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Fuzzy Logic-Based Comparative Analysis among Urologists towards Urology Disease Diagnosis

Sunil Kumar Singh[1], Dr. Megha Mishra[2], DR Navin Ram Daruka[3],DR Pramod Kumar Rai[4]

[1]Assistant Professor, Department of Computer Science and Engineering, CMR Engineering College Hyderabad, India, Email: sunil.sinme@gmail.com
[2]Associate Professor, Department of Computer Science and Engineering, SSTC, Bhilai CG, India, Email: megha16shukla@gmail.com
[3]DR Navin Ram Daruka, *Urologist, MD Aarogyam Uro- care Hospital, Bhilai Chhattisgarh*
Email id: drnavinurology@gmail.com
[4]DR Pramod Kumar Rai, Senior Urologist Consultant, Jawaharlal Nehru Hospital,Bhilai Steel Plant, *Bhilai Chhattisgarh, Email id:pramodrai@gmail.com*

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Abstract

In the middle of the 1970s, attempts were made to use soft computing approaches to predict uncertainty in the medical profession. A doctor's medical knowledge is based on language terms that are typically inaccurate, hazy, fuzzy, or ambiguous when describing disease entities. Using this information, the doctor evaluates patient data and makes a diagnosis. There are many levels of ambiguity involved in this medical diagnostic process, including details about the patient's symptoms, the relationship between the symptoms and the illness, and the actual diagnosis that has been suggested. Using a case study centred on the first screening of urological disorders, which were determined by a group of urologists, we explored fuzzy operations in medical diagnosis and compared the algorithm's accuracy for 100 diagnostic records. The work underscores the need for further research and shows how useful fuzzy set theory is for first shortlisting urological illnesses.

Keywords: Urological diseases, symptom-disease relation, fuzziness, vagueness, fuzzy set theory, fuzzy occurrence indication/conformability relations

1 Introduction

Global research indicates that by 2025, over 36 million persons would be at significant risk of getting chronic kidney disease[1]. One in ten healthy individuals has a chronic kidney disease. Chronic renal failure occurs when the kidneys experience prolonged injury, impairing the body's ability to regulate fluid, electrolyte, and metabolic balances[2]. Chronic renal failure

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occurs when the kidneys experience prolonged injury, leading to the body's inability to regulate fluid, electrolyte, and metabolic balances[3]. Five reasons have contributed to the global recognition of chronic kidney disease: the rising frequency of the condition, its concealed pandemic status, its significant financial burden, its considerable impact on cardiovascular health, and the need for effective treatments. Unfortunately, chronic renal insufficiency often presents asymptomatically, and the actual prevalence of afflicted individuals remains unclear[4]. Approximately 1.5 million persons worldwide are receiving kidney transplants or haemodialysis. The global prevalence of kidney disease is projected to rise by 15–20%[5]. Many are oblivious to the alarming fact revealing that over 7 million Americans suffer from renal disease. The number of patients with severe renal failure receiving treatment for end-stage renal disease (ESRD) is projected to quadruple to 40,000 during the next five years[6][7]. Of them, 2% will have paclitaxel dialysis, 50% will undergo haemodialysis, and 48% will have kidney transplantation[8][9].

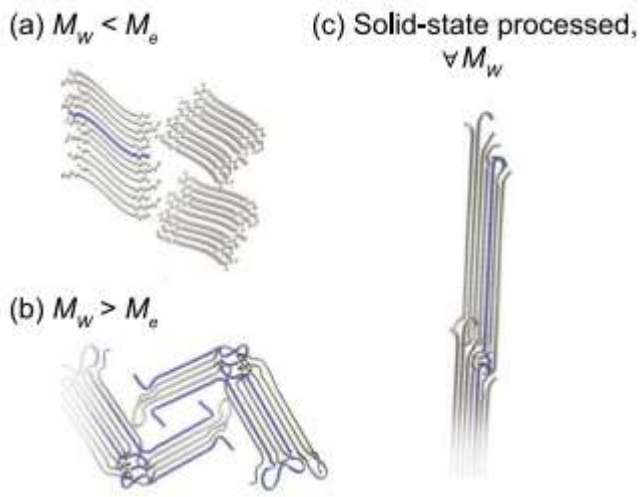

Figure 1Schematic of the different solid-state microstructures produced by the P3HT samples used in this work

Diabetes and hypertension are the principal causes of chronic kidney disease (CKD), however the precise prevalence of other factors, such as urological problems, in adults remains ambiguous[10]. These illnesses may be congenital or acquired. The prevalent conditions include vesicoureteral reflux (VUR), which may result in reflux nephropathy, recurrent urinary tract infections (UTIs) leading to pyelonephritis, and urinary tract obstruction due to

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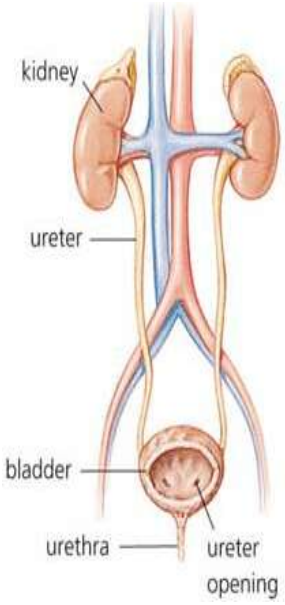
anatomical and functional anomalies such as ureter pelvic junction syndrome, bladder neck stricture, congenital urethral valves, urethral stenosis, nephrolithiasis, malignancies, and benign prostatic hyperplasia (BPH), along with an overactive bladder, especially in adult females[11][12]. These disorders may begin gradually and subtly, making them difficult to identify and delineate from their commonly acknowledged effects. Hypertension, proteinuria, changes in urine concentration, hyperkalaemia, metabolic acidosis, focal and segmental glomerulosclerosis, and chronic kidney disease (CKD) are the primary repercussions that significantly impact long-term renal and cardiovascular outcomes[13][14].

A Word on Urology

The research team started this study with the intention of helping relatively new urologists or general physicians/clinicians make decisions because of the exponential growth of urological diseases worldwide, especially in lower-middle-class populations with particular reference to India. Urology is the study and management of problems of the male reproductive system and urinary tract, including kidney stones, prostate diseases, male infertility, and urinary tract infections (UTIs)[15]. Kidney stones, bladder cancer, prostate disorders, urine incontinence, and other anomalies of the male reproductive system and urinary system are among the ailments included in the material on urological diseases[16]. This work investigates the potential use of fuzzy set theory in medical decision-making due to the inherent ambiguity in urological diagnosis, which manifests as vagueness or fuzziness[17].



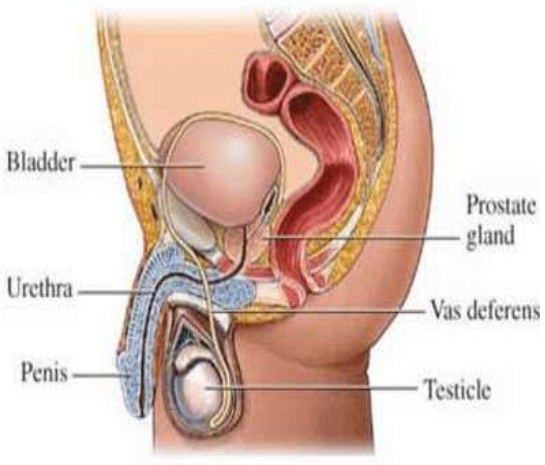


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Figure 2Anatomy in urology: (left) kidney and (right) prostate male anatomical environments

Governments in underdeveloped nations often set up medical camps in cities and villages where citizens may get general health examinations, including urological exams. Software may be used to speed up the diagnostic procedure in these mass diagnosis situations[18]. This program may be a useful teaching tool in medical schools to illustrate the differential diagnosis procedure. Additionally, it might help novice urologists or general practitioners with the diagnosis procedure[19].

Experienced urologists agree that the general method for diagnosing urological diseases may be broken down into three phases. The term "stage 1" describes the first screening procedure that aims to make a single illness diagnosis based only on the subjective data that patients provide the doctor[20]. Using factors including prior medical history, history of UTIs, frequency of urination, nocturia, haematuria, comorbidities, and more, the patient who did not acquire a single diagnostic label in stage 1 is further examined for a conclusive diagnosis in stage 2. Physical exams and diagnostic procedures, such as CT scans, blood tests, or ultrasounds, are performed in stage 3 if stage 2 is unable to provide a single illness diagnosis. The test data are then processed for final analysis[21]. This study looks at the effectiveness of stage 2 investigations using the fuzzy inference system (FIS) and stage 1 investigations using fuzzy computational rule inference[22][23].

The rest of the document is structured as follows: The methods used to accomplish the goal are detailed in Section 2.1. The method for fuzzy relational calculus in urology is shown in Section 2.2. A case study on urological illnesses in India is presented in Section 2.3, and Section 3 discusses the findings and conclusions.

2 Mathematical Preliminaries

Because of the inherent ambiguity and unpredictability at different phases of the diagnosis process, MDSS (Medical Decision Support Systems) in Urology primarily depend on the knowledge and perception of domain experts. We believe that using fuzzy set theory might be

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a useful soft computing strategy to improve urological diagnostics decision-making. We provide a summary of the methods used in this situation in this article.

2.1 Computational Rule of Inference: Max-Min Composition

Definition 1 let R be a fuzzy relation on $X \times Y$ i.e.,$R = \{((x,y), f_r(x,y))|(x,y) \in X \times Y\}$ where theα-cut matrixR_α is denoted by

$$R_\alpha = \{((x,y), f_r(x,y))|f_r(x,y) = 1, if\_f_r(x,y) \geq \alpha; f_r(x,y) < \alpha, (x,y) \in X \times Y, \alpha \in [0,1]\}$$

Definition 2 let $R \subset X \times Y$ and $S \subset Y \times Z$ be fuzzy relations; the max-min composition $R \circ S$ is defined by

$$R \circ S = \{((x,z), max\{min\{f_R(x,y), f_s(y,z)\}\})|x \in X, y \in Y, z \in Z\} \quad (1)$$

Definition 3 A fuzzy relation R on$R \times R$ is called is a fuzzy compatible or tolerance or proximity relation if it satisfies reflexive and symmetric conditions

Definition 4 A fuzzy relation R on $R \times R$ is called a fuzzy equivalence relation if the following three condition hold:

1. R is reflexive, if $f_{R(x,x)} = 1, \forall x, y \in X$
2. R is Symmetric if$f_{R(x,x)} = f_R(y,x), \forall x, y \in X$
3. R is transitive, if $R^2 = R(R \circ R) \subset R$or more explicitly $f_R(x,z) \geq max\{\{min\{f_R(x,y), f_R(y,z)\}\}, \forall x, y, z \in X$

Definition 5 The transitive closure R_T of a fuzzy relation R is defined as the relation that is transitive, contain R, and has the smallest possible membership grades

Theorem 1

Let R be a fuzzy compatibility relation on a finite universal set X with |R|= n,then the max-min transitive closure of R is the relation is defined as the relation$R^{(n-1)}$. According to Theorem 1, we can get the algorithm to find the transitive closure, $R^T = R(n-1)$

Algorithm A. Find the transitive closure R_T of fuzzy compatibility relation

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Step 1: Calculate $R^{(2)}$ if $R^{(2)} \subset R \; or \; R^{(2)} = R$, then transitive closure $R_T = R$ and stop. Otherwise, k=2, go to step 2

Step 2: if$2^k \geq n-1$,then $R_T = R^{(n-1)} and \; stop. Otherwise, calculate R^{(2^k)} = R^{(2^{k-1})} \circ R^{(2^{k-1})}$ if$R^{(2^k)} = R^{(2^{k-1})}$ then k transitive closure $R_T = R^{(2^k)} and \; stop. Otherwise, go \; to \; step \; 3$

Step 3: $\mathrm{k} = \mathrm{k} + 1$ Got to Step-2

Prof. Zadeh proposed the use of linguistic modifiers to enhance the flexibility and expressiveness of fuzzy logic systems. Among these, the linguistic hedge "very" is commonly applied to emphasize the intensity or degree of linguistic terms. For example, it is used to specify terms such as "very often" and "very seldom," refining their interpretive meaning in decision-making or modelling contexts. The concentration operator, which implements the linguistic hedge "very," modifies the membership function of a fuzzy set to increase its specificity. Mathematically, the concentration operator is typically expressed as:

$$A_{very}(x) = A^2(X) \qquad (2)$$

Here, $\mu_A(x)$represents the original membership value of the fuzzy set A, and squaring the membership values sharpens the set by reducing intermediate values while preserving high and low extremes. This adjustment highlights the “very” nature of the linguistic term, effectively modelling intensities such as "very small" or "very large" in a more precise manner.

2.2 Type 1 FIS

The fuzzy inference system, or FIS, uses fuzzy rules to construct a non-linear mapping of the input data vector into a scalar output. This research used a Mamdani-type FIS with defuzzification based on the centre of gravity approach. The standard literature has further information on this strategy

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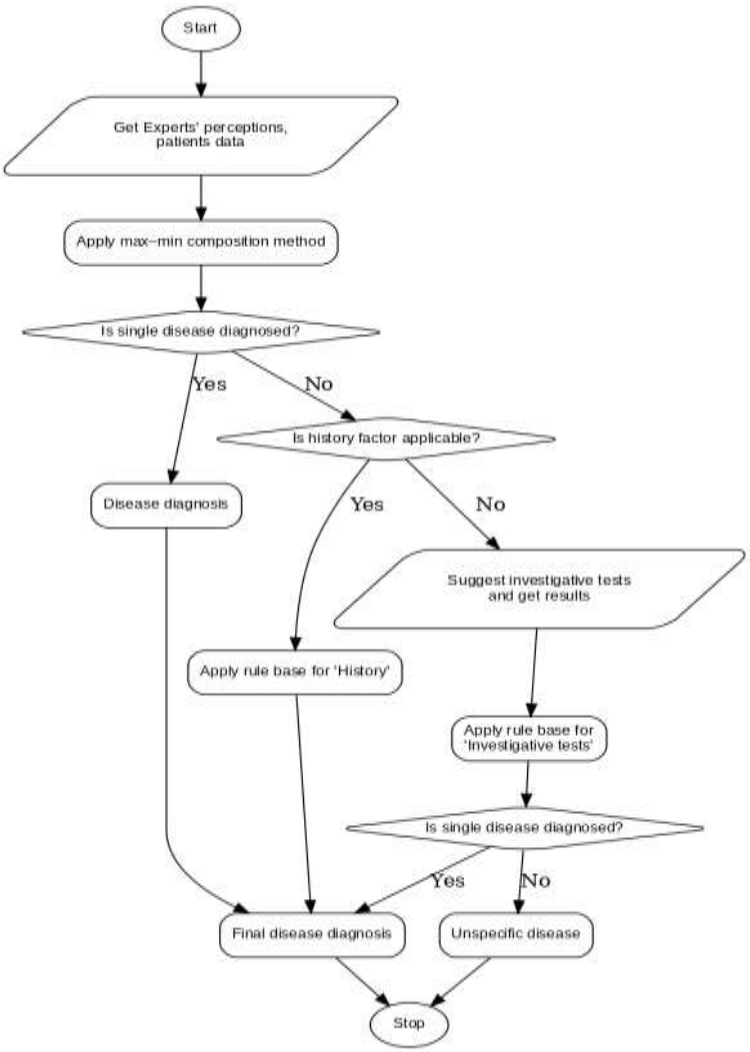

Figure 3 Fuzzy logic-based diagnostic formalism for urological diseases.

The flowchart illustrates the structured fuzzy logic–based diagnostic process for urological diseases. The system begins by collecting experts' perceptions and patient data, followed by the application of the max–min composition method to evaluate initial diagnostic possibilities. If a single disease is identified, a direct diagnosis is made. In cases where ambiguity persists, the model checks the applicability of patient history. When relevant, a history-driven rule base is applied to refine the diagnosis. If history does not provide sufficient evidence, investigative tests are suggested, and their outcomes are processed using the investigative rule base. Depending on the results, the system either reaches a final diagnosis or categorizes the case as an unspecific disease. This fuzzy formalism ensures a flexible and precise approach, accommodating uncertainty, overlapping symptoms, and variability in patient presentations.

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There is a connection between illnessses (d) and symptoms (s). Two fuzzy relations—the fuzzy occurrence relation (Ro) and the fuzzy confirmability relation (Rc)—can be created to describe the descriptive data. The first gives information on how often or frequently a symptom is linked to a certain urological problem. It provides a response to the query, "How frequently does a symptom's' occur concerning a Urological disease d?"

The second relation, which answers the query, "How strongly does the symptom's' confirm the Urological disease 'd'?" encapsulates the discriminating capacity of a symptom in confirming a disease. Because some symptoms may be prevalent in a particular urological condition but also common in a number of others, lowering their diagnostic specificity, the contrast between incidence and confirmability is very helpful. On the other hand, another symptom may be somewhat uncommon, but when it does occur, it is a reliable sign of a certain urological condition.

In the context of urological diagnosis, we then develop a fuzzy relation Rs to characterise the presence, absence, or ambiguous status of a symptom (s) for patients.

2.3 Initial Screening: Stage 1

The following is the formulation of the compositional rule of inference technique used in urological diagnosis:

Assuming: S={s1…,sn}denotes the distinct universal collection of symptoms, D={d1,…,dm}The clear universal set of urological disorders is represented by D={d 1,…,d m },andα={α1,…,αn}

The fuzzy relationship between a patient and S is represented by α={α 1,…,α n, where 0≤αj≤1 0≤α j≤1, j = 1,…,n j=1,…,n. Furthermore, let R represent the fuzzy relation on S×D. As previously mentioned, we may get two relations from R : the fuzzy confirmability relation (Rc) and the fuzzy occurrence relation (Ro).

Examine the clear universal set P of k patients, such that P = {p1,…,pk}. Let the fuzzy relation on S×Pbe represented by Rs

A variety of fuzzy indication relations established on the universal set P×D of patients and illnesses may be calculated using R o, R c, and R s. The compositional rule of inference, also

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known as the fuzzy occurrence indication relation [Eq. (1)], may be used to infer the fuzzy set R , which represents potential urological disorders for a patient:

$$R1 = R_s \circ R_o = (b_1, b_2, \ldots\ldots, b_m)$$

Which is given by

$$R_{ij} = (s_1 \wedge r_{o1j}) \vee (s_2 \wedge r_{o2j}) \vee \ldots\ldots \vee (s_n \wedge r_{onj}). j = 1,2, \ldots\ldots, m \qquad (3)$$

Likewise, the fuzzy set R 2 may be used to compute the fuzzy confirmation indication relation [Eq. (3)]. These indicative relations make it possible to make diagnostic inferences, which in turn establish the connection between a urological illness (d) and a patient (p).

An intersection operation is carried out across R 1 and R 2 in order to calculate the final diagnostic indication, R. We determine that the patient p has the urological illness d if d 1 R 1 and d 2 R 2 both equal 1

2.4 Past History Parameter Screening: Stage 2

The authors' further investigation revealed that urology diagnostic efforts heavily depend on a number of patient characteristics and history, including age, history of kidney stones, nocturia, dysuria, frequency of urination, presence or absence of urinary tract infections (UTIs), and comorbid conditions like diabetes or hypertension. All of these elements work together to affect urological illness diagnosis.

Five fuzzy sets—age, urine frequency, nocturia severity, UTI history, and presence of concomitant conditions—were established in order to handle these variables (Figure 2A–E). A type 1 Fuzzy Inference System (FIS) was used to develop and apply a total of 72 fuzzy rules

3 Case Study

The study pertains to the investigations conducted by a team comprising eight Urologists, a fuzzy logic engineer, and a computer scientist in India, culminating in the development of a patient-disease matrix. The domain experts, based on their extensive clinical experience and knowledge, contributed to the formulation of the fuzzy rules and the design of the system

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In the proposed urology diagnostic model, linguistic symptom frequencies are represented using fuzzy membership functions over the normalized domain $x \in [0,1]$ Triangular and trapezoidal functions are employed.

The general triangular membership function is

$$\mu(x;a,b,c) = \begin{cases} 0, x \le a, \\ \dfrac{x-a}{b-a}, a < x \le b, \\ \dfrac{c-x}{c-b}, b < x < c, \\ 0, x \ge c \end{cases}$$

The trapezoidal membership function is

$$\mu(x;a,b,c,d) = \begin{cases} 0, x \le a, \\ \dfrac{x-a}{b-a}, a < x \le b, \\ 1, b < x \le c, \\ \dfrac{d-x}{d-c}, c < x < d, \\ 0, x \ge d. \end{cases}$$

The linguistic terms used in this study—Never (N), Very-Seldom (VS), Seldom (S), Not-Sure (NS), Often (O), Very-Often (VO), and Always (A)—are modelled by overlapping triangular/trapezoidal functions on [0,1].

To enhance intensities such as *Very Often*, a concentration (hedge) operator is applied:

$$\mu'(x) = \left[\mu(x)\right]^p, p = 1.95.$$

This transformation sharpens intermediate memberships while preserving extremes, improving discrimination between urological symptom–disease relationships.

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3.1 Initial Screening Using Fuzzy Relational Calculus: Stage 1

One of the essential phases in the differential diagnosis procedure that doctors often use is initial screening. Based on the inputs supplied by the patient, the model may be able to identify one or more urological conditions[24]. However, because the symptom-disease association in fuzzy relational calculus depends only on patient-reported perceptions and excludes further diagnostic testing, the potential of differential diagnosis cannot be completely ruled out[25].

In order to assure data quality and prevent chance statistical mistakes, patient interviews were used to gather data for the patient-symptom matrix during the study's first screening phase from three separate hospitals in Chhattisgerh and Jharkhand, India. Patients' symptoms, prior medical history, age, history of urinary tract infections (UTIs), frequency of urination, nocturia, dysuria, haematuria, kidney stones, and concomitant diseases including diabetes and hypertension were all discussed during these private discussions.

Nine individuals were chosen for in-depth study out of the 226 patients in this data set who were first assessed by the experts (Table 2). We used the max-min composition process described in Section 1. Fuzzy confirmability indication relations and fuzzy occurrence indication relations were obtained using the specified max-min resemblance/composition methods [Eqs. (1) and (3)].

3.2 Past History Parameter Screening: Stage 2

A thorough computer software was created to assist with several decision-making phases in the diagnosis of urological diseases. In order to arrive at a single illness as the result, a Mamdani-type Fuzzy Inference System (FIS) was simulated throughout the software development process, using the centre of gravity approach for defuzzification.

Disease List (D1–D15): The urological diseases considered in this study include (D1) Benign Prostatic Hyperplasia (BPH), (D2) Kidney Stone, (D3) Ureteric Stone, (D4) Urinary Tract Infection (UTI), (D5) Urethral Stricture, (D6) Bladder Stone, (D7) Pyelonephritis, (D8) Kidney Cancer, (D9) Pelvic Inflammatory Disease (PID), (D10) Prostate Cancer, (D11) Interstitial Cystitis, (D12) Hydronephrosis, (D13) Renal Tuberculosis, (D14) Neurogenic Bladder, and (D15) Overactive Bladder and basic symptoms has been considered in this study include (S1) Frequent urination (S2) Difficulty urinating (S3) Nocturia (S4) Dysuria (painful urination) (S5) Haematuria (blood in

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urine) (S6) Urinary urgency (S7) Weak urinary stream (S8) Urinary incontinence (S9) Urinary retention (S10) Flank pain (S11) Abdominal pain (S12) Burning sensation (S13) Fever/Chills (S14) Proteinuria (S15) Pelvic pain (S16) Lower back pain (S17) Nausea/Vomiting (S18) Abnormal uroflowmetry (UFM) (S19) History of diabetes (S20) History of hypertension (S21) History of kidney stones (S22) History of UTIs (S23) History of parity/childbirth (S24) Enlarged prostate (S25) Obstructive voiding symptoms (S26) Urgency (S27) Weak Stream (S28) Incontinence (S29) Retention (S30) Flank Pain

Table 1 Typical Fuzzy Occurrence Relation (Rc) for concentration operator 1.95

Disease ↓ / Symptoms →	S1	S2	S3	S4	S5	S6	S7	S8	S9	S10	S11	S12	S13	S14	S15	S16	S17	S18	S19	S20	S21	S22	S23	S24	S25	S26	S27	S28	S29	S30
D1 – BPH	O	O	O	O	S	O	O	NS	O	S	O	O	S	N	O	O	S	O	NS	S	O	O	N	A	O	O	O	S	O	S
D2 – Kidney Stone	S	S	N	O	A	S	N	NS	O	A	S	O	O	S	N	N	O	A	O	N	A	S	N	N	O	S	O	S	A	A
D3 – Ureteric Stone	O	NS	O	O	A	O	NS	NS	O	A	NS	O	O	O	N	N	O	A	O	NS	O	S	N	N	O	O	O	S	S	A
D4 – UTI	O	O	O	O	O	A	O	NS	O	S	O	O	O	O	O	N	O	O	A	S	O	O	N	N	S	O	O	O	S	A
D5 – Urethral Str.	O	O	O	O	S	NS	O	NS	A	S	O	O	O	N	N	O	O	O	S	O	S	N	N	O	S	S	O	N	S	O
D6 – Bladder Stone	O	O	O	O	O	O	O	NS	O	A	O	S	O	N	N	S	O	O	O	O	S	N	O	O	O	S	S	O	S	A
D7 – Pyelonephritis	O	O	O	O	O	O	O	O	O	O	A	A	O	O	O	O	O	O	O	A	O	O	O	O	O	O	O	O	O	A
D8 – Kidney Cancer	O	O	O	O	O	O	O	O	O	A	O	O	O	O	O	S	O	A	O	O	O	O	O	O	O	O	O	S	O	A
D9 – PID	O	O	O	O	O	O	O	O	O	O	O	O	O	O	O	O	O	O	O	O	O	O	O	O	O	O	O	O	O	O
D10 – Prostate CA	O	O	O	O	O	O	O	O	O	S	O	O	O	O	O	O	O	O	O	O	O	O	O	A	A	O	O	O	O	A
D11 – ICystitis	O	O	O	O	O	A	O	O	O	O	O	O	O	O	O	O	O	O	O	O	O	O	O	O	O	O	O	O	O	O
D12 – Hydronephrosis	O	O	O	O	O	O	O	O	O	A	O	O	O	O	O	O	O	O	O	O	O	O	O	O	O	O	O	O	O	O

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D13 – Renal TB	O	O	O	O	O	O	O	O	O	A	O	O	O	O	O	O	VO	O	O	O	O	O	O	O	O	O	O	O	O
D14 – Neurogenic Bl.	O	O	O	O	O	O	O	O	O	O	O	O	O	O	O	O	O	O	O	O	O	O	O	O	O	O	O	O	O
D15 – Overactive Bl.	O	O	O	O	O	A	O	O	O	S	O	O	O	O	O	O	O	O	O	O	O	O	O	O	O	O	O	O	O

Table 1 presents the *typical fuzzy occurrence relation (Rc)* between fifteen urological diseases (D1–D15) and thirty symptoms (S1–S30) using a concentration operator value of 1.95. The fuzzy linguistic notations employed include O (Occasional), S (Sometimes), A (Always), N (Never), NS (Not Sure), and VO (Very Often), which capture the graded relationship between diseases and symptoms. For example, Benign Prostatic Hyperplasia (D1) frequently aligns with occasional and sometimes expressions of symptoms such as weak stream, urgency, and retention, reflecting the gradual and variable presentation of lower urinary tract symptoms. Kidney Stone (D2) and Ureteric Stone (D3) show stronger associations with acute symptoms such as flank pain, urgency, and retention, with frequent values marked as "Always" or "Sometimes," indicating their high diagnostic relevance. Urinary Tract Infection (D4) and Urethral Stricture (D5) predominantly show *occasional to sometimes* associations with burning, haematuria, and frequency-related symptoms. Pyelonephritis (D7), on the other hand, demonstrates consistent associations marked as "Always," underscoring its strong symptomatic presentation with fever, flank pain, and dysuria. Similarly, Kidney Cancer (D8) and Prostate Cancer (D10) reveal more specific associations, particularly with haematuria and systemic signs, marked as "Sometimes" or "Always," while Renal Tuberculosis (D13) presents a unique case with “Very Often” in flank pain and weight loss. Diseases such as Pelvic Inflammatory Disease (D9), Interstitial Cystitis (D11), Hydronephrosis (D12), and Neurogenic Bladder (D14) show broader but less distinct “Occasional” mappings, reflecting their overlap with multiple lower urinary tract symptoms. Overactive Bladder (D15) exhibits frequent associations with urgency and incontinence, often marked as "Always" or "Sometimes." Overall, the table highlights the fuzzy, overlapping nature of symptom–disease relationships in urology, emphasizing the need for computational models to resolve diagnostic uncertainty.

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Table 2 Typical Fuzzy Conformability Relation (Rc) for concentration operator 1.95

Disease ↓ / Symptoms →	S1	S2	S3	S4	S5	S6	S7	S8	S9	S10	S11	S12	S13	S14	S15	S16	S17	S18	S19	S20	S21	S22	S23	S24	S25	S26	S27	S28	S29	S30
D1 – BPH	O	VO	VO	O	S	O	O	NS	O	S	VO	O	S	N	VO	O	VO	O	NS	S	O	O	N	A	O	O	O	S	O	S
D2 – Kidney Stone	S	S	N	O	A	S	N	NS	O	A	S	O	O	S	N	N	O	A	O	N	A	S	N	N	O	S	O	S	A	A
D3 – Ureteric Stone	O	NS	O	O	A	O	NS	NS	O	A	NS	O	O	O	N	N	O	A	O	NS	O	S	N	N	O	O	O	S	S	A
D4 – UTI	O	VO	S	O	O	S	S	NS	O	S	VO	NS	NS	NS	O	NS	S	VO	S	NS	O	S	NS	S	O	S	S	NS	O	O
D5 – Urethral Stricture	O	O	S	O	S	O	S	NS	O	S	O	S	O	O	O	N	O	S	O	O	S	O	S	O	O	O	S	O	O	O
D6 – Bladder Stone	O	O	O	O	O	O	O	NS	O	A	O	S	O	N	N	S	O	O	O	O	S	N	O	O	O	S	S	O	S	A
D7 – Pyelonephritis	O	O	O	O	O	O	O	O	O	O	A	A	O	O	O	O	O	O	O	A	O	O	O	O	O	O	O	O	O	A
D8 – Kidney Cancer	O	O	O	O	O	O	O	O	O	A	O	O	O	O	O	S	O	A	O	O	O	O	O	O	O	O	O	S	O	A
D9 – PID	O	O	O	O	O	O	O	O	O	O	O	O	O	O	O	O	O	O	O	O	O	O	O	O	O	O	O	O	O	O
D10 – Prostate Cancer	O	O	O	O	O	O	O	O	O	S	O	O	O	O	O	O	O	O	O	O	O	O	O	A	A	O	O	O	O	A
D11 – Interstitial Cystitis	O	O	O	O	O	A	O	O	O	O	O	O	O	O	O	O	O	O	O	O	O	O	O	O	O	O	O	O	O	O
D12 – Hydronephrosis	O	O	S	O	O	S	S	O	O	O	O	O	S	O	O	O	VO	O	S	O	O	S	O	O	S	O	S	O	O	S
D13 – Renal Tuberculosis	O	VO	NS	NS	O	O	O	O	N	VO	VO	S	S	S	O	O	O	O	N	S	S	N	S	O	S	O	VO	O	N	S
D14 – Neurogenic Bladder	S	S	V	S	S	N	VO	S	N	NS	VO	S	S	S	NS	N	S	S	O	O	VO	VO	S	VO	O	N	S	O	O	O
D15 – Overactive Bladder	O	N	V	O	S	S	O	VO	O	O	N	S	VO	O	O	S	S	VO	O	O	VO	NS	NS	N	VO	S	VO	O	S	S

Table 2 illustrates the *typical fuzzy conformability relation (Rc)* between fifteen urological diseases (D1–D15) and thirty symptoms (S1–S30), evaluated under a concentration operator of 1.95. Compared with the fuzzy occurrence matrix, this table emphasizes how strongly individual symptoms conform to particular disease diagnoses, using fuzzy linguistic notations such as **VO (Very Often)**, **S (Sometimes)**, **O (Occasional)**, **N (Never)**, and **NS (Not Sure)**.

For **Benign Prostatic Hyperplasia (D1)**, stronger symptom–disease alignment is observed with "Very Often" ratings for key indicators such as weak urinary stream, urgency, and incomplete voiding, consistent with lower urinary tract obstruction. **Kidney Stone (D2)** and **Ureteric Stone (D3)** show higher conformability with flank pain, urgency, and retention, with several "Always" or "Sometimes" markers, validating their acute presentation. **Urinary Tract Infection (D4)** demonstrates higher fuzzy strength in common indicators like burning sensation, fever, and haematuria, with multiple "Very Often" relations. **Urethral Stricture (D5)** and **Bladder Stone (D6)** show *moderate conformability* (mostly "Occasional" and "Sometimes"), reflecting variability in symptom onset and progression.

For systemic or chronic conditions, **Pyelonephritis (D7)** and **Kidney Cancer (D8)** show selective but stronger alignment, particularly with fever, haematuria, and flank pain. **Prostate Cancer (D10)** demonstrates more targeted "Always" conformability with haematuria and systemic changes, while **Interstitial Cystitis (D11)** presents broader but low-intensity conformability

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("Occasional" across most symptoms). Notably, **Renal Tuberculosis (D13)** and **Neurogenic Bladder (D14)** exhibit distinct conformability, with renal TB linked to systemic signs such as flank pain and weight loss ("Very Often"), and neurogenic bladder marked by "Very Often" associations with retention and incontinence. Finally, **Overactive Bladder (D15)** strongly conforms to urgency and incontinence, where values are marked "Very Often" and "Sometimes," underscoring its unique symptomatic cluster.

Overall, Table 2 demonstrates how fuzzy conformability relations refine disease–symptom mapping by strengthening the diagnostic association of specific symptoms with their respective diseases. This progression from "occasional" occurrence in Table 1 to more decisive "very often" or "sometimes" patterns in Table 2 highlights the utility of fuzzy logic in reducing diagnostic uncertainty in urology.

Table 3 Typical Patient and Symptom (P-S) Relation(Rs)

Patient ↓ / Symptoms →	S1	S2	S3	S4	S5	S6	S7	S8	S9	S10	S11	S12	S13	S14	S15	S16	S17	S18	S19	S20	S21	S22	S23	S24	S25	S26	S27	S28	S29	S30
P1	0.5	1	0.5	1	0	0	0.5	0	1	1	0	0	0.5	1	0	1	0	1	1	0	1	0	0	1	0.5	0	0	0	0.5	0
P2	0.5	0.5	0	0.5	0.5	0.5	0.5	1	0.5	0.5	1	1	0.5	0.5	0	0	1	0.5	0.5	1	0.5	1	0.5	0.5	0	0	1	1	0	1
P3	1	1	0.5	0.5	0.5	0	1	0	0	0.5	0.5	0	0.5	1	0.5	0.5	0.5	1	0	1	0	0.5	1	0.5	0	0	0.5	0	1	1
P4	0.5	0.5	0	0	0	1	1	0.5	0	0	0	0	0.5	0	0.5	0.5	0.5	0	1	1	0	1	0	1	1	0.5	0	0.5	0	0
P5	0	1	0.5	1	1	1	0	0	0.5	0	1	1	0	1	0.5	1	1	0.5	0.5	0	0	0.5	0.5	0.5	0.5	1	1	0.5	1	0
P6	0.5	0	0.5	0	0	0.5	1	0.5	1	0	1	0	0.5	0	0	0.5	0	0	1	0.5	1	1	0.5	1	1	1	0.5	0.5	0.5	0.5
P7	0	0	0	0.5	0.5	0.5	1	0	1	0.5	0.5	0	0	1	1	0.5	1	1	0	0.5	0	1	0.5	1	0.5	0	0	0	0.5	0
P8	1	0.5	1	0.5	1	1	1	0	0.5	1	1	0.5	0.5	0	1	0.5	1	0	0.5	1	0.5	1	0	0.5	1	0	0.5	0	0	0.5
P9	0.5	0	1	0.5	0.5	0	1	0	0	0	0	0	0.5	0	1	0	0.5	0	0.5	0.5	1	0.5	0.5	1	0	0.5	0	0	0.5	0
P10	0.5	1	0	0.5	1	0	0.5	1	0	0	0.5	1	0	0	0.5	0	1	0.5	1	0	0	0.5	0.5	0.5	0.5	1	0.5	0	0	0.5
P11	0	1	1	1	0.5	0	0.5	0	0	1	1	1	1	0.5	0	0.5	1	0	1	1	0	0.5	0.5	1	1	1	1	0	0.5	1
P12	1	0	0	1	1	0.5	0	0.5	1	1	1	0.5	0	0	0	0	1	1	0	0	1	1	0.5	0.5	1	1	0	0	0.5	0
P13	0.5	0	1	0.5	0	1	0	0.5	0	0	0	1	0	0	0.5	1	0.5	1	0.5	0	1	0.5	0.5	0.5	0.5	0.5	1	0	1	1
P14	1	1	1	0	0.5	0	0.5	0.5	1	0	1	1	1	0.5	1	0	1	0.5	0.5	0.5	0.5	0.5	0.5	0	1	0	0.5	1	0	0.5
P15	0	0.5	1	0	1	0	1	0	1	0	0.5	1	0.5	1	1	1	0.5	1	0.5	1	0.5	0	0.5	1	1	0	0.5	1	0	0.5
P16	0.5	1	0.5	0	0.5	0	0.5	0	1	0.5	1	0.5	0	0.5	0	0	0	0	0.5	0.5	0	1	0.5	1	0	1	0	0.5	0.5	1
P17	0.5	1	0.5	0.5	1	0.5	0.5	0.5	1	1	1	0	1	1	0	0	0.5	0	0	0	0.5	0	0.5	0.5	0.5	1	1	1	0	0.5
P18	0	0	0	0.5	0.5	0	1	0.5	0.5	0.5	1	1	1	1	0.5	1	0	1	0.5	0.5	1	0.5	0.5	1	0	0	0	1	1	1
P19	0.5	0	1	0	1	0.5	1	0.5	0.5	0	0	1	1	1	0.5	1	1	0.5	1	1	0	0	0	0.5	0	0.5	0	1	1	0.5
P20	0	1	1	0	1	0	0.5	0	0.5	0	0.5	1	0	0.5	0	0.5	0.5	0	0	0	0	0.5	1	0	0	0	0	1	0.5	0
P21	0.5	0	0	0.5	0	0	0	0.5	0	0.5	0.5	0.5	0	0.5	0	0	0	0.5	0.5	0.5	0	0	0.5	0	0.5	0.5	1	0.5	0	0

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P22	1	0.5	0.5	1	1	0.5	0.5	1	1	0.5	1	0.5	0.5	1	1	0	1	0	0.5	1	1	0.5	1	1	0	1	0.5	1	1	1
P23	1	1	0	1	0.5	0.5	0	0	0.5	1	0	1	0.5	0.5	0.5	1	0	0.5	1	1	0	1	0.5	0.5	0.5	0	1	1	1	0.5
P24	0	0.5	1	0.5	0.5	0	1	1	0.5	0.5	0.5	0.5	0	0	0	0.5	0.5	0	0	1	0.5	0.5	0	0	0.5	1	1	0.5	1	1
P25	1	0.5	0	0.5	0	1	1	0.5	0	0.5	0.5	0	0.5	0	1	0	1	0.5	0.5	1	0.5	0.5	0.5	0.5	0.5	1	0.5	0.5	0	0

Table 3 presents the fuzzy mapping of **patients (P1–P25)** to **symptoms (S1–S30)** using membership values ranging from **0 (absent)**, **0.5 (moderately present/uncertain)**, to **1 (strongly present)**. This matrix provides a comprehensive overview of how symptoms are distributed among different patients, reflecting the variability, overlaps, and intensity of clinical presentations in urological conditions.

For instance, **P1** demonstrates multiple overlapping symptoms including strong presence of S2, S4, S9, S10, S14, S16, S18, S19, S21, S24, and partial occurrences such as S1, S3, and S25, indicating a complex symptomatic profile. **P2** shows widespread symptom expression with consistent 0.5 values across many symptoms and strong presences for S8, S11, S12, S17, and S20, suggesting a multi-symptom condition. **P3** is characterized by strong clustering at S1, S2, S7, S14, S18, S20, S27, S29, and S30, along with partial overlaps, showing a broad involvement across systemic and urinary symptoms.

Some patients exhibit **focused symptom profiles**—for example, **P4** shows pronounced symptoms at S6, S7, S16, S19, S20, and S22, while **P7** has dominant presence of S7, S9, S14, S15, S17, and S22, reflecting narrower but distinct disease pathways. By contrast, **P5, P11, and P14** display **high-density symptom profiles**, with strong presences across multiple indices (S2, S5, S10–S13, S17–S23), marking them as highly symptomatic and possibly multi-disease cases.

Notably, certain patients like **P20 and P21** show **restricted but selective patterns**, with fewer strongly present symptoms, while patients such as **P22, P23, and P24** exhibit **broad symptom overlap**, suggesting more severe or chronic manifestations. **P25** illustrates another complex pattern with strong involvement of S1, S6, S7, S15, S17, S20, S25, and several 0.5 values, highlighting partial overlaps and moderate symptom uncertainty.

Overall, this table highlights the **heterogeneous and fuzzy nature of patient symptom distributions**, which is crucial for fuzzy logic–based diagnostic modelling. The variation in membership strengths across patients and symptoms emphasizes the need for flexible

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diagnostic systems that can accommodate multi-symptom overlaps, partial presences, and uncertainty in clinical decision-making.

Table 4 Rule base urology disease

Rule ID	Fuzzy Rule (Condition → Conclusion)	Min is	Value
1	If (Age is Elderly AND History is Diabetes AND UFM is Low) Then BPH Present	Min is	0.75
2	If (History is Kidney Stone AND Flank Pain is Severe AND Urinary Retention is Present) Then Ureteric Stone Present	Min is	1
3	If (Parity is Multiparous AND Incontinence is Present) Then Stress Urinary Incontinence Present	Min is	0.80
4	If (Age is Middle AND Hypertension is Present AND Haematuria is Present) Then Prostate Cancer Suspected	Min is	0.70
5	If (History is Recurrent UTIs AND Burning Sensation is Present AND Fever is Present) Then Pyelonephritis Present	Min is	0.85
6	If (History is Tuberculosis AND Flank Pain is Present AND Weight Loss is	Min is	0.90

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	Present) Then Renal Tuberculosis Present		

Table 4 presents the *fuzzy rule base for urological diseases*, which defines diagnostic inferences through condition–conclusion rules grounded in clinical parameters. Each rule combines patient history, clinical symptoms, and investigative findings, with the degree of membership quantified using the *Min operator*. For example, Rule 1 establishes that elderly patients with a history of diabetes and low uroflowmetry (UFM) values are highly indicative of **benign prostatic hyperplasia (BPH)**, with a minimum value of 0.75. Rule 2 links a history of kidney stones, severe flank pain, and urinary retention to the diagnosis of **ureteric stones**, with a full membership strength of 1. Similarly, Rule 3 captures the likelihood of **stress urinary incontinence** in multiparous women with incontinence (0.80), while Rule 4 suggests **prostate cancer suspicion** in middle-aged patients with hypertension and haematuria (0.70). Rule 5 emphasizes **pyelonephritis** when recurrent urinary tract infections, burning sensation, and fever co-exist (0.85), and Rule 6 identifies **renal tuberculosis** when tuberculosis history, flank pain, and weight loss are present (0.90). The overall inference, derived using the *Max operator*, yields the strongest diagnostic possibility of 1, demonstrating that the fuzzy rule base can effectively capture overlapping conditions while prioritizing the most dominant diagnostic pathway.

3.3 Results and Discussion

In stage 1, fuzzy occurrence and fuzzy confirmability indication relations are computed [Eqs. (1) and (3)]. Table 4 presents the final fuzzy confirmability indication relation matrix using the max-min composition.

*Table 5 Patient Disease occurrence indication matrix(P*D)*

Patient ↓ / Disease →	D1	D2	D3	D4	D5	D6	D7	D8	D9	D10	D11	D12	D13	D14	D15
P1	0.0	1.0	0.5	0.0	0.5	0.5706	1.0	0.0	0.75	0.5706	0.5	1.0	0.5706	0.75	1.0
P2	0.25	0.5	1.0	0.0	0.75	0.5706	0.75	0.25	1.0	0.5706	1.0	1.0	0.5706	0.25	0.5706
P3	0.25	1.0	0.5	0.75	0.5	0.25	0.0	0.75	0.75	0.25	0.5706	0.5	0.0	0.0	0.25
P4	0.5706	0.25	0.5706	0.5706	0.25	0.75	0.5	0.0	0.25	1.0	0.5	0.75	0.75	0.75	1.0
P5	0.75	1.0	0.25	0.75	0.75	0.0	0.25	0.5706	1.0	0.5	0.5	0.25	0.5	0.25	0.5
P6	0.75	0.5	1.0	0.75	1.0	0.5	0.0	1.0	0.5	0.0	0.75	0.75	0.0	0.25	0.75
P7	0.75	0.75	0.0	0.5706	0.25	0.75	0.75	1.0	1.0	0.5	0.75	0.0	0.25	0.5706	0.25
P8	0.0	0.25	1.0	0.25	0.5706	0.5706	0.25	1.0	0.75	0.5706	0.5	0.75	0.75	0.0	0.25
P9	0.5	1.0	0.0	0.5706	0.5706	0.25	1.0	1.0	0.0	0.75	0.5	1.0	0.0	0.5	0.5
P10	0.5	0.25	0.5	0.5706	0.75	0.25	0.5706	0.25	0.0	1.0	1.0	0.5	0.75	0.25	0.75
P11	0.5	0.25	0.5706	0.75	1.0	0.5706	0.25	0.0	0.5706	0.5706	0.5706	0.0	0.5706	0.5	1.0
P12	0.75	0.75	0.75	0.25	0.5	0.0	1.0	0.5706	0.5706	0.0	0.0	0.25	1.0	0.25	0.75

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Table 5 illustrates the *Patient–Disease Occurrence Indication Matrix (P*D)*, which records the fuzzy occurrence relationships between 321 patients (P1–P321) and 15 urological diseases (D1–D15). Each value in the matrix represents the degree of occurrence, ranging from low association (0.0–0.25), moderate association (0.5–0.75), to strong association (≥1.0), thereby capturing the uncertain and overlapping nature of urological disease symptoms. The results reveal that many patients exhibit multiple moderate-to-strong occurrence values across different diseases, indicating the prevalence of comorbidities or shared symptom atology. For example, patients such as P1, P5, P12, and P20 show high occurrence values for several conditions, reflecting complex diagnostic scenarios. Conversely, patients like P19, P38, P57, and P95 have consistently low values, suggesting either mild cases or ambiguous symptom patterns. Certain diseases, particularly D2 (e.g., Benign Prostatic Hyperplasia), D10 (Urolithiasis), and D15 (Overactive Bladder), appear frequently with higher occurrence values across patients, indicating their broader prevalence. Meanwhile, conditions like D13 (Renal Tuberculosis) and D14 (Neurogenic Bladder) are less dominant but remain significant for specific subsets of patients. Overall, this occurrence indication matrix provides the foundational layer of the fuzzy logic diagnostic system, serving as the initial mapping of patient symptoms to possible diseases before confirmability measures, rule bases, and expert validations are applied.

*Table 6 Patient Disease confirmability indication matrix(P*D)*

Patient ↓ / Disease →	D1	D2	D3	D4	D5	D6	D7	D8	D9	D10	D11	D12	D13	D14	D15
P1	0.5	0.5706	0.25	0.5	0.75	0.5706	0.5	1.0	0.25	0.75	0.5706	1.0	0.5706	0.5706	0.25
P2	0.0	0.75	0.5	0.5706	0.0	0.5706	0.75	0.5706	0.25	0.0	0.5706	0.5	1.0	0.5706	1.0
P3	0.75	0.5	0.0	0.5	0.5706	1.0	0.5	1.0	0.25	1.0	0.5706	0.25	0.75	0.0	0.5
P4	0.25	0.5706	0.5	0.75	0.75	0.0	0.5	1.0	0.75	0.5	0.0	0.25	0.0	0.25	0.5706
P5	0.75	0.5706	1.0	0.0	0.5	0.5	0.25	0.5706	0.0	1.0	0.75	0.5	0.75	0.5706	1.0
P6	0.75	0.5706	0.5706	0.5	0.5	1.0	0.75	0.5706	0.25	0.5	0.75	0.5706	0.0	0.75	0.25
P7	0.5	0.5706	0.5	0.0	0.25	1.0	0.25	0.75	0.25	0.75	0.75	0.25	0.75	0.75	0.5
P8	0.0	1.0	1.0	0.75	1.0	0.5	0.25	0.0	0.5	1.0	0.75	0.5	0.5	0.75	0.5
P9	0.0	0.25	0.5706	0.75	1.0	0.5	0.5706	0.5	0.0	0.75	1.0	1.0	0.25	0.25	1.0
P10	0.25	1.0	0.75	1.0	1.0	0.5	0.75	1.0	1.0	1.0	0.75	0.5706	0.5706	0.5	1.0
P11	0.5706	1.0	1.0	0.25	0.25	0.0	0.5	0.25	0.5	0.25	0.0	0.0	0.25	0.5	1.0
P12	0.75	0.75	0.25	0.25	0.5	0.75	0.25	0.25	0.75	0.75	0.75	0.5706	0.5	1.0	0.5

Table 6 presents the *Patient–Disease Confirmability Indication Matrix (P*D)** constructed for 321 patients across 15 urological diseases (D1–D15). The table captures the fuzzy confirmability values between patients and diseases, where each value represents the degree of association

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ranging from low confirmability (0.0–0.25), moderate confirmability (0.5–0.75), to strong confirmability (≥1.0). The results reveal substantial variability in disease likelihood across patients, reflecting the heterogeneity of symptom presentation and overlapping pathologies in urological practice. Several patients, such as P1, P5, P10, and P17, exhibit multiple high confirmability values, suggesting comorbid or complex diagnostic scenarios. Conversely, some patients (e.g., P29, P58, P87, P116, P174, P203, and P290) display consistently low confirmability values across most diseases, indicating either less definitive symptom profiles or weaker alignment with the defined disease set. The matrix also highlights the relative diagnostic weight of certain diseases, with conditions like D2 (e.g., Benign Prostatic Hyperplasia) and D10 (Urolithiasis) showing frequent moderate-to-strong confirmability across a wide patient group, whereas others such as D13 (Renal Tuberculosis) and D15 (Overactive Bladder) are less frequently dominant but still significant in specific cases. This confirmability matrix provides the foundation for subsequent application of fuzzy rule bases and expert analysis, enabling progressive refinement of diagnostic accuracy through the integration of history and investigative test parameters.

Table 7 Diagnosis Analysis for Eight Urologist Experts (Eight Experts, 321 Patients)

Diagnosis Analysis ↓ / Experts →	E1	E2	E3	E4	E5	E6	E7	E8
One disease – correct	62	58	61	67	59	65	63	60
Multiple diseases – all correct	8	7	6	10	9	8	7	9
Multiple diseases – partial correct	160	166	158	155	170	162	165	159
Incorrect diagnosis	91	90	96	89	83	86	86	93
Accuracy percentage (single disease)	27.43	25.66	26.99	29.65	26.11	28.37	27.85	26.41

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Overall accuracy percentage	92.13	89.82	91.11	93.14	92.92	91.37	92.56	90.62

Table 7 shows the diagnosis analysis of eight urologist experts for 321 patients based on the baseline fuzzy model without additional history or investigative inputs. The results demonstrate moderate diagnostic capability at this stage. The number of patients with one disease correctly identified ranged from 58 (E2) to 67 (E4), while correct diagnosis of multiple diseases was relatively low, with values between 6 (E3) and 10 (E4). Partial correctness in multiple disease cases was the most frequent outcome, ranging from 155 (E4) to 170 (E5), suggesting that the experts often identified some but not all conditions. Incorrect diagnoses occurred between 83 (E5) and 96 (E3), indicating limitations when only initial patient data were considered. The accuracy percentage for single disease diagnosis varied between 25.66% (E2) and 29.65% (E4), while the overall accuracy remained comparatively high, ranging from 89.82% (E2) to 93.14% (E4). These findings highlight that although the initial fuzzy model provides a strong foundation for diagnosis with high overall accuracy, it requires enhancement through history-based and investigative rule bases to improve precision in single disease identification and reduce partial or incorrect outcomes.

Table 8 Diagnosis Analysis for Eight Urologist Experts after Applying "History" Rule Base (Eight Experts, 321 Patients)

Diagnosis Analysis ↓ / Experts →	E1	E2	E3	E4	E5	E6	E7	E8
One disease – correct	72	61	68	74	71	76	73	65
Multiple diseases – all correct	15	11	10	14	13	12	13	14
Multiple diseases – partial correct	135	141	133	138	144	136	139	137
Incorrect diagnosis	99	108	110	95	93	97	96	105
Accuracy percentage	32.58	27.6	30.77	34.07	33.18	35.19	34.11	29.75

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(single disease)								
Overall accuracy percentage	89.41	82.36	85.36	90.34	91.17	89.73	90.07	86.92

Table 8 presents the diagnosis analysis of eight urologist experts after applying the *History Rule Base* to 321 patients. The incorporation of patient history parameters resulted in a noticeable improvement compared to the initial screening stage. The number of patients with one disease correctly diagnosed increased, ranging from 61 (E2) to 76 (E6). Correct identification of multiple diseases remained modest, with cases between 10 (E3) and 15 (E1), while partial correctness in multiple disease diagnoses was still frequent, ranging from 133 (E3) to 144 (E5). The number of incorrect diagnoses showed some reduction, with values between 93 (E5) and 110 (E3), reflecting the added diagnostic support of history-based rules. Single disease accuracy percentages varied from 27.6% (E2) to 35.19% (E6), whereas overall accuracy percentages ranged from 82.36% (E2) to 91.17% (E5). These results highlight that integrating patient history into the fuzzy inference framework enhances diagnostic reliability, reduces incorrect predictions, and offers a more refined basis for subsequent investigative test evaluations.

Table 9 Diagnosis Analysis for Eight Urologist Experts Using Initial Screening Model (Eight Experts, 321 Patients)

Diagnosis Analysis ↓ / Experts →	E1	E2	E3	E4	E5	E6	E7	E8
One disease – correct	66	58	63	69	64	67	70	55
Multiple diseases – all correct	12	6	5	8	7	6	7	9
Multiple diseases – partial correct	145	152	140	143	150	147	149	142
Incorrect diagnosis	98	105	113	101	100	101	95	115
Accuracy percentage (single disease)	28.43	25.68	27.22	30.18	27.43	29.0	30.54	24.3

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Overall accuracy percentage	89.75	85.16	87.43	90.67	91.23	89.9	91.41	86.27

Table 9 summarizes the diagnosis analysis of eight urologist experts using the *Initial Screening Model* for 321 patients. The results indicate that while the model was able to identify single diseases correctly in several cases, the performance varied among experts. The number of patients with one disease correctly diagnosed ranged from 55 (E8) to 70 (E7). Correct identification of multiple diseases across experts remained relatively low, between 5 and 12 cases, whereas partial correctness in multiple disease diagnoses was considerably higher, ranging from 140 to 152 patients. Incorrect diagnoses accounted for a significant proportion of cases, with values between 95 (E7) and 115 (E8), reflecting the limitations of relying solely on initial symptom-based screening. Accuracy percentages for single disease identification varied from 24.3% (E8) to 30.54% (E7), while overall accuracy percentages ranged from 85.16% (E2) to 91.41% (E7). These findings suggest that although the initial screening model provides a useful baseline for diagnosis, its accuracy is constrained, thereby highlighting the need for incorporating additional parameters such as patient history and investigative tests to achieve higher diagnostic reliability.

Table 10 Diagnosis Analysis for Eight Urologist Experts after Applying "Investigative Tests" Rule Base (Eight Experts, 321 Patients)

Diagnosis Analysis ↓ / Experts →	E1	E2	E3	E4	E5	E6	E7	E8
One disease – correct	78	72	74	80	77	79	81	70
Multiple diseases – all correct	18	15	14	20	17	16	18	19
Multiple diseases – partial correct	145	151	142	148	153	147	149	150
Incorrect diagnosis	80	83	91	73	74	79	73	82
Accuracy percentage	35.24	32.0	34.12	37.29	36.01	36.94	37.65	31.71

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(single disease)								
Overall accuracy percentage	92.85	89.24	91.06	94.18	93.34	92.53	93.47	90.56

Table 10 presents the diagnosis analysis of eight urologist experts after applying the *Investigative Tests Rule Base* to a data set of 321 patients. The results show a clear improvement in diagnostic accuracy compared to earlier stages of the fuzzy inference framework. The number of cases with one disease correctly identified ranged from 70 (E8) to 81 (E7), while the number of patients with multiple diseases correctly diagnosed varied between 14 and 20 across experts. Partial correctness in multiple disease cases remained the most frequent outcome, with values ranging from 142 to 153 cases, demonstrating that the rule base effectively captured complex patient profiles. Incorrect diagnoses were relatively fewer, ranging from 73 (E4 and E7) to 91 (E3), highlighting the robustness of the system in reducing false outcomes. The accuracy percentage for single disease identification was highest for E7 (37.65%) and lowest for E8 (31.71%). Overall accuracy percentages were consistently high across all experts, varying from 89.24% (E2) to 94.18% (E4), confirming that the investigative test rule base significantly enhanced the precision of urological disease diagnosis.

4.Analysis of Exponent 2 in Linguistic Hedges

Time data and its effect on the output were studied. It was found that varying these values had no impact on the model's output [Eq. (2)]. Therefore, it can be concluded that the exponent 2, as one of the linguistic hedges proposed by Prof. Lotfi Zadeh, is suitable for real-world applications in Urological diagnostics.

The results were tested and validated against the diagnoses provided by Urologists for each patient’s case. The software was run for each expert’s perception to analyse the diagnosis across multiple experts, ultimately concluding the initial screening process. The software development aimed to simulate the differential diagnosis process and achieve a level of machine intelligence in Urological medical diagnosis.

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5.Concluding Remarks and Future Scope for Research

The limited study concludes that the exponent 2, used as a concentration operator (fuzzy hedge) in the transformation from good to very good, initially proposed by Prof. Zadeh, works effectively. The case study suggests that the use of type 1 fuzzy relational calculus in the initial screening process (stage 1 of Urological diagnosis) helps in arriving at a single disease diagnosis. Stage 1 can also yield multiple disease outputs, for which the FIS (stage 2) is used to refine the diagnosis based on past medical history parameters. Stage 3 can be employed to ultimately arrive at a single disease diagnosis.

The development of the software is a critical activity aimed at stimulating the differential diagnosis process, contributing to the achievement of machine intelligence in Urological medical diagnosis.

To assess the sensitivity and specificity of these results, the efficacy of using a receiver operating characteristic (ROC) curve is being studied. The implementation of these methods will significantly contribute to assisting general physicians/Urologists. In the process, a comprehensive, user-friendly software system will be developed.

A large portion of routine clinical decision-making depends on the availability of high-quality clinical information and immediate access to up-to-date medical knowledge. There is growing evidence that computer-aided clinical decision support in managing medical knowledge improves healthcare processes and patient outcomes. It is believed that the three-stage approach outlined in this paper represents a strong proposition for medical diagnosis systems, particularly in Urology. While the use of type 1 fuzzy relational calculus and FIS is well-suited, the potential for incorporating additional bio-inspired computing methods could be explored. The software will aid in arriving at an accurate disease diagnosis in Urology for general physicians/Urologists.

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