World Academy of Science, Engineering and Technology
International Journal of Computer and Information Engineering
Vol:13, No:2, 2019

A Two-Stage Expert System for Diagnosis of Leukemia Based on Type-2 Fuzzy Logic

Ali Akbar Sadat Asl

Abstract**—**Diagnosis and deciding about diseases in medical fields is facing innate uncertainty which can affect the whole process of treatment. This decision is made based on expert knowledge and the way in which an expert interprets the patient's condition, and the interpretation of the various experts from the patient's condition may be different. Fuzzy logic can provide mathematical modeling for many concepts, variables, and systems that are unclear and ambiguous and also it can provide a framework for reasoning, inference, control, and decision making in conditions of uncertainty. In systems with high uncertainty and high complexity, fuzzy logic is a suitable method for modeling. In this paper, we use type-2 fuzzy logic for uncertainty modeling that is in diagnosis of leukemia. The proposed system uses an indirect-direct approach and consists of two stages: In the first stage, the inference of blood test state is determined. In this step, we use an indirect approach where the rules are extracted automatically by implementing a clustering approach. In the second stage, signs of leukemia, duration of disease until its progress and the output of the first stage are combined and the final diagnosis of the system is obtained. In this stage, the system uses a direct approach and final diagnosis is determined by the expert. The obtained results show that the type-2 fuzzy expert system can diagnose leukemia with the average accuracy about 97%.

Keywords**—**Expert system, leukemia, medical diagnosis, type-2 fuzzy logic.

I. Introduction

A. Leukemia

IN people with leukemia, the bone marrow produces abnormal white blood cells. Over time, the accumulation of leukemia cells interferes with the production of normal cells. In each type of leukemia, the progress rate of leukemia is different [1]. The four main types of leukemia are [2]:

- Acute myeloid leukemia (AML)
- Chronic myeloid leukemia (CML)
- Acute lymphocytic leukemia (ALL)
- Chronic lymphocytic leukemia (CLL)

B. Expert Systems

Expert systems are programs to rehabilitate and provide the expertise, skills, and also they are the ability of the qualified experts for reasoning in a specific area.

Expert systems need detailed information about a specific area and strategies for using the information to solve problems.

In order to build a knowledge system, the knowledge should be formulated. In other words, it should be understood in formal formats, and should be provided to the computer; the knowledge must also be changed according to the problem-solving method [3].

Generally, a rule-based expert system consists of three main modules:

- Knowledge base: The rules and information that will be used in decision making are in this module.
- Inference engine: The inference process that is based on the adopted logic and infers inputs according to the rules of the knowledge base.
- Working memory: a space for temporary storage of input data, information and rules used in the inference module.

These modules are communicated by the user interface to the expert system user, the input information from the user and the final report of the final results are transmitted to the user by the user interface [4].

Fig. 1 indicates the structure of an expert system.

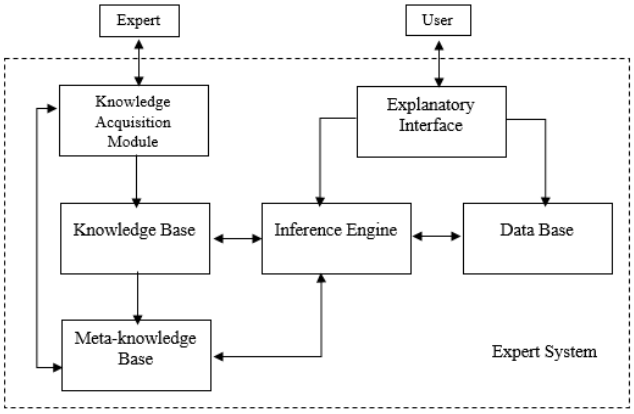

Fig. 1 Architecture of an expert system [5]

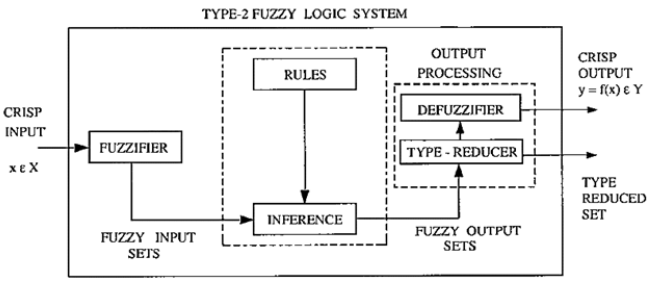

Fig. 2 Components of type-2 fuzzy logic system [8]

C. Type 2 Fuzzy

Uncertainty is an inherent part of the intelligent systems that are used in the real world. It is no secret that the use of the new methods is crucial to control the effects of inappropriate

A.A. Sadat Asl is with the Department of Industrial Engineering Amirkabir University of Technology, Tehran, Iran (phone: +989383106152; e-mail: a.sadatasl@aut.ac.ir).

information. Fuzzy logic can provide mathematical modeling for many concepts, variables, and systems that are unclear and ambiguous and also can provide a framework for reasoning, inference, control, and decision making in conditions of uncertainty. In systems with high uncertainty and high complexity, fuzzy logic is a suitable method for modeling [6]. Type-1 fuzzy sets that are used in conventional fuzzy systems do not completely cover the uncertainty of problems and ambiguity that occurs in intelligent systems. In other words, type 2 fuzzy sets can better control these uncertainties owing to the fact that these sets have more parameters [7]. In type 2 fuzzy sets, unlike type 1 which have a numerical definite membership degree, the membership degree of each element is itself a fuzzy set. Fig. 2 demonstrates the components of type 2 fuzzy systems.

TABLE I
THE MOST IMPORTANT STUDIES OF FUZZY MEDICAL EXPERT SYSTEMS

No.	Authors	Year	Application	Ref.
1	Adeli and Neshat	2010	Diagnosis of heart disease	[9]
2	Kumar and Kaur	2013	Diagnosis of heart disease	[10]
3	Allahverdi et al.	2007	Determination of coronary heart disease risk	[11]
4	Kumar	2013	Diagnosis the heart disease by advanced fuzzy resolution mechanism	[12]
5	Oad et al.	2014	Predict risk level of heart disease	[13]
6	Lavanya et al.	2011	Diagnosis of lung cancer	[14]
7	Malathi and Santra	2013	Diagnosis of lung Cancer disease using neuro-fuzzy logic	[15]
8	Farahani et al.	2015	Diagnosis of lung cancer	[16]
9	Saritas et al.	2003	Diagnosis of prostate cancer	[17]
10	Balanica et al.	2011	Evaluation of breast cancer risk	[18]
11	Latha et al.	2013	Assessment of breast cancer risk prognosis	[19]
12	Patel et al.	2012	Diagnosis of asthma severity	[20]
13	Anand et al.	2013	Detection and estimate of the level of asthma and chronic obstructive pulmonary disease	[21]
14	Zarandi et al.	2010	Diagnosis of asthma	[22]
15	Mayilvaganan and Rajeswari	2014	Human blood pressure classification	[23]
16	Chandra and Singh	2014	High blood pressure diagnosis	[24]
17	Kaur and Kaur	2014	Diagnosis of hypertension	[25]
18	Djam et al.	2011	Management of Malaria	[26]
19	Onuwa	2014	Diagnosis of Malaria	[27]
20	Sharma et al.	2013	Diagnosis of Malaria and Dengue disease	[28]
21	Kadhim et al.	2011	Diagnosis of back pain	[29]
22	Zarei et al.	2012	A fuzzy mathematical model of HIV infection	[30]
23	Imianvan et al.	2011	Diagnosis of HIV	[31]
24	Khanale and Ambilwade	2011	Diagnosis of hypothyroidism	[32]
25	Biyouki et al.	2015	Diagnosis of thyroid disease	[33]
26	Hasan and Chowdhury	2010	Human disease diagnosis	[34]
27	Govinda et al.	2013	Fever diagnosis	[35]
28	Hole and Gulhane	2014	Diagnosis of memory low diseases	[36]
29	Singh et al.	2012	Diagnosis of arthritis	[37]
30	Baig et al.	2012	Detection of critical events during anaesthesia and diagnosis of a hypovolaemia event in anaesthetized patients	[38]
31	Chandra	2014	Analysis and diagnosis of migraine	[39]
32	Ghahazi et al.	2014	Diagnosis of multiple sclerosis	[40]
33	Maftouni et al.	2015	Ankylosing spondylitis diagnosis	[41]
34	Zarandi et al.	2009	Diagnosis of brain tumors	[42]
35	Talukdar et al.	2014	Blood cancer detection	[43]
36	Nosrat Abadi and Mohsen Taheri	2010	Diagnosis of Blood Cancer	[44]
37	Obi and Imianvan	2011	Diagnosis of leukemia	[45]
38	Noorizadeh and Hosseini	2014	Acute leukaemia diagnosis	[46]
39	Harun et al.	2015	Unsupervised pixel segmentation for segmenting the blast in ALL and AML images	[47]
40	Bhattacharjee	2015	Detection of acute lymphoblastic leukemia	[48]
41	Priya et al.	2015	Detection of leukemia in blood microscopic images	[49]
42	Purushotham and Tripathy	2015	Processing the leukaemia images	[50]
43	Amin et al.	2015	Recognition of acute lymphoblastic leukemia cells in microscopic images	[51]
44	Latifi et al.	2015	Acute lymphocytic leukemia in children	[52]
45	Sadat Asl and Zarandi	2017	Diagnosis of types of leukemia	[53]

The process of diagnosing and deciding about the disease is uncertain and complicated. This decision is made based on the expert knowledge and its type of interpretation of the patient's condition. Besides, the interpretation of different experts from

the patient's condition can be various. Thus, we present an expert system for diagnosis of leukemia by using type 2 fuzzy logic.

II. Literature Review

Medical problems, including diagnosis of disease, are always associated with uncertainty, and the use of expert systems by using different logic has always been to assist experts. CREAM system in the field of cardiology, DIAS in the area of diagnosis and consultation of diabetes, MYCIN for diagnosis of bacterial infections, and many other cases are examples of medical expert systems.

Among the reviewed cases, we investigated the researches about creation of medical expert systems for the diagnosis of various diseases that use the fuzzy method for inference. Table I summarizes the fuzzy expert systems for diagnosis of different types of disease. In above studies, no one has considered indirect approach in the field of leukemia. We propose an intelligent system that, in the first stage, uses fuzzy modeling with an indirect approach, where the rules are extracted automatically by implementing a clustering approach.

In order to increase the accuracy of the proposed system, in the diagnosis of leukemia, type 2 fuzzy logic that is more capable than the type 1 fuzzy in uncertainty modeling is used. Using the output of the first phase, according to the doctor's opinion, the inference of the second phase of the system is performed, which led the proposed system to act based on a hybrid indirect-direct approach. The high accuracy of the proposed system demonstrates the proper performance of the proposed system for the diagnosis of leukemia.

III. Proposed System

The proposed system consists of two stages. In the first stage, the inference of the blood test state is determined. In this step, we follow an indirect approach fuzzy modeling where the rules are extracted automatically by implementing a clustering approach. In the second stage, signs of leukemia, duration of disease until its progress and the output of the first phase are combined and the final diagnosis of the system are obtained. In other words, our system uses a hybrid indirect-direct approach for inference.

TABLE II
Normal Range of the Blood Test Items [54]

Blood test item	Women	Men	Children
Hemoglobin	12-16	14-18	9.5-15.5
RBC	4.2-5.4	4.7-6.1	4-5.5
WBC	4500-11000	5000-10000	5000-10000
HCT (%)	37-47	42-52	32-44
PLT	150000-400000	150000-400000	150000-400000

TABLE III
Non-Cancerous Conditions [54]

	Red Cells	White Cells	Platelets
High Counts	▪ Smoking ▪ Carbon monoxide exposure ▪ Chronic lung disease ▪ Kidney disease ▪ Certain forms of heart disease ▪ Alcoholism ▪ Liver disease ▪ Conditions that affect the body's fluid level	▪ Infection ▪ Inflammation ▪ Severe physical or emotional stress (such as fever, injury or surgery) ▪ Burns ▪ Kidney failure ▪ Lupus ▪ Rheumatoid arthritis ▪ Malnutrition, thyroid problems ▪ Certain medicines	▪ Bleeding ▪ Mild to moderate iron deficiency ▪ Problems with bone marrow function
Low Counts	▪ Anemia from too little iron, folic acid or vitamin B12 ▪ Bleeding ▪ Inflammatory bowel disease ▪ Other diseases that might cause malnutrition ▪ Certain drugs	▪ Infection ▪ Chemotherapy and other medicines ▪ Malaria ▪ Alcoholism ▪ AIDS ▪ Lupus ▪ Enlarged spleen	▪ Pregnancy ▪ Idiopathic thrombocytopenic purpura ▪ Thrombotic thrombocytopenic purpura ▪ Hemolytic uremic syndrome ▪ Autoimmune diseases

A. The First Stage of the Proposed System

The first phase of the proposed system is designed to determine whether the blood test is healthy or sick with regard to the factors introduced for the disease by expert. In type 2 fuzzy modeling, Platelet (PLT), Hematocrit (HCT), White Blood Cell (WBC), Red Blood Cell (RBC) and hemoglobin are considered as system inputs, and the blood test state i.e. sickness or healthy blood test is determined. The normal values of the blood test items are given in Table II. However, the violation of the normal range of each item cannot definitely indicate that the blood test is healthy or sick. In other words, if one or more of blood test items are higher or lower than normal range, it cannot definitely indicate the cancerous condition of the blood test for a person.

Many non-cancerous cases and conditions may be associated with high or low blood cell counts. Table III indicates the non-cancerous conditions that contribute to low or high red and white cells and platelets counts. Thus, according to the aforementioned analysis, in the first phase, the proposed system is based on type 2 fuzzy logic according to the individual's gender, viz., adults (women and men) and children. A dataset containing 345 blood tests (113 women, 193 men and 39 children) of a governmental hospital was used for construction and evaluation of the system in the first stage. We should construct the system for women, men and children separately owing to the fact that the difference in normal range of the blood test items for them may create different cancerous

models. For each category, the system is made by almost 80% of the dataset and is appraised by the rest of the dataset. The data of each part are modeled using the MISO system (multiple inputs - single outputs).

Among the various items of blood test, the items PLT, HCT, WBC, RBC, and hemoglobin have been used to determine the inference of the blood test state in diagnosis of leukemia according to the expert. After that, the system is constructed using fuzzy c-means clustering algorithm for clustering of the blood test data. Then, for determining the number of rules, the proposed index by Zarandi et al. is used. This validity index V_{ECAS} can find the number of clusters as the maximum of its function with respect to c as [55]:

$$\boldsymbol{V_{ECAS}} = \boldsymbol{ECAS}\,(\boldsymbol{c}) = \frac{\boldsymbol{EC_{comp}(c)}}{\boldsymbol{max_c(EC_{comp}(c))}} - \frac{\boldsymbol{ES_{sep}(c)}}{\boldsymbol{max_c\left(ES_{sep}(c)\right)}}, \quad (1)$$

$EC_{comp}(c)$ and $ES_{sep}(c)$ are exponential compactness and separation measures, respectively.

$$\boldsymbol{EC_{comp}(c)} = \sum_{i=1}^{c}\sum_{j=1}^{n} \boldsymbol{u_{ij}^{m}}\ \mathbf{exp}\left[-\left(\frac{\|x_i - v_j\|^2}{\boldsymbol{\beta_{comp}}} + \frac{\mathbf{1}}{\boldsymbol{c+1}}\right)\right], \quad (2)$$

$$\boldsymbol{ES_{sep}(c)} = \sum_{i=1}^{c} \mathbf{exp}\left[-\boldsymbol{min_{i\neq k}}\left(\frac{(c-1)\|v_i - v_k\|^2}{\boldsymbol{\beta_{sep}}}\right)\right]. \quad (3)$$

$\beta_{comp} = \frac{\sum_{k=1}^{n}\|x_k - \overline{v}\|^2}{n(i)}$ and $\beta_{sep} = \frac{\sum_{l=1}^{n}\|v_l - \overline{v}\|^2}{c}$, respectively. Furthermore, $n(i)$ is the number of data in cluster i and $\overline{v} = \frac{\sum_{j=1}^{n} x_j}{n}$.

In this study, we obtained the appropriate number of clusters or rules by the validity index. The best number of clusters was obtained 3 clusters for adults and children.

In the next step, the output space is projected onto the input space and the membership functions of the input and output variables are estimated. Eventually, the type 1 fuzzy rule base is transformed into interval type-2 fuzzy rule base with uncertain standard deviation and fixed mean by Liang and Mendel [56] method (for more detail refer to [56]). Fig. 3 demonstrates the interval type 2 fuzzy rule based on blood test for adults and children. After determining the rules, Mamdani inference system is used by multiple inputs-single output modeling with standard operators. Then, the type 2 fuzzy output set needs to be type-reduced and defuzzified to obtain final result.

B. The Second Stage of the Proposed System

After determining the blood test result for each person, in the second stage, symptoms, duration of illness until its progress and the output of the first stage are combined and final diagnosis of the leukemia is obtained. This stage is based on the expert knowledge and follows a direct approach for inference. For this purpose, according to the result of the first stage, the expert analyzes the patient symptoms and duration of them. Based on the physician knowledge, the marked symptoms usually occur in each type of leukemia. Also, if the symptoms suddenly occur, the risk of ALL and AML will increase. In the other hand, if the symptoms occur in a long time, the risk of CLL and CML will increase owing to the fact that in acute myeloid and lymphocytic leukemia the cancer progression rate is high. Thus, their symptoms suddenly occur. Also, in chronic myeloid and lymphocytic leukemia the cancer progression rate is low and their symptoms occur in a long time.

After the inference of symptoms state and duration of disease until its progress, the proposed system combines the output of stage 1 and finally diagnoses leukemia. The system predicts the presence or suspicion of presence or absence of leukemia. If a patient suffers from leukemia, the proposed system determines type of leukemia by the knowledge base acquired by the expert. If the system predicts suspicion of presence of leukemia, the patient should refer to a physician to investigate the presence or absence of cancer cells using biopsy. Below is a part of the inferential general rules that lead to the diagnosis of leukemia:

- Rule 1: If Blood Test is *sick* and Sick Time is *sudden start* and Sick Sign is *ALL*. Then Assessment is *ALL*
- Rule 2: If Blood Test is *sick* and Sick Time is *sudden start* and Sick Sign is *AML*. Then Assessment is *AML*
- Rule 3: If Blood Test is *sick* and Sick Time is *long time* and Sick Sign is *CLL*. Then Assessment is *CLL*
- Rule 4: If Blood Test is *sick* and Sick Time is *long time* and Sick Sign is *CML*. Then Assessment is *CML*

TABLE IV
ANALYSIS OF THE LEUKEMIA SYMPTOM

Symptoms	CML	CLL	AML	ALL
Vomit			✓	✓
Headache	✓			
Anorexia			✓	✓
Enlarged lymph nodes		✓		
Infection		✓	✓	
Enlarged liver or spleen			✓	✓
Anemia	✓	✓	✓	✓
Asthenia	✓		✓	
Sweating		✓		
Bleeding			✓	
Fatigue			✓	
Weight Loss	✓	✓		
Fever		✓	✓	
Confusion	✓			
Shortness of breath	✓			

C. Evaluation of the Proposed System

After logging into the expert system environment, the user is entered into blood test inference screen that must submit the requested items in order to infer blood test state. After entering the information by the user, the system infers the blood test and reports its state to the user. Fig. 4 shows the inference of the blood test of a patient. After the blood test inference stage, the user clicks on the next and then new screen is opened. In the new screen the user should mark the symptoms. This window is shown in Fig. 5. Then, by clicking on the final diagnosis button, the expert system gives the final result to the user. The proposed expert system has the ability to diagnose leukemia with the average accuracy of about 97%.

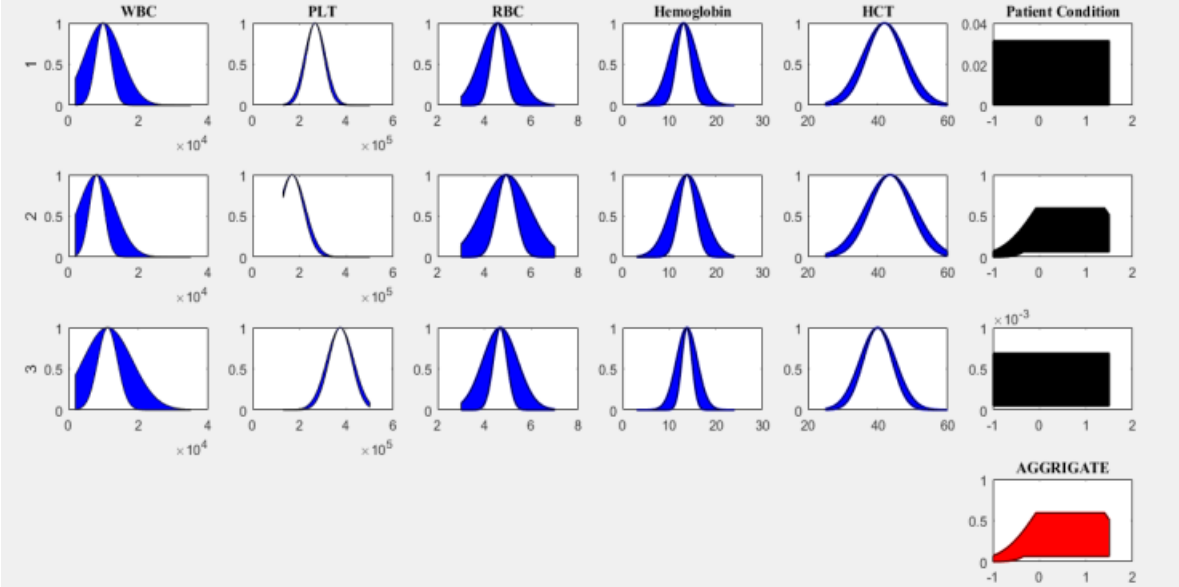

Fig. 3 (a) Interval type 2 fuzzy rule based of the proposed system for women's blood tests

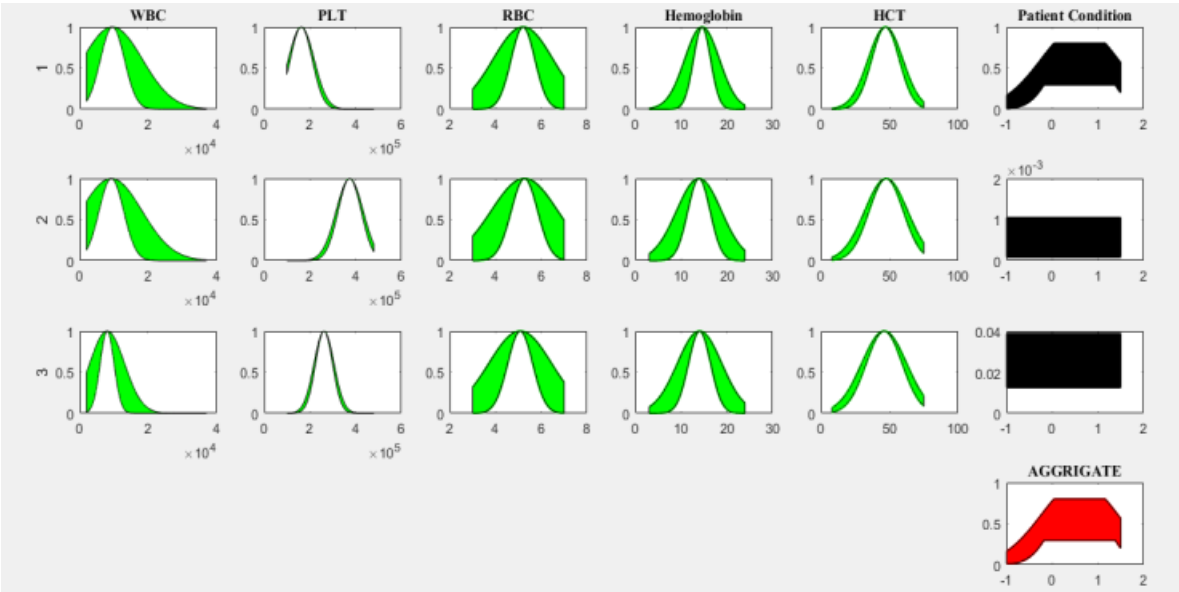

Fig. 3 (b) Interval type 2 fuzzy rule based of the proposed system for men's blood tests

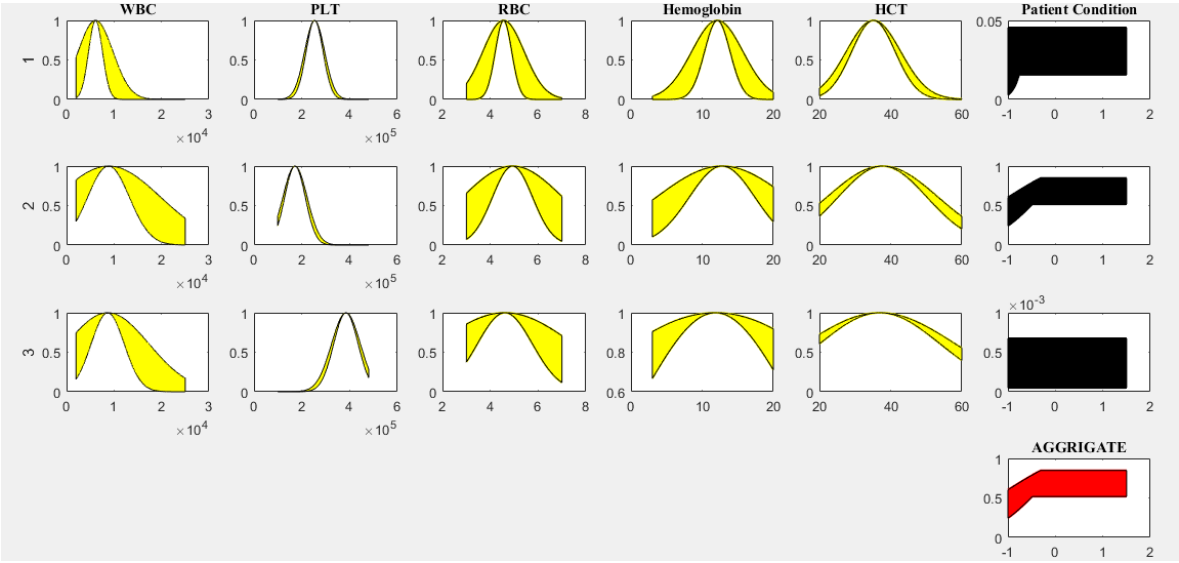

Fig. 3 (c) Interval type 2 fuzzy rule based of the proposed system for children's blood test

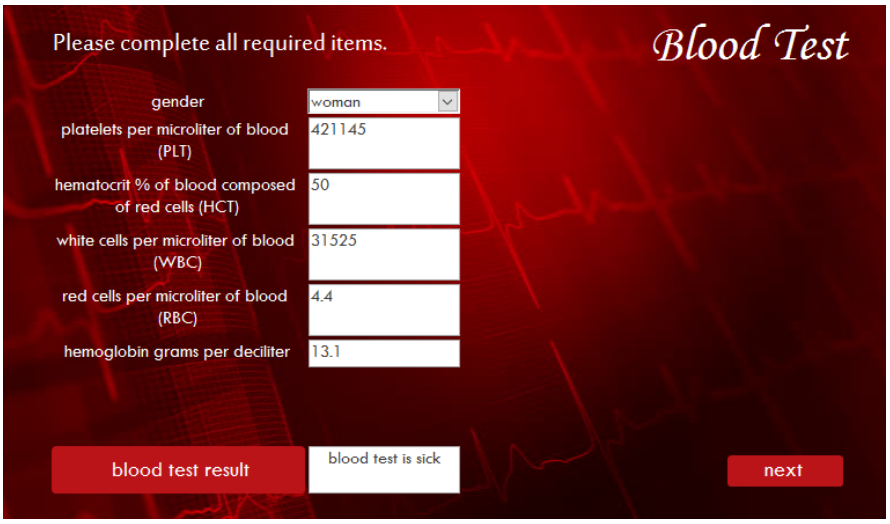

Fig. 4 The inference screen of the blood test of a patient

IV. Conclusion

The prevalence of leukemia is increasing day by day and it is becoming a global epidemic. Increasing cancer cells in the bone marrow produces leukemia. Leukemia is a progressive and malignant disease of the blood-forming organs of the body.

Since a timely and accurate diagnosis of leukemia has a major impact on the way and cost of treatment, and the amount of lesions resulting from it, it is very important to provide an intelligent system for the diagnosis of this disease. In addition, fuzzy logic can provide a framework for reasoning, inference, control, and decision making in conditions of uncertainty.

In systems with high uncertainty and high complexity, fuzzy logic is a suitable method for modeling. Due to the greater ability of type 2 fuzzy logic in uncertainty modeling, in this paper, we presented a type 2 fuzzy expert system for diagnosis of leukemia. The proposed system includes two stages. In the first stage, the inference of the blood test state is determined. In this step, we use Mamdani inference system with standard operators. In the second stage, leukemia symptoms, duration of disease until its progress and the output of the first stage are integrated and the final diagnosis of the system is obtained. By relying on the results, the type-2 fuzzy expert system can diagnose leukemia with the average accuracy about 97%.

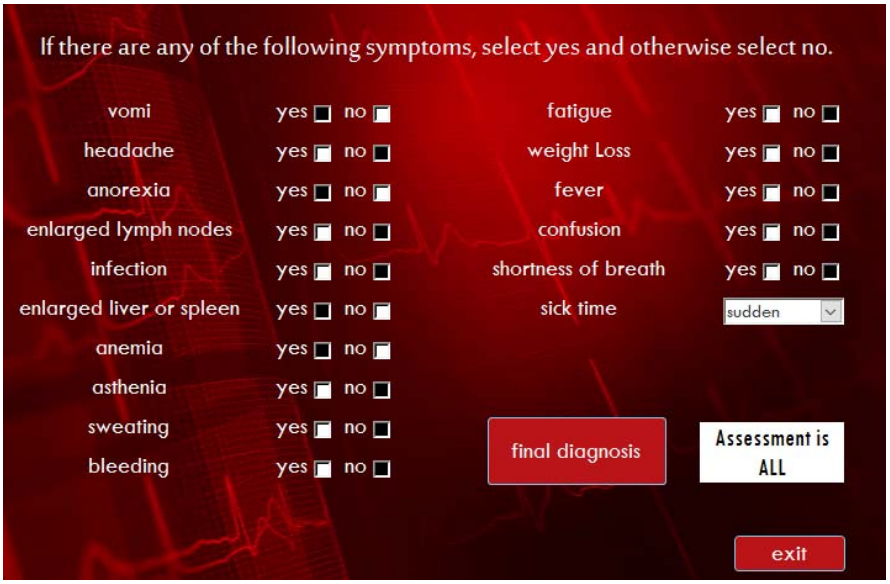

Fig. 5 The inference screen of the blood test of a patient

REFERENCES

[1] Leukemia & Lymphoma Society of Canada Website. http://www.llscanada.org/leukemia.
[2] Cancer Treatment Centers of America Website. https://www.cancercenter.com/leukemia/types.
[3] Frank Puppe, Systematic Introduction to Expert Systems, Knowledge Representations and Problem-Solving Methods, Springer-Verlag, 1993.
[4] J Liebowitz, Introduction to expert systems. Mitchell Publishing, 1988.
[5] George J.Klir, Bo Yuan, Fuzzy Sets and Fuzzy Logic: Theory and Application. Prentice Hall P T R, 1995.
[6] Sadatasl, Ali Akbar, Mohammad Hossein Fazel Zarandi, and Abolfazl Sadeghi. "A combined facility location and network design model with multi-type of capacitated links and backup facility and non-deterministic demand by fuzzy logic." Fuzzy Information Processing Society (NAFIPS), 2016 Annual Conference of the North American. IEEE, 2016.
[7] Alireza Sadeghian, Jerry M. Mendel, Hooman Tahayori (Editors), Advances in Type-2 Fuzzy Sets and Systems: Theory and Applications, Springer, 2013.
[8] Nilesh N Karnik, Jerry M Mendel, and Qilian Liang. Type-2 fuzzy logic systems. Fuzzy Systems, IEEE Transactions on, 7(6):643–658, 1999.
[9] Ali. Adeli, Mehdi. Neshat," A Fuzzy Expert System for Heart Disease Diagnosis", Proceedings of the International Multiconference of Engneers and Computer Scientists 2010 Vol I, IMECS 2010, march 17-19, 2010, Hong Kong.
[10] Kumar, Sanjeev, and Gursimranjeet Kaur. "Detection of heart diseases using fuzzy logic." Int. J. Eng. Trends Technol.(IJETT) 4.6 (2013).
[11] Allahverdi, Novruz, Serhat Torun, and Ismail Saritas. "Design of a fuzzy expert system for determination of coronary heart disease risk." Proceedings of the 2007 international conference on Computer systems and technologies. ACM, 2007.
[12] Kumar, Dr AV Senthil. "Diagnosis of heart disease using Advanced Fuzzy resolution Mechanism." International Journal of Science and Applied Information Technology (IJSAIT) 2.2 (2013): 22-30.
[13] Oad, Kantesh Kumar, Xu DeZhi, and Pinial Khan Butt. "A fuzzy rule based approach to predict risk level of heart disease." Global Journal of Computer Science and Technology 14.3-C (2014): 17.
[14] Lavanya, K., MA Saleem Durai, and N. Ch Sriman Narayana Iyengar. "Fuzzy rule based inference system for detection and diagnosis of lung cancer." International Journal of Latest Trends in Computing 2.1 (2011): 165-171.
[15] Malathi, A., and A. K. Santra. "Diagnosis of Lung cancer disease using neuro fuzzy logic." CARE Journal of applied research (2013).
[16] Farahani, Farzad Vasheghani, MH Fazel Zarandi, and Abbas Ahmadi. "Fuzzy rule based expert system for diagnosis of lung cancer." Fuzzy Information Processing Society (NAFIPS) held jointly with 2015 5th World Conference on Soft Computing (WConSC), 2015 Annual Conference of the North American. IEEE, 2015.
[17] Saritas, Ismail, Novruz Allahverdi, and Ibrahim Unal Sert. "A fuzzy expert system design for diagnosis of prostate cancer." a a 1 (2003): 50.
[18] Balanică, Victor, et al. "Evaluation of breast cancer risk by using fuzzy logic." University Politehnica of Bucharest Scientific Bulletin, Series C 73.1 (2011): 53-64.
[19] Latha, K. C., et al. "Visualization of risk in breast cancer using fuzzy logic in matlab environment." International Journal of Computational Intelligence Techniques 4.1 (2013): 114.
[20] Patel, Ashish, et al. "Decision support system for the diagnosis of asthma severity using fuzzy logic." Proceedings of the International Multiconference of Engineers and Computer Scientists. Vol. 1. 2012.
[21] Anand, S. Krishna, R. Kalpana, and S. Vijayalakshmi. "Design and implementation of a fuzzy expert system for detecting and estimating the level of asthma and chronic obstructive pulmonary disease." World Applied Sciences Journal 23.2 (2013): 213-223.
[22] Zarandi, MH Fazel, et al. "A fuzzy rule-based expert system for diagnosing asthma." Scientia Iranica. Transaction E, Industrial Engineering 17.2 (2010): 129.
[23] Mayilvaganan M and K. Rajeswari, Human Blood Pressure Classification Analysis using Fuzzy Logic Control System in Datamining, by, International Journal of Emerging Trends & Technology in Computer Science , 3(1), 2014, 305-306.
[24] Chandra, Vishal, and Pinki Singh. "Fuzzy Based High Blood pressure Diagnosis." International Journal of Advanced Research in Computer Science & Technology 2.2 (2014): 1.
[25] Kaur, Rupinder, and Amrit Kaur. "Hypertension diagnosis using fuzzy expert system." International Journal of Engineering Research and Applications (IJERA) National Conference on Advances in Engineering and Technology, AET-29th March. 2014.
[26] Djam, X. Y., et al. "A fuzzy expert system for the management of Malaria." (2011).
[27] Onuwa, OJEME BLESSING. "Fuzzy expert system for malaria diagnosis." Oriental J. of Computer Science and Technology 7 (2014): 273-284.
[28] Sharma, Priyanka, et al. "Decision Support System for Malaria and Dengue Disease Diagnosis (DSSMD)." International Journal of Information and Computation Technology, 3 (7) (2013): 633-640.
[29] Kadhim, Mohammed Abbas, M. Afshar Alam, and Harleen Kaur. "Design and implementation of fuzzy expert system for back pain diagnosis." International Journal of Innovative Technology & Creative Engineering 1.9 (2011): 16-22.
[30] Zarei, Hassan, Ali Vahidian Kamyad, and Ali Akbar Heydari. "Fuzzy modeling and control of HIV infection." Computational and mathematical methods in medicine 2012 (2012).
[31] Imianvan, A. A., U. F. Anosike, and J. C. Obi. "An Expert System for the Intelligent Diagnosis of HIV/AIDs Using Fuzzy Cluster Means

Algorithm." Global Journal of Computer Science and Technology (2011).
[32] Khanale, P. B., and R. P. Ambilwade. "A fuzzy inference system for diagnosis of hypothyroidism." Journal of Artificial Intelligence 4.1 (2011): 45-54.
[33] Biyouki, S. Amrollahi, I. B. Turksen, and MH Fazel Zarandi. "Fuzzy rule-based expert system for diagnosis of thyroid disease." Computational Intelligence in Bioinformatics and Computational Biology (CIBCB), 2015 IEEE Conference on. IEEE, 2015.
[34] Hasan, Mir Anamul, and Ahsan Raja Chowdhury. "Human disease diagnosis using a fuzzy expert system." arXiv preprint arXiv:1006.4544 (2010).
[35] Govinda Rao, S., M. Eswara Rao, and D. Siva Prasad. "Fever Diagnosis Rule-Based Expert Systems." International Journal of Engineering Research & Technology (IJERT) 2.8 (2013).
[36] Hole, Komal R., and Vijay S. Gulhane. "Expert System for Diagnosis of Memory Low Diseases." International Journal 2.1 (2014).
[37] Singh, Sachidanand, et al. "Diagnosis of arthritis through fuzzy inference system." Journal of Medical systems 36.3 (2012): 1459-1468.
[38] Baig, Mirza Mansoor, Hamid Gholamhosseini, and Michael J. Harrison. "Fuzzy logic based smart anaesthesia monitoring system in the operation theatre." WSEAS Transactions on Circuits and Systems 11.1 (2012): 21-32.
[39] Chandra, Vishal. "Fuzzy expert system for migraine analysis and diagnosis." International Journal of Science and Research 3.6 (2014): 956-959.
[40] Ghahazi, M. Arabzadeh, et al. "Fuzzy rule based expert system for diagnosis of multiple sclerosis." Norbert Wiener in the 21st Century (21CW), 2014 IEEE Conference on. IEEE, 2014.
[41] Maftouni, Maede, et al. "Type-2 fuzzy rule-based expert system for Ankylosing spondylitis diagnosis." Fuzzy Information Processing Society (NAFIPS) held jointly with 2015 5th World Conference on Soft Computing (WConSC), 2015 Annual Conference of the North American. IEEE, 2015.
[42] M.H. Fazel Zarandi, M. Zarinbal, M. Izadi, Systematic image processing for diagnosing brain tumors: A Type-II fuzzy expert system approach, 2009.
[43] Talukdar, Nur Alom, Daizy Deb, and Sudipta Roy. "Automated blood cancer detection using image processing based on fuzzy system." IJARSC, ISSN-2277-128X 4.8 (2014).
[44] H. Islami Nosrat Abadi, S. Mohsen Taheri, A Fuzzy Expert System for Diagnosis of Blood Cancer, in the proceeding of 6th International Conference of ICT Management.
[45] Obi, J. C., and A. A. Imianvan. "Interactive neuro-fuzzy expert system for diagnosis of leukemia." global journal of computer science and technology (2011).
[46] Noorizadeh, Maliheh, and Rahil Hosseini. "Acute Leukaemia Diagnosis using A Fuzzy Expert System." Proc. of the 14th Fuzzy Systems Association Conference, Tabriz, Iran. 2014.
[47] Harun, Nor Hazlyna, et al. "Unsupervised segmentation technique for acute leukemia cells using clustering algorithms." World Academy of Science, Engineering and Technology International Journal of Computer, Control, Quantum and Information Engineering 9 (2015): 253-59.
[48] Romel Bhattacharjee, White Blood Cells' Segmentation for the Detection of Acute Lymphoblastic Leukemia, Journal of Basic and Applied Engineering Research, ISSN: 2350-0255; Volume 2, Number 2; January-March, 2015, pp. 99-103
[49] Priya, D. Kavi, et al. "Detection of leukemia in blood microscopic images using fuzzy logic." Int. J. Engg. Res. & Sci. & Tech 240 (2015).
[50] Purushotham, Swarnalatha, and B. K. Tripathy. "A Comparative Analysis of Depth Computation of Leukaemia Images using a Refined Bit Plane and Uncertainty Based Clustering Techniques." Cybernetics and Information Technologies 15.1 (2015): 126-146.
[51] Amin, Morteza Moradi, et al. "Recognition of acute lymphoblastic leukemia cells in microscopic images using k-means clustering and support vector machine classifier." Journal of medical signals and sensors 5.1 (2015): 49.
[52] Latifi, Farzaneh, et al. "Designing a Fuzzy Expert System and Nervous System for Computerized Diagnosis of Acute Lymphocytic Leukemia in Children Comparing Their Function." Third International Conference on Applied Research in Computer Engineering and Information Technology, 2015.
[53] Sadat Asl, Ali Akbar, and Mohammad Hossein Fazel Zarandi. "A Type-2 Fuzzy Expert System for Diagnosis of Leukemia." North American Fuzzy Information Processing Society Annual Conference. Springer, Cham, 2017.
[54] Leukemia & Lymphoma Society Website. http://www.lls.org/managing-your-cancer/lab-and-imaging-tests/understanding-blood-counts
[55] Zarandi, MH Fazel, M. R. Faraji, and M. Karbasian. "An exponential cluster validity index for fuzzy clustering with crisp and fuzzy data." Scientia Iranica. Transaction E, Industrial Engineering 17.2 (2010): 95.
[56] Liang, Qilian, and Jerry M. Mendel. "Interval type-2 fuzzy logic systems: theory and design." IEEE Transactions on Fuzzy systems 8.5 (2000): 535-550.