FUZZY LOGIC RELIABILITY BLOCK DIAGRAM APPROACH FOR PATIENT HEALTH MONITORING USING R PROGRAMMING

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Abstract

In this research, a new approach using fuzzy logic and reliability block diagram (RBD) techniques is used to ensure the reliability of patient health monitoring systems. This technique handles uncertainties in health information, while RBD assesses system reliability by displaying factor relations. The RBD model construct for system components and measure reliability using probabilistic models. Fuzzy logic identifies the effect of uncertainties on overall reliability. Using this approach in a simulated health monitoring scenario, using R, we demonstrate its effectiveness and potential to increase reliable health monitoring for improved patient outcomes and healthcare efficiency. Furthermore, the awareness gained from this study can be directed beyond healthcare such as modern process control and environmental sensing.

Keywords: Fuzzy logic, reliability block diagram, health care, efficiency, R programming, membership function.

I. Introduction

The engineering of reliability is essential to the effectiveness, safety, and economic viability of technologies across various sectors. However, reliability models tend to minimize the complexity and unpredictability that characterize modern technology. Fuzzy logic highlights the potential for this new model with a framework to deal with the fundamental inaccuracy and uncertainty observed in the real-world process of decision-making. By providing the interpretation of qualitative and fuzzy models, fuzzy logic simulates human logic and allows challenging decision-making in uncertain situations. This adaptability and quickness provide a perfect model for improving conventional reliability engineering techniques.

Fuzzy logic and artificial intelligence together indicate the most significant development in analysis of reliability. The application of AI methods like artificial neural networks and algorithm development permits applications using fuzzy logic to keep evolving. Since the outcome, by gradually understanding using data, clients will improve their methods for making decisions. The ability of fuzzy inference systems to evolve and prosper in difficult and unexpectedly shifting environments could be increased through this combination of factors. Reliability block diagrams (RBDs) are needed for evaluating the system's reliability to highlight the relationships between components and their influence on the general effectiveness of the entire system. Even though systems sometimes fail to prepare for the inherent uncertainty of real-world systems, conventional RBDs are effective at predicting dependent scenarios.

This paper provides an approach for integrating fuzzy logic with health information from patients. To provide an understanding of a person's medical scenario, the approach evaluates the possibility related to each risk factor and takes into factor the person's family history, lifestyles, prior medical history, and factors in the environment. Fuzzy logic, FALCON, and BP in combination might improve the diagnostic rate of MSSA patients, according to study findings of Modai, I et al. [1]. The ecological relevance of Asian tiger mosquitoes for infectious diseases has been evaluated by Proestos, Y et al. [2] using fuzzy logic. Fuzzy logic plays an essential function in evaluating human resources performance, as Sadegh Amalnick, M et al. [3] indicate. In their idea, Davoodi, R et al. [4] had higher accuracy than conventional algorithms for forecasting ICU patient mortality using the Deep Rule-Based Fuzzy System (DRBFS). A fuzzy-based Bayesian model has been developed by Rallapalli, S.et al. [5] in the campaign over COVID-19 to help quickly isolate SARS-CoV-2 RNA by determining the most effective sets for wastewater sampling.

Li, S et al. [6] improved performance in the context of interference challenges by providing a network of sensors health forecasting framework using a system base model with attribute reliability (BRB-r). Reliability is essential for the implementation of blockchain technology in medical care, based on Du, X et al. [7]. Dovc, K et al. [8] studied the performance of AHCL and HCL methods for controlling glucose levels to an intermittent baseline of 150 mg/dL as implementing fuzzy logic in the FLAIR learning. Abd Rahman, N H et al. [9] addressed an observation on the centrality of the healthcare system's accuracy. The medical information research studies done by Sebastian, L et al. [10], Vijayan, K et al. [11], and Vennila, J et al. [12], [13] mainly using R programming.

II. Methods

This study's primary objective is to show how the fuzzy logic idea and reliability block design can be used effectively in a simulated health observation situation to increase reliability, which in turn can lead to better patient outcomes and more efficient healthcare delivery. The following steps were used in methodological parts.

- Step 1: Construction of RBD model
- Step 2: Integration with fuzzy logic concept
- Step 3: Simulation in R
- Step 4: Evaluating the results.

III. Case Scenarios

Based on the above methodological concept, we consider few examples and demonstrate the effectiveness of using fuzzy logic concept and the results obtained are discussed below:

I. Case Scenario One

In this scenario, fuzzy logic and reliability are incorporated to evaluate the overall reliability level of a system composed of two components based on their individual reliabilities and predefined thresholds. Let the predefine thresholds be as follows: high is 0.65, average is 0.39 and low is 0.21; and let the individual reliability for two components follow U (0,1). The system accuracy can be classified to be high, average, or low according to this inference outcome.

II. Case Scenario Two

This scenario includes a health assessment system that evaluates the health status of patients as per their blood pressure, cholesterol, and Body Mass Index (BMI). Applying predefined membership functions, the system classifies “healthy” or “unhealthy” based on the vital statistics of health status of patients. The case studies reveal that, how the system assesses each patient data to measure their overall health status, providing valuable awareness for healthcare filed to constitute notified findings and interventions.

II. Case Scenario Three

In this scenario, a patient's health evaluation status, based on variables such as age, body mass index (BMI), heart rate, cholesterol and blood pressure, can be obtained using the code in concern. The information has been organized into various health status groups for each evidence.

IV. Results and Discussion

I. Output for Case Scenario One

For case scenario one, on executing the R coding a bar diagram is obtained, note that here the programme has been executed thrice to depictive 3 different types of output, also to ensure the randomness of the reliability for the components A and B, they are randomly assigned a value from Uniform (0,1) distribution. The outputs are as shown in figure 1, figure 2 and figure 3.

From figure1, observe that when the when the reliability of Component A= 0.0884 and of component B = 0.2487 the overall system reliability fuzzy logic is Low. It can be observed from figure 2 that when the reliability of Component A= 0.4799 and of component B= 0.3713 the overall system reliability based on fuzzy logic is Medium. From figure 3 we notice that when the reliability of Component A= 0.7317 and of component B= 0.5334, the overall system reliability based on fuzzy logic is High.

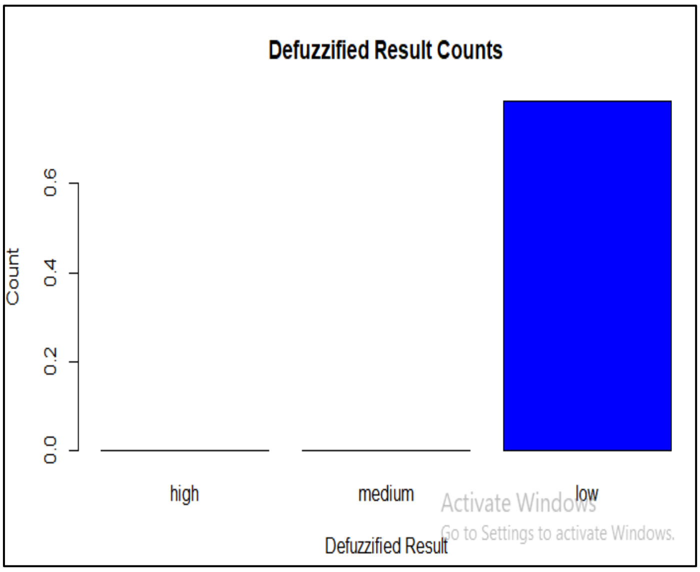

Figure 1: *Low system reliability when A=0.0884; B=0.2487*

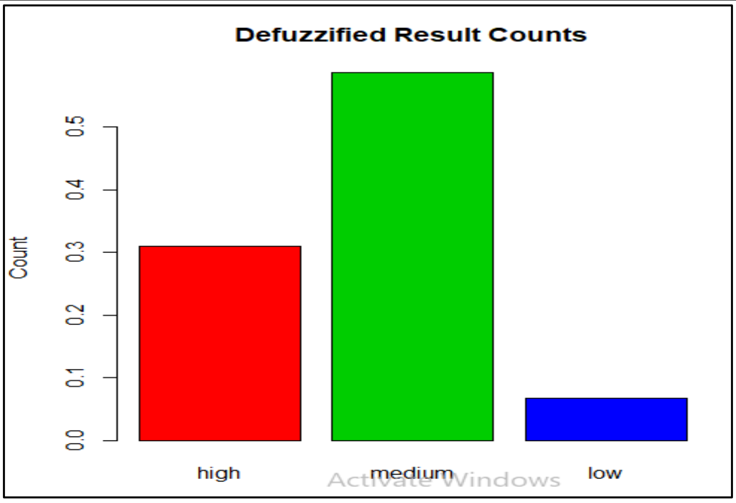

Figure 2*: Medium system reliability when A=0.4799; B=0.3713*

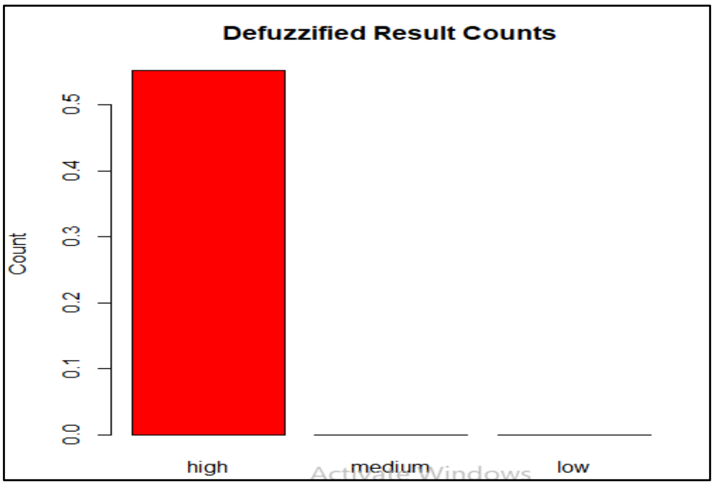

Figure 3*: High system reliability when A=0.7317; B=0.5334*

Thus, by considering the individual reliability of component, A and B, the code in R determines the overall reliability of the system. It identifies high, medium, and low reliability levels and gives results based on fuzzy. This approach permits screening variables based on changes in component reliability. The findings obtained are useful for decision-making on efficiency, baseline, and improvements to system designs. Based on predetermined requirements, the fuzzy inference evaluates components A and B and demonstrates its validity. Furthermore, in practical applications, reliability evaluation would need to consider additional variables such as factor mutuality and the active using environment.

II. Output for Case Scenario Two

For case scenario two, the R coding ensures that based on the varying random inputs regarding the vital statistics of blood pressure (BP), Cholesterol and BMI for the patient list provided, the output gives an accurate prediction on the health status of these individuals using fuzzy membership function. A patient is termed “healthy” if either one of the two conditions are met.

- Condition 1: BP is between 120 and 140, Cholesterol is between 100 and 240 and BMI is between 18.5 and 25.
- Condition 2: BP is less than or equal to 120, Cholesterol is less than or equal to 200

and BMI is between 18.5 and 25. The output for case scenario 2 is shown in Table 1.

Table 1: *Output table for case scenario 2*

Patient "ABC". with BP 92 & Chol 245 & BMI 23 Health Status: unhealthy
Patient "PQR" with BP 127 & Chol 185 & BMI 21 Health Status: healthy
Patient "XYZ" with BP 171 & Chol 300 & BMI 33 Health Status: unhealthy

From the above table we draw the following inference, for patient "ABC" although BMI of 23 is within the specified range (18.5, 25), BP of 92 is less than the specified range , and cholesterol level of 245 is above specified range with respect to condition 1 and hence the patient is labeled "unhealthy"; on verifying these vital statistics as per condition 2 , we notice that although BMI of 23 is within the specified range (18.5, 25) and BP of 92 is less than 120 but the cholesterol level of 245 is above specified range and hence the patient is labeled "unhealthy". Since neither of the two conditions are met the overall health status is "unhealthy"

For patient "PQR", BP of 127 is within the specified range (120, 140), cholesterol level of 185 within the specified range (100, 240) and BMI of 21 is within the specified range (18.5, 25) with respect to condition 1 and hence the patient's overall health status is "healthy".

For patient "XYZ", BP is 171, Cholesterol is 300 and BMI is 33; all these vital statistics are above the permissible range with respect to condition 1 and hence the patient's overall health status is "unhealthy".

Since the vital statistics of patients are unique to every individual, the coding has been framed in a manner so as to incorporate the fuzzy nature of vital statistics namely Blood pressure, Cholesterol and BMI and gives an assured reliability of the health status of individuals. The fuzzy membership functions for Blood pressure, Cholesterol and BMI are depicted in figure 4.

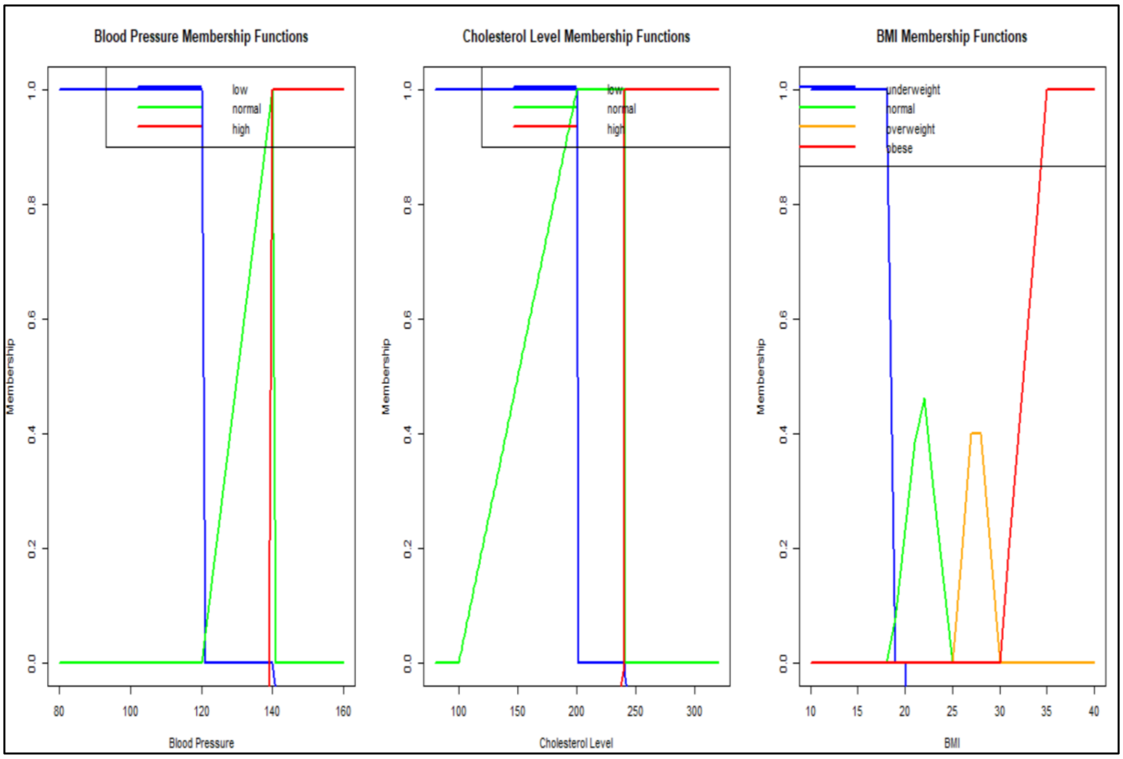

Figure 4: *Fuzzy membership functions for Blood pressure, Cholesterol and BMI generate using R coding*

From the above result for case scenario 2, observe that the health assessment system shown is a significant tool in healthcare practice, supporting clinicians in managing notified results and upgrading patient outcomes through directed interventions and monitoring.

III. Output for Case Scenario Three

For case scenario three, the R coding is done in such a manner that each time we run the code the parameters of the vital statistics taken on random uniform nos. within a specific range as mentioned in the code and accurately determines the inference with respect to each of the varying vital statistics. of a patient. Given below in table 2 are three randomly generated outputs along with their accurate inference

Table 2: *Output table for case scenario 3*

Patient 1:					
	Age	BMI	Heart Rate	Cholesterol	BP
	40	25	97	179	95
	age_inference	bmi_inference	hr_inference	chol_inference	bp_inference
	Medium	Medium	Medium	Low	Low
Patient 2:					
	Age	BMI	Heart Rate	Cholesterol	BP
	19	26	88	297	132
	age_inference	bmi_inference	hr_inference	chol_inference	bp_inference
	Low	Medium	Medium	High	Medium
Patient 3:					
	Age	BMI	Heart Rate	Cholesterol	BP
	60	27	70	222	67
	age_inference	bmi_inference	hr_inference	chol_inference	bp_inference
	High	Medium	Low	High	Low

Observe in Table 2; based on the predefined thresholds; for patient 1, Age (40), BMI (25), Heart Rate (97) are categorized as ‘Medium’; Cholesterol (179), BP (95) are categorized as ‘Low’. Similarly, for Patient 2, Age (19) is categorized as ‘Low’; BMI (26), Heart Rate (88), BP (132) are categorized as ‘Medium’; and Cholesterol (297) is categorized as ‘High’ and for Patient 3, Age (60), Cholesterol (179) are categorized as ‘High’; BMI (27) is categorized as ‘Medium’; Heart Rate (70), BP (67) are categorized as ‘Low’.

The given R code generates random values for a patients Age, BMI, Heart Rate, Cholesterol and BP, and then classify each of these values into categories (High, Medium and Low) based on predefined thresholds. Thus, a thorough assessment of the health of an individual along a number of factors can be executed, permitting focus to be given to medication prescribed along with specific diseases.

V. Conclusion

This study gives the combination of fuzzy logic and machine learning with reliability block diagrams. It represents a capable boundary in reliability engineering. This method gives a complete procedure for measuring a patient's health status over observing many health parameters. It gives a meaningful valuation of the patient's complete health status. But it is worthwhile to notice that while fuzzy logic provides a useful framework for health evaluation, clinical decision and skill must also be measured when interpreting the findings and making healthcare assessments. Fuzzy logic with reliability block diagram recommends a great structure for evaluating the reliability of health systems. This gives to improvements in diagnostic accuracy, patient care, and healthcare outcomes. The health evaluation gives actionable awareness for patients and their healthcare providers, highlighting the significance of active health controlling and aimed interventions to maintain ideal health and well-being.

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