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Classification and Analysis of Patients' diagnosis : A Case Study in Gynecology

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Abstract : The important factor in the medical field is disease-symptom knowledge base and symptom-patient relationship which influences the patients, disease diagnosis. Gynecological symptoms consisting of clinical findings, diagnosis and treatment of a disease involves uncertainty and imprecision. The symptoms narrated by patients lead to similar types with varying degree of occurrence and confirmability. As such, the patients need to be classified with respect to vaguely narrated symptoms.

Sanchez [1, 2] introduced a fuzzy relation R between symptom S and Disease diagnosis D which he refers to as *medical knowledge* which expresses the association between symptoms and disease diagnosis. In fact, the use of compositional rule of inference is being assumed [1,2] to describe the state of a patient in terms of diagnosis, and this very rule is also effectively used in the present research article.

In this present paper, the disease-symptom-patient relationship is being used to arrive at disease diagnosis in the initial screening process of differential diagnosis. The output of this initial screening process shows that the disease by which a patient is suffering from as well as the classification of patients, are completely dependent on the narrated symptoms. The paper also analyses the output of an initial screening process with the classification details. Besides other details of the study, it has been concluded that the patients suffering from same disease get classified in similar classes at certain possibility value.

Keywords: Fuzzy Logic, Max-Min Composition, Similarity Measures, Fuzzy Relational Calculus

I. INTRODUCTION

In the last two decades, system based on other paradigms like Information Theory and Fuzzy Set Theory has been developed. Isabel [Ramnarayan et al, 2003, 2004; Britto, 2004][3] is an information theory based pediatric diagnostic system. The early work in use of Fuzzy Set Theory for medical diagnosis was done by Sanchez [1979][2], Soula [1980], Esogbue [1979; 80][4], Adlassnig [1980; 1985; 1986; 1995][5-7] and Kolarz [1986; 1989][6,7] with their colleagues in Vienna. They developed the CADIAG systems for diagnosis of medical conditions such as rheumatic disorders and pancreatic diseases [8].

The medical knowledge mainly consists of symptom-disease relationship which constitutes one type of imprecision and uncertainty in the diagnostic process and the knowledge related to patient's state 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 Ultrasonic, X-ray etc. The knowledge provided by each of these sources carries with it varying degrees of uncertainty. The past history given by patient may be subjective, exaggerated, under estimated or incomplete. Mistakes may be made in the physical examination and symptoms may be overlooked. The measurements provided by laboratory tests are often of limited precision and the exact borderline between normal and abnormal pathological result is often unclear. The diagnostic tests 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. Considering the uncertainty in the observed symptoms of the patient and uncertainty in the relation of the symptom to a disease entity, it is hard for the physician to state that the diagnosis is accurate. However, the study reported in this sequel is centered on only the tactic knowledge of the identified eight gynaecologists and on the linguistic descriptions of the symptoms by the patients about the systems.

The desire to better understand and teach this difficult and important technique of medical diagnosis has prompted attempts to model the process with the use of Fuzzy Set Theory[10]. The prime characteristic of Fuzzy Set Theory is its capability of expressing knowledge in a linguistic way, allowing a system to be described by simple, human-friendly rules, which is known as interpretability, makes Fuzzy Set Theory attractive from medical point of view.

Gynecology (science of woman) refers to the health of Female Reproductive System as: Uterus, Vagina and Ovaries, while Obstetrics deals with the care of woman's reproductive tracts and their children during pregnancy (prenatal period), child birth and the postnatal period. Because of inherent uncertainty in the form of vagueness / fuzziness is resident in gynecology, in this paper, an attempt has been made to explore the possibility of using Fuzzy Set theoretic operations in medical decision making.
The remaining part of the paper is organized as follows. Section II details about the techniques used to achieve the objective. Section III demonstrates the approach to Fuzzy Relational Calculus in Gynecology. Section IV contains the case study in gynecological diseases in India while results and discussion are presented in Section V.

II. METHODOLOGY

Fuzzy Set

a. A fuzzy set $\underset{\sim}{A}$ is defined by an ordered pair, a binary relation –

$$\underset{\sim}{A} = \{(x, \mu_{\underset{\sim}{A}} (x)) \mid x \in X , \mu_{\underset{\sim}{A}} (x) \in [0,1]\} \quad (1)$$

Where $\mu_{\underset{\sim}{A}}(x)$ is a membership function which specifies grade or degree to which any element x in $\underset{\sim}{A}$ belongs to the fuzzy set $\underset{\sim}{A}$. $\underset{\sim}{A}$ is a fuzzy set; X is Universe or universe of Discourse. Elements with 0 degree of membership in a fuzzy set are usually not listed in the fuzzy set [9].

b. If the universe of discourse X is **discrete and finite**, fuzzy set $\underset{\sim}{A}$ is –

$$\underset{\sim}{A} = \left\{\frac{\mu_{\underset{\sim}{A}}(x_1)}{x_1} + \frac{\mu_{\underset{\sim}{A}}(x_2)}{x_2} + \ldots\right\} = \left\{\Sigma_i \frac{\mu_{\underset{\sim}{A}}(x_i)}{x_i}\right\} \quad (2)$$

c. If the universe of discourse X is **continuous and infinite**, fuzzy set $\underset{\sim}{A}$ is –

$$\underset{\sim}{A} = \left\{\int \frac{\mu_{\underset{\sim}{A}}(x)}{x}\right\} \quad (3)$$

Computational Rule of Inference: Max-Min Composition

Let R be a relation that relates, or maps, elements from universe X to universe Y and let S be a relation that relates, or maps, elements from universe Y to universe Z. We can find a relation, T that relates the same elements in universe X that R contains to the same elements in universe Z that S contains. This relation can be found out using composition operation. There are various forms of Fuzzy Composition; the paper uses max-min composition for the diagnosis.

Suppose R is a fuzzy relation on Cartesian product X x Y, S is a fuzzy relation on Y x Z and T is a fuzzy relation X x Z, then fuzzy max-min composition is defined in terms of the set theoretic notation and membership notation as follows[9].

T = R o S i.e.

$$\mu_T(x, z) = \vee_{y \in Y}(\mu_R (x, y) \wedge \mu_S (y, z) \quad (4)$$

In this approach formulated by Sanchez (1979)[1,2], the physician's medical knowledge is represented as a fuzzy relation between symptoms and diseases. The max-min composition corresponds to the fuzzy conditional statement "*if R then T by S*". 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.

Prof. Zadeh proposed the use of linguistic modifier which is commonly used. Amongst which we use 'Very' linguistic hedge to indicate very often & very seldom linguistic terms. The concentration operator takes the form as

$$A_{very}(x) = A^2(x) \quad (5)$$

From this basis, then the fuzzy set T of the possible diseases of the patient can be inferred by means of computational rule of inference. Using max-min composition procedure the indication relation is computed as –

$$R1 = Rs \text{ o } S \quad (6)$$

Similarity Measures in data manipulations

Cosine Amplitude Method

It makes use of a collection of data samples, n data samples. If these data samples are collected, they form a data array, $X = \{x_1, x_2, ... x_n\}$. Each of the elements x_i, in the data array X is itself a vector of length m, i.e.

$$X_i = \{ x_{i1}, x_{i2},\ldots\ldots x_{im}\} \quad (7)$$

Each of the data samples can be thought of as a point in m-dimensional space, where each point needs m coordinates for a complete description. Each element of a relation r_{ij}, results from a pair wise comparison of two data samples, say xi and x_j, where the strength of the relationship between data sample x_i and data sample x_j is given by the membership value expressing that strength i.e. $r_{ij} = \mu R(x_i, y_j)$. The relation matrix will be of the size n x n. The relation will be reflexive and symmetric so a Tolerance relation. The Cosine Amplitude method calculates r_{ij} as [9]:

$$r_{ij} = \frac{\left|\sum_{k=1}^{m} x_{ik} x_{jk}\right|}{\sqrt{\left(\sum_{k=1}^{m} x^2{}_{ik}\right)\left(\sum_{k=1}^{m} x^2{}_{jk}\right)}} \text{ , Where } 0 \le r_{ij} \le 1 \quad (8)$$

Max-Min Method

The method is computationally similar to Cosine Amplitude method. It is found through simple min and max operations on pairs of the data points x_{ij} and is given by [9]:

$$r_{ij} = \frac{\sum_{k=1}^{m} \min(x_{ik}, x_{jk})}{\sum_{k=1}^{m} \max(x_{ik}, x_{jk})} \quad (9)$$

If we look at the information about gynecological diseases and conditions including uterine fibroid tumours, ovarian cysts, Polycystic Ovarian Syndrome (PCOS) , endometriosis, and vulvodynia, as well as many other female reproductive system abnormalities, we get – Cervical Health (18), Common Uterine Conditions (2), Diseases of the Uterus (25), Ovarian Conditions (6), Vaginal Health(49) different category counts and their related symptoms for which a (Disease x Symptom) relation can be formed. When a patient comes to Gynecologist with the complaints and past history, the thought process of the doctor begins. Here the (Symptom x Patient) relation can be defined.

The computational framework proposes two types of fuzzy relations which exist between symptoms (s)- diseases (*d*). These are: Fuzzy Occurrence Relation (R_o) and Fuzzy Confirmability Relation (R_c). The first provides knowledge about the tendency or frequency 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 fuzzy relation describes discriminating power of the symptom to confirm disease; it corresponds to the question, *"How strongly does symptom,'s' confirm disease d?".* The distinction between Occurrence and Confirmability 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 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 disease. We then obtain the fuzzy relation R_s specifying the presence, absence or not-known status of symptom (*s*) for the patients[10].

Two relations R_o & R_c are gathered from many experts to get their opinion about Fuzzy Occurrence and Fuzzy Confirmation values in linguistic terms as often in natural language physicians use simple terms to receive symptom information from patient like - symptom 's' is always seen, symptom 's' is never seen etc. The model uses similar terms to describe terms linguistically as a beauty of Fuzzy Logic to deal with human language. The linguistic terms used are A – Always, O – Often, NS – Not Specific, S – Seldom, N-Never.

With this the Fuzzy Occurrence and Confirmability relations takes the form of statements as - "Symptom 's' Always occurs in disease D and Not specific confirms the disease".

To model the linguistic terms mathematically we assigned membership grades of 1, 0.75, 0.5, 0 in fuzzy sets R_o and R_c for the linguistic terms Always, Often, Not Specific, Never respectively. The use of Equation 5 in section II is made to get the membership values to linguistic hedge "Very" as – 0.5625 & 0.0625 to Very Often and Very Seldom respectively. Upon defining the relations and linguistic hedges, perceptions were received from many experts for the R_o and R_c relations.

Initial Screening[11]

The paper described a medical decision problem as - The fuzzy set framework has been utilized in several different approaches to model the diagnostic process. In the approach formulated by Sanchez [1979][1,2], the physician's medical knowledge is represented as a fuzzy relation between symptoms and diseases.

Let the crisp universal set of symptoms be $S = \{s_1, s_2, \ldots, s_n\}$ and the crisp universal set of diseases be $D=\{d_1, d_2, \ldots, d_m\}$. Let fuzzy set $A = (a_1, a_2, \ldots, a_n)$ be the fuzzy relation on the patient and the set S of symptoms, where $0 \le \alpha_j \le 1$; j =1, 2, …. , n. fuzzy set A is given by physician's diagnosis. Let R be the fuzzy relation on the set S of symptoms and the set D of diseases. From this relation R, the two fuzzy relations R_o & R_c are defined. If there are k patients, then the crisp universal set of patients are $P = \{p_1, p_2, \ldots, p_k\}$. Let Q be the fuzzy relation on the set P of patients and the set S of symptoms. Let R_s be the fuzzy relation on the set S of symptoms and the set P of Patients.

Using relations R_o, R_c (section II) and R_s, we can now calculate for different indication relations defined on the universal set P x D of patients and diseases. The fuzzy set R_1 of the possible diseases of the patient can be inferred by means of compositional rule of inference, which we call it as Fuzzy Occurrence Indication relation. (Equation 6)

$R_1 = R_s \circ R_o \equiv (b_1, b_2, \ldots, b_m)$ which is given by:

$$R_{1j} = (s_1 \wedge r_{o1j}) \vee (s_2 \wedge r_{o2j}) \vee \cdot \cdot \cdot \vee (s_n \wedge r_{onj}).\ j=1, 2, \ldots m. \quad (10)$$

Similarly the fuzzy set R_2 we calculate Fuzzy Confirmation Indication relation. (Equation 10) (System Flow Chart step 7). From these indication relations different diagnostic conclusions could be drawn that would ultimately result into the decision on *p-d* relationship. For calculating the final diagnostic indication, R - the intersection operation over R_1 and R_2 was used.

$$R = \text{Min}\,(R_1, R_2) \tag{10}$$

If R = 1, we conclude patient p suffers from disease d for the specific entry of R.

Here ends the Initial screening process which if results in single disease outcome, the diagnosis ends else to rule out one disease from the output of initial screening, physical examination, further tests like, USG, X-ray, Blood tests are carried out to arrive at final diagnosis[11].

The study related to the investigations carried out in Pune, Ahmednagar and Ambejogai, India to finally arrive at patient / disease matrix using Fuzzy Set Theory is carried out by a group of eight domain experts (gynaecologists), a fuzzy logic professional and a computer scientist in Pune. The domain experts, based on their 20 years experience confirmed that there are 31 commonly observed gynaecological diseases and 123 related symptoms. The experts need not have to read the books nor to look at their hospital records to write down their expertise on symptom/disease occurrence and confirmation relationship linguistic classes. The expert's perception based on their tactic knowledge with approximate reasoning is key to success in medical diagnosis.

The first part of the case study focuses on classifying the experts depending on their perceptions. The suggested computational procedure for this classification is based on the two similarity measures: 1 Cosine Amplitude method and 2. Max-Min method. The second part of the case study initiates the process of initial screening to arrive at some diagnosis by one expert and also with multiple experts.

The medical documents are not expressed using probability and not mathematically but linguistically as stated in section III. So a different approach is needed to model this type of method. While collecting the expert's perception, the experts recorded their views linguistically and the respective membership values (mentioned in bracket) as –

A - Always (1), Very Often - VO (0.5625), O - Often (0.75), NS - Not Specific (0.5), S - Seldom (0.25), VS - Very Seldom (0.0625) and N - Never (0) - were to tabulate the Fuzzy Occurrence and Fuzzy Confirmation relations [11].

The Computational Procedure

To explain the computational procedure, a sample set of 9 diseases (out of 31 identified), 17 related symptoms (out of 123) are considered as shown in Table1 and the names of diseases and symptoms:. We presuppose that if symptom s_j is not a symptom of disease d_i, then the fuzzy occurrence and confirmation table entries for the $[d_i, s_j]$ will be 'Never' i.e. '0'. In this illustrative example, 'Never' or '0' entry symptoms are not considered as they result in '0' value after the application of max-min calculation. (Table 1). Similar is the case with Patient-Symptom relationship [11].

TABLE 1

COMPUTATION OF FUZZY CONFIRMABILITY RELATION QUERY:"HOW STRONGLY DOES SYMPTOM 'S' CONFIRM WITH DISEASE D?"

	S_1	S_2	S_3	S_4	S_5	S_6	S_7	S_8	S_9	S_{10}	S_{11}	S_{12}	S_{13}	S_{14}	S_{15}	S_{16}	S_{17}
D_1	N	N	N	N	N	N	VS	N	O	N	A	A	O	N	N	N	N
D_2	N	N	O	N	N	N	N	N	O	N	N	N	N	A	O	A	N
D_3	N	O	O	A	O	A	A	A	O	N	N	N	N	N	N	N	N
D_4	N	N	N	A	N	A	N	N	A	N	N	N	N	N	N	N	N
D_5	N	N	N	N	VO	A	A	A	N	O	N	N	N	N	N	N	N
D_6	VO	N	N	N	N	N	VO	N	O	N	A	VO	US	N	N	US	N
D_7	O	N	VO	A	N	N	N	N	A	N	N	N	N	N	O	N	N
D_8	O	O	A	VO	O	N	N	N	N	N	VO	N	N	N	N	A	S
D_9	N	N	N	N	N	N	N	N	N	US	A	N	N	N	N	N	N

Case Study Part I : Initial Screening Using Fuzzy Relational Calculus

To follow the initial screening part of research study, the data on patient/symptom matrix is collected from three different hospitals in Pune and Ambejogai, India, by interviewing the patients so as to avoid collecting happenstance data in statistics. During the personal conversation with the patients, questions were asked about their complaints, past history, age, Last Menstrual Period (LMP), Pre-Menstrual Changes (PMC) details, number of children, history about hypertension, Diabetics etc. This patient's data of 226 patients was initially scanned by the experts and a sample set of 9 patients is considered here (Table 2). The max-min procedure mentioned in section II was followed and the software developed is using C# DOTNET as platform to process the information set[13].

TABLE 2

PATIENT SYMPTOM RELATION

	P_1	P_2	P_3	P_4	P_5	P_6	P_7	P_8	P_9
S_1	0	0	0	0	0	0.5	0	0	0
S_2	0	0	0	0	0	0	0	0	0
S_3	1	0	0	0	1	0	0	0	1
S_4	1	0	0	0	1	1	0	0	0.5
S_5	0	1	0	0	0	0	0	0	0
S_6	0	0	0	0	0	0	1	0	0
S_7	0	0	0	0	0	0	0	0.5	0
S_8	0	0	0	0	0	0	1	0	0

S_9	0	0	0	0	0	0	0	0	0
S_{10}	0	0	0	0	0	0	0	0	0
S_{11}	0	1	0	1	0	1	0	0	0
S_{12}	0	0	0	0	0	0	0	0	0
S_{13}	0	0	0	0	0	0.5	0	0	0
S_{14}	0	0	0	0	0	0	0	0	0
S_{15}	0	0	0	0	0	0	0	0	0
S_{16}	0	1	1	0	0	0	0.5	0.5	0
S_{17}	0	0	0	0	0	0	0	0	0.5

Typical max-min calculation procedure is as follows -

(X_2,Z_1) = Max (min(0,0), min(0,0), min(0.5625,1), min(0,1), min(0,0), min(0,0), min(0,0), min(0,0), min(0.5625,0), min(0 ,0), min(0,0), min(0,0), min(0,0), min(1,0), min(0.5625,0), min(1,0), min(0,0))

= Max(0,0,0.5625,0,0,0,0,0,0,0,0,0,0,0,0,0,0) = 0.5625

Using this procedure, we have obtained Fuzzy Occurrence Indication Relation and Fuzzy Confirmability Indication Relation[13].

Case Study Part II : Patients Classification

To explain the computational procedure of fuzzy similarity measures for classification of patients, out of 226 patients and 123 related symptoms, a sample set of 9 patients and 8 related symptoms are considered.

After application of the cosine amplitude (Equation 4) and max-min method (Equation 5), we get relation R which is fuzzy tolerance relation which is converted to fuzzy equivalence relation (Equations 3, 7, 8) and the resultant matrix of size 9 x 9 which is shown in Table 3 and 4 respectively [12].

TABLE 3

CLASSIFICATION OF PATIENTS: FUZZY EQUIVALENCE RELATION OBTAINED USING COSINE AMPLITUDE METHOD (9 PATIENTS, 8 SYMPTOMS)[12]

	P_1	P_2	P_3	P_4	P_5	P_6	P_7	P_8	P_9
P_1	1	0.754	0.657	0.37	0.37	0.616	0.5	0.616	0.37
P_2	0.754	1	0.657	0.37	0.37	0.616	0.5	0.616	0.37
P_3	0.657	0.657	1	0.37	0.37	0.616	0.5	0.616	0.929
P_4	0.37	0.37	0.37	1	0.806	0.37	0.37	0.37	0.806
P_5	0.37	0.37	0.37	0.806	1	0.37	0.37	0.37	0.37
P_6	0.616	0.616	0.616	0.37	0.37	1	0.5	1	0.37
P_7	0.5	0.5	0.5	0.37	0.37	0.5	1	0.5	0.37
P_8	0.616	0.616	0.616	0.37	0.37	1	0.5	1	0.37
P_9	0.37	0.37	0.929	0.806	0.37	0.37	0.37	0.37	1

TABLE 4

CLASSIFICATION OF PATIENTS: FUZZY EQUIVALENCE RELATION OBTAINED USING MAX-MIN METHOD (9 PATIENTS, 8 SYMPTOMS)[12]

	P_1	P_2	P_3	P_4	P_5	P_6	P_7	P_8	P_9
P_1	1	0.61	0.39	0.188	0.188	0.39	0.333	0.39	0.188
P_2	0.61	1	0.39	0.188	0.188	0.39	0.333	0.39	0.188
P_3	0.39	0.39	1	0.188	0.188	0.39	0.333	0.39	0.188
P_4	0.188	0.188	0.188	1	0.806	0.188	0.188	0.188	0.78
P_5	0.188	0.188	0.188	0.568	1	0.188	0.188	0.188	0.568
P_6	0.39	0.39	0.39	0.188	0.188	1	0.333	1	0.188
P_7	0.333	0.333	0.333	0.188	0.188	0.333	1	0.333	0.188
P_8	0.39	0.39	0.39	0.188	0.188	1	0.333	1	0.188
P_9	0.188	0.188	0.188	0.78	0.568	0.188	0.188	0.188	1

Same methods are applied to all 226 patients and 123 symptoms to get the resultant fuzzy equivalence relation to arrive at final conclusion.

III. ANALYSIS

The first part of the case study, i.e. in initial screening part, Fuzzy Occurrence and Fuzzy Confirmability indication relations are computed using Equation 6.

Table 5 shows the result of classification of all 226 patients at possibility value 1. The patients not shown in the Table 5 are not yet got classified in any class at defined possibility value 1.

TABLE 5
PATIENT CLASSES USING COSINE AMPLITUDE AND MAX-MIN METHOD
(ALL 226 PATIENTS)

Cosine Amplitude Method	Max-Min Method
(1, 42, 144), (5, 50), (9, 102), (19, 162), (22, 215, 225), (28, 44), (35, 151,165), (57, 198, 220), (60, 89), (117, 148, 155), (119, 172, 222), (143, 149), (189, 205), (223, 224)	(5, 50), (9, 102), (19, 162), (22, 215, 225), (28,44), (35, 151, 165), (1, 42, 144), (28, 43) (60, 89), (117, 148, 155), (119, 172,222), (143, 149), (157, 198, 220), (189, 205), (223, 224)

Table 5 shows, patients P_1, P_{42} and P_{144} get classified in one class, patients P_5 and P_{50} in another class and so on. Table 6 shows the actual analysis of diagnosis of patients for some of the classes, which is exactly same, indicating the classification of patients correctly matches with the diagnosis of the patient using Initial screening. It can be observed that the patients P_1, P_{42} and P_{144} get classified in one class using Fuzzy similarity measures techniques and the initial screening model gives the same diagnosis as "Uterine Prolapse". Same is the case with remaining patients.

TABLE 6
ANALYSIS OF INITIAL SCREENING MODEAL AND CLASSIFICATION MODEL
(ALL 226 PATIENTS)

Class	Patient Id	Disease suffering from
(P_1, P_{42}, P_{144})	P_1	Uterine Prolapse ,
	P_{42}	Uterine Prolapse
	P_{144}	Uterine Prolapse
(P_5, P_{50})	P_5	PID
	P_{50}	PID
(P_9,P_{102})	P_9	Abortion
	P_{102}	Abortion
(P_{19}, P_{162})	P_{19}	Dysfunctional Uterine Bleeding (DUB) , Uterine Fibrobid , Adenomyosis
	P_{162}	Dysfunctional Uterine Bleeding (DUB) , Uterine Fibrobid , Adenomyosis

IV. CONCLUDING REMARKS AND FUTURE SCOPE FOR RESEARCH

It can be concluded that the diagnosis by the model exactly correlates with the output of classification output. The patients get classified exactly as per the diseases they suffer from. The case study demonstrates the utility of one of the soft computing approaches in medical diagnosis, and suggests a twofold modelling approach. Initial screening or short listing of patient- wise diseases followed by a refined model using additional data should be able to arrive at the correct diagnosis. In the study the output of initial screening process is checked against the actual diagnosis given by the experts. The overall accuracy is 87.12%. The result of classification of patients using the two fuzzy similarity measures shows exactly similar classification. This classification in turn is verified with the output of initial screening which gives 100% match. So we can conclude that the patients suffering from same disease get classified in similar classes at possibility value 1.

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