy expert system

Accurate medical diagnosis requires extracting information and data in order to make a proper decision about either the health or possible diseases of a patient. However, medical related data collected from patients may be uncertain. A fuzzy expert system

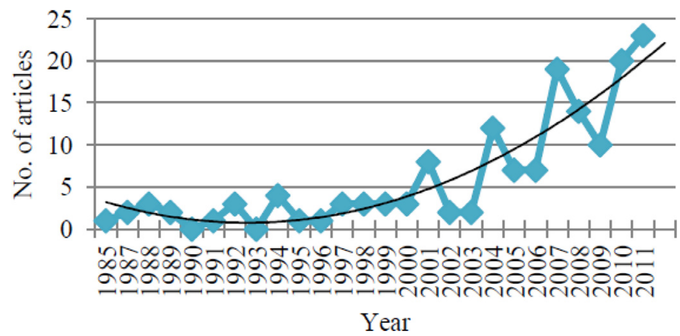

Fig. 1. Diagram of using fuzzy expert system in medical science (Sikchi et al., 2013).

is proposed to first capture diagnostic knowledge from physicians, then uncertain patient inputs are gathered through a questionnaire. This kind of model can also be applied to many systems, such as a medical decision support system (DSS). The quality of medical care is expected to improve through the use of DSS to assist physicians in making correct clinical decisions (Conejar & Kim, 2014).

The proposed fuzzy system, demonstrated in Fig. 2, maps the symptoms from a patient questionnaire, i.e. the input, to the final decision on the risk level of disease, i.e. the system output. The questionnaire used both by general practitioners and specialists to gather patient information is the input to the fuzzy system. After the questionnaire is completed, a fuzzy system processes it as the input data. The proposed processing module is a decision support system which generates a risk level of disease as the final result. The final decision on the severity of the subject's disease, however, is made by the expert physician. Therefore, this approach embodies a human-in-the-loop feedback control system (Chipalkatty, 2012; Girardi et al., 2016; Passino, Yurkovich, & Reinfrank, 1998).

The structure of the proposed fuzzy system shown in Fig. 2 consists of three steps. First, if the value provided for each symptom is crisp number, a fuzzification step is needed to provide fuzzy values. Based on comments provided by physicians in Table 1, fuzzy rules are formed as the second step. For example, if the patient expresses his feeling on symptom r_1 as Low and the physician's comment for this symptom is Maybe, the associated rule generates a rule as "IF r_1 (input) is Low, THEN risk level (output) is Maybe." The inference part in Fig. 2 is formed by all associated rules provided from experts. Since there is a combination of symptoms, many different rules might be triggered in the inference engine. To quantify the triggered rules, an inference method such as Mamdani (Mamdani, 1974) or TSK (Takagi & Sugeno, 1985) can be applied. In this study, the Mamdani method was chosen due to its wide usage in various fuzzy systems. The Mamdani inference operator calculates the result of the rules based on the following mathematical expression (Ning, Lau, & Wong, 2006),

$$\mu(X,Y) = \phi[\mu_A(X), \mu_B(Y)] = \mu_A(X) \wedge \mu_B(Y) \tag{1}$$

where an implication operator is denoted by ϕ, the input membership function by$\mu_A(X)$, the output membership function by$\mu_B(Y)$ and intersection function by$\wedge$. Next, maximum approach (Union) is used for aggregation. To evaluate the final output, a centroid defuzzification method is carried out as the third step because of its simplicity and popularity. Finally, the output value of the model is a crisp number which shows the risk level of the disease under consideration. Different from other fuzzy expert systems used for disease diagnosis, the proposed framework considers modeling input uncertainty in that the output of the proposed fuzzy system is a set of crisp numbers forming a distribution while the traditional fuzzy system only generates one crisp output.

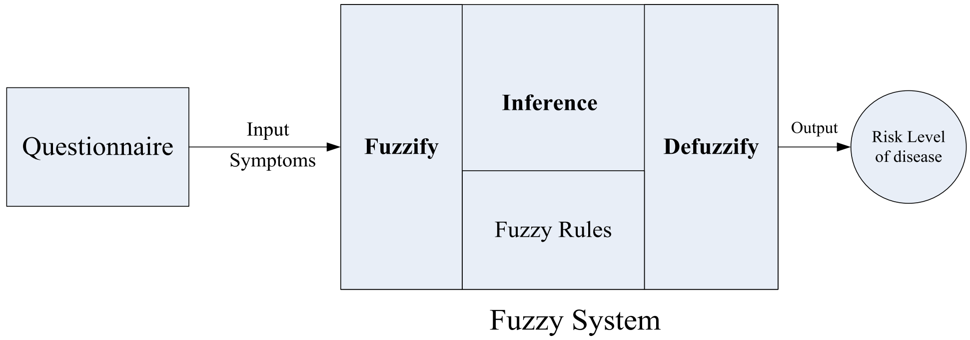

Fig. 2. The fuzzy design of the system.

Table 1
Fuzzy value table for the disease profile.

Relevant symptoms	Fuzzy value of a symptom					
	Zero	Very Low	Low	Moderate	High	Very High
r_1						
r_2						
…						
r_k						

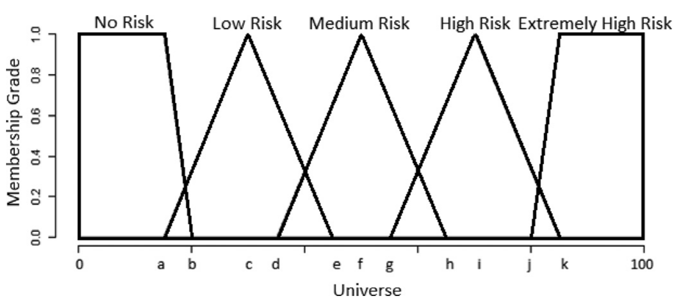

Fig. 3. The fuzzy sets for the certainty of disease presence, where No Risk: (0, 0, a, b), Low Risk: (a, c, e), Medium Risk: (d, f, h), High Risk: (g, i, k) and Extremely High Risk: (j, k, 100, 100).

3. Knowledge acquisition and representation using fuzzy expert system

Physicians, or medical experts, often make decisions about a patient's health status based on their symptoms. Since different physicians may have different judgements on the severities of various symptoms, it is difficult to model physicians' medical expertise. Our approach is to take the average of physicians' assessments on each symptom. Since the physicians' comments can be modeled as fuzzy or linguistic variables, the average method is applied to fuzzy numbers (Jahantigh, Malmir, & Avilaq, 2017). They may also consider different symptoms and make a decision based on a combination of those symptoms. Thus, to model the diagnostic process, the following steps are proposed:

- Make a list of related symptoms for each disease considered.
- Obtain the physicians' assessment on each symptom.
- Calculate the average of all the assessments for each symptom.

After accomplishing the above steps, a summary of the comments, as shown in Table 1, can be obtained. Table 1 illustrates six fuzzy values for each related symptoms ri, $i = 1, \ldots, k$ as a disease profile.

The notation r_i represetns the i^{th} symptom of a disease where $i = 1,2,\ldots, k$ and k is the total number of symptoms. The assessments are linguistic terms which can be represented by fuzzy values.

The physicians' assessments are provided in linguistic terms, given as: No Risk, Low Risk, Medium Risk, High Risk and Extremely High Risk, which can be represented by a triangular or a trapezoidal fuzzy number. Skilled physicians must provide suitable values for every entry in a disease profile table based on their experiences. This process should be carried out for every disease in the set of considered diseases. Fig. 3 demonstrates the fuzzy graph of possible physician comments of a symptom related to a disease.

The membership functions for the physicians' assessments are given in Eqs. (2)–(6),

$$\mu_{No}(x) = \begin{cases} \gamma_1(x) = 1 & x < a \\ \gamma_2(x) = \frac{b-x}{b-a} & a \le x < b \end{cases} \tag{2}$$

$$\mu_{Low}(x) = \begin{cases} \theta_1(x) = \frac{x-a}{c-a} & a < x \le c \\ \theta_3(x) = \frac{e-x}{e-c} & c < x < e \end{cases} \tag{3}$$

$$\mu_{Medium}(x) = \begin{cases} \lambda_1(x) = \frac{x-d}{f-d} & d < x \le f \\ \lambda_3(x) = \frac{h-x}{h-f} & f < x < h \end{cases} \tag{4}$$

$$\mu_{High}(x) = \begin{cases} \varphi_1(x) = \frac{x-g}{i-g} & g < x \le i \\ \varphi_3(x) = \frac{k-x}{k-i} & i < x < k \end{cases} \tag{5}$$

$$\mu_{Extremely\ High}(x) = \begin{cases} \eta_1(x) = \frac{x-j}{k-j} & j < x < k \\ \eta_2(x) = 1 & k \le x \end{cases} \tag{6}$$

In this study, five physicians were asked to weigh in on certain symptoms of a given disease. The weights that each physician assigned to certain symptoms are expressed in fuzzy linguistic terms as very low, rarely, low, medium, frequently, high, and very high. A questionnaire collects severity of all symptoms a patient feels so that a physician can examine the possibility whether a patient suffers from a certain disease or not. Since patients may be uncertain about the severity of each symptom, they might guess. It means the inputs in the questionnaire are also uncertain. To mitigate the impact of uncertainty on a DSS, this study provides two approaches for patients to express the severity of symptoms. Specifically, patients may express the symptom severity either by fuzzy linguistic terms or a range of numbers from zero to one hundred. Using the first approach, patients simply choose up

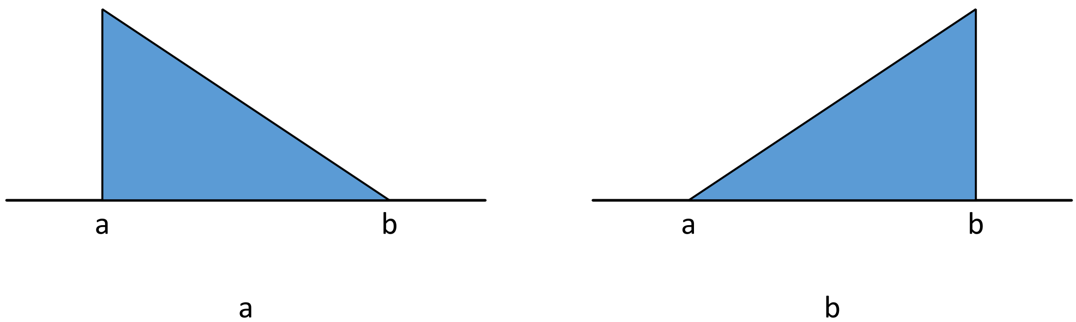

Fig. 4. Two numbers as input with different tendency – (a): tendency on a and (b): tendency on b.

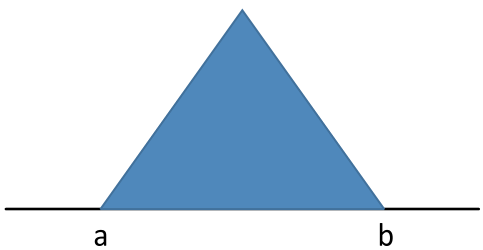

Fig. 5. Two numbers as input without any tendency.

to two linguistic expressions that best describe each symptom. In this study, five fuzzy variables are adopted to represent the linguistic terms as very low, low, moderate, high, and very high. In the second approach, patients evaluate each symptom in the questionnaire as a numerical range (a, b) where $a < b$ and $a, b \in [0, 100]$. The following sections describe both approaches in detail.

3.1. First approach for uncertain inputs: multiple linguistic entries

In this approach, subjects may express the severity level as multiple choices. They are allowed to choose up to two selections. For example, he may check “low” and “moderate” for the severity of any symptom. These two selections should be consecutive linguistic terms. Next, a combination of all entries for different symptoms will be used to trigger corresponding rules. Each rule that is fired will then generate a risk level as a response. Finally, the frequency of all possible responses resulting from different combinations will be counted. The most frequent risk level will be assigned as the final diagnosis. This procedure will be described in detail in an example in Sections 4 and 5.

3.2. Second approach for uncertain inputs: multiple numeric entries

In this approach, patients may express the severity of symptoms in a range $R = [a,b]$ where $R \subset [0, 100]$ because they may not be completely sure about the severity they feel in one number. If they enter only one number, the procedure would be a regular fuzzy expert system as reviewed previously. In the case that they enter more than one number, the proposed system will generate random numbers within the interval (a, b) and subsequently generate multiple results. Running more iterations will result in a more accurate risk level. In this study, however, 100 simulation runs are conducted. Each simulated entry generates a risk level. Random number generation depends on the numbers given by the subject, which could be as follows:

- If two numbers (a, b) are specified, patients will be asked about which value, a or b, tends to be the more accurate description of a symptom. For example, a patient may report a severity range of (70, 80). He is more inclined to 70 than 80. In this case, he is more sure about 70 which defines his tendency in the reported range. Then, based on this range, the system will provide numerous random numbers via a triangular distribution, which selects a most likely value as the side which subject tends to. Fig. 4 shows two different tendencies.

If two numbers are given by patients who do not have any tendency, then the system will generate random numbers based on the triangular distribution between a and b where the average is the middle value in the interval $(a,\ a+b/2,\ b)$. For example, a patient may report a range of (70, 80) without a tendency. The system will generate random numbers using the interval (70, 75, 80) Fig. 5 illustrates a triangular distribution.

- Another case is the variant from Fig. 5 where the triangle may not be symmetrical. Patients may enter three numbers (a, m, b) when the tendency number m is within the range (a, b). In this case the proposed system will generate multiple random numbers and simulate different entries using a triangular random generator (Amini, Chang, & Malmir, 2016). This generator will create numbers by tending toward the middle value. For example, if a patient reports (70, 75, 90) for the severity, Fig. 6a shows this type of triangular distribution. Other types of triangular distributions can be found in Fig. 6b.

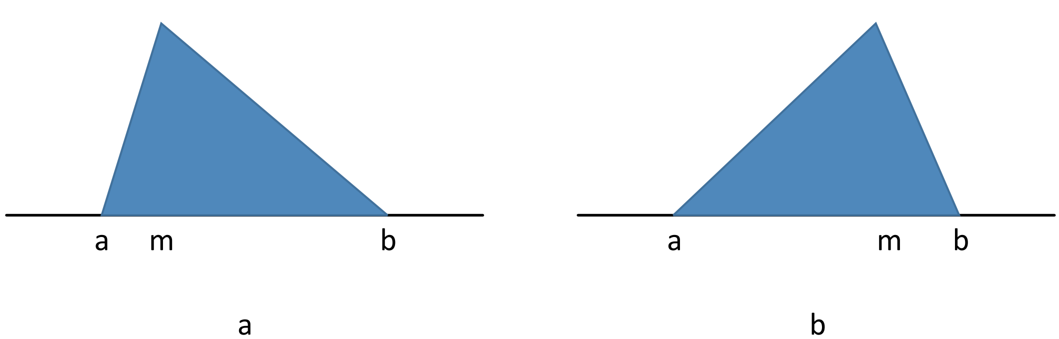

Fig. 6. Three numbers as input with different tendency (m).

Table 2
Profile for *kidney stone* based on five physicians' experience.

Properties features	Zero	Very Low	Low	Moderate	High	Very High
Bad smell urine	No	Low	Maybe	High	Maybe	High
Chill and fever	No	Ext. High	Ext. High	High	High	High
Dysuria	No	No	Low	High	Ext. High	Ext. High
Flank pain bilateral	No	No	Low	Maybe	Maybe	Ext. High
Flank pain unilateral	No	No	Maybe	Maybe	Ext. High	Ext. High
Frequency and urgency	No	Low	Maybe	Maybe	Ext. High	Ext. High
Hematuria	No	Ext. High	Ext. High	Ext. High	Ext. High	Ext. High
Nausea and vomiting	No	Ext. High	Ext. High	Maybe	Low	No
Urine pus	No	Low	Maybe	Maybe	Maybe	High

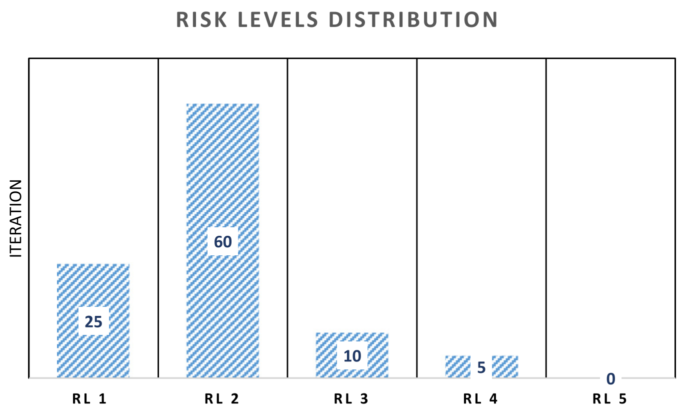

Fig. 7. The distribution of different risk levels in a 100 simulation runs (RL – Risk Level).

If patients report two or more numbers for severity of symptom, multiple numbers inside the range defined are simulated. Then the proposed model treats each simulated number as one set of entry and provides a risk level as a result. Risk levels provided by simulated entries are then summarized in a distribution represented in a bar chart. As an illustration, Fig. 7 shows a summary of 100 simulation runs at different risk levels represented by different bars. Physicians can use this risk level distribution information to support their diagnostic decisions.

The proposed method is capable of generating a ranking distribution of risk levels of a disease as shown in Fig. 7, where RL stands for risk level. This distribution is made by considering the uncertainty patients may have which previous studies did not consider. By having the ranking distribution, physicians are able to provide better information considering patients' uncertain inputs. Patients' uncertainty could be very important and effective with some fatal diseases. In the next section, a couple of kidney diseases will be used in a case study to demonstrate the proposed fuzzy expert system with uncertainty considerations.

4. A fuzzy decision support example: kidney disease diagnosis

One of the main public health problems in the world is kidney disease (Jha, Garcia-Garcia, & Iseki, 2013). About 10% of the global population is affected with a kidney disease. The most known kidney diseases are kidney infection, kidney stone, renal tubular, proteinuria, IgA nephropathy, nephroangiosclerosis, chronic renal failure, and polycystic kidney disease (eMedMD – A Medical and Health Information Site, 2015). Researchers have strived to develop theories to model diagnostic procedures regarding kidney diseases. To this end, Ahmed, Kabir, Mahmood, and Rahman (2014) introduced a fuzzy expert system to diagnose kidney disease. Seven factors were considered to measure the probability of having the disease, as follows: nephron functionality, blood sugar, systolic and diastolic blood pressure, age, weight, and alcohol intake. Finally, the method produced an output number ranging from 0 to 10, with 0 for healthy and 10 for extremely sick. Muslim, Kurniawati, and Sugiharti (2015) introduced an expert system based on the Mamdani fuzzy inference systems to diagnose chronic kidney disease. Chen, Zhang, Zhu, Xiang, and Harrington (2016) aimed to diagnose the same disease using two fuzzy classifiers, fuzzy optimal associative memory, and fuzzy rule-building expert system. Norouzi, Yadollahpour, and Mirbagheri (2016) applied integrated intelligent fuzzy expert systems to predict renal failure in chronic kidney disease. None of these systems considered patient uncertain inputs. This case study demonstrates how patients can express their uncertainty about their symptoms potentially related to kidney disease.

In this study, two of the main kidney related diseases are considered to demonstrate how the proposed expert system performs. Kidney stone and kidney infection diseases along with their symptoms are measured. Table 1 is used to form the required information about these two diseases. A typical example of a set of symptoms is given in Tables 2 and 3. These are the major symptoms directly associated with these two diseases. There are some minor symptoms such as proteinuria, hypertension, leukocyturia, and fasting blood sugar and patient meta data, such as age and sex, which are not directly associated with diagnosis of these diseases, however they could be considered along with other major symptoms.

Jahantigh et al. (2017) studied kidney stone and kidney infection related symptoms as well as some other kidney related diseases. These symptoms are incorporated in the current study as shown in Table 2. The second column called "Zero" in Table 2 is added to indicate that a patient feels no abnormality on a symptom. If the patient feels that this symptom does not apply to him, an answer of NO will be used so that this symptom will not be included for any further consideration. Moreover, the profile tables for two kidney diseases are updated according to assessments from five expert physicians who provided the information needed on each symptom. Obviously, physicians with different professional levels and experience have different opinions about a symptom. Therefore, multiple fuzzy numbers may be generated for each symptom. To summarize all opinions, we took the average of these fuzzy numbers to capture knowledge about each symptom. There are multiple methods for fuzzy average, such as generalized means (Merigó & Casanovas, 2010) and ordered weighted averaging operations (Yager & Kacprzyk, 2012). Selecting an appropriate method depends on the specific application. If the set of numbers is small, an exhaustive method should work. Otherwise, the use of a heuristic method is required. In this study, a simple fuzzy average of every five values of each element is taken (Jahantigh et al., 2017). Tables 2 and 3 show the profile tables for two diseases according to five expert physicians.

In addition, the weights and ratings given by a group of physicians for the kidney stone and kidney infection symptoms are shown in Tables 4 and 5 where the weights of linguistic values are represented as Very Low as 1, Low as 2, Medium as 3, High as 4, and Very High as 5.

Fig. 8 demonstrates the fuzzy definition for the symptom: flank pain bilateral, which maps severity levels of the symptoms

Table 3
Profile for *kidney infection* based on five physicians' experience.

Properties features	Zero	Very Low	Low	Moderate	High	Very High
Abrupt fever and chill	No	No	Low	High	High	Maybe
Cloudy urine	No	Low	High	High	Ext. High	Ext. High
Dysuria	No	Low	Maybe	High	High	Ext. High
Hematuria	No	No	Maybe	Ext. High	Ext. High	Ext. High
Hesitancy	No	High	Ext. High	Ext. High	Ext. High	Ext. High
Nausea and vomiting	No	Ext. High	Ext. High	Maybe	Low	No
Nocturia	No	Low	Low	Maybe	Ext. High	Ext. High
Purulent urine	No	Low	Low	High	High	Ext. High
Suprapubic pain	No	Ext. High	Ext. High	High	Maybe	Low
Flank pain unilateral or bilateral	No	No	Maybe	Maybe	High	High
Urinary frequency	No	Low	High	High	High	Ext. High

Table 4
Fuzzy weight profiles for *kidney stone* according to the physicians' experience.

Symptoms	Linguistic weight	Numeric weight
Flank pain bilateral	Low	2
Flank pain unilateral	Medium	3
Hematuria	Very High	5
Chill and fever	High	4
Nausea and vomiting	High	4
Bad smell urine	High	4
Frequency and urgency	Medium	3
Urine pus	High	4
Dysuria	High	4

Table 5
Fuzzy weight profiles for *kidney infection*, according to the physicians' experience.

Symptoms	Linguistic weight	Numeric weight
Dysuria	High	4
Urinary frequency	Low	2
Cloudy urine	Moderate	3
Purulent urine	High	4
Hematuria	Moderate	3
Nocturia	High	4
Hesitancy	High	4
Suprapubic pain	High	4
Abrupt fever and chill	Moderate	3
Flank pain unilateral or bilateral	Moderate	3
Nausea and vomiting	Low	2

Table 6
Fuzzy numbers of the severity levels.

Severity level	Fuzzy number's type	Fuzzy values
Zero	Trapezoid	(0,0,3,5)
Very Low	Trapezoid	(3,10,20,30)
Low	Trapezoid	(25,30,40,45)
Moderate	Triangular	(40,50,60)
High	Trapezoid	(55,60,70,80)
Very High	Trapezoid	(75,80,100,100)

assigned as fuzzy numbers shown in Table 6. Other symptoms can also be similarly constructed.

Fig. 9 shows the definitions for fuzzy output variables for kidney stone and kidney infection risks. Figs. 8 and 9 help physicians assign the risk level of the disease which they diagnose a patient based on his symptoms without considering patient uncertain inputs. For example, if the crisp input on flank pain bilateral is 55 as shown in Fig. 8, then the possibilities of a patient having kidney stone are 0.5 for both moderate and high respectively. Suppose the overall assessment based on all symptoms is 60. The risk toward a kidney stone is medium at possibility 0.33 and high at possibility 0.33 according to Fig. 9 and Eqs. (8) and (9).

Based on Eqs. (2)–(6), the membership function for the physicians' comments on kidney stone and kidney infection risks can be obtained as follows:

$$\mu_{No}(x) = \begin{cases} 1 & x < 15 \\ \frac{20-x}{5} & 15 \le x < 20 \end{cases} \tag{7}$$

$$\mu_{Low}(x) = \begin{cases} \frac{x-15}{15} & 15 < x \le 30 \\ \frac{45-x}{15} & 30 < x < 45 \end{cases} \tag{8}$$

$$\mu_{Medium}(x) = \begin{cases} \frac{x-35}{15} & 35 < x \le 50 \\ \frac{65-x}{15} & 50 < x < 65 \end{cases} \tag{9}$$

$$\mu_{High}(x) = \begin{cases} \frac{x-55}{15} & 55 < x \le 70 \\ \frac{85-x}{15} & 70 < x < 85 \end{cases} \tag{10}$$

$$\mu_{Extremely\ High}(x) = \begin{cases} \frac{x-80}{5} & 80 < x < 85 \\ 1 & 85 \le x \end{cases} \tag{11}$$

Tables 2 and 3 were later used as the sources for kidney stone and kidney infection related information to make the fuzzy rules, where symptoms represent the inputs obtained from a patient as crisp values. A total of 80 rules (refer to Tables 2 and 3) are formed to interpret the fuzzy input values into diagnosing diseases. However, due to the space limitation, only a few rules are listed as follows:

The rules shown in Table 7 were captured by the specialists' experience and knowledge about the different severity levels of all symptoms related to Kidney infection and Kidney stone diseases. Therefore, the system can be considered as a kind of fuzzy knowledge management system. The system was coded with the R "SETS" package. The coded procedure first considers the symptoms-related data in the questionnaire along with simulated entries. Then, using different possible levels of the symptoms and considering the fuzzy rule based system formed by Tables 2 and 3, the risk level of each disease is obtained. At the end, by counting results of each result generated for each subject, a final decision can be made.

So far this example follows a traditional fuzzy system development. To accommodate for user input uncertainty, the implementation of Section 3.1 for kidney disease diagnosis is illustrated in the next section.

5. The proposed fuzzy decision support system for kidney diseases considering patient input uncertainty

The proposed DSS fuzzy system for kidney diseases allows patients to express their uncertainty by entering the severity level of reported symptoms. Two approaches are considered for data entry. Either the patients may choose two linguistic terms on one symptom, or they could define a range of numbers with an associated tendency over it. Then, using the first approach, the

Table 7
Fuzzy rules of the system: a sample of 80 rule DSS for kidney diseases.

Rule #1	If	Hematuria	Is	VH or H or M[a]	Then	Kidney Infection Risk is:	Extremely High
Rule #2	If	Hematuria	Is	L	Then	Kidney Infection Risk is:	Medium
Rule #3	If	Hematuria	Is	VL or Zero	Then	Kidney Infection Risk is:	No
Rule #4	If	Dysuria	Is	VH or H	Then	Kidney Stone Risk is:	Extremely High
Rule #5	If	Dysuria	Is	VL or Zero	Then	Kidney Stone Risk is:	No
Rule #6	If	Dysuria	Is	M	Then	Kidney Stone Risk is:	High
Rule #7	If	Dysuria	Is	L	Then	Kidney Stone Risk is:	Low
Rule #8	If	Suprapubic Pain	Is	VL or L	Then	Kidney Infection Risk is:	Extremely High
Rule #9	If	Suprapubic Pain	Is	H	Then	Kidney Infection Risk is:	Medium
Rule #10	If	Suprapubic Pain	Is	M	Then	Kidney Infection Risk is:	High
Rule #11	If	Suprapubic Pain	Is	VH	Then	Kidney Infection Risk is:	Low
Rule #12	If	Suprapubic Pain	Is	Z	Then	Kidney Infection Risk is:	No

[a] Notations are: Z: Zero, VL: Very Low, L: Low, M: Moderate, H: High, VH: Very High and the criteria are No Risk, Low Risk, Medium Risk, High Risk and Extremely High Risk.

system will generate results based on all the choices subjects have chosen. The second approach generates multiple random numbers in the intervals created and generates one result per simulated entry. Both approaches generate multiple scenarios for each patient. Kidney stone and kidney infection diseases-related fuzzy rule based system were conducted as a case study.

The case study consists of 40 real patients. Half of the patients were randomly selected to express the severity of symptoms using linguistic terms (Section 3.1) and the rest used the numeric level method (Section 3.2). They were all examined by an experienced female kidney specialist during a four-day period. They were asked to fill out the designed questionnaire. Tables 16 and 17 are the values that patients selected using linguistic terms for the severity of each symptom, and Tables 18 and 19 are the values that patients selected using numeric values, which are presented in Appendix B. The following subsections provide more discussion through a real case on two different approaches in details.

5.1. Linguistic terms for patient input uncertainty

Suppose that a male patient presents his symptom severities using linguistic terms as shown in Table 6. He selects his suprapubic pain level as “Low” and “Normal” because he is not sure about the exact severity experienced. In this study, a total of 16 symptoms were considered to diagnose the kidney stone and kidney infection risk levels. Each object’s outcome is independent of the others.

By fuzzifying the linguistic input variables, corresponding fuzzy rules are triggered. The rules triggered are then put into the inference process, which is used to determine the output fuzzy set. For each rule, a degree is obtained. Then, a combination of the rules fired will generate a risk distribution. For example, if subject number 1 has entered 3 symptoms with two linguistic terms, then the system will generate 8 possible combinations. A defuzzification process is required to generate a crisp value for the certainty level of risk. In this study, the centroid method was used to defuzzify the final fuzzy set. Finally, using the aggregated resulting defuzzified numbers, a physician can diagnose the kidney illnesses.

5.2. Numerical range for patient input uncertainty

In this case, each level of risk is formed as a fuzzy number of either a triangular or trapezoidal function as shown in Fig. 1. Suppose the male patient used in the previous discussion expresses his suprapubic pain using up to three numbers such as (70, 75, 90). Then, the triangular random generator (as discussed in Section 3.2) uses these numbers to create a simulated number between 70 and 90, with the most likely estimate at 75. This range has a distribution similar to that in Fig. 6a. For each uncertain numeric symptom related to one subject, 100 series of entries are generated per its distribution.

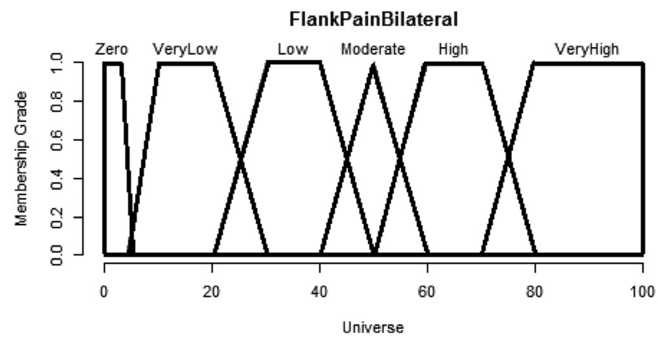

Fig. 8. The fuzzy levels of symptoms.

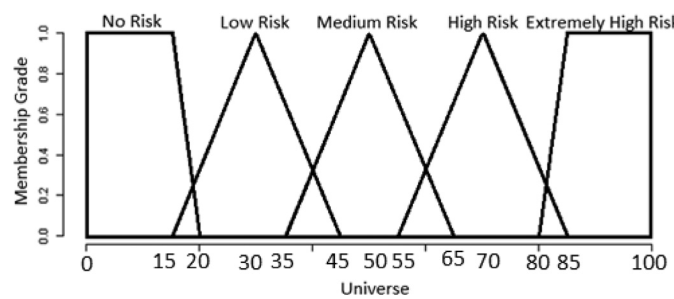

Fig. 9. The fuzzy levels of kidney stone and kidney infection risks, where No Risk: (0, 0, 15, 20), Low Risk: (15,30,45), Medium Risk: (35,50,65), High Risk: (55,70,85) and Extremely High Risk: (80,85,100,100).

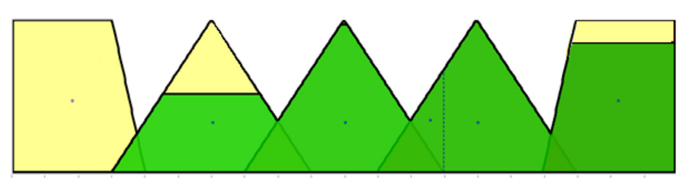

Fig. 10. The aggregated output fuzzy set of kidney stone risk for one simulation run of patient 1. (For interpretation of the references to color in this figure, the reader is referred to the web version of this article.)

To determine the area, center of gravity and the membership functions associated with triggered rules, Fuzzylite software is used. The final shape of one simulation run by which we came up with the risk level is shown in Fig. 10. The green color areas are fired risk levels based on resulted membership grade where yellow color areas are not triggered.

Defuzzifying the final shape gives the risk level of disease. Each numeric risk can be translated to a linguistic risk. For example, a risk of 70 means “High” risk level.

The simulated entries and the calculated results of the first simulation run on kidney stone and kidney infection risks for one

Table 8
Data for the defuzzification process of kidney stone risk-related polygon for patient #21.

Simulated entry	Triggered rules	Area (A)	Center of gravity (C)	Weight (W)
70	#1	10	50	2
40	#2	10	50	3
38	#3	25	91.189	5
40	#4	25	91.189	4
73	#5	11.25	24.147	4
60	#6	10	50	4
44	#7	8.4	50	3
88	#8	25	91.189	4
70	#21	10	70	4

Table 9
Data for the defuzzification process of kidney infection risk-related polygon for patient #21.

Simulated entry	Triggered rules	Area (A)	Center of gravity (C)	Weight (W)
88	#9	25	91.189	4
80	#10	25	91.189	2
60	#11	25	91.189	3
70	#12	10	70	4
38	#13	10	50	3
59	#14	26.3	84.858	4
77	#15	18.56	90.846	4
70	#16	10	50	4
54	#17	8.4	70	3
70	#18	10	50	3
40	#19	10	50	3
73	#20	10	24.147	2

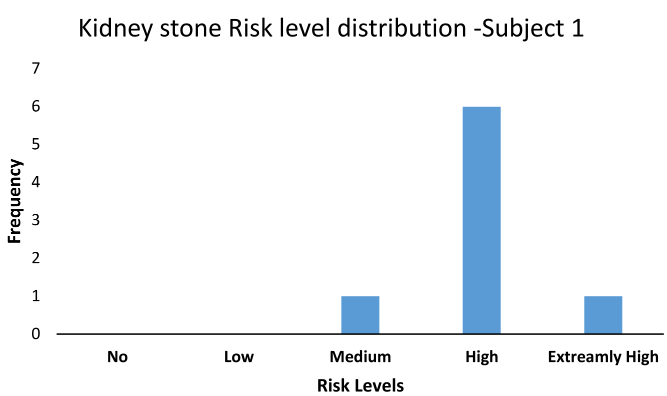

Fig. 11. Frequency of kidney stone risk level of a sample patient.

real subject (patient #21 in Table 18) are shown in Tables 8 and 9, as an example.

The values of the first column in Table 8, represents the simulated severity of the symptoms reported by patient #21. For example, the first number, 70, is reported as severity of flank pain bilateral for patient #21 (in Table 18) as a certain value while the third number, 38, is a random number generated from the interval 30–50 for the severity of hematuria reported by the same patient. The system processes each entry (either simulated or linguistic) and finds the associated risk level. The process of simulation is repeated 100 times and the outcome of each fuzzy run is recorded. Then, by counting the total numbers of each resulting risk level, the system reports the most frequent level as the result. Fig. 11 shows the frequency of results for the kidney stone risk level of patient #21. Triggered rules descriptions related to the first run are available in Appendix A.

5.3. Performance analysis

Tables 10 and 11 show the final risk level values obtained from 40 sample subjects, where the first 20 subjects reported symptoms as linguistic terms and the rest reported numeric values. In Table 10, the first 20 subjects' data were processed via the first approach, which adopts multiple linguistic entries, while the next 20 subjects' data were processed via the second approach, which uses multiple numeric entries. Table 10 contains three diagnosis columns, which gives the diagnoses from the female kidney specialist, the proposed system, and the real patient diagnosis, respectively. The next two precision columns compare the physicians diagnose and proposed system result with real diagnosis. As this table demonstrates, the second uncertain input approach provided better results than the first approach. This result suggests that second approach may be able to model patients' uncertainty level more precisely than the first approach.

Summarized from Tables 10 and 11, we compare the results from experts' opinions and the two proposed Fuzzy DSS approaches for accommodating user input uncertainty. We considered the fuzzy terms "High" for risk of a disease as the actual result "Yes", the fuzzy term "Medium" to the actual result "Risky", and fuzzy terms "Low" and "Very Low" to the actual result "No". Table 12 shows the number of successful diagnoses comparing the proposed method to physicians. It is shown that the proposed fuzzy DSS approaches outperform the physician in this experiment. The numeric approach is slightly better than the linguistic approach in diagnosing kidney stone.

5.3.1. Statistical inference on diagnosis results

A statistical inference for two samples (Montgomery, 2016) is applied to compare the diagnosis results obtained from the proposed expert system to those obtained from a physician. This comparison is applied to both input approaches using the hypothesis where ρ_1 and ρ_2 are the percentages of successful diagnostics of the proposed method and physicians, respectively. The hypotheses are:

$$H_0 : \rho_1 = \rho_2$$

$$H_1 : \rho_1 > \rho_2$$

Table 10
Results comparison of diagnosis of the proposed expert system and a physician (using linguistic values).

Subject's no.	Diagnosis results (risk level)						Precision (Physician)	Precision (System)
	Physician		Proposed system		Actual results			
	Kidney Stone	Kidney infection	Kidney stone	Kidney infection	Kidney stone	Kidney infection		
#1	High	Low	High	High	Yes	Yes	√	√√
#2	Low	Low	Low	Medium	No	Risky	√	√√
#3	Low	High	Low	Medium	No	Yes	√√	√
#4	No	Low	High	High	Yes	Yes		√√
#5	High	High	High	High	Risky	Yes	√	√
#6	No	No	No	No	No	No	√√	√√
#7	Medium	Low	Medium	Low	Risky	No	√√	√√
#8	Medium	Low	Medium	High	Risky	Yes	√	√√
#9	No	No	No	Medium	No	Yes	√	√
#10	No	No	No	No	No	No	√√	√√
#11	No	Low	Low	High	No	Yes	√	√√
#12	No	No	No	Medium	No	Risky	√	√√
#13	High	High	High	High	Yes	Yes	√√	√√
#14	Low	High	Medium	High	Yes	Yes	√	√
#15	Low	No	Low	High	No	Yes	√	√√
#16	No	No	No	No	No	No	√√	√√
#17	Medium	Low	Medium	Low	Risky	No	√√	√√
#18	Medium	Medium	Medium	Medium	Yes	Yes		
#19	Low	Medium	Low	High	Yes	Yes		√
#20	Medium	Low	Medium	Medium	Risky	Risky	√	√√

Table 11
Results comparison of diagnosis of the proposed expert system and a physician (using uncertain numeric values).

Subject's no.	Diagnosis results (risk level)						Precision (Physician)	Precision (System)
	Physician		Proposed system		Actual results			
	Kidney stone	Kidney infection	Kidney stone	Kidney infection	Kidney stone	Kidney infection		
#21	Medium	High	High	High	Yes	Yes	√	√√
#22	No	No	No	No	No	No	√√	√√
#23	High	Low	High	High	Yes	Yes	√	√√
#24	Medium	High	High	High	Yes	Yes	√	√√
#25	High	High	High	High	Yes	Yes	√√	√√
#26	Low	Low	Medium	Low	Risky	No	√	√√
#27	No	High	Low	High	No	Yes	√√	√√
#28	Low	Low	Low	Medium	No	Risky	√	√√
#29	Low	No	Low	Medium	No	Yes	√	√
#30	No	Medium	No	Yes	No	Yes	√	√√
#31	Medium	Low	Medium	Low	Risky	No	√√	√√
#32	Low	High	Low	Medium	No	Yes	√√	√
#33	Medium	Low	Medium	High	Risky	Yes	√	√√
#34	Low	High	High	High	Yes	Yes	√	√√
#35	No	No	No	No	No	No	√√	√√
#36	No	No	No	Medium	No	Risky	√	√√
#37	Medium	Low	High	Medium	Risky	Risky	√	√
#38	No	High	High	High	Yes	Yes	√	√√
#39	High	High	High	High	Yes	Yes	√√	√√
#40	No	No	No	Medium	No	No	√√	√

Table 12
The number of successful diagnostics (out of 20 cases each).

Uncertain entry type	Disease	Physician	Proposed fuzzy DSS system
Linguistic	Kidney stone	15 (75%)	16 (80%)
	Kidney infection	9 (45%)	17 (85%)
Numeric	Kidney stone	15 (70%)	19 (95%)
	Kidney infection	13 (65%)	17 (85%)

where the test statistic $z_0 = \frac{\hat{\rho}_1 - \hat{\rho}_2}{\sqrt{\hat{\rho}(1-\hat{\rho})(\frac{1}{n_1}+\frac{1}{n_2})}}$, and two binomial parameters of interests, ρ_1 and ρ_2, are the estimators of the population proportions, defined as $\hat{\rho}_i = x_i/n_i$, x_i is the number of successful diagnoses and n_i is the number of all cases, $i = 1,2$. The sample size for each disease in each comparison is twenty.

The fixed significance level of rejection criterion is $Z_0 > Z_\alpha$ with the P-value of $P = 1 - \Phi(Z_0)$. For a 95% significant level chosen, i.e., $\alpha = 0.05$, the critical rejection value is $Z_\alpha = 1.645$. Table 13 shows the comparison results as well as the P-values.

The test results suggest that there is no significant difference between the diagnosis results obtained by the proposed system and the actual results for the kidney stone diagnoses case using the linguistic entry method. However, using the second entry method with a numerical interval, the proposed system provides better diagnostics results than physicians. For kidney infection, the expert systems using linguistic and numeric uncertain entry methods outperform the physicians at 99.6% and 99.8% significant levels, respectively.

Obviously, the proposed system still needs some improvements to obtain more precise results, although mostly works well. For

Table 13
Inference results of kidney disease diagnoses comparing expert systems using two uncertainty entry methods to physicians.

Uncertainty entry type	Disease	Z_0	$Z_0 > 1.645$	P-value	Result
Linguistic	Kidney stone	0.379	×	0.352	The hypothesis H_0 cannot be rejected
	Kidney infection	2.652	√	0.004	The hypothesis H_0 is rejected
Numeric	Kidney stone	3.542	√	0.000	The hypothesis H_0 is rejected
	Kidney infection	2.921	√	0.002	The hypothesis H_0 is rejected

Table 14
The proposed method vs machine learning algorithms.

Method	Disease	
	Kidney infection	Kidney stone
Logistic regression	50%	52.5%
Naïve Bayes	37.5%	50%
The proposed method	85%	87.5%

example, sometimes a large uncertainty range may affect the accuracy of the final result. For instance, patient number 29 provided 11 entries out of all symptoms with uncertainty, which results in having a Medium risk level for kidney infection, while the actual result is Yes. As seen, the physician also could not diagnose the subject's risk level of diseases. Sometimes no reason can be given for why the system is inaccurate. For example, both the physician and proposed system provided an inaccurate risk assessment for patient number 18. This could be due to her high age or rare exceptions.

5.3.2. Comparison of the proposed method with machine learning methods

This session examines the possibility of applying machine learning methods for the same task as shown in the proposed Fuzzy DSS for kidney diseases. In general, fuzzy expert systems work well when rules can be extracted from human experts even when there is not that much samples to work with. On the other hand, machine learning methods often require a large number of samples to train their models. In this section, the proposed Fuzzy DSS method is compared with two machine learning (ML) methods: Naïve Bayes and Logistic Regression algorithms based on 40 samples for kidney diseases.

Five folds cross-validation has been applied to obtain the accuracy of the ML models. Here are the summary of the results (Correctly Classified Instances) (Table 14):

As it was expected, the results in the table above shows a low classification accuracy given by the Naïve Bayes and Logistic Regression algorithms due to the lack of enough data to train the ML models. On the other hand, the rules in Fuzzy DSS comes from experts' opinion, which are actually formed by experiences on many sample data already observed. The proposed Fuzzy DSS does not require many data as the ML methods usually need.

In fuzzy systems experts have automated the proposed system. This means the system was trained to map the levels of severity of symptoms to a risk level of disease as 'No', 'Low', 'Medium', 'High' or 'Extremely High'. In fact, the fuzzy rules are playing the same rule as training phase in machine learning algorithms where fuzzy rules are extracted by experts' knowledge while training machines needs large amount of observed samples. This is the main difference between machine learning methods and fuzzy expert systems.

6. Conclusion and future studies

This paper explores a fuzzy decision support system and considers uncertainty due to patient inputs. The proposed system aims to help physicians make faster and more accurate medical diagnoses as applied to several typical diseases only by entering their associated symptoms' values as the input cases. The group-based decision making nature of this method avoids medical misdiagnosis, which has been a dilemma for both patients and physicians recently.

Two patient input methods were proposed. The first approach adopts the choice of up to two linguistic variables, while the second approach uses a numerical range that allows patients to express their uncertainty levels. By applying the simulation on uncertain values on multiple input variable combinations, a ranking distribution of different risk levels of a disease provides more informative results than current fuzzy systems reviewed in the literature. A case study on forty kidney patients showed that the second approach outperformed the first approach slightly in diagnosing kidney stone. The proposed Fuzzy DSS is an appropriate tool than other machine learning alternatives because a moderate number of samples are available for model training.

The proposed Fuzzy DSS framework considers uncertain user inputs as well and can be applied to many applications. The presented methodology has been proven a reliable tool to help physicians diagnose two kidney diseases. The case study results show that diagnostic accuracy is higher than physician diagnoses in three out of four cases. The proposed system can be used as a decision support system to assist less experienced physicians. The proposed fuzzy input methods could not only be applied to other diseases, but also be extended to other applications where inputs are uncertain.

Appendix A. Triggered Rules for the first subject

See Table 15

Appendix B. Physicians' comments on each symptom of 20 randomly selected real patients

As mentioned in the paper, only those major symptoms directly associated with the diseases studied are considered to generate the final results. However, there are some signs or features such as age, sex, proteinuria, hypertension, and fasting blood sugar, which are not directly associated with diagnosing these diseases, but they can be considered along with other major symptoms as a combination. In this study, however, since our results were accurate enough, we did not consider them in further procedures.

As shown in the tables below, (Tables 16–19) Leukocyturia, also called white blood cells (WBCs), has a value originally, but, it has been converted to a number of between zero and 100 in this paper. For example, the values for first ten patients are as follows:

86.3	15.7	30.1	10.8	23.5	36.6	26.8	22.9	34.1	19.6

The same procedure can be applied for other patients recorded in Tables 17–19.

Note that the bold numbers in Tables 18 and 19 are the tendency selected by patients.

Table 15
Triggered rules for the first subject.

Rule no.	Rule description
1	if FlankPainBilateral is Moderate or FlankPainBilateral is High then KidneyStoneRisk is MediumRisk
2	if FlankPainUnilateral is Low or FlankPainUnilateral is Moderate then KidneyStoneRisk is MediumRisk
3	if Hematuria is Low or Hematuria is Moderate or Hematuria is VeryLow or Hematuria is High or Hematuria is VeryHigh then KidneyStoneRisk is ExtremelyHighRisk
4	if ChillAndFever is Low or ChillAndFever is VeryLow then KidneyStoneRisk is ExtremelyHighRisk
5	if NauseaAndVoming is High then KidneyStoneRisk is LowRisk
6	if BadSmellUrine is Low or BadSmellUrine is High then KidneyStoneRisk is MediumRisk
7	if FrequencyAndUrgency is Low or FrequencyAndUrgency is Moderate then KidneyStoneRisk is MediumRisk
8	if Dysuria is VeryHigh or Dysuria is High then KidneyStoneRisk is ExtremelyHighRisk
9	if Dysuria is VeryHigh then KidneyInfectionRisk is ExtremelyHighRisk
10	if UrinaryFrequency is VeryHigh then KidneyInfectionRisk is ExtremelyHighRisk
11	if CloudyUrine is VeryHigh or CloudyUrine is High then KidneyInfectionRisk is ExtremelyHighRisk
12	if PurulentUrine is High or PurulentUrine is Moderate then KidneyInfectionRisk is HighRisk
13	if Hematuria is Low then KidneyInfectionRisk is MediumRisk
14	if Nocturia is Moderate then KidneyInfectionRisk is MediumRisk
15	if Hesitency is Low or Hesitency is VeryHigh or Hesitency is High or Hesitency is Moderate then KidneyInfectionRisk is ExtremelyHighRisk
16	if Suprapubic is High then KidneyInfectionRisk is MediumRisk
17	if AbruptFeverAndChill is High or AbruptFeverAndChill is Moderate or AbruptFeverAndChill is VeryHigh then KidneyInfectionRisk is HighRisk
18	if FlankPainBilateral is High or FlankPainBilateral is VeryHigh then KidneyInfectionRisk is HighRisk
19	if FlankPainUnilateral is Low or FlankPainUnilateral is Moderate then KidneyInfectionRisk is MediumRisk
20	if NauseaAndVoming is High then KidneyInfectionRisk is LowRisk
21	if UrinePus is High then KidneyStoneRisk is HighRisk

Table 16
Physicians' comments on each symptom of the selected real patients.

Symptom	Patient									
	1	2	3	4	5	6	7	8	9	10
Sex	Male	Female	Male	Female	Female	Female	Female	Male	Male	Male
Age	39	41	68	52	74	21	18	59	47	29
Flank pain bilateral	High	Very Low	Normal	Low	High	Very Low	High	Low-Normal	Low	Zero
Flank pain unilateral	High	High	High	High	Low	Low	High	Normal-High	Very Low	Low
Hematuria	High	Low-Normal	Very Low	High	Low-Normal	High	Very high	Zero	Low	Very Low
Chill and fever	Low	High	Low-Normal	High	Low	Zero	Low-Normal	Low	Zero	Zero
Nausea and vomiting	High	Low-Normal	Very Low	Very high	High	Zero	High	Very high	Very Low	Very Low
Bad smell urine	normal	Normal-High	Low-Normal	High	High	Normal	Low-Normal	High	Low-Normal	Low
Frequency and urgency	Low	Normal	Normal	High	Low	Normal	Normal	Normal	Normal	Normal
Dysuria	High	High	High	Low-normal	Very high	Zero	Low-normal	Normal-high	Very low	Low
Urinary frequency	High	Low-normal	Very high	Low-normal	Very high	Very low	High	High	Low-normal	Very low
Cloudy urine	High	Low-normal	Normal-high	Low-normal	High	Low-normal	High	High	Low-normal	Low
Purulent urine	Low-normal	Normal-high	High	High	High	Low-normal	Low	Normal	High	Low-normal
Leukocyturia (WBC)	16,000	5200	7400	4450	6400	8400	6900	6300	8020	5800
Nocturia	Normal-high	Low	Zero	Low-normal	Normal-high	Low	Low	Zero	Low-normal	Zero
Hesitancy	High	Very Low	Normal-High	High	Very high	Zero	Normal	Normal	Low-Normal	Low
Suprapubic pain	Low-Normal	High	High	Low-Normal	High	Low-Normal	Low-Normal	Low	Normal	Very Low
Abrupt fever and chill	Low	High	Low	High	High	Very low	Zero	Zero	Zero	Zero
Urine pus	Normal	Low-normal	High	Normal	High	Low	Normal-high	Normal-high	Low-normal	Zero
Proteinuria (mg)	658	740	560	140	1010	95	459	1700	160	132
Hypertension (mmHg)	141/92	135/100	180/113	125/89	165/102	122/85	130/87	158/99	176/105	121/83
Fasting blood sugar	102	94	72	81	164	88	134	119	108	71
Risk Level Kidney Stone	High	Low	Low	No	High	No	Medium	Medium	No	No
Kidney Infection	Low	Low	High	Low	High	No	Low	Low	No	No

Where the conditions are: Z: Zero, VL: Very Low, L: Low, M: Moderate, H: High, VH: Very High and the criteria are No Risk, Low Risk, Medium Risk, High Risk and Extremely High Risk.

Table 17
Physicians' comments on each symptom of the selected real patients.

Symptom		Patient									
		11	12	13	14	15	16	17	18	19	20
Sex		Female	Female	Male	Female	Male	Male	Male	Female	Male	Female
Age		29	56	61	20	46	24	19	83	71	43
Flank pain bilateral		Very low	Very low	High	Low	Low-normal	Zero	Low	High	Low	High
Flank pain unilateral		Low-normal	Zero	Very high	High	Normal	Very low	High	Very high	High	High
Hematuria		Low	Zero	High	Normal-high	Low-normal	Normal-high	Very high	Normal	Normal	Low-normal
Chill and fever		Normal-high	Low-normal	Low-normal	Very high	Normal-high	Low-normal	Zero	Normal-high	High	Zero
Nausea and vomiting		Very low	Very low	High	Low	Normal-high	Low	High	High	Low-normal	Normal-high
Bad smell urine		Normal	Low-normal	Low-normal	High	Low-normal	Normal	Low-normal	Normal	Low	Normal-high
Frequency and urgency		Low	Normal	High	High	Normal	Low-normal	High	High	Normal-high	High
Dysuria		Very high	Low-normal	High	High	Normal-high	Very low	Zero	Normal-high	High	Low-normal
Urinary frequency		Normal	Very low	Very high	Normal-high	Low	Zero	Low	High	High	Low
Cloudy urine		Very low	Low-normal	Normal-high	Low-normal	Low-normal	Low-normal	Normal-high	Low-normal	Low-normal	Low
Purulent urine		Normal-high	Low	High	Normal-high	Low-normal	Low-normal	Zero	Normal	High	Normal-high
Leukocyturia (WBC)		6200	9600	6100	7200	18,100	5300	2800	10,800	8200	6700
Nocturia		Low	Low-Normal	Very high	Low-Normal	Normal-High	Zero	Low-Normal	Low-Normal	High	Normal-High
Hesitancy		Normal	Low	High	Normal	Zero	Low-Normal	Low-Normal	Normal	Normal-High	Low-Normal
Suprapubic pain		Very high	Zero	Normal	High	Low	Zero	Normal	Low-Normal	Normal	Very Low
Abrupt fever and chill		Normal-High	Very Low	Low-Normal	Very high	Low-Normal	Low	Zero	Normal	Normal-High	Zero
Urine pus		Zero	Low-Normal	High	Normal	Low-Normal	Zero	Normal-High	Normal-High	Low-Normal	Normal
Proteinuria (mg)		280	81	1500	943	800	110	138	699	358	574
Hypertension (mmHg)		138/90	152/116	156/94	180/110	159/98	133/88	120/90	141/101	165/118	127/85
Fasting blood sugar		101	84	312	107	63	91	95	150	116	140
Risk level	Kidney Stone	No	No	High	Low	Low	No	Medium	Medium	Low	Low
	Kidney Infection	Low	No	High	High	No	No	Low	Medium	Medium	Low

Table 18
Physicians' comments on each symptom of the selected real patients.

Symptom	Patient									
	21	22	23	24	25	26	27	28	29	30
Sex	Female	Male	Male	Female	Female	Female	Female	Female	Male	Male
Age	72	33	29	79	25	20	37	47	42	41
Flank pain bilateral	70	0	**60**–70	60	40	50	**10**–30	20	30–50	40
Flank pain unilateral	40	30	60–**70**	60–**80**	60	70	40–60	70	50	10
Hematuria	30–50	**20**–40	60	50	**50**–70	80	30	30–**50**	40–60	30
Chill and fever	40	0	30	40–60–70	70–80–90	40–70	50–70	60	50–70	0
Nausea and vomiting	**70**–80	10	60–**70**	70	**40**–50	60	20	30–**50**	50–70	20
Bad smell urine	60	30	50	50	70	**30**–50	50	40–60	30–50–60	30–50
Frequency and urgency	**40**–60	40–50–60	30	60–70–80	60	50	40	**50**–60	50	50
Dysuria	70–**90**	30	60	**50**–70	70	40–70	80	60	50–70	10
Urinary frequency	80	**20**–40	60	70	40–60	70	50	40–60	30	30–50
Cloudy urine	60	40	70	30–50	30–40–50	70	20	30–**50**	**30**–50	40–60
Purulent urine	70	30–50	30–50	**50**–60	50–70	40	50–70	**40**–60	30–50	70
Leukocyturia (WBC)	6400	5800	16,000	10,800	7200	6900	6200	5200	18,100	8020
Nocturia	40–50–70	0	50–70	40–60	30–40–50	40	30	40	50–70	30–50
Hesitancy	70–**80**	20–30–40	60	50	50	50	40–50–60	20	0	30–50
Suprapubic pain	70	20	40–50	20–50	60	30–50	80	60	30	**50**–60
Abrupt fever and chill	50–**60**	0	30	50	70–**90**	0	40–60	60–70–80	30–50	0
Urine pus	70	0	40–**50**	50–60–70	**50**–60	50–70	0	30–50	30–50	30–50
Proteinuria (mg)	1010	132	658	699	943	459	280	740	800	160
Hypertension (mmHg)	165/102	121/83	141/92	141/101	180/110	130/87	138/90	135/100	159/98	176/105
Fasting blood sugar	164	71	102	150	107	134	101	94	63	108
RiskHigh	No	High	Medium	Low	Medium	No	Low	Low	No	No
leveHigh	No	Low	Medium	High	Low	Low	Low	No	No	No

Table 19
Physicians' comments on each symptom of the selected real patients.

Symptom		Patient									
		31	32	33	34	35	36	37	38	39	40
Sex		Male	Male	Male	Male	Female	Female	Female	Female	Male	Male
Age		22	60	55	66	17	49	36	55	63	27
Flank pain bilateral		**30**–50	50	20–50	30–40–50	10	20	**70**–90	30	60	0
Flank pain unilateral		60	70	40–60	70	40	0	60	70	80	20
Hematuria		70–**90**	20	0	30–**50**	70	0	20–50	70	60	30–60
Chill and fever		0	30–50	30–40–50	70	0	40–60	0	60	30–50	40–70
Nausea and vomiting		60–70–80	10	70–80–90	40–50	0	**10**–30	50–80	70–80–90	70	40
Bad smell urine		40–70	30–60	60	40	50	40–60	50–70	60	30–50	50
Frequency and urgency		60	**50**–70	50	50–70	50	50	60	70	60	40–60
Dysuria		0	60	50–70	40–**60**	0	40–60–70	30–50	30–50	70	10
Urinary frequency		**30**–50	80	60–70–80	60	10–20–30	**10**–30	**40**–60	30–50	70–**90**	0
Cloudy urine		50–70	30–60	70	30–50	**40**–70	30–50	40	30–50	40–70	20–40
Purulent urine		0	60	50	**60**–80	30–50	40	50–70	60	70	30–50
Leukocyturia (WBC)		2800	7400	6300	8200	8400	9600	6700	4450	6100	5300
Nocturia		40–60	0	0	60–70–80	**40**–70	30–70	40–60	40–60	90	0
Hesitancy		30–60	50–70	50	40–60	0	20–30–40	40–60	50–**70**	30–50–60	30–50
Suprapubic pain		50	70	20–**40**	50	30–50	0	10–20–30	40–70	50	0
Abrupt fever and chill		0	30	0	40–60	10–20–30	20	0	**60**–80	30–50	40
Urine pus		40–60	70	30–60	40–70	40	30–50	50	50	70	0
Proteinuria(mg)		138	560	1700	358	95	81	574	140	1500	110
Hypertension (mmHg)		120/90	180/113	158/99	165/118	122/85	152/116	127/85	125/89	156/94	133/88
Fasting blood sugar		95	72	119	116	88	84	140	81	312	91
Risk level	Medium	Low	Medium	Low	No	No	Low	No	High	No	No
	Low	High	Low	Medium	No	No	Low	Low	High	No	No

Supplementary materials

Supplementary material associated with this article can be found, in the online version, at doi:10.1016/j.eswa.2017.06.031.

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