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Application of Fuzzy Logic for Presentation of an Expert Fuzzy System to Diagnose Anemia

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Abstract

There has been an accumulation of data in medical centers and interpreting the tacit knowledge in such raw data is extremely helpful for disease diagnosis, stemming reasons of an illness and efficacious actions for curing it. In this study, we employed a fuzzy logic approach to propose a model to diagnose some cases of Anemia or being aware of high probability of its occurrence.

Keywords: Anemia, Anemia Diagnosis Fuzzy Model, Expert Fuzzy System, Fuzzy Logic

1. Introduction

Anemia is a common disease particularly in Iran afflicting people from different age groups[1]. There are a large number of people suffering from different types of Anemia. Since Anemia has various symptoms some of which are similar to symptoms of other diseases, it is difficult to either diagnose it or pinpoint its probability. Fuzzy set approaches are introduced as one of the methods providing proper precision and interpretability[2].

A fuzzy based algorithm consists of if-else fuzzy rule sets to enable Experts to interpret. The article is organized as follows: In section 2 Anemia is explicated. Definition of fuzzy systems and method used for producing rules in this article are presented in section 3 and 4, respectively. Section 5 includes if-else fuzzy rules and employed fuzzy system is explained in section 6. System simulation is presented in section 7 and finally section 8 concludes the paper.

2. Anemia Disease

In order to analyze information as well as collecting and extracting data mining rules we considered laboratory of Amol medical center as an information source.

The mentioned database includes five common characteristics to diagnose different types of Anemia. These characteristics are as follows:

Irritability, asthma, tachycardia, memory weakness and nose bleeding. Anemia is a disease which leads to shortage of red blood cells needed to provide sufficient Oxygen. Recognizing different types of this disease will help us to detect its symptoms and to prevent it.

3. Types of Anemia

In this subsection we introduce most common types of Anemia.

- Iron deficiency Anemia: Iron deficiency is referred to circumstances where the amount of Iron existing in blood is decreased drastically. This kind of Anemia is common between teenagers and women before their Menopause. Blood loss due to menstruation, internal bleeding in stomach and intestine, excessive blood donation may result in this disease. Moreover, wrong food habits or sever intestine disease may cause Anemia[3].
- Folic Acid deficiency Anemia: This kind of Anemia is resulted from lack of folic acid in blood which is

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usually caused by insufficient inclusion of vegetables in food regime. Additionally, alcoholic drinks may worsen the disease. During pregnancy or in childhood, when Folic acid consumption is higher, Anemia may emerge. It may also occur as side effects of other problems and blood disorders[4].
- Sickle cell Anemia: This type is an inherited lifelong disease occurs when a special and abnormal kind of red blood cells exists. It is fatal, dangerous and unpreventable.

4. Fuzzy System

Fuzzy systems have the ability to decide and control a system using knowledge of an expert. They are mostly profitable in systems with sophisticated environments where a clear and obvious model of the system is not achievable. These cases the system is considered as a black box. Then, conclusions and decisions are made based on sample inputs and their results. Anemia diagnosis is complicated as there are various symptoms and types. Figure 1 depicts a generic schematic of disease diagnosis adaptive model using fuzzy system. The most prominent reason for using fuzzy system is existence of compound parameters, various symptoms and excessive similarity between diseases[5]. As per Figure 1, symptoms are fed to fuzzy system; it determines how close they are to each disease and present it as its output.

5. Basic Concepts in Fuzzy Systems

In order to model concerning concepts we exploited rules in the form of equation 1 [5–7].

$$if\ x_1\ is\ A_1^1, \ldots, x_m\ is\ A_m^1\ then\ y = B^1 \qquad (1)$$

Utilized membership functions are triangular, yet they have different number of variables. This difference roots in natural quiddity of parameters such as degree of anemia.

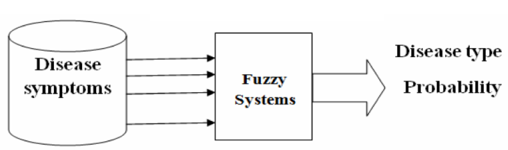

Figure 1. The operation of fuzzy system.

The most paramount reasons justifying use of fuzzy systems are[8,9]:

- The sophistication of natural world which leads to an approximate description or a fuzzy system for modeling.
- Necessity of providing a pattern to formulate mankind knowledge and applying it to actual systems.

Using fuzzy logic, in this paper a novel method is proposed to diagnose the most common versions of Anemia in humans. To do so, five symptoms of the disease are utilized. These are more beneficial for diagnosing the disease comparing to other symptoms. Based on these five symptoms we try to diagnose three types of Anemia mentioned in previous section. Thus, the following procedure is considered to define expert fuzzy system.

- Defining input-output sets which accept normalized input-output pairs.
- Generating if-else fuzzy rules based on input-output pairs.
- Creating fuzzy rule base.
- Implementing fuzzy system based on fuzzy rules.

6. Input-output Parameters of Fuzzy Systems

As mentioned before we used five symptoms of this disease as input parameters including: 1. Irritability, 2. Tachycardia, 3. Memory weakness, 4. nose bleeding, 5. chronic fatigue.

Based on these five symptoms we investigate three types of Anemia. It is noticeable that utilizing these symptoms the disease might not be diagnosed for sure as the nature of this issue includes uncertainty; however, here we tried to calculate probability of each disease relied on these symptoms and those who are more susceptible to Anemia could be detected. Therefore, the above mentioned fuzzy system has three outputs each of which demonstrates the severity of each type of Anemia.

Iron deficiency, Folic acid deficiency and sickle cell are three types of Anemia investigated in this study. Table.1 illustrates the influence of each symptom.

To determine the type of disease we used FIS tool in Matlab shown in Figure 2 (generic model of the system). This system includes five input fields regarding symptoms which affect diagnosis of Anemia. Three linguistic

Table 1. Influence of symptoms on different types of Anemia

Type of Anemia\ Symptoms	Irritability	Tachycardia	Memory weakness	Bleeding	Chronic fatigue
Iron deficiency	effective	effective			
Folic acid shortage	effective		Effective		effective
Inherited anemia (sickle cell)		effective		effective	effective

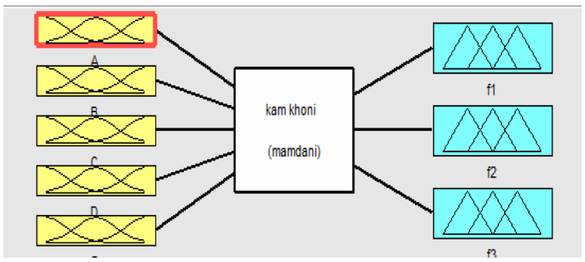

Figure 2. Generic model of expert fuzzy system to determine Anemia.

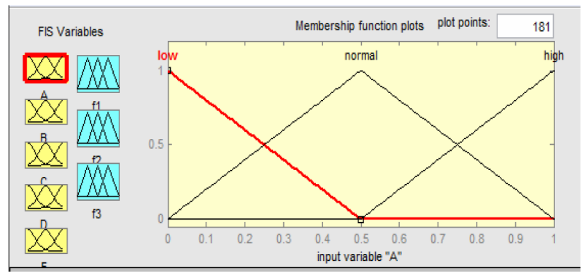

Figure 3. Membership function for irritability input.

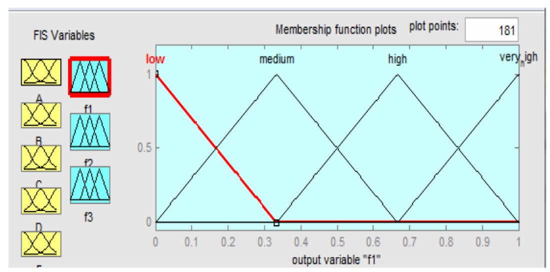

Figure 4. Membership function for output which represents probability of iron deficiency type of diseases.

variable groups are assigned to each field; low, normal, high. Furthermore, there are three output fields which show probability of catching each type of Anemia.

Output is divided into four groups with special linguistic variables assigned to them; low, normal, high, very high. Figures 3 and 4 demonstrate one of the membership functions of input-output parameters after normalization (in zero and one domain).

Implementing rules base

A simple approach to generate fuzzy rules is to classify a range of input characteristics using a finite number of fuzzy membership functions (e.g., triangular membership function and assigning linguistic variables to each class). After space classification single method to achieve fuzzy rules for each pattern is considered for all possible combinations of antecedents (input characteristics). This method will be problematic in case of large number of antecedents. In these situations, we cannot use this method as the number of possible conditions increases exponentially.

To solve this problem, we proposed a novel method to avoid large number of candidate rules in each stage. Moreover, generating rules in each stage with N antecedents is performed based on input rules of previous stage with N-1 antecedents so that exponential growth of number of rules is prevented. In this method only candidate rules are checked. Our method is based on two following principals[10]:

- Degree of support for a combination of data items which does not increase when the number of data items grows.
- A combination of N data items has high degree of support if all its subsets with N-1 members have high degree of support.

7. Generating Candidate Rules with 1 and 2 Antecedents

To avoid mass generating of candidate rules we consider degree of support criterion which is introduced by the following equation[11].

$$s(A_j \Rightarrow Classh) = \frac{1}{m} \sum_{x_p \in Classh} \mu_{A_j}(x_p) \qquad (2)$$

where μ_{Aj} (x_p) is the degree of adaptability between pattern x_p and antecedent R_j . M and h are the number of training patterns and class label, respectively.

Hence, we generate all one dimensional rules (with one antecedent) and determine a threshold limit for degree of support. Afterwards, we choose the rules whose degree of support is higher than the threshold. Then, using these rules we generate two dimensional candidate rules which are based on two previously mentioned principals:
1- Their antecedents do not include similar characteristics as their combination will result in a meaningless rule.
2. They have similar consequent class.

8. Generating Rules with Higher Dimensions

To generate candidate rules with more than two antecedents we use a similar approach and consider the same principals. Three dimensional rules are generated by combining one and two dimensional candidate rules. We merely check those three dimensional rules whose subset of two dimensional rules only consists of candidate two dimensional rules (second principal). For instance the following rule (equation 3) is checked,

$$\text{If X1 is A1 and X2 is A2 and X3 is A3} \rightarrow \text{C1} \qquad (3)$$

if three following two dimensional candidate rules(equations 4) exist:

$$\begin{aligned} &\text{If X1 is A1 and X2 is A2} \rightarrow \text{C1} \\ &\text{If X1 is A1 and X3 is A3} \rightarrow \text{C1} \qquad (4) \\ &\text{If X2 is A2 and X3 is A3} \rightarrow \text{C1} \end{aligned}$$

This will prevent iteration of useless and time consuming procedure.

9. Fuzzy if-else Rules

Using aforementioned definitions and considering Table 1, we write if-else candidate rules with 1, 2, and 3 antecedents as follows. It is worth mentioning that we have included all one dimensional rules (with one antecedent) considering laboratory consultant's viewpoint. As the number of characteristics is not large, this will not cause any problem.

1. If (A is high) then (f1 is very_high)(f2 is high)
2. If (A is low) then (f1 is low)(f2 is low)
3. If (A is normal) then (f1 is medium)(f2 is low)
4. If (B is low) then (f1 is low)(f3 is low)
5. If (B is high) then (f1 is very_high)(f3 is very_high)
6. If (B is normal) then (f1 is medium)(f3 is medium)
7. If (C is low) then (f2 is low)
8. If (C is normal) then (f2 is medium)
9. If (C is high) then (f2 is high)
10. If (D is low) then (f3 is low)
11. If (D is normal) then (f3 is high)
12. If (D is high) then (f3 is very_high)
13. If (E is normal) then (f2 is low)(f3 is medium)
14. If (E is low) then (f2 is low)(f3 is low)
15. If (E is high) then (f2 is high)(f3 is very_high)
16. If (A is high) and (B is high) then (f1 is very_high)
17. If (A is low) and (B is low) then (f1 is low)
18. If (A is normal) and (B is normal) then (f1 is medium)
19. If (A is high) and (C is high) then (f2 is high)
20. If (A is low) and (C is low) then (f2 is low)
21. If (A is normal) and (C is low) then (f2 is low)
22. If (B is high) and (D is high) then (f3 is very_high)
23. If (B is low) and (D is low) then (f3 is low)
24 If (B is high) and (E is high) then (f3 is very_high)
25 If (D is high) and (E is high) then (f3 is very_high)
26 If (B is low) and (E is low) then (f3 is low)
27 If (D is low) and (E is low) then (f3 is low)
28 If (B is normal) and (E is normal) then (f3 is medium)
29 If (A is high) and (E is high) then (f2 is high)
30 If (C is high) and (E is high) then (f2 is high)
31 If (A is low) and (E is low) then (f2 is low)
32. If (A is normal) and (E is low) then (f2 is low)
33. If (C is low) and (E is low) then (f2 is low)
34. If (A is low) and (E is normal) then (f2 is low)
35. If (A is normal) and (E is normal) then (f2 is low)
36. If (C is low) and (E is normal) then (f2 is low)
37. If (B is high) and (D is high) and (E is high) then (f3 is very_high)
38. If (A is high) and (C is high) and (E is high) then (f2 is high)
39. If (A is low) and (C is low) and (E is low) then (f2 is low)
40. If (A is normal) and (C is low) and (E is low) then (f2 is low)
41. If (A is low) and (C is low) and (E is normal) then (f2 is low)
42. If (A is normal) and (C is low) and (E is normal) then (f2 is low).

10. Building Fuzzy System

In this study we utilize product inference engine, singleton fuzzifier and center average defuzzifier in order to build fuzzy system. In our inference engine we also used Mamdani product implication and individual-rule based inference combined with algebraic summation and mulitplication for t-norms and max for s-norms. Thus, product inference engine can be written as denoted by equation 2 [11].

$$\mu_{B'}(y) = \max_{l=1}^{n}[\sup(\mu_{A'}(x)\bigcup_{i=1}^{k}\mu_{A_i^l}(x_i)\mu_{B'}(y))] \qquad (5)$$

Therefore, designed fuzzy system based on above inference engine is calculated as shown by equation (3) [11].

$$f(x) = \frac{\sum_{l=1}^{n} y^{-1}(\prod_{i=1}^{k}\mu_{A_i^l}(x_i))}{\sum_{l=1}^{n}(\prod_{i=1}^{k}\mu_{A_i^l}(x_i))} \qquad (6)$$

where x_i denote certain i^{th} input, $\mu_{A\,i}^{t}(x_i)$ stands for membership function of ith input and $\bar{y}$ is average center of ith output fuzzy set.

In this fuzzy system, singleton fuzzifier and average defuzzifier are utilized. Singleton fuzzifier is widely applied as it simplifies calculation of inference engine. Moreover, center averages defuzzifier is the most popular defuzzifier used in fuzzy systems and fuzzy control systems owing to its simplicity, justifiability and continuity. Center average defuzzifier is calculated as shown in equation 7.

$$s(A_j \Rightarrow Classh) = \frac{1}{m}\sum_{x_p \in Classh}\mu_{A_j}(x_p) \qquad (7)$$

11. Simulation of Expert Fuzzy System

We used Matlab software to simulate our system as it provides a suitable environment for such simulations. Results obtained from experiments conducted on 30 people show that in 26 cases the results of expert fuzzy system were similar to correct diagnosis and only in four cases a mismatch occurs. Uncertain circumstances in disease diagnosis and large number of symptoms may cause these mismatches. Figure 5 depicts one of the experiment cases. This sample shown in the figure shows inherited Anemia which is diagnosed by expert fuzzy system. Considering five parameters- low irritability, normal tachycardia, high memory weakness, high bleeding and normal chronic fatigue- our system shows 'High' value for inherited Anemia (see Figure 2.).

It should be noticed that the more occurrence severity, the more potential occurrence. In Figures 5, 6, 7 and 8 we present results obtained from mutual effect of some symptoms on Anemia which is derived in simulated model.

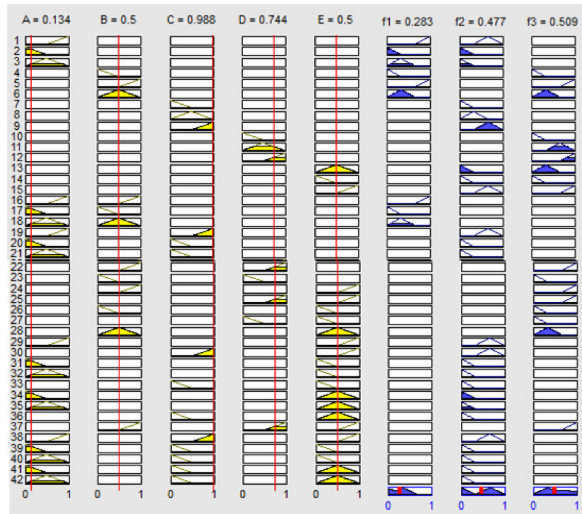

Figure 5. Experimental results of a sample stated by simulating the modeling.

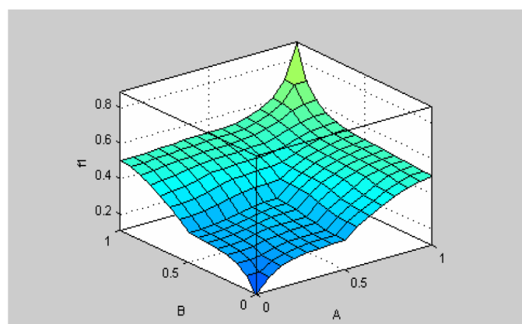

Figure 6. The result of mutual effect of irritability and tachycardia on iron deficiency Anemia.

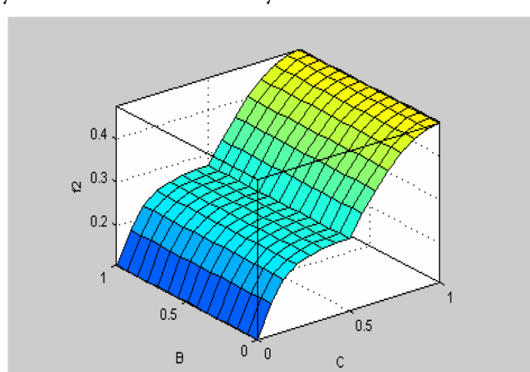

Figure 7. Mutual effect of tachycardia and memory weakness on Folic acid Anemia.

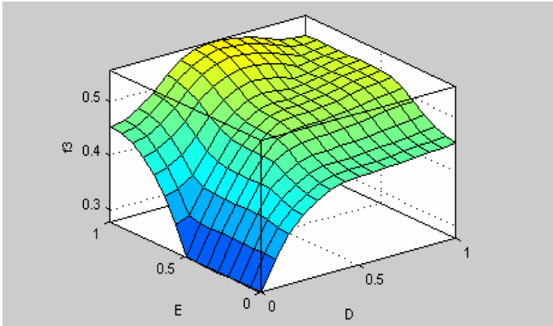

Figure 8. Mutual effect of chronic fatigue and bleeding on inherited Anemia (sickle cell Anemia).

12. Conclusion

Achievements of medical research together with proposed expert fuzzy system enable us to diagnose some cases of Anemia which is a complicated task. It is predictable that if other symptoms of Anemia are also applied to this system, it would able to diagnose all types of Anemia.

13. References

1. Shahshahani HJ, Attar M, Yavari MT. A study of the prevalence of iron deficiency and its re-lated factors in blood donors of Yazd, Iran. Transfus Med. 2003; 15(4):287–93.
2. Zadeh LA. Fuzzy logic, neural networks and soft computing. Comm ACM. 1994; 3(3):77–84.
3. Mohammadpour A. Clinical nursing in diagnos-tic tests. Marandizpublication, Gonabad. 2000 [Persian].
4. Hoffbrand AV, Weir DG. The history of folic acid. Br J Haematol. 2001; 113(3):279–89.
5. Ishibuchi H, Murata T, Turksen IB. Single-objective and two-objective genetic algorithms for selecting linguistic rules for pattern classifi-cation problems. Fuzzy Set Syst. 1997 Jul; 89(2):135–49.
6. Haase VH, Steinmann C, Vejda S. Access to knowledge: better use of the internet. Proceed-ings of the Informing Science + IT Education Conference, IS2002; 2002. p. 618–27.
7. Cordon O, de Moya F, Zarco C. Fuzzy logic and multiobjective evolutionary algorithms as soft computing tools for persistent query learning in text retrieval environments. Proceedings of the IEEE International Conference on Fuzzy Sys-tems; 2004. p. 571–76.
8. Mercier A, Beigbeder M. Fuzzy proximity rank-ing with boolean queries. Proceedings of the 14th Text REtrieval Conference (TREC 2005); 2005. p. 433–42.
9. Yap K-H, Wu K. A soft relevance framework in content-based image retrieval systems. IEEE Trans Circ Syst Video Tech. 2005; 15(12):1557–68.
10. Mamdani E, Assilian S. An experiment in ligus-tic synthesis with a fuzzy logic controller. Int J Man Mach Stud. 1975; 7:1–13.
11. Ishibuchi H, Nozaki K, Yamamoto N, Tanaka H. Construction of fuzzy classification systems with rectangular fuzzy rules using genetic algo-rithm. Fuzzy Set Syst. 1994; 65:237–53.