ISSN: 2277-9655
Scientific Journal Impact Factor: 3.449
(ISRA), Impact Factor: 1.852

IJESRT

INTERNATIONAL JOURNAL OF ENGINEERING SCIENCES & RESEARCH TECHNOLOGY

Framing Fuzzy Rules using Mamdani Model for Effective Sickle Cell Diagnosis

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Abstract

In the world of medicine fuzzy logic play an important role in medical field for effective diagnosis. Fuzzy system has been effectively applied to solve the problems, classification and modeling in significant number of applications. Nowadays applying the fuzzy logic is increasing in the field of medical diagnosis gradually. In this paper we have shown how mamdani model and fuzzy rules combine together for proficient and cost effective diagnosis of hemoglobin disease-sickle cell anemia.

Keywords: Fuzzy logic , Memdani Model, Fuzzy rule, sickle cell anemia, medical diagnosis.

Introduction

Hemoglobin disease are a group of blood disorders passed down through families in which there is an abnormal production or structure of the hemoglobin protein. Hemoglobin disease happens when the part of the red blood cell that carries oxygen throughout the body is changed. This part that is changed is called hemoglobin. Hemoglobin is important because it picks up oxygen in the lungs and carries it to the other parts of the body. The most common examples of hemoglobin disease are sickle cell anemia. Sickle cell anemia is caused by an abnormal type of hemoglobin called hemoglobin S [1].Hemoglobin is a protein inside red blood cells that carries oxygen to the body's tissues. In sickle cell disease the red blood cells become fragile and shaped like crescents or sickles. These abnormal cells deliver less oxygen to the body's tissues. People with sickle cell disease can develop anemia. They also may have some jaundice and body pain [2].

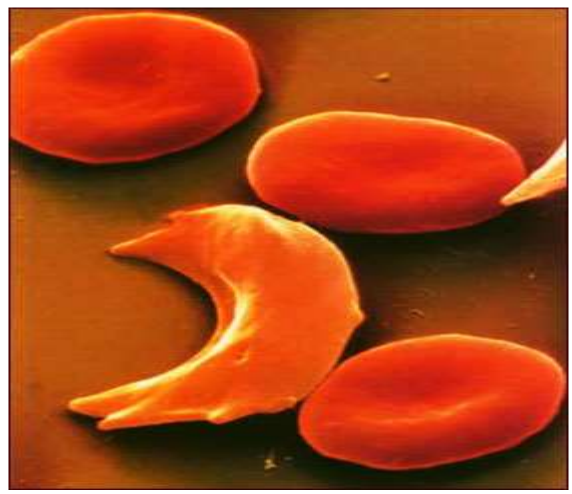

Figure 1- shap of the red blood cell in sickle cell anemia

ISSN: 2277-9655
Scientific Journal Impact Factor: 3.449
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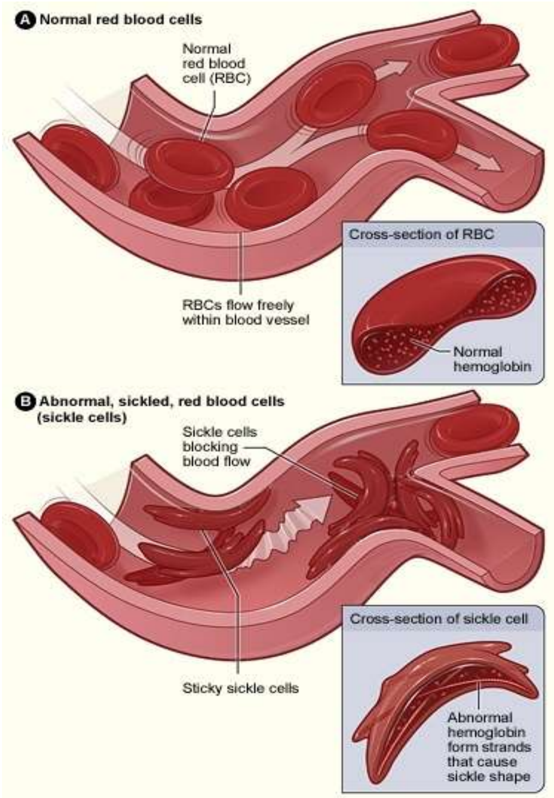


Figure 2- abnormal red blood cell in sickle cell anemia

Fuzzy logic is a method to provide specific path for diagnosis and decision making because of their approaches to deal with uncertainties and ambiguity in the knowledge and information. In the world of medicine fuzzy logic play an important role in medicine field for suggestive diagnostic remedies. The Medical practitioners identified possible and promising areas for implementation of fuzzy logic for medical diagnosis. Fuzzy systems have been effectively applied to problems in classification, modeling control and in a significant number of applications. In many fields of medicine fuzzy logic based approaches have been developed and used. Nowadays applying the fuzzy system is increasing in the field of medical diagnosis gradually. FL is based on Fuzzy Set Theory that was established by Lofti A. Zadeh in 1965.Currently, fuzzy sets are equipped with their own mathematical foundations, rooting from set theory basis and multi-valued logic (Braae and Rutherford 1979) [3].In this paper we have shown how Memdani Model with fuzzy rules combines together for proficient and cost effective diagnosis of sickle cell anemia. Fuzzy set theory and fuzzy logic are highly suitable for developing knowledge based system in medical field for diagnosis of diseases. This paper is organized as follows in section 2 the proposed method is described. In section 3 framing of fuzzy rules have been explained and in section 4, 5 and 6 experimental results with system and conclusion are given.

Proposed method

The proposed method is an extended version of E.P.Ephzibah and Dr.V.Sundarapandian, they developed a fuzzy expert system for effective diagnosis of heart disease [4]. In this paper the rules are generated based on the support sets. The dataset is built up from the blood test carried out on a patient and by the symptoms from which they are suffering. It contains elements of three classes: patients with primary, secondary and without sickle cell disease. The proposed method consists of three inputs, one output and ten rules are considered. Present system is used for diagnosis of sickle cell. This diagnosis is based on three input variables (1) symptoms score expressed as a percentage of severity of symptoms, (2) hemoglobin A and (3) hemoglobin S. A fuzzy set is a collection of different objects with different degree of membership. The membership value takes interval in between 0 to1.A fuzzy inference model can be created using the properties of fuzzy set. There are two major models of fuzzy system, Mamdani [5] and Takagi-Sugeno (T-S) [6] model. Mamdani type fuzzy systems use linguistic fuzzy sets as resulting variables in fuzzy rules but in the T-S type fuzzy systems employ a linear combination of input variables as a rule resulting variable. Sugeno method of fuzzy inference was Introduced in 1985 [Sug85], it is similar to the Mamdani method in many respects. First two parts of the fuzzy inference system, fuzzifying the inputs value and applying the fuzzy operator are exactly same the main difference between Mamdani and Sugeno is that the Sugeno output membership functions are either linear or constant. This work has been implemented using Mamdani type. Based on the expert's knowledge, experience and through the information fuzzy rules were created. These formed rules help us to guess the disease using fuzzy device. The input is the score of symptoms and blood test [Hbl A, Hbl S] and the output of the system is to get a value 1 to 0 that indicates the severity of the disease.

Mamdani fuzzy model

The most commonly used fuzzy inference model is Mamdani method (Mamdani & Assilian, 1975) which was proposed, by Mamdani and Assilian. Their work was inspired by Zadeh (Zadeh, 1973) [7]. In Mamdani's model the fuzzy inference is modeled by Mamdani's minimum operator, the conjunction operator is min, the t-norm from

ISSN: 2277-9655
Scientific Journal Impact Factor: 3.449
(ISRA), Impact Factor: 1.852

compositional rule is min and for the aggregation of the rules the max operator is used. They used this proposed method to explain the working with the rules, Such that

Rule1: IF x is A_1 OR y is B_1 THEN z is C_1
Rule2: IF x is A_2 AND y is B_2 THEN z is C_2
Rule3: IF x is A_3 THEN z is C_3

if part of the rule, "*x* is A" is called antecedent or premise, while then part of the rule, "*y* is B_1" is called consequent or conclusion.

The process of fuzzy logic is that:

Step 1: Fuzzification-The first step is to take the crisp inputs, x_0 and y_0 and determine the membership value of these inputs belong to each of the proper fuzzy sets. According to Fig3 (a) one obtains

$\mu\ A_1(x_0) = 0.5$, $\mu\ A_2(x_0) = 0.2$, $\mu B_1(y_0) = 0.1$, $\mu B_2(y_0) = 0.7$

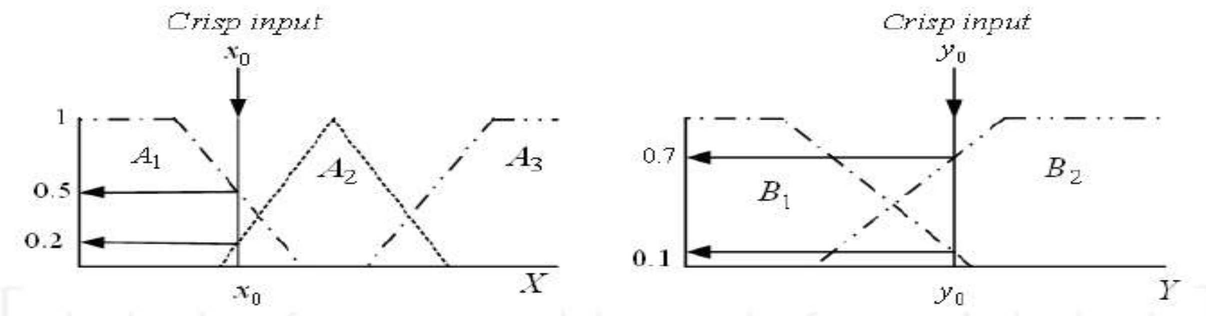
The fuzzified inputs are applied to the antecedents of the fuzzy rules. The fuzzy operator (AND or OR) is used to obtain a single number that represents the result of the antecedent estimation. To evaluate disjunction of the rules antecedents, Operation [OR] union is used:

$\mu_{A\cup B}(x) = \max\{\mu_A(x), \mu_B(x)\}$

Similarly, in order to evaluate the conjunction of the rule antecedents, the [AND] intersection is applied:

$\mu_{A\cap B}(x) = \min\{\mu_A(x), \mu_B(x)\}$

The result is given in the Figure 3(b). To find the membership function of the consequent, the most common method is to cut the consequent membership function at the level of the antecedent truth; this method is called clipping. Because top of the membership function is sliced, the clipped fuzzy set loses some information. However, clipping is preferred because it involves fewer complexes and generates an aggregated output surface that is easier to defuzzifying. Another method, named scaling, provide a better approach for preserving the original form of the fuzzy set. (See Figure no.3(c)).just see blow figure no. 3(a,b,c).



(a) Fuzzification

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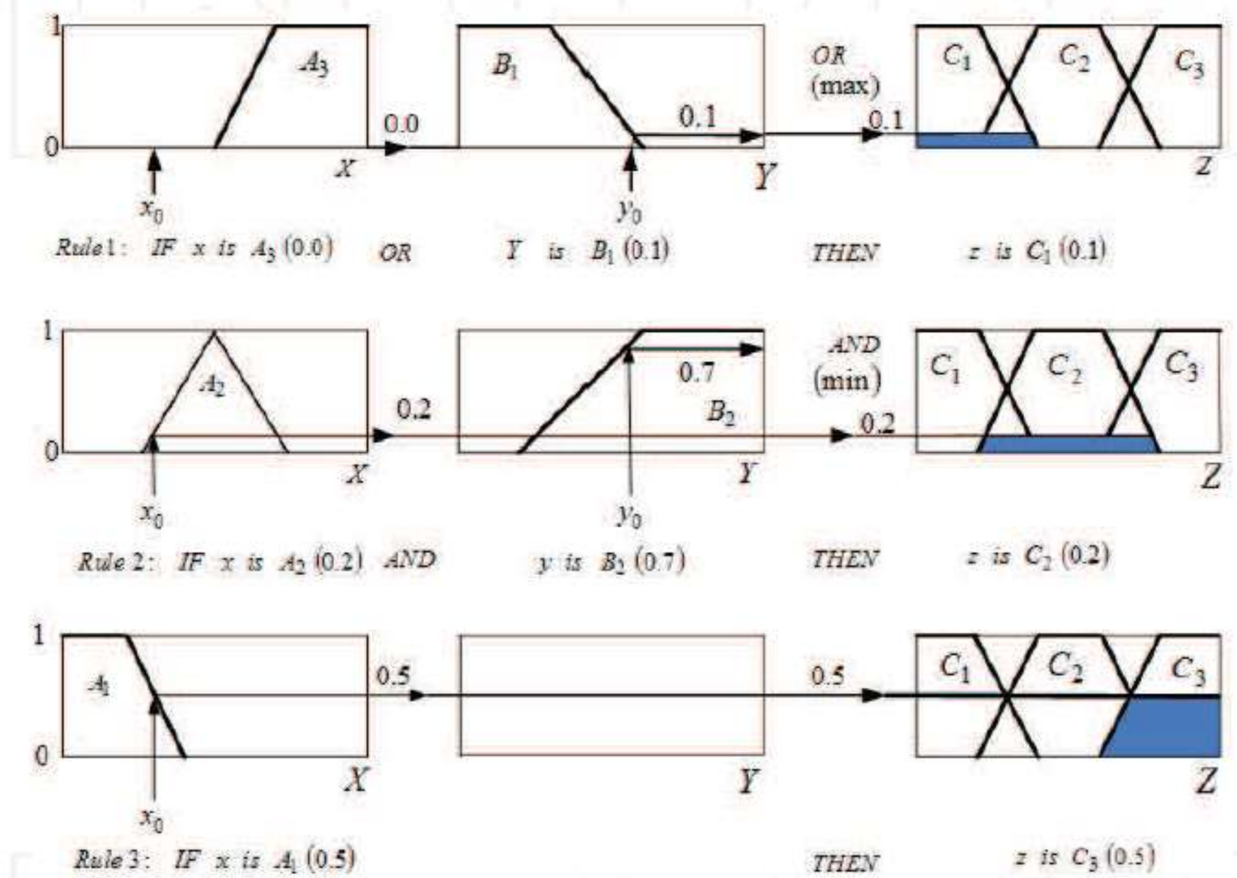
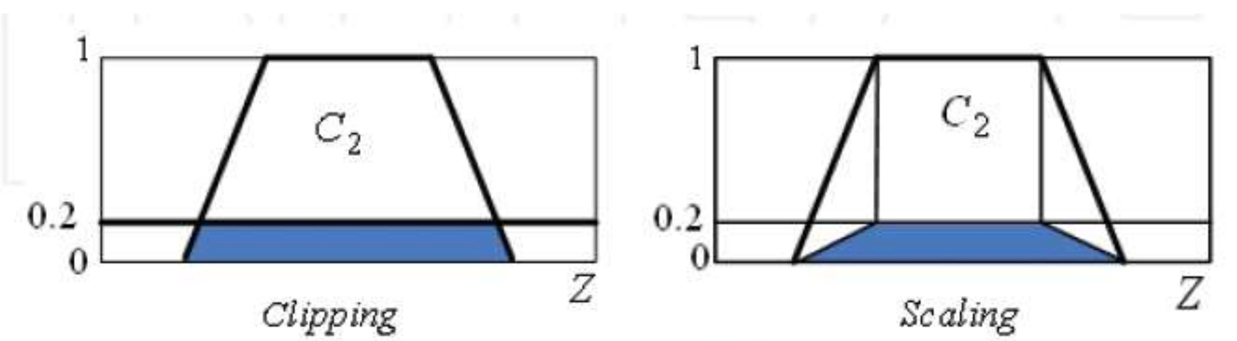


(b) Rules evaluation



(c) Clipping and scaling

Figure no.-3(a,b,c)

Step 3: Aggregation of the rule outputs

The memberships functions of all rule consequents previous clipped or scaled are combined into a single fuzzy set (see Fig. 4(a)).

Step 4: Defuzzification

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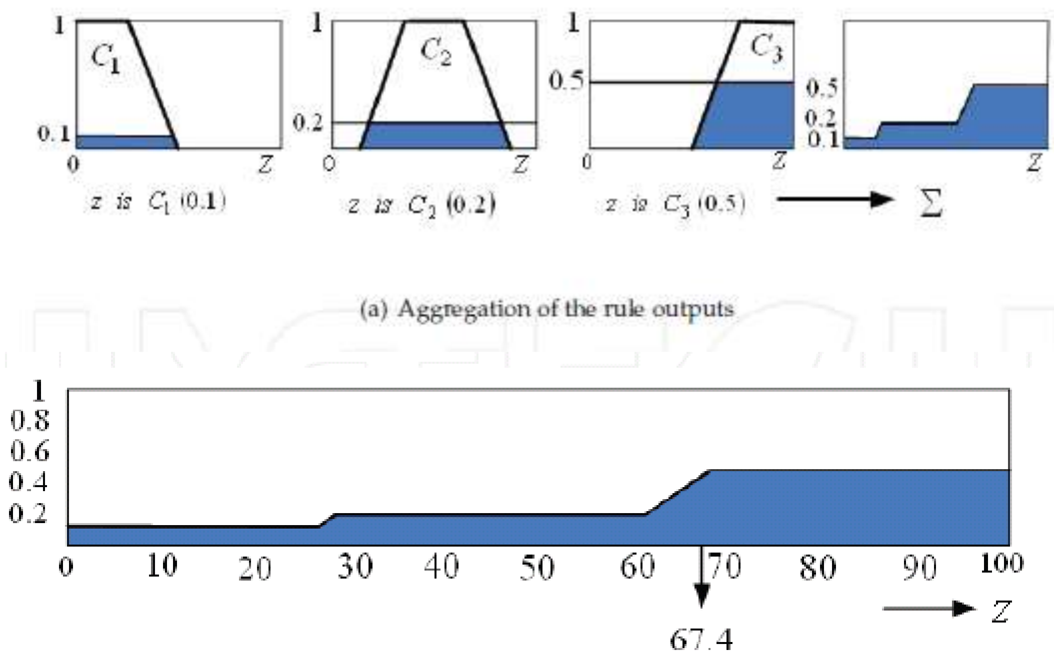
The most accepted defuzzification method is the centroid method. It finds a point representing the center of gravity (COG) of the aggregated fuzzy set A, on the interval [a, b].A practical estimation can be obtained by calculating it over an example of points. According to (Fig. 4(b)) in our case results

$$COG = \frac{(0+10+20)\times 0.1 + (30+40+50+60)\times 0.2 + (70+80+90+100)\times 0.5}{0.1+0.1+0.1+0.2+0.2+0.2+0.2+0.5+0.5+0.5+0.5} = 67.4$$



(b) Defuzzification

Figure no. 4(a, b)

Framing fuzzy rules

Fuzzy set operations are similar to crisp set operations. In Fuzzy Logic, the truth of any statement is a matter of degree. Fuzzy Logic operators are defined as follows:

The logical OR operator denotes the elements that belong to either the set A or B or both sets A and B and is identical to the union operator. The logical AND operator denotes the elements that belong to both sets A and B and is identical to the intersection operator. The logical NOT operator denotes the complement of a set A. The answer is max, min and complements operations. These operators are defined, respectively, as

$\mu_{A\cup B}(x) = \max\{\mu_A(x),\mu_B(x)\}$

$\mu_{A\cap B}(x) = \min\{\mu_A(x),\mu_B(x)\}$

$\mu_{A'}(x) = 1- \mu_A(x)$

Fuzzy inference systems have if–then rules that indicate a relationship between the input and output fuzzy sets. Fuzzy relations present union or interaction between the elements of two or more sets. Let U and V be two universes of discourse. R (U, V) is a fuzzy relation in the product space U x V and is characterized by the membership function $\mu_R(x,y)$ where $x\in U$ and $y\in V$ and $\mu_R(x,y)\in[0,1]$. Fuzzy relations play a vital role in fuzzy inference systems. Interpreting an if–then rule involves two distinct steps. The first step is to evaluate premise which involves fuzzifying the input and applying any necessary fuzzy operators. The second step is inference or applying the result of the premise to conclusion, which is mainly, evaluates the membership function.

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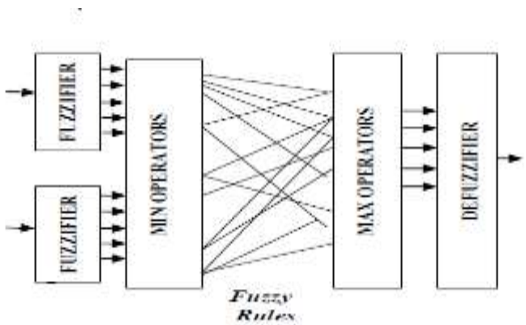

Figure no- 5

It was Mamdani (1977) who first proposed the minimum implication, and later Larsen (1980) proposed the product implication. A fuzzy rule base system must have a set of fuzzy rules R. A single if–then rule assumes the form "if x is Z_X then Y is Z_Y". An example of a rule might be "if hemoglobin A is low and hemoglobin S is high then patient have sickle cell anemia". For a multiinput and multioutput system, the rules are represented as R = (R1, R2, R3,….Rn).

Table 1 shows sample fuzzy rule base for sickle cell. The rule base for sickle cell has symptoms score, hemoglobin A and hemoglobin S as input parameters to the system. These input parameters were used to generate 10 rules for the inference model for sickle cell disease.

Some of the rules can be interpreted as follows:

Rule 1: If symptoms score is low and hemoglobin A is normal and hemoglobin S is absent Then no sickle cell.

Rule 2: If symptoms score is low and hemoglobin A is low and hemoglobin S is absent Then no sickle cell.

Rule 3: If symptoms score is low and hemoglobin A is medium and hemoglobin S is absent Then no sickle cell.

Rule 4: If symptoms score is medium and hemoglobin A is normal and hemoglobin S is present Then primary stage of sickle cell.

Rule 5: If symptoms score is medium and hemoglobin A is low and hemoglobin S is present Then secondary stage sickle cell.

Rule 6: If symptoms score is medium and hemoglobin A is medium and hemoglobin S is present Then secondary stage sickle cell.

Rule 7: If symptoms score is sever and hemoglobin A is low and hemoglobin S is present Then secondary stage of sickle cell.

Rule 8: If symptoms score is sever and hemoglobin A is low and hemoglobin S is absent Then primary stage of sickle cell.

Rule 9: If symptoms score is medium and hemoglobin A is medium and hemoglobin S is absent Then subclinical stage of sickle cell.

Rule 10: If symptoms score is sever and hemoglobin A is normal and hemoglobin S is absent Then subclinical stage of sickle cell.

Table no 1- Rule Antecedent & Rule Consequence:

Rule No.	Antecedent [IF]			Consequence Sickle Cell
	Symptoms Score	**Hlb A**	**Hlb S**	**[THEN]**
1	Low	Normal	Abs	No Sickle cell
2	Low	Low	Abs	No Sickle cell
3	Low	Med	Abs	No Sickle cell
4	Med	Normal	Pres	Primary
5	Med	Low	Pres	Secondary
6	Med	Med	Pres	Secondary
7	Sever	Low	Pres	Secondary
8	Sever	Low	Abs	Primary
9	Med	Med	Abs	Subclinical
10	Sever	Normal	Abs	subclinical

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Experimental results

The process of fuzzy inference model is that: First step is fuzzyfication in which crisp value of input data are gathered and converted to fuzzy membership value using fuzzy linguistic variables and degree of membership functions. After that an assumption is made based on set of rules and finally, in the defuzzification step resulting fuzzy output value is converted in to crisp output value using the membership functions. Using fuzzy linguistic variable and membership functions are defined based on the expert's knowledge and advice. The output field refers to the presence and absence of sickle cell disease in the patient.

About the features and their fuzzy values:

The first input variable is the symptoms score type for which there are 3 values like low, medium and high. High and medium is the support set for Sickle cell patients where as the low type is in the support set for no sickle cell disease. The next input variable is hemoglobin A. There are three fuzzy regions namely, "low", "medium" and "normal". The value for low and medium Hbl A belongs to the support set for sickle cell patients. The value for normal Hbl A belongs to the support set for no sickle cell disease. The next input is the hemoglobin S, for which there are two values like "absent" or "present". The value "present" is in the support set for patients with sickle cell disease. "absent" value is in the support set for patients with no sickle cell disease. The output shows the stages of the sickle cell disease in the patient.

System testing

About the input/output features and their membership values:

Input value and their membership value-

Symptoms score- Low- 0-2.5
Med- 2-5.5
High- 5-10

Hemoglobin A- Low- 0- 0.5
Med- 0.4-0.7
High- 0.6-1

Hemoglobin S- Absent- 0-.02
Present- 0.01-1

Output value and their membership value-

Normal - 0-0.20
Subclinical - 0.15-0.4
Primary - 0.3-0.6
Secondary - 0.5-1

Table No.2 testing result

Patient no.	Symptom Score	Hbl- A	Hbl- S	Output of FIS	Doctors Diagnosis
1	4	0.6	0	0.4	Subclinical
2	8	0.4	0.3	0.6	Primary
3	2	0.5	0	0.2	No Sickle Cell
4	5	0.1	0.4	0.7	Secondary
5	4	0.4	0	0.3	Subclinical
6	9	0.2	0.5	0.85	Secondary
7	0.25	0.5	0	0.2	No Sickle Cell
8	6	0.4	0	0.4	Subclinical
9	4	0.4	0.6	0.8	Secondary
10	7	0.6	0.5	0.6	Primary

Conclusion

In this paper a system that combines together memdani model and fuzzy rules for proficient and cost effective diagnosis of sickle cell anemia. This fuzzy inference system with mamdani model in contrast with other methods improves results. The expert's information, knowledge and support sets have been used in framing the fuzzy rules. The proposed model proves to be more capable, efficient and cost effective in diagnosing sickle cell disease.

ISSN: 2277-9655
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