CHAPTER: 18

FUZZY RULE BASED MODEL FOR THE PREDICTION OF BLOOD CANCER

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ABSTRACT

In this study, we developed a fuzzy rule-based inference system for diagnosing and classifying blood cancer. This system processes symptom inputs to deliver a confirmed diagnosis and stage of the disease. It computes membership functions for input and output variables, utilizing expert domain knowledge to formulate and store rules in the rule base. These rules are activated when matching symptoms are detected. The final section includes a case study demonstrating the practical application of the inference system in predicting blood cancer.

***Keywords**: Inference system, Fuzzy rule, Symptoms, stages, Blood cancer*

1. INTRODUCTION

The human body consists of countless living cells that typically grow, divide, and die in a regulated manner. Cancer initiates when cells in a specific area begin to proliferate uncontrollably. While cancer often results in tumor formation, blood cancer differs as it involves malignant cells in the blood, bone marrow, or lymphatic system. These cancerous cells can spread through the bloodstream or lymphatic vessels to other regions of the body [1].

The symptoms of blood cancer are weight loss, fever, enlarged spleen, lymph nodes, frequent or unusual infection, abnormal bleeding, night sweats, bone or joint pain, short of breath, bruising of the skin, fatigue and loss of energy. Medical diagnostic processes are inherently complex and challenging. Patients present with various symptoms, and doctors must interpret these to identify the underlying disease, a task that is prone to errors. As noted by physician Roscol L. Pullen in the preface of a 1944 medical textbook, diagnosing diseases, particularly at an early stage, is fraught with difficulties. Incorrect treatment due to diagnostic errors can significantly impact patients' health. The process of disease diagnosis inherently involves a degree of uncertainty [9,10].

Blood cancer is a leading cause of death globally for both men and women. This term broadly encompasses cancers that affect the blood, bone marrow, or lymphatic system. There are three primary types of blood cancer: leukemia, lymphoma, and multiple myeloma. Leukemia involves the malignancy of blood cells, lymphoma pertains to cancerous tumors in the lymphatic system, and myeloma affects plasma cells, which are responsible for producing antibodies in the bone marrow [10].

The American Cancer Society projects that in the year 2024, there will be 44,600 new cases of leukemia with 21,780 related deaths, 75,190 new cases of lymphoma with 20,620 deaths, and 20,520 new cases of myeloma with 10,610 deaths. For the year 2023, an estimated 141,210 individuals are expected to be diagnosed with one of these three types of blood cancer. Among them, approximately 53,010 are anticipated to succumb to the disease [1].

2. FUZZY INFERENCE SYSTEM

The fuzzy inference system employs a rule-based approach that utilizes fuzzy logic to capture various types of knowledge related to a problem. It also models the interactions and relationships between different variables [7,8,9].

The proposed system features five input variables, one output, and 243 rules designed for diagnosing blood cancer. The diagnosis relies on inputs including weight loss, fever, night sweats, lymph node abnormalities, and bleeding. The output provides the patient's diagnosis and indicates the severity of the blood cancer, categorized into four distinct stages.

3. MEMBERSHIP FUNCTIONS FOR INPUT AND OUTPUT FUNCTIONS

A membership function determines how each value in the input range is assigned a degree of membership between 0 and 1, represented by μ. In our system, we compute the membership function for each input variable (symptom) as well as the output variable (disease).

3.1 **Input Functions**: For every input variable, the membership function is defined as follows:

3.1.1 Weight Loss: A weight loss of more than 10% within six months could be indicative of blood cancer symptoms.

For calculating the membership function we use three linguistic variable low, medium and high. We scale the range 0 – 10.

$$\mu_L(X_1) = \begin{cases} 1 & 0 \le x \le 2 \\ 3 - x & 2 < x \le 3 \end{cases} \qquad \mu_M(X_1) = \begin{cases} x\text{-}2 & 2 \le x \le 3 \\ 1 & 3 < x < 5 \\ 6 - x & 5 \le x < 6 \end{cases}$$

$$\mu_H(X_1) = \begin{cases} \dfrac{x-5}{2} & 5 \le x < 7 \\ 1 & x \ge 7 \end{cases}$$

3.1.2 Fever: A temperature range of 97^0 F to 99^0 F is considered normal, but if it exceeds 101^0 F, further investigation for blood cancer is necessary.

$$\mu_L(X_2)=\begin{cases}1 & 97\le x\le 98.6\\ \frac{100-x}{1.4} & 98.6<x\le 100\end{cases}\qquad \mu_M(X_2)=\begin{cases}\frac{x-99}{1} & 99\le x\le 100\\ 1 & 100<x<101\\ \frac{102-x}{1} & 101\le x\le 102\end{cases}$$

$$\mu_H(X_2)=\begin{cases}\frac{x-101}{2} & 101\le x<103\\ 1 & x\ge 103\end{cases}$$

3.1.3 Night Sweats: Night sweats can be classified as low, medium, or high depending on their severity. We scale the range from 0 to 100 to calculate the membership function.

$$\mu_L(X_3)=\begin{cases}1 & 0\le x\le 10\\ \frac{25-x}{15} & 10<x\le 25\end{cases}\qquad \mu_M(X_3)=\begin{cases}\frac{x-18}{7} & 18\le x\le 25\\ 1 & 25<x<45\\ \frac{56-x}{11} & 45\le x\le 56\end{cases}$$

$$\mu_H(X_3)=\begin{cases}\frac{x-50}{20} & 50\le x<70\\ 1 & x\ge 70\end{cases}$$

3.1.4 Lymph Nodes: If there exists lymph nodes more than 1.5 cm, then there exists symptoms of blood cancer. The range of lymph nodes in case of blood cancer is 0.5 cm to 1.5 cm.

$$\mu_L(X_4)=\begin{cases}1 & 0\le x\le 0.30\\ \frac{6-10x}{3} & 0.30<x\le 0.60\end{cases}\qquad \mu_M(X_4)=\begin{cases}\frac{10x-4}{2} & 0.4\le x\le 0.6\\ 1 & 0.6<x<1\\ \frac{12-10x}{2} & 1\le x\le 1.2\end{cases}$$

$$\mu_H(X_4)=\begin{cases}\frac{10x-10}{5} & 1\le x<1.5\\ 1 & x\ge 1.5\end{cases}$$

3.1.5 Abnormal Bleeding: If there exist bleeding more than 13 days than there exists symptoms of blood cancer.

$$\mu_H(X_5)=\begin{cases}\frac{x-6}{2} & 6\le x<8\\ 1 & x\ge 8\end{cases}$$

$$\mu_M(X_5)=\begin{cases}\frac{x-2}{2} & 2\le x<4\\ 1 & 4<x<6\\ \frac{8-x}{2} & 6\le x\le 8\end{cases}$$

$$\mu_L(X_5)=\begin{cases}1 & 0\le x\le 2\\ \frac{4-x}{2} & 2<x\le 4\end{cases}$$

3.2 Pictorial representation of Inputs Membership Functions:

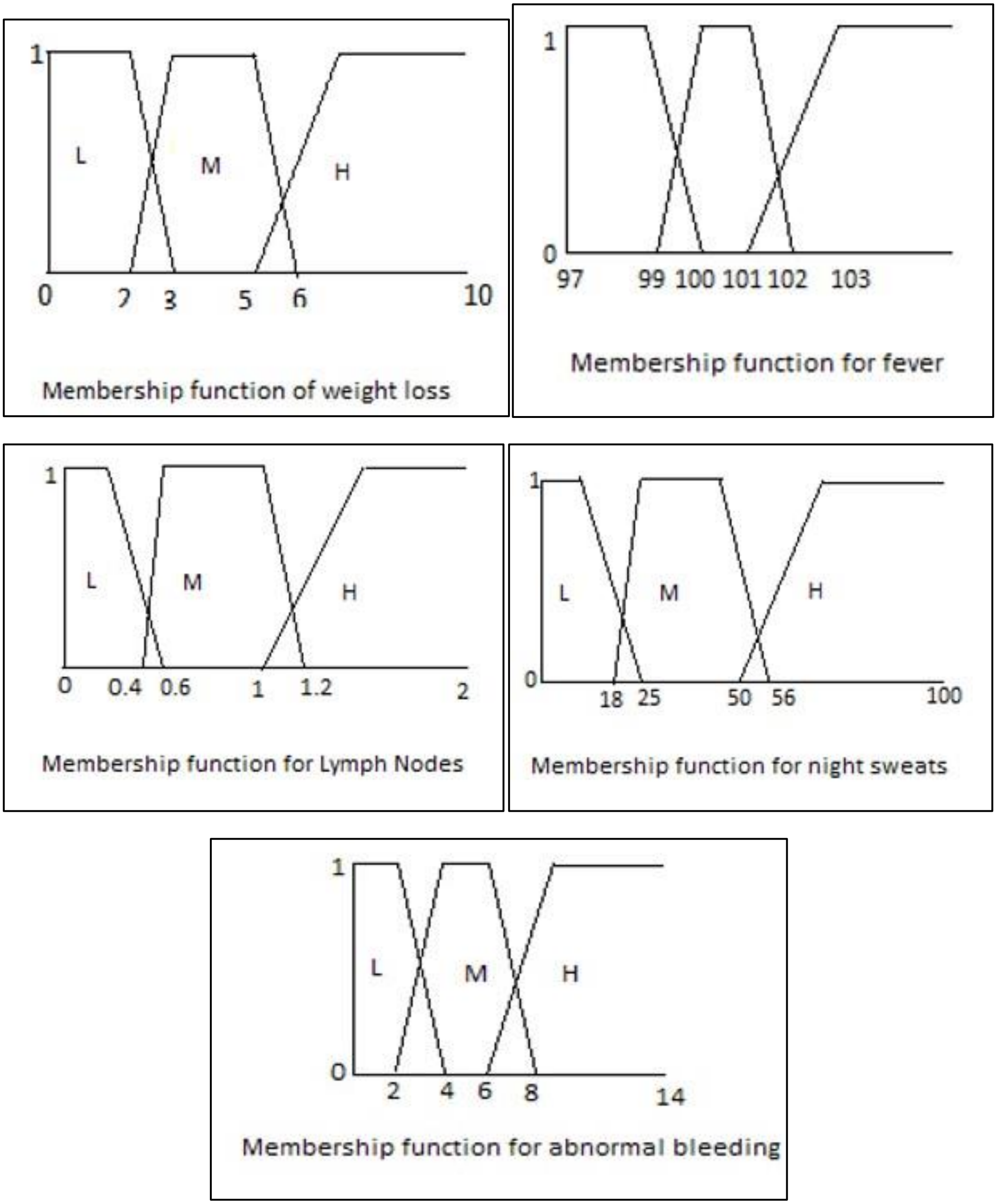

Figure 1: Membership function for input variables

3.3 Output Functions: In the proposed system, the output variable is categorized into the following fuzzy sets: stage (1), stage (2), stage (3), and stage (4), if the patient has blood cancer. The membership function for the output variable is defined as follows:

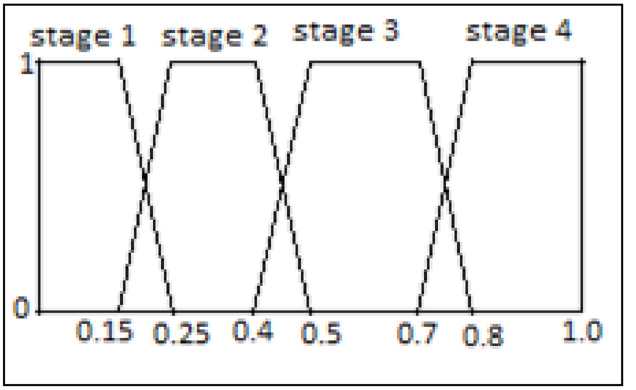

Figure 2: Membership function for output variable

4. CASE STUDY

We have demonstrated the performance of the diagnosis system using blood cancer as an example. For illustration purposes, we consider five inputs for blood cancer: weight loss as X_1, fever as X_2, night sweats as X_3, lymph nodes as X_4 and abnormal bleeding as X_5.

4.1 Let the input values of the person to be evaluated:

$X_1= 4.5$, $X_2=101.5$, $X_3=40$, $X_4=0.35$ and $X_5=6.5$

4.2 Fuzzification of the crisp values of inputs:

$$\mu_L(X_1) = 0 \quad \mu_L(X_2) = 0 \quad \mu_L(X_3) = 0 \quad \mu_L(X_4) = 0.6 \quad \mu_L(X_5) = 0$$
$$\mu_M(X_1) = 1 \quad \mu_M(X_2) = 0.5 \quad \mu_M(X_3) = 1 \quad \mu_M(X_4) = 0 \quad \mu_M(X_5) = 0.25$$
$$\mu_H(X_1) = 0 \quad \mu_H(X_2) = 0.25 \quad \mu_H(X_3) = 0 \quad \mu_H(X_4) = 0 \quad \mu_H(X_5) = 0.33$$

4.3 Fire the rule bases that correspond to these inputs Based on the value of the fuzzy membership function values for the example, under consideration, the following rules apply:

Rule 1: If X_1 is medium, X_2 is medium, X_3 is medium, X_4 is low and X_5 is medium then Y is blood cancer and stage 3.

Rule 2: If X_1 is medium, X_2 is high, X_3 is medium, X_4 is low and X_5 is medium then Y is blood cancer and stage 3.

Rule 3: If X_1 is medium, X_2 is medium, X_3 is medium, X_4 is low and X_5 is high then Y is blood cancer and stage 3.

Rule 4: If X_1 is medium, X_2 is high, X_3 is medium, X_4 is low and X_5 is high then Y is blood cancer and stage 4.

4.4 Execute the Inference System: We use the "root sum squares" (RSS) method to combine the effects of all applicable rules.

Stage 1 = $\sqrt{\sum_{i \in s_1} \left(\mu_{Ri}\right)^2} = 0$

Stage 2 = $\sqrt{\sum_{i \in s_2} \left(\mu_{Ri}\right)^2}$ = 0

Stage 3 = $\sqrt{\sum_{i\in s_3}\left(\mu_{Ri}\right)^2}$ = $\sqrt{(0.25)^2+(0.25)^2+(0.25)^2}=0.43$

Stage 4 = $\sqrt{\sum_{i\in s_4}\left(\mu_{Ri}\right)^2}$ = 0.25

4.5 Defuzzification: We use "fuzzy centroid algorithm" for defuzzification. The defuzzification of the data into a crisp output is accomplished by combining the results of the inference process and then computing the "fuzzy centroid" of the area. The weighted strengths of each output member function are multiplied by their respective output membership function center points and summed. Finally, this area is divided by the sum of the weighted member function strengths and the result is taken as the crisp output.

4.6 Output of the decisions of the expert system:

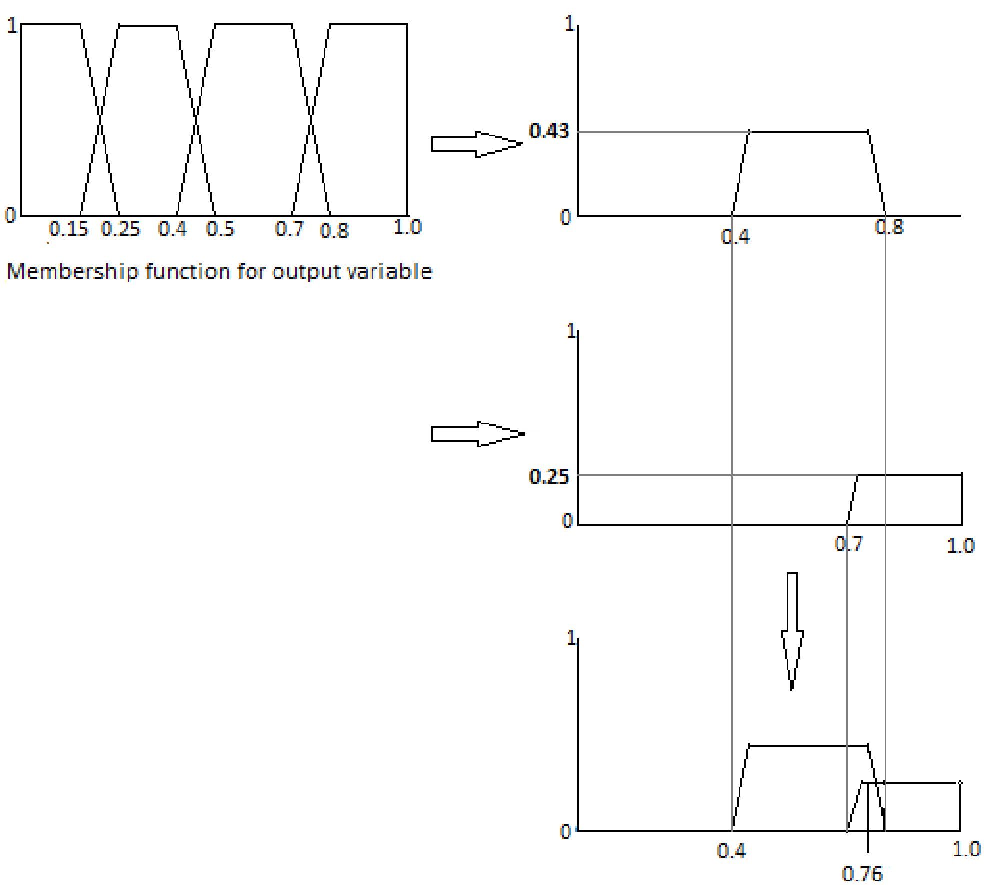

Figure 3: Output of the expert system

5. CONCLUSION

This paper presents the development of a fuzzy rule-based inference system for predicting blood cancer. The system's performance has been demonstrated through an example, highlighting its diagnostic capabilities. Future work will focus on enhancing the system's accuracy and efficiency using MATLAB.

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