



A computer-aided diagnostic system for kidney disease

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Background: Disease diagnosis is complicated since patients may demonstrate similar symptoms but physician may diagnose different diseases. There are a few number of investigations aimed to create a fuzzy expert system, as a computer aided system for disease diagnosis.

Methods: In this research, a cross-sectional descriptive study conducted in a kidney clinic in Tehran, Iran in 2012. Medical diagnosis fuzzy rules applied, and a set of symptoms related to the set of considered diseases defined. The input case to be diagnosed defined by assigning a fuzzy value to each symptom and then three physicians asked about each suspected diseases. Then comments of those three physicians summarized for each disease. The fuzzy inference applied to obtain a decision fuzzy set for each disease, and crisp decision values attained to determine the certainty of existence for each disease.

Results: Results indicated that, in the diagnosis of seven cases of kidney disease by examining 21 indicators using fuzzy expert system, kidney stone disease with 63% certainty was the most probable, renal tubular was at the lowest level with 15%, and other kidney diseases were at the other levels. The most remarkable finding of this study was that results of kidney disease diagnosis (e.g., kidney stone) via fuzzy expert system were fully compatible with those of kidney physicians.

Conclusion: The proposed fuzzy expert system is a valid, reliable, and flexible instrument to diagnose several typical input cases. The developed system decreases the effort of initial physical checking and manual feeding of input symptoms.

Keywords: Computer-aided diagnosis, Diagnosis, Expert systems, Fuzzy logic, Kidney diseases

Introduction

According to global research by the year 2011, chronic kidney disease will affect more than 36 million people around the world with a serious risk. Among nine seemingly healthy people, the research shown that one person has some symptoms of chronic kidney diseases [1].

Chronic renal failure is a severe and irreversible disorder of kidney function that prevents body from balancing fluids, electrolytes, and metabolism [2]. The five important causes of increased global attention to chronic kidney disease include growing prevalence of the disease, the hidden actual outbreak, high cost, subsequent increase of cardiovascular diseases, and increased efforts to find effective solutions to prevent disease progression [3]. Unfortunately, chronic renal failure is usually asymptomatic, and the exact number of patients is unclear. Currently, 1.5 million people around the world are under hemodialysis or kidney transplantation. If governments and people disregard it, this statistic may be doubled within the next few years. Iran has the highest international statistics for the prevalence of kidney diseases, since kidney diseases

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indicate 15% to 20% growth in Iran. Data shows that Iran has more than 7 million renal failure patients, and other people are not aware of this possible disease. In 2005, 22,376 patients in Iran with advanced renal failure were treated with end-stage renal disease (ESRD) methods (2% peritoneal dialysis, 50% hemodialysis, and 48% kidney transplantation). This number is expected to raise to more than 40,000 people, over the next five years [4].

The natural development of various diseases, the unclear nature of medical data, and the intrinsic vagueness of medical problems require a reliable framework that can deal with the ambiguity by permitting variable and multiple class memberships and facilitating approximate reasoning. Therefore, the fuzzy logic is a valuable tool for describing medical concepts by dealing with them as fuzzy sets [5,6]. Fuzzy logic applied in medical systems [7] almost 20 years after its introduction by Zadeh [8]. Moreover, it has recently prompted interesting implementations [9,10]. Medical diagnosis and prognosis problems are the prime examples of decision making in the face of uncertainty. Dealing with uncertainties is a common problem in pattern recognition, and use of the fuzzy set theory has given rise to many new methods of pattern recognition for medical diagnosis [11]. Disease diagnosis is complicated since patients may demonstrate similar symptoms, but the expert physician may diagnose different diseases. Therefore, this study will assist expert physicians when they have fuzziness in that thinking process [12,13]. The current study introduces a simple and efficient method to create fuzzy expert systems for medical diagnosis. The methodology is general and can be used to diagnose a wide range of diseases. In order to demonstrate the concept of this article, first we study kidney are going to propose our general method which can be used for diagnosis of different diseases. Then, we will apply the proposed method to the collected data in order to create a prototype computer program that can infer accurate diagnosis decisions based on patient data.

Methods

Medical diagnosis problems

Diagnosis and prognosis are the tasks of medical science. The most important problems in medical diagnosis and prognosis are [14]:

- i) Limited observation and subjectivity of the specialist,
- ii) uncertainties and incompleteness in medical knowledge, and
- iii) short time influence on diagnosis.

These difficulties must be recognized during a medical decision. A patient may demonstrate a set of symptoms that can be attributed to several diseases, but these symptoms may not be strictly numerical. In observing these symptoms, physicians with different professional levels and clinical experience may differ in their diagnoses, resulting in misdiagnosis. In addition, due to unknown noise in the acquisition process, the use of computers in medical diagnosis and prognosis has become necessary, especially due to the increasing size and number of medical data.

Fuzzy expert system for medical diagnosis

Through this study, a fuzzy expert system developed that employed a set of fuzzy membership functions and rules instead of applying Boolean logic for reasoning about data. Leung et al [15] defined a general structure of the fuzzy system as the main part of a fuzzy use. The following four stages, carried out in order, describe the structure:

- 1) Fuzzy functions: Membership functions defined on the input variables are applied to their actual values to determine the degree of truth for each rule premise.
- 2) Deduction: The truth value for the premise of each rule is computed and applied to the conclusion part of each rule, resulting in one fuzzy subset to be assigned to each output variable for each rule.
- 3) Combination: All fuzzy subsets assigned to each output variable are combined to form a single fuzzy subset for each output variable.
- 4) Defuzzification: This is an optional step that is used when the fuzzy output set needs to be converted to a crisp number.

Medical diagnosis often entails careful examination of a patient to test the existence and strength of symptoms related to a suspected illness in order to decide whether or not the patient suffers from that illness [11]. Because, for example, a symptom such as hematuria may be very strong for one patient but moderate or very weak for another patient. The method of combining a set of symptoms (features and their strengths) to accurately obtain a

diagnosis is determined by the physicians' experience. In the current study, we utilized the physicians' experience and saved them in sets of fuzzy tables. Three physicians were asked about the possibility of a disease according to patients' symptoms. For increasing accuracy and in order to achieve better result, comments from a greater number of physicians could be investigated. However, findings of this study revealed that the comments of three physicians are enough. Through this study, the general model is developed for n physicians and was examined and resolved for three physicians.

Fuzzy deduction applied to create a computer program that can automatically realize the certainty whether a patient with identified symptoms suffers from any one of a set of suspected illnesses. This certainty for every suspected disease specified by a crisp percentage value. We assumed a set of m diseases S and defined a collective set of n features I relevant to these diseases. Let

$$S = \{s_1, s_2, s_3, \dots, s_m\}$$

$$I = \{i_1, i_2, i_3, \dots, i_n\}$$

In order to identify patients' symptoms, they tested against all symptoms in set I and a fuzzy value allocated to each symptom. Fuzzy values chosen from the following set:

{Very Low, Low, Moderate, High, Very High}

For example, one feature can be determined as < Hematuria, Moderate >. By checking the ill person for all n features of set I and ascribing a suitable fuzzy value for each feature, the set of patient's symptoms S would be obtained as follows:

$$U_n = \{<i_1, v_1>, <i_2, v_2>, <i_3, v_3>, \dots, <i_n, v_n>\}$$

Where v_i is the fuzzy value allocated to the feature i_i when testing the patient, $i = 1, \dots, n$.

Adaptation of fuzzy model

Any given disease has a set R of $k \leq n$ related features, which is a subset of collective features set I . Table 1 indicates an empty fuzzy table for the disease profile, and it illustrates five fuzzy values for each related feature $r_i, i = 1, \dots, k$.

Expert physicians must offer suitable values for every entry in the disease profile table based on their experiences. This should be carried out for every disease in the set of considered diseases S . To demonstrate how should tables be filled, Tables 2 and 3 are two typical example profile tables for two diseases according to an expert physician. Similar profile tables also obtained for the rest of the considered diseases in the set S .

In order to diagnose various diseases, some linguistic variables can be assigned including *Yes*, *Maybe*, and *No* as triangular or trapezoidal fuzzy sets. In this study, trapezoidal fuzzy sets considered, as demonstrated in Fig. 1.

$$\mu_{No}(x) = \begin{cases} f_1(x) = 1 & x < a \\ f_2(x) = \frac{b-x}{b-a} & a \leq x < b \end{cases} \quad (1)$$

Table 1. Fuzzy value table for the disease profile

Relevant feature	Fuzzy value of the symptom				
	Very Low	Low	Moderate	High	Very High
r_1					
r_2					
...					
r_k					

Table 2. Profile for kidney stone based on a physician's experience

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

Table 3. Profile for kidney infection according to physician experience

Properties feature	Very Low	Low	Moderate	High	Very High
Dysuria	Maybe	Maybe	Yes	Yes	Yes
Urinary frequency	Maybe	Yes	Yes	Yes	Yes
Cloudy urine	Maybe	Yes	Yes	Yes	Yes
Purulent urine	Maybe	Maybe	Yes	Yes	Yes
Hematuria or leukocyturia	No	Maybe	Yes	Yes	Yes
Nucturia	Maybe	Maybe	Maybe	Yes	Yes
Hesitency	Yes	Yes	Yes	Yes	Yes
Suprapubic	Yes	Yes	Yes	Maybe	Maybe
Abrupt fever and chill	No	Maybe	Yes	Yes	Maybe
Unilateral or bilateral flank pain	No	Maybe	Maybe	Yes	Yes
Nausea and vomiting	Yes	Yes	Maybe	No	No
Spumy urine	Yes	Yes	Maybe	Yes	Maybe

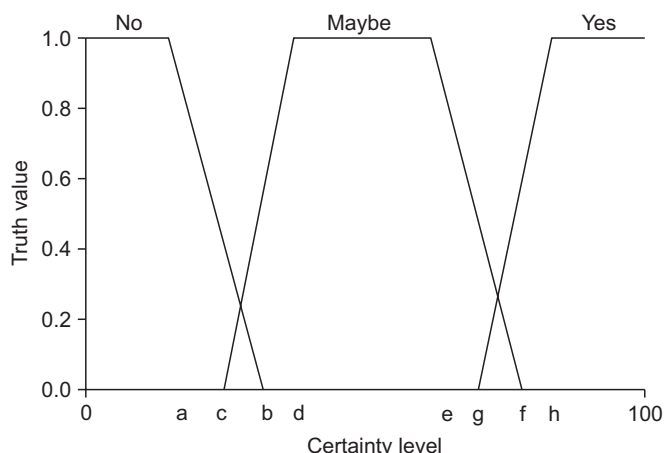


Figure 1. The fuzzy sets for the certainty of disease presence. No: (0, 0, a, b), Maybe: (c, d, e, f), Yes: (g, h, 100, 100).

$$\mu_{Maybe}(x) = \begin{cases} g_1(x) = \frac{x-c}{d-c} & c \leq x < d \\ g_2(x) = 1 & d \leq x < e \\ g_3(x) = \frac{f-x}{f-e} & e \leq x < f \end{cases} \quad (2)$$

$$\mu_{Yes}(x) = \begin{cases} h_1(x) = \frac{x-g}{h-g} & g \leq x < h \\ h_2(x) = 1 & h \leq x \end{cases} \quad (3)$$

In this study, each physician also asked to weight certain symptoms for a given disease S_j . For instance, a physician asked to identify the importance of dysuria symptom in diagnosis of kidney stone disease. The weightings that each physician assigned to certain symptoms were linguistic variables and selected from the following set:

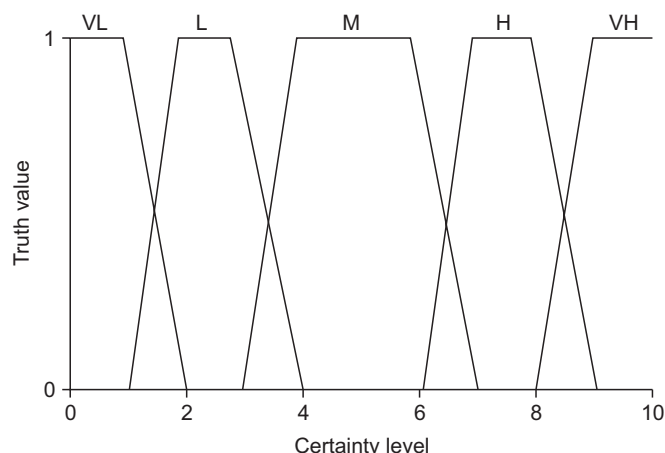


Figure 2. The fuzzy sets for the weight of the symptoms in a suspected disease diagnosis. H, High (6, 7, 8, 9); L, Low (1, 2, 3, 4); M, Moderate (3, 4, 6, 7); VH, Very High (8, 9, 10, 10); VL, Very Low (0, 0, 1, 2).

{Very Low, Low, Medium, High, Very High}

Similarly, the following trapezoidal fuzzy sets defined for the linguistic variables, as demonstrated in Fig. 2.

Weights and ratings given by a physician for the symptoms of kidney stones and kidney infections were in Tables 4 and 5.

Fuzzy pattern recognition for medical diagnosis

Disease symptoms set M are obtained when a patient is examined for diagnosis. A typical example for a set of symptoms is given in Tables 6 and 7 for two different diseases, which shows fuzzy values for all features in the collective set I . These profile tables are considered for

Table 4. Fuzzy weight profile for kidney stone according to a physician's experience

Properties feature	Very Low	Low	Medium	High	Very High
Flank pain bilateral			•		
Flank pain unilateral				•	
Hematuria			•		
Chill and fever			•		
Nausea and vomiting				•	
Bad smell urine			•		
Frequency and urgency					•
Urine pus			•		
Dysuria		•			

Table 5. Fuzzy weight profile for kidney infection according to a physician's experience

Properties feature	Very Low	Low	Medium	High	Very High
Dysuria				•	
Urinary frequency			•		
Cloudy urine				•	
Purulent urine				•	
Hematuria or leukocyturia					•
Nucturia			•		
Hesitency		•			
Suprapubic			•		
Abrupt fever and chill				•	
Unilateral or bilateral flank pain			•		
Nausea and vomiting			•		
Spumy urine			•		

Table 6. Typical symptoms for a given input case

Feature	Fuzzy value
Flank pain bilateral	Moderate
Flank pain unilateral	Moderate
Hematuria	High
Chill and fever	Low
Nausea and vomiting	Moderate
Bad smell urine	Moderate
Frequency and urgency	High
Urine pus	Very Low
Dysuria	Very High

Table 7. Typical symptoms for a given input case

Feature	Fuzzy value
Dysuria	Very High
Urinary frequency	Very High
Cloudy urine	High
Purulent urine	Low
Hematuria or leukocyturia	High
Nucturia	Moderatet
Hesitency	High
Suprapubic	High
Abrupt fever and chill	High
Unilateral or bilateral flank pain	Low
Nausea and vomiting	Very Low
Spumy urine	Low

all diseases, but here there are tables for two diseases in order to demonstrate how they should be filled out. The strength of a non-measurable feature can logically be determined by a fuzzy value; however, other measurable features, such as proteinuria, hypertension, and blood sugar, can be identified by real values in different scales. The subsection number 2.7 presents those fuzzy features.

Considering q number of physicians observing the

disease S_j , the comment of each physician regarding the symptom r_i about the possibility of disease S_j calculated as

$$x_{ijp} \in \{No, Maybe, Yes\} \tag{4}$$

where $i \in \{1, 2, \dots, n\}$, $j \in \{1, 2, \dots, m\}$, $p \in \{1, 2, \dots, q\}$.

Since each {Yes, Maybe, and No} fuzzy set is defined as fuzzy numbers, x_{ijp} is equal to one of the defined fuzzy numbers.

$$x_{ijp} = (a_{ijp}, b_{ijp}, c_{ijp}, d_{ijp}) \tag{5}$$

Comments incorporated using the method by Tsaur et al [16], which combines comments of some experts in order to judge an alternative and makes an overall valuation of the fuzzy judgment. Hybrid fuzzy diagnosis of the possibility of disease S_j with regards to symptoms r_i can be calculated as

$$x_{ij} = (a_{ij}, b_{ij}, c_{ij}, d_{ij}) \tag{6}$$

where $a_{ij} = \frac{1}{q} \sum_{p=1}^{p=q} a_{ijp}$, $b_{ij} = \frac{1}{q} \sum_{p=1}^{p=q} b_{ijp}$, $c_{ij} = \frac{1}{q} \sum_{p=1}^{p=q} c_{ijp}$, $d_{ij} = \frac{1}{q} \sum_{p=1}^{p=q} d_{ijp}$.

Then, the trapezoidal fuzzy number x_{ij} transformed to a crisp number. Assume x_{ij} is the defuzzification of x_{ij} using the center of area method. Thus, the aim is to find a reasonable interval, so that if x_{ij} is classified in that interval, determination of whether it belongs to Yes or Maybe or No linguistic variable could be made. Then, the answer should be considered to Equations 1–3.

$$f_2(x_0) = g_1(x_0) \rightarrow x_0 = \frac{bd - ac}{(b - a) + (d - c)} \tag{7}$$

$$g_3(x_1) = h_1(x_1) \rightarrow x_1 = \frac{eh - fg}{(e - f) + (h - g)} \tag{8}$$

Hence:

- If $x_{ij} \in (0, x_0]$, then the overall fuzzy decision is *No*.
- If $x_{ij} \in (x_0, x_1]$, then the overall fuzzy decision is *Maybe*.
- If $x_{ij} \in (x_1, 100]$, then the overall fuzzy decision is *Yes*.

Then, a hybrid profile table for each kidney disease is made, in order to facilitate the further utilization of these hybrid diagnosis in the next steps.

Similarly, in order to obtain the total weight of each feature in the diagnosis of disease S_j , w_{ijp} can be assumed to be the given weight for r_i symptoms in the diagnosis of disease S_j by physician p . Therefore, w_{ijp} is defined as one of the above-mentioned trapezoidal fuzzy numbers:

$$w_{ijp} \in \{\text{Very Low, Low, Medium, High, Very High}\} \tag{9}$$

where $i \in \{1, 2, \dots, n\}$, $j \in \{1, 2, \dots, m\}$, $p \in \{1, 2, \dots, q\}$.

So, each of the {Very Low, Low, Medium, High, Very

High} fuzzy sets are defined as fuzzy numbers. Thus, w_{ijp} as equation 10, is equal to one of the fuzzy numbers related to {Very Low, Low, Medium, High, Very High}.

$$w_{ijp} = (e_{ijp}, f_{ijp}, g_{ijp}, h_{ijp}) \tag{10}$$

Hybrid fuzzy weight of symptoms r_i in diagnosis of disease S_j is calculated as

$$w_{ij} = (e_{ij}, f_{ij}, g_{ij}, h_{ij}) \tag{11}$$

where $e_{ij} = \frac{1}{q} \sum_{p=1}^{p=q} e_{ijp}$, $f_{ij} = \frac{1}{q} \sum_{p=1}^{p=q} f_{ijp}$, $g_{ij} = \frac{1}{q} \sum_{p=1}^{p=q} g_{ijp}$, $h_{ij} = \frac{1}{q} \sum_{p=1}^{p=q} h_{ijp}$.

The trapezoidal fuzzy number w_{ij} is transformed to a crisp number using the center of area method.

If w_{ij} is the defuzzification of w_{ij} , let:

$s[f]$ = the crisp number obtained for feature f

$r_{ij} = j^{\text{th}}$ relevant feature of the i^{th} disease

$P_{ij} [r_{ij}, v]$ = certainty of the presence of the i^{th} disease when relevant feature r_{ij} has a crisp number x_{ij}

δ_{ij} = diagnosis decision of the i^{th} disease based on relevant feature r_{ij}

k_i = total number of relevant features for the i^{th} disease

w_{ij} = hybrid weight of the r_{ij} feature in diagnosing the i^{th} disease

σ_i = overall diagnosis decision for the i^{th} disease.

The impact of the r_{ij} feature on the diagnosis decision can be directly obtained from the hybrid profile table $P_{ij} [r_{ij}, v]$. According to the hybrid diagnosis of the three physicians, the fuzzy value v is obtained from the patient's symptoms for the feature r_{ij} as $s[r_{ij}]$. The effect δ_{ij} is one of the fuzzy sets Yes, Maybe, and No, denoted as

$$\delta_{ij} = P_{ij} [r_{ij}, s[r_{ij}]] \tag{12}$$

By summarizing the impact of all k_i related features, the overall diagnosis decision for the i^{th} disease would be acquired by

$$\sigma_i = \left(\sum_{j=1}^{j=k_i} w_{ij} \delta_{ij} \right) / \left(\sum_{j=1}^{j=k_i} w_{ij} \right) \tag{13}$$

The weighting factor w_{ij} is introduced to help physicians determine that some features have more or less importance than other features when diagnosing a disease; therefore, appropriate relative values should be set to the

weights. If physicians consider all features with the same importance, the weighting factor is equal for all features. In this case, the weighting step is not necessary and there is no need to fill the weight tables. Then, Equation 13 can be simplified as;

$$\sigma_i = \frac{1}{k_i} \sum_{j=1}^{j=k_i} \delta_j \tag{14}$$

The final step is to acquire crisp values that specify the certainty of existence for every disease in set S.

The model application

Three physicians considered in the model for this case study. Considering the set of diseases S, expert physicians' experiences obtained in a set of fuzzy tables which each set determined the profile for one illness. In order to denote assurance of the illness existence, three trapezoidal fuzzy sets (Yes, Maybe, and No) considered, as are demonstrated in Fig. 3. Entries in the disease profile tables would be chosen from these fuzzy sets.

$$\mu_{No}(x) = \begin{cases} 1 & x < 10 \\ \frac{20-x}{10} & 10 \leq x < 20 \end{cases} \tag{15}$$

$$\mu_{Maybe}(x) = \begin{cases} \frac{x-10}{20-10} & 10 \leq x < 20 \\ 1 & 20 \leq x < 60 \\ \frac{70-x}{70-60} & 60 \leq x < 70 \end{cases} \tag{16}$$

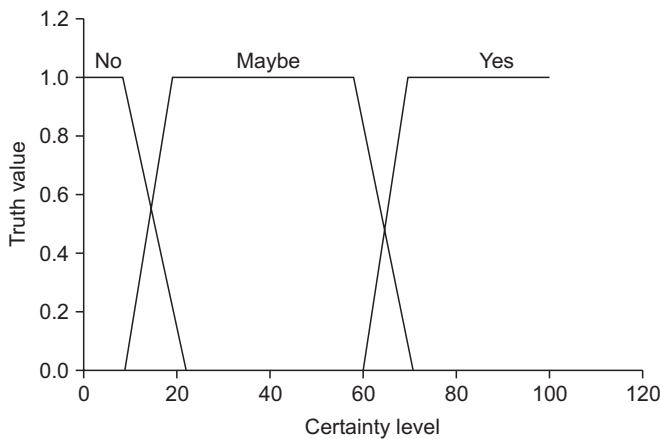


Figure 3. Fuzzy sets for the certainty of the presence of disease.

$$\mu_{Yes}(x) = \begin{cases} \frac{x-60}{70-60} & 60 \leq x < 70 \\ 1 & x \geq 70 \end{cases} \tag{17}$$

Related intervals for No, Maybe, and Yes defined as No = (0, 0, 10, 20), Maybe = (10, 20, 60, 70), Yes = (60, 70, 100, 100); and X₀ = 15, X₁ = 65.

The following example demonstrates how the model works:

- Suppose that a given disease s_i has 10 associated symptoms, all of which have identical weight in the diagnosis. Therefore,

$$k_i = 10$$

$$w_{ij} = 1; \text{ for all, } j = 1, \dots, 10.$$

- Suppose that comments by three physicians are combined using the mentioned method. When applying Equation 14 to realize the diagnostic decisions (δ_{ij}, j = 1, ..., 10), the result is 7 Yes, 2 Maybe, and 1 No.

- The overall diagnostic decision is
- $$\sigma_i = (7 \text{ Yes} + 2 \text{ Maybe} + 1 \text{ No})/10$$

This fuzzy set is illustrated in Fig. 4.

- The center of area method is considered for defuzzification. Let:

- c_i = the centroid of the overall diagnosis decision fuzzy set
- c_y = the centroid for the Yes fuzzy set
- q_i = certainty of the presence of the considered disease s_i in percent

Therefore, the crisp decision value for disease d_i is calculated as shown in Equation 18. If the results are Yes for all related symptoms of d_i, the decision is 100%.

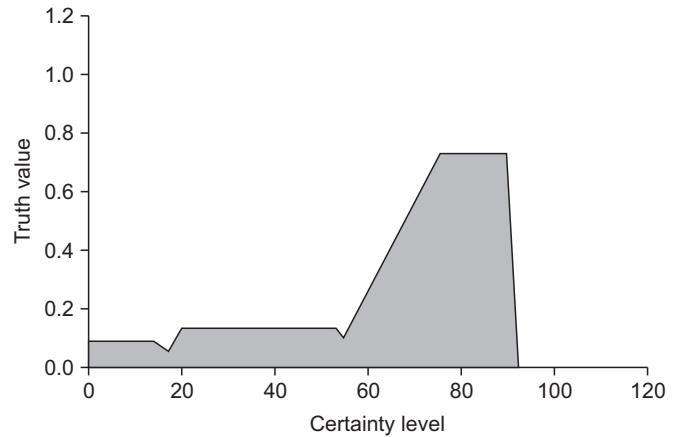


Figure 4. Fuzzy set representing the overall diagnosis decision for the example case. c_i = 0.55, c_y = 0.87, q_i = 90%.

$$q_i = (c_i/c_y) \times 100\% \tag{18}$$

For this example, the values of c_i and c_y are 0.55 and 0.87, respectively, demonstrating that the certainty of the presence of the considered disease is 89%, as shown in Fig. 4.

Features with different type of value

For symptoms that have a different type of value such as type or color, attributes other than severity are important in disease diagnosis. For example, for urinary symptom, the color of a patient’s urine (e.g., yellow, white, or orange) can prompt medical diagnosis of a certain disease. Consequently, a physician diagnoses the disease depending on the patient’s urine color and in accordance with medical experience. For instance, yellow color of urine can lead a physician’s diagnosis to *Maybe* for kidney stone disease.

Displacement of measurement attributes

In this research, the signs for quantifiable features such as hypertension and edema are determined as a numeric value. For the sake of simplicity, fixed tables arranged by the physician may be employed to map these numeric values into fuzzy values from the set {Very Low, Low, Moderate, High, Very High}. This solution may be sufficient in some cases; however, the following describe a solution that is more precise and avoids unexpected changes. Glomerular filtration rate (GFR), a test used to determine kidney function, is used for illustration of the point. GFR estimates how much blood passes through

tiny filters, or glomeruli, in the kidneys each minute [17].

Fig. 5 shows five fuzzy sets that map percentage values of GFR. As shown in the figure, GFR levels were very low (0–15), low (15–38), medium (30–60), mild to moderate (60–90), and high (90 and above).

Suppose that the following information is saved in the profile table of disease d_i :

- If the GFR is Medium; certainty of the existence of d_i will be *Maybe*.
- If the GFR is High, certainty of the existence of d_i will be *Yes*.

Therefore, the diagnosis decision δ_{ij} for disease d_i according to the GFR value of 8% is the upper limit of two fuzzy sets: 0.3 *Maybe* and 0.6 *Yes*, as illustrated in Fig. 6. This can be included in Equation 13 to evaluate the overall decision.

The above solution can be generalized to contain features that are identified by two numeric values, such as blood pressure, leading to four possible fuzzy sets. The minimum rule should be employed to combine the pairs of fuzzy sets by the AND operator [11].

Results

In the current study, we presented diagnosis decisions acquired by the developed prototype fuzzy expert system using a typical case study. A cross-sectional descriptive study was conducted in a kidney clinic in Tehran. During the nine-week study, 85 patients randomly considered against the suspected diseases in the clinic. Medical diagnosis fuzzy rules formulated and applied using MAT-LAB

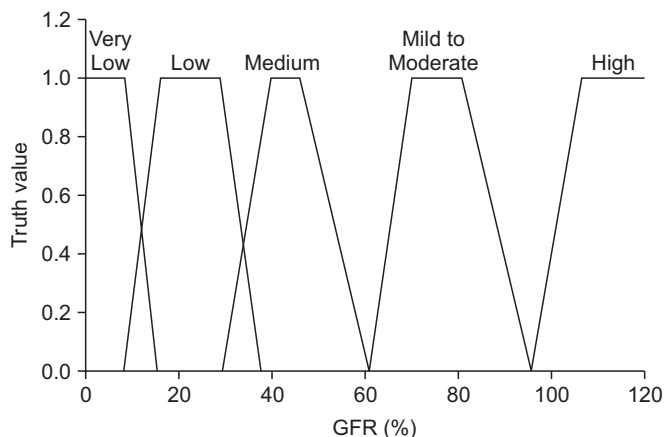


Figure 5. Fuzzy sets for glomerular filtration rate (GFR) values.

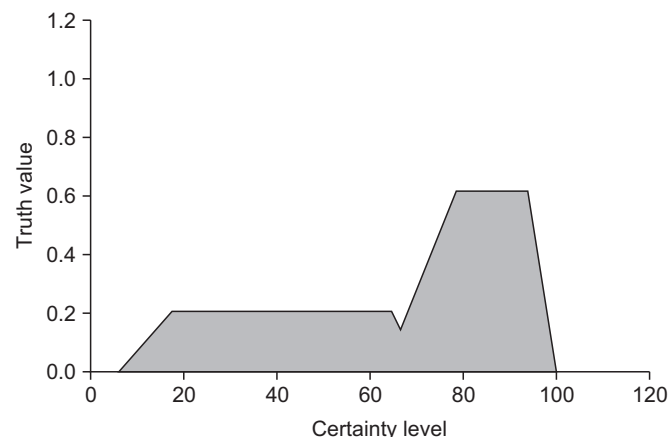


Figure 6. Fuzzy set of the diagnosis decision for a glomerular filtration rate of 8%.

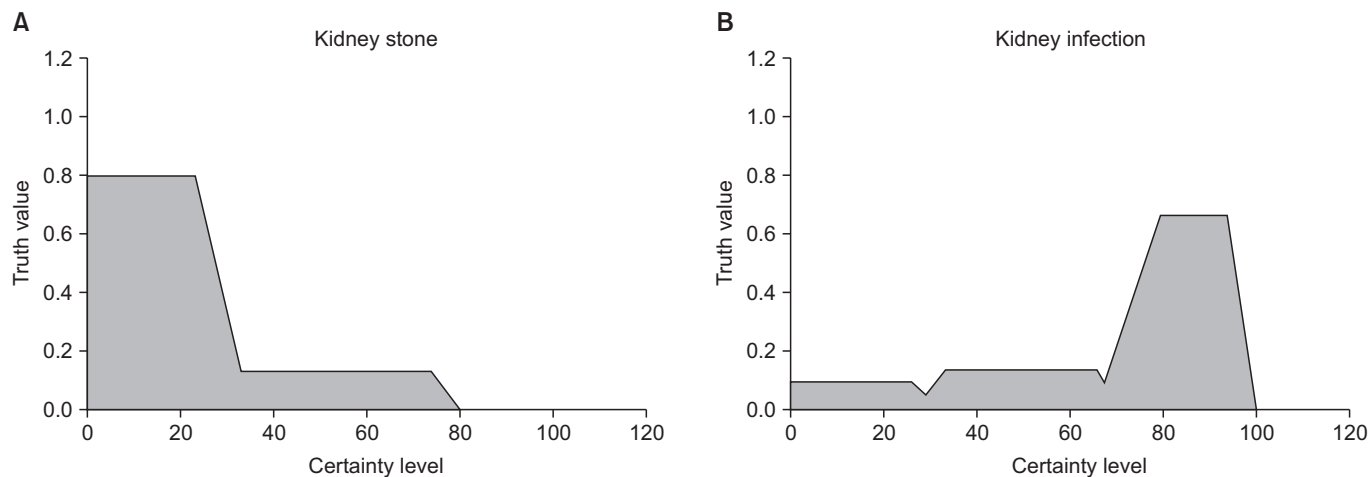


Figure 7. Output fuzzy sets for the diagnosis decision of two infections.

software (Mathworks, Natick, MA, USA). The prototype system checked for seven suspected kidney infections, that were more common in the nation, and considered a total of 21 features. Symptoms identified by physically examining a patient and manually feeding the input into the prototype program. Obtained diagnosis decisions for all suspected diseases are presented in Table 6 and 7, and output fuzzy sets for the overall diagnosis of two diseases with common symptoms are illustrated in Fig. 7 (refer to Tables 2 and 3).

Based on the input symptoms, the prototype expert system gave a high certainty level of 63.3% for kidney stone and lower levels for all other suspected infections (Table 8). In addition, the result agreed completely with the diagnosis of human expert physicians. Appropriate selection of membership functions for the three fuzzy sets as *Yes*, *Maybe*, and *No* also improved the final results. In the present study, we employed the shapes shown in Fig. 3 and tried various parameter values in order to increase the output certainty level of the most possible disease and decrease that of all others.

Discussion

This paper explained how to understand a specific disease process in its early stages using quantitative analysis and qualitative evaluation of the medical data. Applying fuzzy pattern recognition diagnosis methods in medical issues can simply handle the problems already solved using traditional recognition techniques. The present study aimed to develop a new method in fuzzy logic that can

Table 8. Obtained diagnosis decisions for the case study

Disease	Certainty level (%)
Kidney infection	0.451
Polycystic kidney disease	0.399
Nephroangiosclerosis	0.282
Kidney stone	0.633
Chronic renal failure	0.381
Renal tubular acidosis	0.151
IgA nephropathy	0.282

IgA, immunoglobulin A.

be used to diagnose kidney diseases. A methodology presented that utilizes the experience of skilled physicians and saves it in fuzzy tables to indicate disease profiles. The most obvious finding of the study was that results of diagnoses of kidney diseases (e.g., kidney stone) using the proposed fuzzy expert instrument which was fully compatible to those of kidney physicians. Complete agreement with the diagnosis of human expert physicians obtained in many experiments with various input symptoms in each case study. The created system may be augmented to decrease the effort of initial physical examination and manual feeding of input symptoms. Although, empirical findings in this study provide a new understanding of fuzzy medical diagnosis, the study has some limitations. First, the number of patients and controls used in the study was relatively small. Second, the findings were limited by use of a cross-sectional design. Association of these factors should be investigated in future recognition-based technique studies. Another cohort could be considered in order to test the efficiency

of this method. Third, efficiency of existing standard algorithms for analyzing in medical diagnosis can be improved by applying other hybrid soft-computing techniques. Also, the use of fuzzy integrated methods can be more efficient in decision making problems [18]. Further research regarding the role of fuzzy logic would greatly help in solving medical diagnosis problems.

Conflicts of interest

The authors have no conflict of interest to declare.

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