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A Medical Diagnosis of Cataract Using Intuitionistic Fuzzy Sets

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Abstract

Accurate decision-making in medical diagnosis investigations is complex due to the impreciseness of the patient's symptoms in a disease that may or may not be accurate. Uncertainty is the characteristic relation between symptoms and disease. Uncertainty is best handled by linguistic variables. Intuitionistic Fuzzy Sets (IFSs) help model imprecision in decision-making problems like medical diagnosis. We propose an intuitionistic fuzzy method for the diagnosis of the cause of cataract and various factors responsible for cataract in different patients of the age group above 40 years. This model is based on the physician's medical knowledge of the relation between the patients and of symptoms and types of cataracts using IFSs. For this purpose, we describe a state of a patient, knowing the results of his/her medical tests by the degree of membership and degree of non-membership based on the relationship between symptoms and various types of factors and types of cataracts. By the intuitionistic fuzzy max–min–max relation, we identify the disease with the maximum membership value for various patients. We illustrate the methodology with the case study of Indian patients in the Jharkhand region. The study included 50 patients over 40 years of age, of both genders, attending the general hospital for checkup or diagnosis of cataract. Causes of cataract and types of cataracts affecting the patients. Our study found that diabetes is the main cause of cataract for most patients. Patients with diabetes have posterior and cortical types of cataracts.

Keywords: Cataract, Diagnosis, Intuitionistic fuzzy sets, Medical decision-making, Uncertainty, Linguistic variables, Diabetes, Posterior cataract, Cortical cataract, Jharkhand patients.

1 | Introduction

National programme for control of blindness (2012-2013) states the prevalence of blindness due to cataract is about 62.6% and the cataract surgical rate in Jharkhand is 2617 in the population of 3, 11, 69,272. In India, nearly 74% of adults 60 years and older have cataracts or have undergone cataract surgery, according to population-based study [1]. Cataracts are a very common eye condition that occurs when one gets older the

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lens inside your eye gradually changes and becomes less transparent (Clear). A lens that has turned misty, or cloudy, is said to have a cataract. The common symptoms being blurry vision, trouble seeing at night, seeing colors as faded Diplopia and frequent changes in prescription glasses. The causes are mostly due to old age, diabetes, hypertension, obesity, smoking and UV radiations.

In medical diagnosis, the description of symptoms given by patients is vague with terms like severe, mild, very severe or normal. These terms are defined by linguistic terms. The state of the patient can be categorized as yes, no or maybe category. The categorization can be best described by the Intuitionistic Fuzzy Set (IFS). An IFS is best to deal with this vagueness and imprecision involved in medical diagnosis.

Atanassov [2] introduced the concept of IFSs as a generalization of a fuzzy set. Many researchers have confirmed the resourcefulness of IFS in medical decision-making problem due to its significance in due to vagueness or representation of imperfect knowledge. The earliest work of medical diagnosis was proposed by Sanchez [3].

De Kumar et al. [4] presented an application of IFSs in Sanchez's [3] approach of medical diagnosis. Extension of Sanchez [3] work was carried by Saikia et al. [5] where an application of intuitionistic fuzzy soft sets was carried out in medical diagnosis. Szmidt and Kacprzyk [6], applied similarity measure for IFSs for Medical Diagnostic reasoning.

Michael and Bron [7] presented a model of normal and pathological aging-related to cataract. Shora et al. [8] designed a knowledge-driven Intuitionistic Fuzzy Decision Support for finding out the causes of obesity.

Thong and Hoang Son [9] for enhancing the accuracy of Intuitionistic fuzzy recommender systems in medical diagnosis. Santosa et al. [10] made an expert system of cataract eye disease diagnosis by using the Fuzzy Mamdani method. Cheng et al. [11] demonstrated the risk of cataract associated with radiation exposure from neuro-interventional procedures.

We describe an attempt to provide a formal model of the process to diagnose the eye disease "cataract", with the most affecting factor and types of cataract" by using IFS theory and implement it in the form of treatment recommendation system. This is the system by which the physician uses his medical knowledge to infer a diagnosis from the symptoms displayed by the patients his lab test result and medical history.

The paper is organized as follows: In Section 1 we introduce the problem, followed by Section 2 of preliminaries of the IFSs. In Section 3 we discuss the case study of the problem. Section 4 and 5 the results and conclusions of our study.

2 | Preliminaries

2.1 | Intuitionistic Fuzzy Relation

Let X and Y are two sets. An Intuitionistic Fuzzy Relation (IFR) R from X to Y is an IFS of X× Y characterized by the membership function μ_R and non-membership function νR [12]. An IFR R from X to Y will be denoted by R (X→Y).

2.2 | Max-Min-Max Composition

Let Q (X→Y) and R (Y→Z) be two IFRs. The max-min-max composition R○Q is the IFR from X to Z, defined by membership function and the non-membership function.

$$\mu_{R^\circ Q}(x,z) = \vee \quad (\mu_Q(x,y) \wedge \mu_R\,(y,z)y.$$

and the non-membership function

$$\vartheta_{R^\circ Q}\,(x,z) = \wedge(\vartheta_Q(x,y) \vee \vartheta_R(y,z)| \text{ for all } (x,z) \in X \times Z \text{ and for all } y \in Y, \quad (1)$$

where V= maximum value and Λ= minimum value.

2.3 | Selection Index

Is defined as follows:

$$ST = \mu T - \nu T * (\pi T), \pi T = 1 - \mu T - \nu T. \quad (2)$$

2.4 | Linguistic Variable

A linguistic variable is a word in the natural language, say English, which is an attribute having a collection of words as its value called linguistic values (L. values) [13]. Certain examples (*Table 1*) will clarify these concepts.

Table 1. Linguistic variables.

L. Variable	L. Values
Speed	Fast, medium, slow
Temperature	Hot, warm, cold or high, medium, low
Pressure	High, medium, low
Height	Tall, medium, short
Pain	Mild, moderate, low

The entire linguistic variable can take numerical values. When we deal with two or more linguistic values of the linguistic variable; an ordering, which is in built-in our mind, comes into the picture. For example for the linguistic variable 'speed,' the linguistic value fast medium and slow are ordered as:

Fast ≥ Medium ≥ Slow.

Here the ordering based on the numerical value of speed. Preference relations are expressed by linguistic variables (*Table 2*).

Table 2. Linguistic value and intuitionistic fuzzy values.

Linguistic Value	Intuitionistic Fuzzy Values
Very low (VL)	(0.1,0.9)
Low (L)	(0.15,0.25)
Medium low (ML)	(0.25,0.35)
Medium (M)	(0.5,0.4)
Medium high (MH)	(0.55,0.25)
High (H)	(0.85,0.15)
Very high (VH)	(0.9,0.1)

2.5 | Distance Measure in Intuitionistic Fuzzy Sets

Let $A = \{(x, \mu A(xi), \nu A(xi), \pi A(xi)): x\epsilon X\}$ and $= \{(x, \mu B(xi), \nu B(xi), \pi B(xi)): x\epsilon X\}$ be two IFS in $X = \{x1, x2, x3 \dots xn\}, i = 1,2, \dots n.$ based on the geometric interpretation of IFS, Szmidt and Kacprzyk [6], proposed the following four distance measure between A and B:

2.5.1 | The hamming distance

$$D_H(A,B)=\frac{1}{2}\sum_{i=1}^{n}(|\mu_A(x_i) - \mu_B(x_i)| + |\nu_A(x_i) - \nu_B(x_i) + |\pi_A(x_i) - \pi_B(x_i)|).$$

2.5.2 | Normalized hamming distance

$$Dn - H(A, B) = \frac{1}{2n}\sum_{i=1}^{n} |\mu A(xi) - \mu B(xi)| + |\nu A(xi) - \nu B(xi)|. \quad (3)$$

3 | Algorithm

Step 1. Data of relation between patients and symptoms and symptoms and diseases is converted into intutionistic fuzzy sets.

Step 2. IFS composition relation between patients and diseases is derived using the above two tables.

Step 3. Relation between symptoms and cataract is represented by IFS.

Step 4. Now applying max min max composition between patient and symptoms and symptoms and type of cataracts.

Step 5. Using normalized hamming distances approach for each patient from the considered set of possible diagnosis the lowest distance points out a proper diagnosis.

4 | Case Study

Consider a set of patient P={(P1, P2, P3, P4) and set of symptoms S={ very blur vision, moderate blur vision, blur vision, headache} and disease-causing cataract F ={diabetes, hypertension, smoking, alcohol}. Also consider a set of different types of cataract C={ posterior subcapsular, cortical cataract, nuclear cataract, and mixed cataract}.

The data of various relations between patients and their various symptoms (*Tables 3* and *4*) and symptoms and various diseases (*Table 5*) are given below have been collected from a hospital by untrained educated personnel who was unaware of cataract status. The data is represented by linguistic variables (*Table 3*) and later converted into IFS form (*Table 4*).

Table 3. Linguistic relation between patients and symptoms.

Patient	VBV	MBV	BV	HD
1	Very high	Medium high	Medium low	Low
2	Medium high	Medium low	Medium low	High
3	Very low	Very low	Medium low	Very low
4	Low	Medium	Very low	Medium low

Table 4. IFS relation between patients and symptoms.

Patients	VBV	MBV	BV	HD
1	(0.9,0.1)	(0.55,0.25)	(0.25,0.35)	(0.15,0.28)
2	(0.55,0.25)	(0.25,0.35)	(0.25,0.35)	(0.85,0.25)
2	(0.1,0.9)	(0.1,0.9)	(0.25,0.35)	(0.1,0.9)
4	(0.15,0.28)	(0.5,0.4)	(0.1,0.9)	(0.25,0.35)

Table 5. IFS relation between symptoms and diseases.

Symptoms	Diabetes	Hypertension	Smoking	Alcohol
VBV	(0.85,.15)	(0.75,0.1)	(0.55,0.25)	(0.1,0.9)
MBV	(0.85.0.15)	(0.25,0.35)	(0.15,0.28)	(0.25,0.35)
BV	(0.25,0.35)	(0.15,0.28)	(0.1,0.9)	(0.5,0.4)
HD	(0.1,0.9)	(0.85,0.15)	(0.15,0.28)	(0.15,0.28)

Using *Eq. (1)* we obtain the following result (*Table 6*).

TABLE 6. IFS composition relation between patients and diseases

Patient	Diabetes	Hypertension	Smoking	Alcohol
1	(0.85,0.15)	(0.75,0.1)	(0.55,0.25)	(0.25,0.28)
2	(0.55,0.25)	(0.85,0.25)	(0.5,0.25)	(0.25,0.28)
3	(0.25,0.35)	(0.15,0.35)	(0.1,0.9)	(0.25,0.4)
4	(0.5,0.28)	(0.25,0.28)	(0.15,0.25)	(0.25,0.35)

Next we are taking a set of different types of cataract C(Posterior subcapsular, cortical cataract, nuclear cataract and mixed cataract) and constructing an intuitionistic fuzzy relation between symptoms S (VBV, MBV, BV, HD) and types of cataract C(Posterior subcapsular, cortical cataract, nuclear cataract and mixed cataract) M (S→C). Relation between symptoms and types of cataract.

Table 7 .IFS relation between symptoms and cataract.

Symptoms	Posterior	Cortical	Nuclear	Mixed
VBV	(0.85,0.15)	(0.85,0.15)	(0.5,0.4)	(0.55,0.25)
MBV	(0.75,0.1)	(0.85,0.25)	(0.15,0.28)	(0.25,0.35)
BV	(0.15,0.28)	(0.25,0.35)	(0.1,0.9)	(0.15,0.25)
HD	(0.25,0.35)	(0.1,0.9)	(0.15,0.28)	(0.5,0.4)

Now applying max min max composition *Eq. (1)* between *Table 3* and *Table 7* we get a relation (*Table 8*).

Table 8. IFS relation between patients and type of cataract.

Patient	Posterior	Cortical	Nuclear	Mixed
1	(0.85,0.15)	(0.85,0.15)	(0.5,0.28)	(0.55,0.25)
2	(0.55,0.25)	(0.85,0.25)	(0.5,0.28)	(0.55,0.25)
3	(0.15,0.35)	(0.25,0.35)	(0.1,0.9)	(0.15,0.35)
4	(0.5,0.28)	(0.5,0.28)	(0.15,0.35)	(0.25,0.28)

From *Table 8* we can get the decision that which patient is having what type of cataract.

Using *Eq. (3)* for calculating normalized hamming distance between *Tables 3* and *4* we get a relation between Patients and the cause factor of cataract (*Table 8*).

Table 9. Normalized Hamming distance analysis reveals patient-cause correlations for cataract.

Patients	Diabetes	Hypertension	Smoking	Alcohol
1	0.146	0.193	0.203	0.287
2	0.325	0.077	0.2	0.266
3	0.375	0.477	0.39	0.20
4	0.35	0.318	0.133	0.255

Using *Eq. (3)* for calculating normalized hamming distance between *Table 4* and *Table 7*.

Table 10. Normalized Hamming distance analysis reveals patient-cause correlations for cataract.

Patient	Posterior	Cortical	Nuclear	Mixed
1	0.098	0.133	0.228	0.196
2	0.252	0.087	0.312	0.225
3	0.477	0.362	0.367	0.362
4	0.256	0.341	0.138	0.216

5 | Results

5.1 | Cause of Cataract in Patients

From *Table 6*, we observe: Patient 1 has diabetes (0.85) and hypertension (0.75), with the highest membership value for diabetes (0.85) followed by hypertension (0.75). Patient 2 is affected by hypertension (0.85). Patient 3 is affected by both diabetes and alcohol consumption (0.25). Patient 4 is affected by diabetes (0.50). These results show that diabetes is the main cause of cataract for most patients.

5.2|Type of Cataract in Patients

From *Table 8*, we obtain: Patient 1 suffers from both posterior and cortical cataracts, indicating a mixed cataract. Patient 2 has a cortical cataract. Patient 3 shows a very low level of cortical cataract. Patient 4 has both posterior and cortical cataracts but not a mixed form—one eye may have posterior cataract while the other has cortical cataract.

5.3|Hamming Distance Approach

Using normalized Hamming distances across the set of possible diagnoses, the lowest distance indicates the most likely diagnosis. Patient 1's lowest distance corresponds to diabetes as the major risk factor for cataracts. Patient 2's lowest distance corresponds to hypertension. Patient 3's lowest distance corresponds to alcohol consumption. Patient 4's lowest distance corresponds to smoking. The first two cases are confirmed, as diabetes and hypertension have membership values above 0.40. We also find that the lowest distances are associated with posterior and cortical cataracts, and that hypertension, alcohol consumption, and smoking are all linked to cortical cataract, consistent with findings in papers [4], [13], [14–17].

6|Conclusion

We conclude by observing from *Tables 9* and *10* that Patient 1 has diabetes, and the prevalence of diabetic patients is higher in posterior and cortical cataracts [13], [17]. Patient 2 has hypertension, which is associated with cortical cataract. Patient 3 has diabetes and consumes alcohol; alcohol consumption is associated with posterior cataract. Patient 4 has diabetes, which is associated with posterior and cortical cataracts.

From the Hamming distance approach, we find that Patient 1 has the lowest value associated with posterior and then cortical cataracts; hypertension, alcohol consumption, and smoking are also linked to cortical cataract. Patient 2 has the lowest value for cortical cataract. Patient 3 has the lowest Hamming distance for cortical and mixed cataracts. Patient 4 has the lowest value for nuclear cataract. These findings are supported by researchers in papers [4], [13], [14–17].

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