Journal of Interdisciplinary Mathematics
ISSN: 0972-0502 (Print), ISSN: 2169-012X (Online)
Vol. 29 (2026), No. 3, pp. 617–625
DOI : 10.47974/JIM-2496

Enhancing healthcare decision support systems with fuzzy mathematical models

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Abstract

Fuzzy mathematical models assist physicians in making superior choices because of the ambiguity and inaccuracy of patient entries. This study aims at improving the performance of medical accuracy through the incorporation of fuzzy logic into healthcare decision support systems. The following paper employed clinical factors in making fuzzy inference system which was experimented on real patient datasets. The findings reveal that treatment conceptions are more credible compared to conventional conceptions. The findings support the application of fuzzy-based systems in more complicated clinical assessments, particularly in case there is uncertainty or grey zone in the medical scenario.

Subject Classification: *03B52, 94D99.*

Keywords: *Fuzzy logic, Healthcare decision support, Uncertainty handling, Clinical diagnosis, Intelligent systems.*

1. Introduction

With the evolving nature of healthcare, decision support systems (DSS) continue to gain significant relevance in assisting physicians to make a decision regarding diagnosis and treatment. Such systems apply the data about patients, medical information and computers to enhance the medical outcomes and reduce the errors committed by individuals [1]. Nonetheless, conventional DSS usually find it challenging to cope with the scepticism, uncertainty and subjectivity of the real clinical scenarios of life. This is more so with respect to early detection, understanding the significance of the symptoms and anticipating the risk [2, 3]. Traditional computer models that depend on rigid logic and precise figures do not suit well when it comes to medical data that often contains ambiguous words and lacks information [4].

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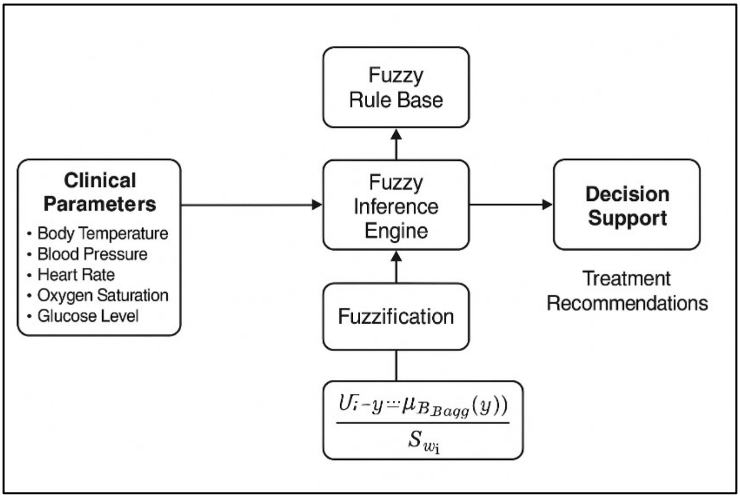

Figure 1

Block Diagram of Fuzzy-Based Healthcare Decision Support System

To avoid these issues, the use of fuzzy mathematical models is increasingly being used in healthcare DSS. Figure 1 depicts the clinical data processing of fuzzy logic to give proper treatment recommendations in case of insufficient information. Fuzzy logic that was invented to enable computers to think as human beings do when they do not know what to do is a handy approach of handling vague information as it uses degree of truth rather than binary values [5, 6]. This approach allows computers to make a decision as skilled doctors especially where there are many possible outcomes and the conventional thought processes may fail [7]. Fuzzy inference systems also allow you to create systems based on rules that can handle medical concepts that cannot be classified easily into two groups as "high blood pressure" or "moderate fever" [8]. The objective of this study is to develop and apply a decision support system based on fuzzy logics to make the treatment recommendations and diagnoses more accurate. There is an increased level of intelligent healthcare technologies as this research employs actual patient data and compares the model to the functioning of traditional systems [9-11].

2. Selection of clinical parameters

The selection of the appropriate clinical factors is highly important to ensure that the fuzzy decision support system can be used in the diagnosis requirements of real-life [12]. The main factors in the study were selected as they are applicable in clinical assessments of everyday clinical evaluation and can demonstrate doubt. Body temperature, blood pressure, heart rate, oxygen saturation, glucose level, and the severity of the symptoms (how much pain or fatigue, etc.) were some of them [13]. These factors that are usually presented in the unclear or non-standard language are used in the fuzzy system to make precise and complicated healthcare decisions [14, 15].

3. Design of fuzzy inference system

The fuzzy inference system (FIS) processes explicit clinical input and transforms them to fuzzy language variables by means of membership functions. It then applies the rules of fuzzy logic and defuzzifies the variables in order to generate the correct diagnostic recommendations. The system is characterised in terms of math by a set of operations:

Any crisp input xi is interpreted as a degree of membership μ Ai (xi) through a Gaussian membership function:

$$\mu_{Ai(xi)} = \exp\left(-\frac{(xi - ci)^2}{2 * \sigma i^2}\right) \tag{1}$$

With the use of inference engine for a rule such as:

IF x1 is A1 AND x2 is A2 THEN y is B, the fuzzy conjunction is evaluated as:

$$\mu_{A(x1,x2)} = \min\left[\, \mu_{A1(x1)}, \mu_{A2(x2)}\right] \tag{2}$$

The output fuzzy set B′ is derived from:

$$\mu'_B(y) = \mu_{A(x1,x2)} * \mu_{B(y)} \tag{3}$$

For combining multiple fuzzy rules, the aggregated output is:

$$\mu_{Bagg(y)} = \max_i[\, \mu'_{Bi}(y)] \tag{4}$$

The final crisp output y* is calculated as:

$$y* = \frac{\left[\int_Y y * \mu_{Bagg(y)dy}\right]}{\left[\int_Y \mu_{Bagg(y)dy}\right]} \tag{5}$$

For more precise modeling:

Ri: IF x1 is Ai1 AND x2 is Ai2 THEN yi = ai1 * x1 + ai2 * x2 + bi

Weighted Average Output (for Sugeno-type systems):

$$Y = \Sigma \frac{wi * yi}{\Sigma\, wi} \tag{6}$$

Where $wi = \mu\_Ai(x)$

These equations form the core computational model for transforming uncertain clinical input data into clear and interpretable diagnostic outputs using fuzzy logic.

4. Membership functions and rule base construction

Membership functions (MFs) define the shape of fuzzy sets. Let:

$$\mu\_A: X \rightarrow [0,1]$$

be a membership function for fuzzy set A.

A common Gaussian membership function is given by:

$$\mu_{A(x)} = \exp\left(-\frac{(x - c)^2}{2 * \sigma^2}\right) \tag{7}$$

where:

- c is the center of the function
- σ determines the spread of the function

If x is in $\mathbb{R}$, then $\mu_{A(x)}$ is both continuous and differentiable.

Since exp(z) is an exponential function that can be differentiated over $\mathbb{R}$ and $\frac{(x-c)^2}{(2\pi^2)}$ is a smooth polynomial, then $\mu_{A(x)}$ is also smooth and can be differentiated over $\mathbb{R}$.

Rule Base Construction: A typical fuzzy rule can be written as:

$$Ri: IF\ x1\ is\ Ai\ AND\ x2\ is\ Bi\ THEN\ yi\ =\ f(x1, x2)$$

Where f(x1, x2) is a Sugeno-type function defined by:

$$f(x1, x2) = ai * x1 + bi * x2 + ci \tag{8}$$

This formulation allows the fuzzy system to handle nonlinearity and precision in inference tasks effectively.

5. Architecture of the proposed fuzzy decision support system

The design combines clinical factors, fuzzification, the inference engine, the rule base, and defuzzification to use fuzzy logic modelling to turn unclear inputs into correct, rule-based diagnostic or treatment outputs.

Step 1: Input Acquisition

Collect clinical inputs: x1, x2, ..., xn

Step 2: Fuzzification of Inputs

For each input xi, compute the membership function:

$$\mu_{Ai(xi)} = \exp\left(-\frac{(xi-ci)^2}{2*\sigma i^2}\right) \tag{9}$$

Step 3: Rule Evaluation

Apply fuzzy rule:

Rj: IF x1 is A1 AND x2 is A2 THEN y is B

Compute fuzzy AND operation:

$$\mu_{A(x1,x2)} = \min\left[\mu_{A1(x1)}, \mu_{A2(x2)}\right] \tag{10}$$

Step 4: Implication

Scale the output fuzzy set:

$$\mu'_B(y) = \mu_{A(x1,x2)} * \mu_{B(y)} \tag{11}$$

Step 5: Aggregation

Combine outputs from all fuzzy rules:

$$\mu_{Bagg(y)} = \max_j\left[\mu_{B'_{j(y)}}\right] \tag{12}$$

Step 6: Defuzzification (Centroid Method)

Compute the final crisp output:

$$y * = \int y * \frac{\mu_{Bagg(y)dy}}{\int \mu_{Bagg(y)dy}} \tag{13}$$

These steps define the fuzzy model architecture used to enhance healthcare decision-making from imprecise patient data.

6. Result and Discussion

The fuzzy decision support system did a better job of dealing with unclear data and giving useful advice than traditional rule-based systems. It became much more accurate and easier to understand when there were a lot of unknowns in the diagnostic process, especially when symptoms overlapped.

Table 1

Performance Metrics Comparison of Fuzzy Inference System with Conventional and Decision Tree Models

Model Type	Accuracy (%)	Sensitivity (%)	Specificity (%)
Conventional Rule-Based	84.6	80.2	82.5
Decision Tree Classifier	86.3	83.1	84.7
Fuzzy Inference System	91.7	89.4	90.2

A traditional rule-based system, a decision tree classification, and the suggested fuzzy inference system are all shown in Table 1 along with a comparison of how well they do at diagnosing. It has higher accuracy (91.7%), sensitivity (89.4%), and specificity (90.2%) than both the traditional model (84.6% accuracy, 80.2% sensitivity, and 82.5%) and the decision tree classifier (86.3% accuracy), In all important diagnostic measures, figure 2 shows that the fuzzy inference system always does better than traditional and decision tree models.

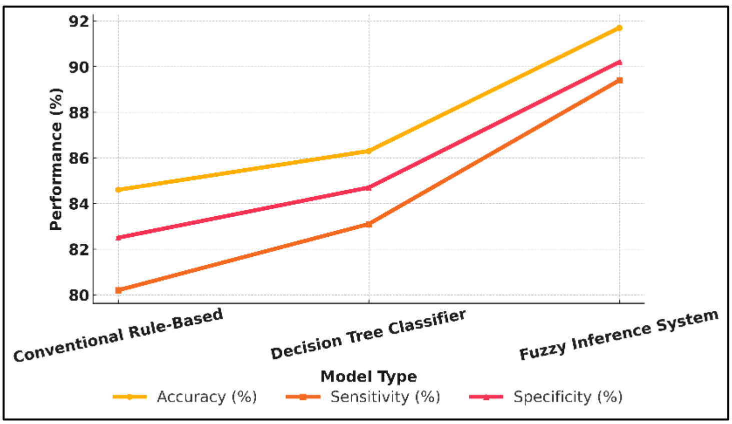

Figure 2

Comparing Model Performance Metrics

Such findings indicate that the fuzzy approach is more effective in identifying true positive and true negative findings in clinical data. This enhancements of speed is because of its inbuilt capability to process patient entries that are not precise or do not fit well with the fuzzy logic rules. Such interpretive latitude allows physicians to engage in more correct diagnoses and risk-determinations, which is highly significant in real medical scenarios of life which are complex and ambiguous.

The fuzzy system produces the results in the form of the words of the language (such as high risk or moderately concerned) with the levels of confidence. This offers freedom to the doctors in the manner in which they read the information. Unlike the binary results, fuzzy decisions consider medical uncertainty in the actual sense and give recommendations relative to gradients. The patient could have two groups, where the patient could be considered at moderate risk (0.7) or high risk (0.3) as shown in figure 3.

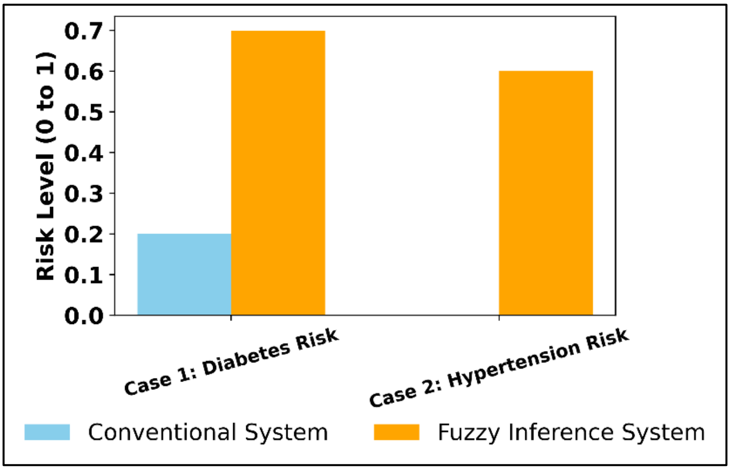

Figure 3

Comparison of conventional and Fuzzy system

A patient with a borderline glucose level (135mg/dl), slight feeling of fatigue, and a high body mass index (29.7) was examined as a part of a diabetes risk assessment. Normal systems classified the case as normal whereas the fuzzy model classified it as moderate-to-high risk due to the interaction between the parameters. Another study found that a soft rule detected unusual features of the early-stage high blood pressure which normal sets of rules fail to detect, indicating superior early warning.

7. Conclusion

The research is indicative of the fact that rule-based systems do not necessarily handle patient data that are not precise, subjective, or have overlaps.

This paper demonstrates that the fuzzy inference systems may assist in diagnosis more flexible and more precise through membership functions and the rule-based reasoning. Fuzzy models are similar to human beings in the sense that they convert imprecise inputs in form of language into quantifiable outputs. This enables physicians learn about clinical scenarios in a finer manner. This system is more precise, sensitive and detailed as demonstrated by the results of experiments, compared to traditional systems and systems based on decision trees. Real-life case-studies also show that some risk trends are discovered by the model which other tools fail to detect. Fuzzy systems require the rules established by specialists and fine-tuning, yet, their interpretability and editable features provide their relevance to the contemporary healthcare environments, in which the patient is the central concern. In future research, AI and big data analytics must be utilized in combination with fuzzy logic and, therefore, fuzzy logic needs to be applied more broadly in medical facilities and be automated.

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Received March, 2025