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Fuzzy Logic Approach for Diagnosis of Diabetics

[1]R. Radha and [2]S.P. Rajagopalan
[1]Department of Computer Science, S.D.N.B. VAISHNAV College For Women,
Chromepet, Chennai-44, India
[2]Mohamed Sathak Group of Educational Institutions, Chennai-5 India

Abstract: Fuzzy logic is a computational paradigm that provides a mathematical tool for dealing with the uncertainty and the imprecision typical of human reasoning. A prime characteristic of fuzzy logic is its capability of expressing knowledge in a linguistic way, allowing a system to be described by simple, human-friendly rules. The fuzzy set framework has been utilized in several different approaches to modeling the diagnostic process. In this paper Diabetes related diseases and their symptoms are taken. The physician's medical knowledge is represented as a fuzzy relation between symptoms and diseases. Thus, given the fuzzy set A of the symptoms observed in the patient and the fuzzy relation R representing the medical knowledge that relates the symptoms in set S to the diseases in set D, then the fuzzy set B of the possible diseases of the patient can be inferred by means of the compositional rule of inference. Fuzzy membership values for representing different symptoms are framed and they are used for forming the relations.

Key words: Fuzzy logic, diabetes, fuzzy max-min relations, membership values

INTRODUCTION

Indeed, the complexity of biological systems may force us to alter in radical ways our traditional approaches to the analysis of such systems. Thus, we may have to accept as unavoidable a substantial degree of fuzziness in the description of the behavior of biological systems as well as in their characterization. This fuzziness, distasteful though it may be, is the price we have to pay for the ineffectiveness of precise mathematical techniques in dealing with systems comprising a very large number of interacting elements or involving a large number of variables in their decision trees (Zadeh, 1969).

Zadeh (1969) himself anticipated very early that medical diagnosis would be the most likely application domain of his theory. Any expert knows that his medical knowledge, which helps for diagnosis, consists of nearly 70% of uncertain data. Based on the patients vague descriptions of symptoms and his own experience in the field of medicine helps him to diagnose the disease properly. Any formalism disallowing uncertainty is therefore inapt to capture this knowledge which leads to the danger of fallacies due to misplaced precision.

The power of fuzzy sets in medicine: As in any other area of modern life, computers are omnipresent in medicine, from the hospital accounting computer to the high-end MRI scanner. In particular, computers are used as tools to abet medical professionals in resolving search problems. Numerous techniques have been applied over the past few decades to solve medical problems: expert systems, artificial neural networks, linear programming and database systems are but a sampling of the approaches used.

Fuzzy logic is a computational paradigm that provides a mathematical tool for dealing with the uncertainty and the imprecision typical of human reasoning. A prime characteristic of fuzzy logic is its capability of expressing knowledge in a linguistic way, allowing a system to be described by simple, human-friendly rules. This characteristic, also known as interpretability, renders fuzzy logic-based systems attractive from the medical point of view.

Although medical knowledge, concerning the symptom-disease relationship constitutes one source of imprecision and uncertainty in the diagnostic process, the knowledge concerning the state of the patient constitutes another. The physician generally gathers knowledge about the patient from the past history, physical examination, laboratory test results and other investigative procedures such as X-ray and ultrasonic. The knowledge provided by each of these sources carries with it varying degrees of uncertainty. The past history offered by the patient may be subjective, exaggerated, under estimated, or incomplete. Mistakes may be made in the physical examination and symptoms

Corresponding Author: R. Radha, Department of Computer Science, S.D.N.B. Vaishnav College For Women, Chromepet, Chennai-44, India Tel: 044-22412696

may be overlooked. The measurements provided by laboratory tests are often of limited precision and the exact borderline between normal and pathological is often unclear. X-rays and other similar procedures require a correct interpretation of the results.

Thus, the state and symptoms of the patient can be known by the physician with only a limited degree of precision. In the face of the uncertainty concerning the observed symptoms of the patient as well as the uncertainty concerning the relation of the symptoms to a disease entity, it is nevertheless crucial that the physician determine the diagnostic label that will entail the appropriate therapeutic regimen. The desire to better understand and teach this difficult and important technique of medical diagnosis has prompted attempts to model this process, most recently, with the use of fuzzy sets. These models vary in the degree to which they attempt to deal with different complicating aspects of medical diagnosis such as the relative importance of symptoms, the varied symptom patterns of different disease stages, relation between diseases themselves and the stages of hypothesis formation, preliminary diagnosis and final diagnosis within the diagnostic process itself. These models also form the basis for computerized medical expert systems, which are usually designed to aid the physician in the diagnosis of some specified category of diseases.

The background work involved: The fuzzy set framework has been utilized in several different approaches to modeling the diagnostic process. In the approach formulated by Sanchez (1979), the physician's medical knowledge is represented as a fuzzy relation between symptoms and diseases. Thus, given the fuzzy set A of the symptoms observed in the patient and the fuzzy relation R representing the medical knowledge that relates the symptoms in set S to the diseases in set D, then the fuzzy set B of the possible diseases of the patient can be inferred by means of the compositional rule of inference

$$B = A \circ R \qquad \text{or} \quad \mu_{B(d)} = \max_{s \in S}[\min(\mu_{A(s)}, \mu_{R(s,d)})]$$

for each $d \in D$. This max-min composition corresponds to the fuzzy conditional statement if A then B by R. The membership grades of observed symptoms in fuzzy set A may represent the degree of certainty of the presence of the symptom or its severity. The membership grades in fuzzy set B denote the degree of certainty with which we can attach each possible diagnostic label to the patient. The fuzzy relation R of medical knowledge should constitute the greatest relation such that given the fuzzy relation Q on the set P of patients and S of symptoms and the fuzzy relation T on the set P of patients and D of diseases, then

$$T = Q \circ R \tag{1}$$

Thus, relations Q and T may represent, respectively, the symptoms that were present and diagnoses that were consequently made for a number of known cases. By solving the fuzzy relation equation (1) for R, the accumulated medical experience can be used to specify the relation between symptoms and diseases that was evidenced in the previous diagnoses. The maximal solution to Eq. (1) must be chosen for R in order to avoid arriving at a relation that is more specific than our information warrants. However. This can lead to cases in which R shows more symptom-disease association than exists in reality. Therefore, it may be necessary to interpret the results of applying relation R to a specific set of symptoms as a diagnostic hypothesis rather than as a confirmed diagnosis.

Zadeh (1965) defined fuzzy relations: If L (A×B) is the set of all fuzzy sets in the Cartesian product A×B of crisp sets A and B, then a fuzzy relation is a subset of L (A×B) (Lucas, 1998). Having three sets A, B and C, to compose fuzzy relations $Q \subseteq L\ (A\times B)$ and $R \subseteq L\ (B\times C)$ to get another fuzzy relation $T \subseteq L\ (A\times C)$, Zadeh introduced the combination rule of a max-min-composition: $T = Q \circ R$ is defined by the following membership function

$$\mu_T(x,y) = \max_{y\in B} \min\{\mu_R(x,y); \mu_R(y,z)\},$$
$$x \in A, y \in B, z \in C$$

Accordingly we can represent relations

$$(T \subseteq P \times D) = (Q \subseteq P \times S) \circ (R \subseteq S \times D)$$

and for possible disease for a patient can be derived from

$$(B \subseteq D) = (A \subseteq S) \circ (R \subseteq S \times D)$$

The model proposes two types of relations to exist between symptoms and diseases: an occurrence relation and a confirm ability relation. The first provides knowledge about the tendency or frequency of appearance of a symptom when the specific disease is present; it corresponds to the question, How often does symptom s occur with disease d?. The second relation describes the discriminating power of the symptom to confirm the presence of the disease; it corresponds to the question, How strongly does symptom s confirm disease d?. The distinction between occurrence and confirm ability is useful because a symptom may be quite likely to occur with a given disease but may also commonly occur with several other diseases, therefore limiting its power as a discriminating factor among them. Another symptom, on the other hand, may be relatively rare with a given disease, but its presence may nevertheless constitute almost certain confirmation of the presence of the disease.

In CADIG II (a medical expert system) the fuzzy relations between symptoms and diseases are given in the form of rules and associated fuzzy relationship tupels (frequency of occurrence o, strength of confirmation c); their general formulation is (Sanchez, 1979; Adlassing, 1986):

* IF antecedent THEN consequent WITH (o,c)

In particular the following fuzzy relationships exist (Phuong *et al*.,); k = set of symptom combinations SC_i);

- S_i,D_j (Occurrence relationship) $R^o_{SD} \subset \Sigma\times\Delta$
- S_i,D_j (Confirmation relationship) $R^c_{SD} \subset \Sigma\times\Delta$
- Sc_i,D_j (Occurrence relationship) $R^o_{SCD} \subset K\times\Delta$
- Sc_i,D_j (Confirmation relationship) $R^c_{SCD} \subset K\times\Delta$
- S_i,S_j (Occurrence relationship) $R^o_{SS} \subset \Sigma\times\Sigma$
- S_i,S_j (Confirmation relationship) $R^c_{SS} \subset \Sigma\times\Sigma$
- D_i,D_j (Occurrence relationship) $R^o_{DD} \subset \Delta\times\Delta$
- D_i,D_j (Confirmation relationship) $R^C_{DD} \subset \Delta\times\Delta$

In this study Diabetes Syndrome and its relative disease are taken for discussion. Here Diabetes related diseases and its symptoms are discussed and the different kind of affected patients are considered. In this fuzzy relations and compositions are used to derive at a conclusion as which patient has what symptoms and based on that what disease they may have has been discussed.

To deduce diseases $D_j \in D$ suffered by patient $P_k \in P$ from the observed symptoms $S_i \in S$ three max-min compositions as inference rules are used

- Hypotheses and confirmation $R^1_{PD} = R_{PS} \circ R^c_{SD}$ defined by

$$\mu_{R^1_{PD}}(P_K,D_j) = \max_{S_i}\min\{\mu_{R_{PS}}(P_K,S_i);\mu_{R^c_{SD}}(S_i,D_j)\}$$

- Exclusion (by present symptoms) $R^2_{PD} = R_{PS} \circ (1\text{-} R^c_{SD})$ defined by

$$\mu_{R^2_{PD}}(P_K,D_j) = \max_{S_i}\min\{\mu_{R_{PS}}(P_K,S_i);1-\mu_{R^c_{SD}}(S_i,D_j)\}$$

- Exclusion (by absent symptoms) $R^3_{PD} = (1\text{-}R_{PS})\circ R^c_{SD})$ defined by

$$\mu_{R^3_{PD}}(P_K,D_j) = \max_{S_i}\min\{1-\mu_{R_{PS}}(P_K,S_i);\mu_{R^c_{SD}}(S_i,D_j)\}$$

Diabetes overview: Diabetes is a set of related diseases in which the body cannot regulate the amount of sugar (glucose) in the blood (emedicinehealth.com).

Glucose in the blood gives us the energy-the kind we need when we walk briskly, run for a bus, ride a bike, take an aerobics class and for our day-to-day chores. Glucose in the blood is produced by the liver from the foods we eat. In a healthy person, several hormones, one of which is insulin, regulate the blood glucose level. Insulin is produced by the pancreas, a small organ near the stomach that also secretes important enzymes that help in the digestion of food. Insulin allows glucose to move from the blood into liver, muscle and fat cells, where it is used for fuel. People with diabetes either don't produce enough insulin (type 1 diabetes) or cannot use insulin properly (type 2 diabetes), or both. In diabetes, glucose in the blood cannot move into cells and stays in the blood. This not only harms the cells that need the glucose for fuel, but also harms certain organs and tissues exposed to the high glucose levels.

Type 1 diabetes: The body stops producing insulin or produces too little insulin to regulate blood glucose level. Type 1 diabetes is typically recognized in childhood or adolescence. It used to be known as juvenile-onset diabetes or insulin-dependent diabetes mellitus. Type 1 diabetes can occur in an older individual due to destruction of pancreas by alcohol, disease, or removal by surgery or progressive failure of pancreatic beta cells, which produce insulin. People with type 1 diabetes generally require daily insulin treatment to sustain life.

Type 2 diabetes: The pancreas secretes insulin, but the body is partially or completely unable to use the insulin. This is sometimes referred to as insulin resistance. The body tries to overcome this resistance by secreting more and more insulin. People with insulin resistance develop type 2 diabetes when they do not continue to secrete enough insulin to cope with the higher demands. At least 90% of patients with diabetes have type 2 diabetes. Type 2 diabetes is typically recognized in adulthood, usually after age 45 years. It used to be called adult-onset diabetes mellitus, or non–insulin-dependent diabetes mellitus. These names are no longer used because type 2 diabetes does occur in younger people and some people with type 2 diabetes need to use insulin. Type 2 diabetes is usually controlled with diet, weight loss, exercise and oral medications. More than half of all people with type 2 diabetes require insulin to control their blood sugar at some point in the course of their illness.

Beside this there are other forms of diabetes like Gestational diabetes, Pre-diabetes etc.

Complications of diabetes: Both forms of diabetes ultimately lead to high blood sugar levels, a condition called hyperglycemia. Over a long period of time, hyperglycemia damages the retina of the eye, the kidneys, the nerves and the blood vessels.

- Damage to the retina (diabetic retinopathy) is a leading cause of blindness.
- Damage to the kidneys (diabetic nephropathy) is a leading cause of Kidney failure.
- Damage to the nerves (diabetic neuropathy) is a leading cause of foot wounds and ulcers, which frequently lead to foot and leg amputations.
- Damage to the nerves in the autonomic nervous system can lead to paralysis of the stomach (gastroparesis), chronic diarrhea and an inability to control heart rate and blood pressure with posture changes.
- Diabetes accelerates atherosclerosis, or the formation of fatty plaques inside the arteries, which can lead to blockages or a clot (thrombus), which can then lead to heart attack, stroke and decreased circulation in the arms and legs (peripheral vascular disease).
- Diabetes predisposes people to high blood pressure and high cholesterol and triglyceride levels. These independently and together with hyperglycemia increase the risk of heart disease, kidney disease and other blood vessel complications.
- Diabetic ketoacidosis is a serious condition in which uncontrolled hyperglycemia (usually due to complete lack of insulin or a relative deficiency of insulin) over time creates a buildup in the blood of acidic waste products called ketones. High levels of ketones can be very harmful. This typically happens to people with type 1 diabetes who do not have good blood glucose control. Diabetic ketoacidosis can be precipitated by infection, stress, trauma, missing medications like insulin, or medical emergencies like stroke and heart attack.
- Hyperosmolar hyperglycemic nonketotic syndrome is a serious condition in which the blood sugar level gets very high. The body tries to get rid of the excess blood sugar by eliminating it in the urine. This increases the amount of urine significantly and often leads to dehydration so severe that it can cause seizures, coma, even death. This syndrome typically occurs in people with type 2 diabetes who are not controlling their blood sugar or have become dehydrated or have stress, injury, stroke, or medications like steroids.

In the short run, diabetes can contribute to a number of acute (short-lived) medical problems.

In this paper four types of diabetic diseases are taken and using the fuzzy equivalence relations how a patient can be diagnosed is explained. They are Diabetes general, Diabetic ketoacidosis (DKA), Diabetic nephropathy, Diabetic retinopathy.

Symptoms for diabetic general (initial stage): Fatigue, weight loss, Polydipsia, Polyuria, altered mental status, Polyhpagic

Symptoms of diabetic ketoacidosis: Nausea and vomiting, dehydration, abdominal pain, low blood pressure, Polyuria, thirsty, loss of appetite, dry skin, dry mouth.

Symptoms of diabetic nephropathy: Loss of appetite, nausea and vomiting, Polyuria, swelling of legs and puffiness around the eyes, itching, easy bruising, pale skin, headaches, numbness in the feet or hands, disturbed sleep, bleeding, high blood pressure, bone pain, decreased sexual interest and erectile dysfunction.

Symptoms of diabetic retinopathy: All the symptoms similar to staring stage of diabetic, mild to severe blurring or vision loss, cataract, glaucoma.

Defining the problem: The problem is with the given symptoms of patients one has to diagnosis which patient has what disease and in what degree of disease he is in. The symptoms are named as s1, s2, s3, s4, s5 and s6. The diseases diabetic general, DKA, diabetic nephropathy and diabetic retinopathy are named as d1, d2, d3, d4, respectively. The observation is made on 40 patients and for the purpose of understanding four patients p1, p2, p3, p4 who suffer from these diseases are taken for discussions and explained of how to find out who has what or what combinations of diseases.

Symptom s1 = Fatigue, Weight loss, Polydipsia (Excessive thirst), Polyuria (Excessive urination), altered mental status (Agitation, unexplained irritability, inattention, extreme lethargy or confusion), weight around waist, high triglyceride (>150), low level HDL (<40 for men, <50 for women)
Symptom s2 = Polyphagia (Excessive eating)
Symptom s3 = Nausea and vomiting, Dehydration, abdominal pain, low Blood Pressure
Symptom s4 = Loss of appetite, increased heart rate

Symptom s5 = Swelling of legs, puffing around eyes, high Blood Pressure (130/85 mm HG or higher), itching, bleeding, bone pain, A1C> = 8
Symptom s6 = blurry vision, retinal swelling (macular oedema), leaking blood vessels

Let S denote the crisp universal set of all symptoms S = {s1, s2, s3, s4, s5, s6}

Let D be the crisp universal set of all diseases D = (d1, d2, d3, d4)

Let P be the crisp of universal set of all patients. P = {p1, p2, p3, p4}

Perez-Ojeda (1976) designed a prototype system to be used in the search for an adequate strategy to simulate an approximate reasoning model in medical decision making and he gave examples of typical elements of medical knowledge. Elementary knots and arcs could graphically construct the network of medical knowledge. Accordingly the above problem can be modeled with the relations (always, frequently, don't know, rarely, never) by mathematical probability modifiers where relations are given the membership values(1, 0.75, 0.5, 0.25, 0), respectively

$$d_1 \xrightarrow{\text{always}} s_1$$

$$d_1 \xrightarrow{\text{frequently}} s_2$$

$$d_3 \xrightarrow{\text{always}} s_5$$

$$d_4 \xrightarrow{\text{always}} s_5$$

$$d_2, d_3 \xrightarrow{\text{frequently}} (s_1 \text{ AND } s_2)$$

$$d_4, d_1 \xrightarrow{\text{rarely}} s_4$$

and so on.

Some of the numerical values can be expressed in terms of fuzzy values like weight around waist, high blood pressure, low blood pressure, HDL value, LDL value, triglyceride, A1C value etc and others can be expressed in terms of linguistic terms which can be again converted into fuzzy values for processing.

Fuzzy-Membership values can be found using the following expression

Weight around waist for men: $\int_{35}^{60} \frac{x-35}{25}$

Weight around waist for women: $\int_{32}^{60} \frac{x-32}{28}$

High triglyceride can be divided into three stages as normal, borderline high, reaching high and very high. These can be expressed as

Triglyceride Normal: $\int_{100}^{150} \frac{x-100}{50}$

Triglyceride borderline high: $\int_{150}^{200} \frac{x-50}{50}$

Triglyceride reaching high: $\int_{200}^{500} \frac{x-200}{300}$

Triglyceride very high: $\int_{500}^{\alpha} 1$

Low level HDL: $\int_{20}^{40} \frac{x-20}{20} + \int_{40}^{\alpha} \frac{1}{x}$

This value can be complemented to map correct interpretation.

Blood pressure can be expressed in terms of systolic/diastolic range. They can be expressed in terms of normal, pre-hypertension, HBP-stage-I, HBP-stage-II

Fuzzy membership for Blood pressure Systolic can be expressed as follows:

BP Normal can be expressed as: $\int_{100}^{120} \frac{x-100}{20}$

BP Pre-hypertension as : $\int_{120}^{129} \frac{x-120}{9}$

BP High-stage-I as : $\int_{140}^{159} \frac{x-140}{19}$

BP High-stage-II as : $\int_{160}^{\alpha} 1$

Fuzzy membership for Blood Pressure Diastolic can be expressed as follows:

BP Normal as : $\int_{50}^{80} \frac{x-50}{30}$

BP Pre-Hypertension as : $\int_{80}^{89} \frac{x-80}{9}$

BP Low-stage- I as : $\int_{90}^{99} \frac{x-90}{9}$

BP Low-stage-II as : $\int_{100}^{\alpha} 1$

Likewise wherever the numerical crisp values are available they are converted into fuzzy membership values and are used in forming the equations. Many symptoms are combined and expressed as one for e.g., s1 which is a combination of symptoms. Each individual symptoms are expressed in terms of fuzzy values and in order to form one single combination their min-max combination is considered.

Let Rs = P X S where μ_{Rs} (p, s) ($p \in P$, $s \in S$) This indicate the degree to which the symptom s is present in patient p.

Let Ro = S × D, where μ_{Ro} (s, d) ($s \in S$, $d \in D$) indicates the frequency of occurrence of symptom s with disease d.

Let Rc = S X D, where μ_{Rc} (s, d) corresponds to the degree to which symptom s confirms the presence of disease d.

In this example, we will determine the fuzzy occurrence and confirmability relations from expert medical documentation. Since this documentation usually takes the form of statements such as Symptom s seldom occurs in disease d or Symptom s always indicates disease d we assign membership grades of 1, 0.75, 0.5, 0.25 and 0 in fuzzy set Ro and Rc for the linguistic terms always, frequently, don't know, rarely and never, respectively. We use a concentration operation to model the linguistic very such that

$$\mu_{\text{very}A}(x) = \mu^2_A(x)$$

Assume that the following medical documentation exists concerning the relations of symptoms s1, s2, s3, s4, s5, s6 to diseases d1, d2, d3 and d4.

All missing relational pairs of symptoms and diseases are assumed to be unspecified and are given a membership grade of 5. From our medical documentation we construct the following matrices of relations Ro, Rc $\in$ S x D

$$Ro = \begin{array}{c} \\ s1 \\ s2 \\ s3 \\ s4 \\ s5 \\ s6 \end{array} \begin{array}{c} \begin{array}{cccc} d1 & d2 & d3 & d4 \end{array} \\ \begin{bmatrix} 1 & .75 & .75 & .5 \\ .75 & .25 & .25 & .5 \\ 0 & .06 & .75 & .25 \\ .25 & .75 & .06 & .25 \\ 0 & .75 & 1 & .25 \\ .25 & .25 & .5 & 1 \end{bmatrix} \end{array}$$

$$Rc = \begin{array}{c} \\ s1 \\ s2 \\ s3 \\ s4 \\ s5 \\ s6 \end{array} \begin{array}{c} \begin{array}{cccc} d1 & d2 & d3 & d4 \end{array} \\ \begin{bmatrix} .75 & .75 & .75 & .25 \\ 1 & .25 & .25 & .5 \\ 0 & 1 & .75 & .5 \\ .25 & 1 & .75 & .5 \\ 0 & .5 & 1 & .25 \\ .25 & .5 & .5 & 1 \end{bmatrix} \end{array}$$

Now assume that the given fuzzy relation Rs specifying the degree of presence of symptoms s1, s2, s3, s4, s5 and s6 for three patients p1, p2, p3 and p4 are as follows

$$Rs = \begin{array}{c} \\ p1 \\ p2 \\ p3 \\ p4 \end{array} \begin{array}{c} \begin{array}{cccccc} s1 & s2 & s3 & s4 & s5 & s6 \end{array} \\ \begin{bmatrix} .8 & .8 & .1 & 0 & 0 & .1 \\ .5 & .1 & .9 & .7 & .2 & .2 \\ .5 & .2 & .6 & .8 & 1 & .3 \\ .5 & .5 & .3 & .2 & .2 & 1 \end{bmatrix} \end{array}$$

Using relations Rs, Ro and Rc, we can now calculate four different indication relations defined on the set P×D of patients and diseases. The first is the occurrence indication R_1 defined as R_1= Rs ° Ro

For our example, R_1 is given by the following matrix:

$$R_1 = \begin{array}{c} \\ p1 \\ p2 \\ p3 \\ p4 \end{array} \begin{array}{c} \begin{array}{cccc} d1 & d2 & d3 & d4 \end{array} \\ \begin{bmatrix} .8 & .75 & .7 & .5 \\ .5 & .7 & .75 & .5 \\ .5 & .75 & 1 & .5 \\ .5 & .5 & .5 & 1 \end{bmatrix} \end{array}$$

The confirmability indication R_2 relation is calculated by R_2 = Rs ° Rc;

This results in

$$R_2 = \begin{array}{c} \\ p1 \\ p2 \\ p3 \\ p4 \end{array} \begin{array}{c} \begin{array}{cccc} d1 & d2 & d3 & d4 \end{array} \\ \begin{bmatrix} .8 & .75 & .75 & .5 \\ .5 & .9 & .75 & .5 \\ .5 & .8 & 1 & .5 \\ .5 & .5 & .5 & 1 \end{bmatrix} \end{array}$$

The nonoccurrence indication R_3 is defined as R_3 = Rs ° (1-Ro) and specified here

$$R_3 = \begin{array}{c} \\ p1 \\ p2 \\ p3 \\ p4 \end{array} \begin{array}{c} \begin{array}{cccc} d1 & d2 & d3 & d4 \end{array} \\ \begin{bmatrix} .25 & .75 & .75 & .5 \\ .9 & .9 & .7 & .75 \\ 1 & .6 & .8 & .75 \\ .75 & .75 & .5 & .5 \end{bmatrix} \end{array}$$

Finally, the nonsymptom indication R_4 is given by $R_4 = (1 - Rs) \circ Ro$
And equals

$$R_4 = \begin{array}{c} \\ p1 \\ p2 \\ p3 \\ p4 \end{array} \begin{array}{c} \begin{array}{cccc} d1 & d2 & d3 & d4 \end{array} \\ \begin{bmatrix} .25 & .75 & 1 & .9 \\ .75 & .75 & .8 & .8 \\ .75 & .5 & .5 & .7 \\ .5 & .75 & .8 & .5 \end{bmatrix} \end{array}$$

From these four indication relation we may draw different types of diagnostic conclusions. For instance, we may make a confirmed diagnosis if disease d for patient p if μ_{R2} (p, d) = 1. Although this is not the case for any of our four patients, does seem to indicate, for instance, that disease d3 is strongly confirmed for patient p3 and disease d4 for patient p4 whereas 90% chance of disease d2 for patient p2. We may make an excluded diagnosis for a disease d in patient p if μ_{R3} (p, d) = 1 or if μ_{R4} (p, d) = 1. In our example, we may exclude disease d1 as a possible diagnosis for patient p3, disease d2 and d3 are excluded for patient p1, disease d1 and d2 are exclude for patient p4 but likely to be affected by disease d3 and d4. Finally, we may include in our set of diagnostic hypotheses for patient p and disease d such that the inequality (Lucas, 1998, 1999; Tautu and Wagner, 1978)

$$0.5 < \max [\mu_{R1} (p, d), \mu_{R2} (p, d)]$$

is satisfied. In our example, both diseases d1 and d2 are suitable diagnostic hypotheses for patient p1 and diseases d2, d3 are suitable diagnostic hypotheses for patient p2 and diseases d3 for patient p3, whereas the only acceptable diagnostic hypotheses for patient p4 is disease d4.

CONCLUSION

In this 40 patients data has been collected and the above relation is formed with that. But for the purpose of understanding it is explained with 4 patients data which can be done the same way for hundreds of data also. The future work is to use fuzzy association for analyzing the data and use of fuzzy database to store the input and applying the fuzzy association method in this database for efficient diagnoses.

Fuzzy set theory is not an alternative tool, but an enhancement of classical AI approaches. By virtue of fuzzy sets, symbolic systems may exhibit continuous behavior and thus address medical problems more adequately.

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