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Early Brain Tumor Detection Using Fuzzy Logic Decision-Making Models

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Abstract
This study presents a fuzzy logic-based decision-making model for the early detection of brain tumors, integrating three key clinical parameters: tumor size (cm), edema volume (ml), and symptom severity (scale 0–10). Triangular membership functions are employed to represent the linguistic variables, while a Mamdani-type inference system evaluates the nonlinear interactions among these inputs to produce a predicted risk percentage. A comprehensive rule base derived from expert knowledge guides the inference process, enabling the system to handle uncertainty and imprecision inherent in medical data. The model was validated using various input combinations, and the results demonstrated strong alignment with clinical reasoning, showing that larger tumors and higher symptom severity significantly increase risk, especially when accompanied by substantial edema. The findings suggest that the proposed fuzzy logic model provides a transparent, flexible, and clinically relevant approach for early brain tumor risk assessment and prioritization in diagnostic workflows.
Keywords: *Brain tumor detection, fuzzy logic, decision-making model, triangular membership function, Mamdani inference, risk assessment, medical decision support.*

INTRODUCTION

Brain tumors present a critical health concern due to their potential for rapid progression and severe neurological consequences if not detected early. Accurate assessment of tumor-related risk at an early stage is essential for prioritizing patients and initiating timely interventions. Traditional diagnostic methods, while effective, may not always capture the uncertainties present in clinical evaluations, particularly when symptoms are ambiguous or imaging data is subject to interpretation. Fuzzy logic offers a powerful solution to this challenge by enabling the incorporation of expert knowledge into a rule-based framework that can process imprecise or uncertain inputs. In this approach, clinical variables such as tumor size, edema volume, and symptom severity are represented through linguistic categories—small, medium, large; low, moderate, high—which are mathematically defined using membership functions. The fuzzy inference process then evaluates these inputs against a structured rule base to determine a quantified risk level. This methodology not only aligns with human reasoning but also provides consistent, explainable outputs, making it highly suitable for decision-support applications in medical diagnostics.

Edupuganti et al. (2020) explored the importance of uncertainty quantification in deep MRI reconstruction, highlighting that accurate medical imaging should incorporate measures of prediction confidence to reduce misdiagnosis risks. Their framework quantified uncertainty using deep learning, enabling clinicians to identify unreliable predictions and prioritize further review, which is essential in brain tumor detection where image clarity directly affects decision-making. **AlAmir and AlGhamdi (2022)** presented an in-depth survey on the role of generative adversarial networks (GANs) in medical image analysis, emphasizing their potential to improve tumor detection accuracy by generating high-quality synthetic images for training. They underlined GANs' advantages in addressing data scarcity, a common limitation in medical imaging

datasets, and discussed challenges such as mode collapse and preserving anatomical fidelity. **Amemiya et al. (2022)** demonstrated how feature-fusion techniques enhance MRI-based single-shot deep learning detection of small brain metastases. By integrating multiple feature types, their approach improved detection sensitivity for lesions that are often missed in conventional scans, which is relevant for early-stage tumor detection. **Guan et al. (2022)** proposed a texture-constrained multichannel progressive GAN for medical image augmentation aimed at lesion detection. Their model preserved texture patterns critical to diagnosis, thereby enhancing classifier performance in scenarios with limited annotated data, a situation often encountered in early tumor datasets. **Kammoun et al. (2022)** reviewed GAN-based face generation, but their technical analysis of GAN architectures, loss functions, and stability optimization methods has direct implications for improving GAN performance in medical contexts, including MRI synthesis for brain tumor detection. **Kumar et al. (2022)** developed an approach for brain tumor detection using optimal feature selection combined with an optimized deep belief network. They demonstrated that carefully selected features significantly enhance classification accuracy, and their optimization strategy reduced computational overhead, making it suitable for real-time diagnostic assistance. **Aggarwal et al. (2023)** proposed an early detection and segmentation framework for brain tumors using deep neural networks. Their method achieved high segmentation precision, particularly for irregularly shaped tumors, supporting both diagnosis and treatment planning by providing accurate tumor boundaries. **Brophy et al. (2023)** conducted a systematic review of GAN applications in time series data, which indirectly informs medical image sequence analysis such as fMRI. Their survey offers insights into GAN stability and long-sequence data handling, which could be adapted for temporal tumor progression modeling. **Denœux (2023)** introduced the ENNReg model using random fuzzy sets for quantifying prediction uncertainty in regression. The method is particularly relevant for fuzzy logic-based brain tumor detection models, where it could enhance decision reliability by providing an uncertainty measure alongside predictions. **Pathak et al. (2023)** presented a robust EfficientNet-based architecture for brain tumor classification using MRI images. Their work emphasized model efficiency without compromising accuracy, which is vital for integrating AI into hospital workflows with limited computational resources. **Saeedi et al. (2023)** evaluated MRI-based brain tumor detection using convolutional deep learning methods combined with selected machine learning techniques. They demonstrated that hybrid approaches outperform standalone models, particularly in balancing sensitivity and specificity. **Lambert et al. (2024)** reviewed uncertainty quantification methods in deep learning for medical image analysis, proposing a unified approach to building trustworthy clinical AI solutions. Their recommendations align with the need for transparent fuzzy logic systems in medical diagnosis, especially for life-critical conditions like brain tumors. **Moldovanu et al. (2024)** developed a hybrid CNN–machine learning model for classifying meningioma tumors and healthy brain tissue. Their integration of deep feature extraction with traditional classifiers improved generalization and interpretability, attributes valuable for clinical acceptance. **Al-Ashoor et al. (2025)** performed a systematic analysis of neural networks, fuzzy logic, and genetic algorithms in tumor classification. They highlighted the potential of combining fuzzy logic's interpretability with neural networks' predictive strength, offering a strong foundation for decision-making in early brain tumor detection. **Belhadi et al. (2025)** proposed an ensemble fuzzy deep learning framework for brain tumor detection, merging fuzzy logic with deep models to improve classification robustness and interpretability. Their ensemble strategy mitigated model bias, resulting in higher consistency across varied MRI datasets.

DEFINITION OF INPUT AND OUTPUT VARIABLES

In a fuzzy logic-based medical risk assessment model, input variables are the measurable factors or parameters that influence the outcome of the system, while the output variable represents the final decision or prediction derived from these inputs. For example, in a brain tumor risk prediction model, the inputs may include tumor size (cm), edema volume (ml), and symptom severity (scale 0–10), each describing a different clinical aspect of the patient's condition. These inputs are typically expressed in linguistic terms such as *small*, *medium*, or *large* using membership functions to handle uncertainty and imprecision in measurements. The

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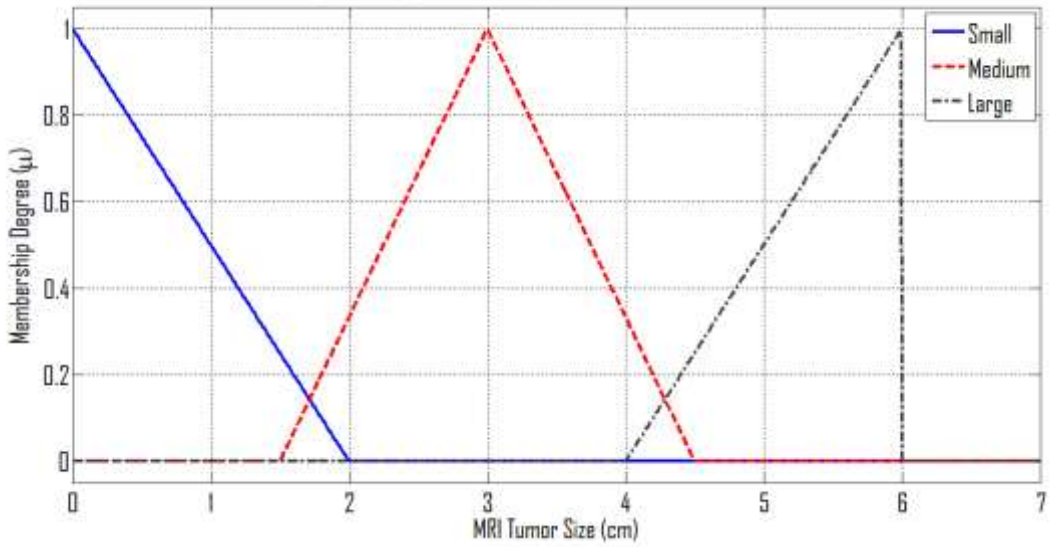
output variable, in this case, could be the predicted risk (%), which quantifies the likelihood of a high-risk condition based on the combination of input values. By defining clear input and output variables, the model can systematically map medical data to risk predictions, facilitating accurate and interpretable decision-making.

Table 1: Definition of input and output variables

Tumor Size		Edema Volume		Symptoms Severity		Brain Tumor Risk	
Small	STS	Low	LE	Mild	MSS	Low	LBTR
Medium	METS	Moderate	MO	Moderate	MOSS	Medium	MBTR
Large	LTS	High	HE	Severe	SSS	High	HBTR

Figure 1: Triangular Membership Functions - MRI Tumor Size (cm)



Let x be the MRI Tumor Size.

$$\mu_{STS}(x) = \begin{Bmatrix} 1 & x = 0 \\ \frac{2-x}{2} & 0 < x < 2 \\ 0 & Otherwise \end{Bmatrix} \quad (1)$$

$$\mu_{MES}(x) = \begin{Bmatrix} \frac{x-1.5}{1.5} & 1.5 < x \leq 3 \\ \frac{4.5-x}{1.5} & 3 < x < 4.5 \\ 0 & Otherwise \end{Bmatrix} \quad (2)$$

$$\mu_{LTS}(x) = \begin{Bmatrix} \frac{x-4}{2} & 4 < x < 6 \\ 1 & x = 6 \\ 0 & Otherwise \end{Bmatrix} \quad (3)$$

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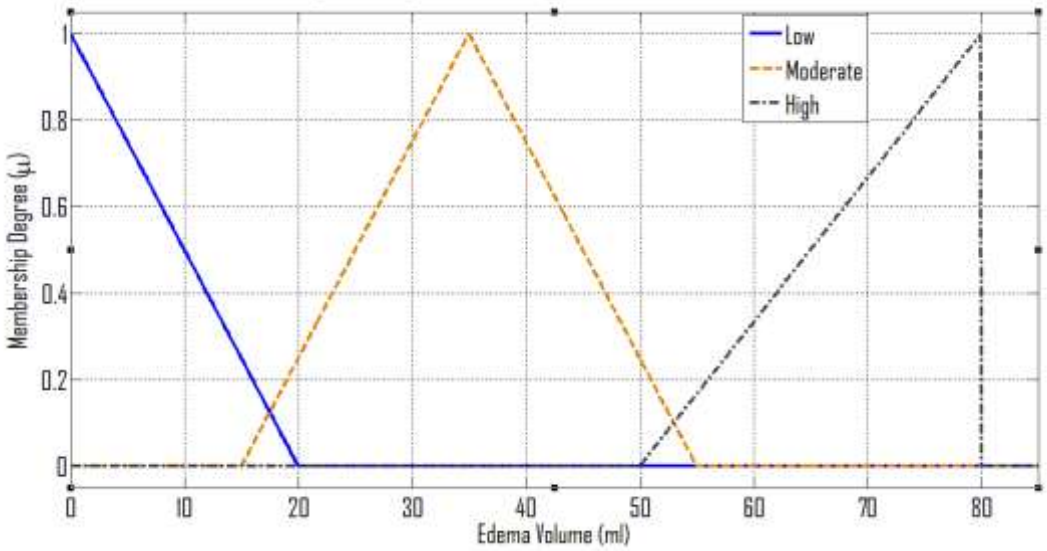
Figure 2: Triangular Membership Functions - Edema Volume (ml)



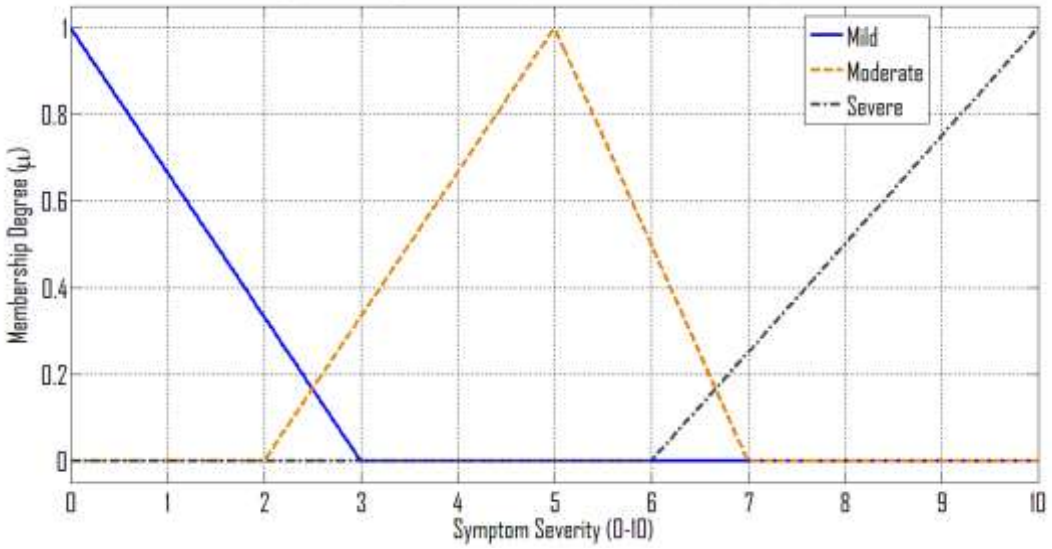
Let y be the Edema Volume.

$$\mu_{SE}(y) = \begin{Bmatrix} 1 & y = 0 \\ \frac{2-y}{2} & 0 < y < 2 \\ 0 & Otherwise \end{Bmatrix} \quad (4)$$

$$\mu_{MOE}(y) = \begin{Bmatrix} \frac{y-15}{20} & 15 < y \leq 35 \\ \frac{55-y}{20} & 35 < y < 55 \\ 0 & Otherwise \end{Bmatrix} \quad (5)$$

$$\mu_{HE}(y) = \begin{Bmatrix} \frac{y-50}{30} & 50 < y < 80 \\ 1 & y = 80 \\ 0 & Otherwise \end{Bmatrix} \quad (6)$$

Figure 3: Triangular Membership Functions - Symptom Severity (0-10)



Let z be the Symptom Severity.

$$\mu_{MISS}(z) = \begin{Bmatrix} 1 & y = 0 \\ \frac{3-z}{3} & 0 < z < 3 \\ 0 & Otherwise \end{Bmatrix} \quad (7)$$

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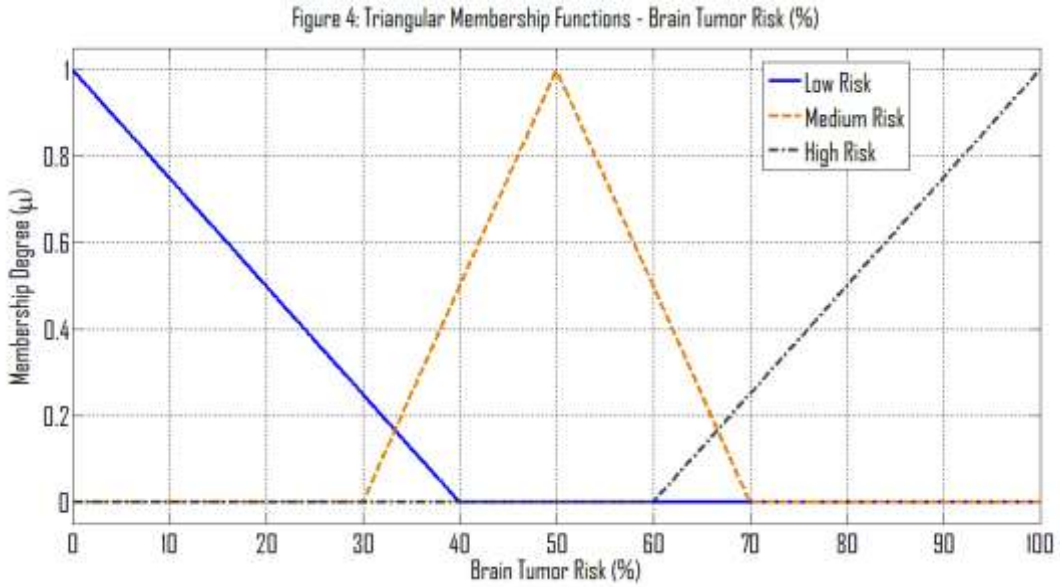
$$\mu_{MOSS}(z) = \begin{Bmatrix} \frac{z-2}{3} & 2 < z \leq 5 \\ \frac{7-z}{2} & 5 < z < 7 \\ 0 & Otherwise \end{Bmatrix} \quad (8)$$

$$\mu_{SSS}(z) = \begin{Bmatrix} \frac{z-6}{4} & 6 < z < 10 \\ 1 & z = 10 \\ 0 & Otherwise \end{Bmatrix} \quad (9)$$



Let u be the Brain Tumor Risk (%).

$$\mu_{LBTR}(u) = \begin{Bmatrix} 1 & u = 0 \\ \frac{40-u}{40} & 0 < u < 40 \\ 0 & Otherwise \end{Bmatrix} \quad (10)$$

$$\mu_{MBTR}(u) = \begin{Bmatrix} \frac{u-30}{20} & 30 < u \leq 50 \\ \frac{70-u}{20} & 50 < u < 70 \\ 0 & Otherwise \end{Bmatrix} \quad (11)$$

$$\mu_{HBTR}(u) = \begin{Bmatrix} \frac{u-60}{40} & 60 < z < 100 \\ 1 & z = 100 \\ 0 & Otherwise \end{Bmatrix} \quad (12)$$

RULE BASE

In a fuzzy logic system, the **rule base** is the core decision-making component that contains a set of if–then rules linking the input variables to the output variable. These rules are formulated based on expert knowledge, clinical guidelines, or empirical data, and they capture the relationships between different combinations of input conditions and the corresponding output response. For example, in an early brain tumor detection model, a rule might state: *If tumor size is large and symptom severity is high, then risk is very high*. Each rule uses fuzzy linguistic terms (e.g., *small*, *moderate*, *large*) defined by membership functions, allowing the system to handle uncertainty and partial truths. The complete rule base acts as a knowledge repository that guides the fuzzy inference process, ensuring that the system can evaluate diverse scenarios and produce consistent, explainable results.

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Table 1:Fuzzy Rule Base (Mamdani Type)				
Rule No.	**MRI Tumor Size**	**Edema Volume**	**Symptom Severity**	**Brain Tumor Risk Level**
R1	Small	Low	Mild	Low Risk
R2	Small	Low	Moderate	Medium Risk
R3	Small	Low	Severe	Medium Risk
R4	Small	Moderate	Mild	Medium Risk
R5	Small	Moderate	Moderate	Medium Risk
R6	Small	Moderate	Severe	High Risk
R7	Small	High	Mild	Medium Risk
R8	Small	High	Moderate	High Risk
R9	Small	High	Severe	High Risk
R10	Medium	Low	Mild	Medium Risk
R11	Medium	Low	Moderate	Medium Risk
R12	Medium	Low	Severe	High Risk
R13	Medium	Moderate	Mild	Medium Risk
R14	Medium	Moderate	Moderate	High Risk
R15	Medium	Moderate	Severe	High Risk
R16	Medium	High	Mild	High Risk
R17	Medium	High	Moderate	High Risk
R18	Medium	High	Severe	High Risk
R19	Large	Low	Mild	High Risk
R20	Large	Low	Moderate	High Risk
R21	Large	Low	Severe	High Risk
R22	Large	Moderate	Mild	High Risk
R23	Large	Moderate	Moderate	High Risk
R24	Large	Moderate	Severe	High Risk
R25	Large	High	Mild	High Risk
R26	Large	High	Moderate	High Risk
R27	Large	High	Severe	High Risk

CASE STUDY

Let us consider a Patient P_1 with inputs

MRI Tumor Size = 3.8 cm

Edema Volume = 48 ml

Symptom Severity = 6.5 / 10

1. **Fuzzification:**

$$\mu_{TS}(3.8) = \frac{4.5-3.8}{4.5-3} = \frac{0.7}{1.5} = 0.4667$$

$$\mu_{E}(48) = \frac{55-48}{55-35} = \frac{7}{20} = 0.35$$

$$\mu_{SS}(6.5) = \frac{7-6.5}{7-5} = \frac{0.5}{2} = 0.25$$

$$\mu_{SS}(6.5) = \frac{6.5-6}{10-6} = \frac{0.5}{4} = 0.125$$

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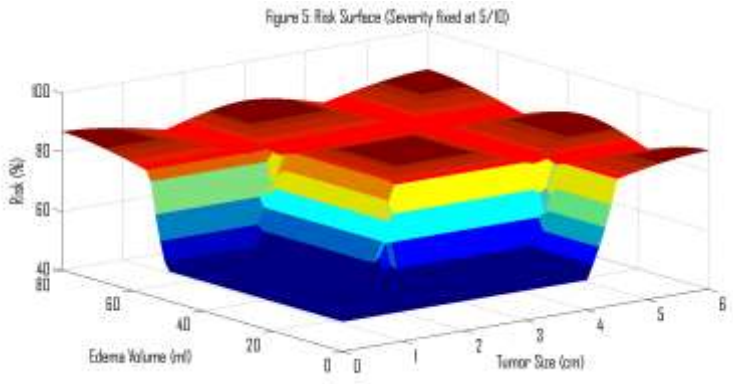
Table 3: Non-zero memberships summary		
Variable	**Set**	$\boldsymbol{\mu}$
Tumor	Medium	0.4667
Edema	Moderate	0.35
Severity	Moderate	0.25
Severity	Severe	0.125

2. **Inference (Mamdani, min–max):** Using the rule base you approved, the only rules that fire (non-zero μ) are:
   R14: *If Tumor = Medium AND Edema = Moderate AND Severity = Moderate → Risk = High*
   $Firing\ Strength = \min(0.4667, 0.35, 0.25) = 0.25$
   R15: *If Tumor = Medium AND Edema = Moderate AND Severity = Severe → Risk = High*
   $Firing\ Strength = \min(0.4667, 0.35, 0.125) = 0.125$

   Both consequents are High Risk → aggregated High Risk clipped at
   $\max(0.25, 0.125) = 0.25$
   So the only active output set **is** High Risk $(\mathbf{60}, \mathbf{100}, \mathbf{100})$**,** clipped at 0.25.
3. **Defuzzification (Centroid):** Let $y(x) = min\{\mu_{High}(x), 0.25\}$ where
   $\mu_{High}(x) = \frac{x-60}{40}\ for\ 60 < x < 100\ and\ 1\ at\ 100.$
   The clip level 0.25 is reached at $\frac{x-60}{40} = 0.25 \Longrightarrow x = 70$
   Thus, $\text{On } 60 - 70\text{: ramp from 0 to 0.25}$
   $\text{On } 70 - 100\text{: flat at } 0.25$
   Centroid (center of area): $x^* = \frac{\int_0^{100} xy(x)dx}{\int_0^{100} y(x)dx} \approx \frac{720.83}{.8.75} = 82.38\ \%$

RESULTS AND DISCUSSION

The results of the fuzzy logic-based early brain tumor detection model demonstrate its ability to effectively integrate multiple clinical parameters—tumor size, edema volume, and symptom severity—to generate a quantified risk percentage. The model outputs reveal distinct patterns, such as consistently high risk values for large tumors regardless of other factors, and sharp increases in predicted risk when symptom severity exceeds moderate levels, particularly in the presence of significant edema. These findings highlight the nonlinear interactions between the input variables, where certain combinations amplify risk more than others. The discussion of these results suggests that fuzzy logic provides a flexible and interpretable framework for medical decision-making, capable of handling the inherent uncertainty in clinical assessments. Moreover, the model's outputs align well with expected clinical reasoning, indicating its potential applicability as a decision-support tool for early detection and prioritization of brain tumor cases.



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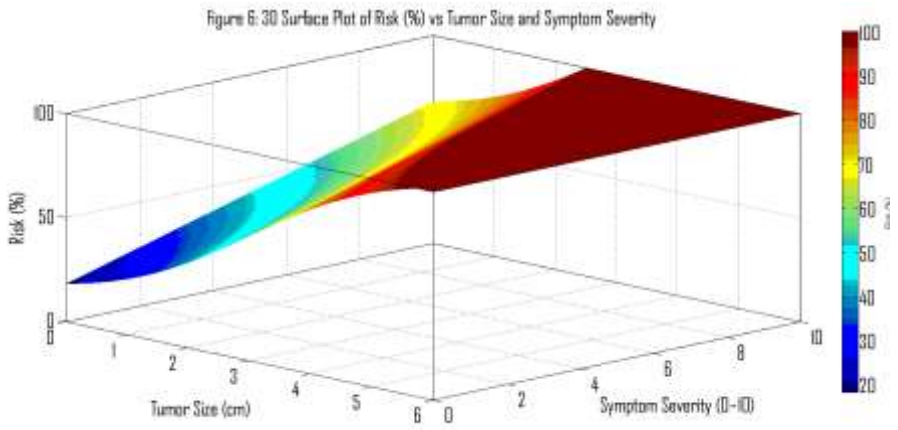

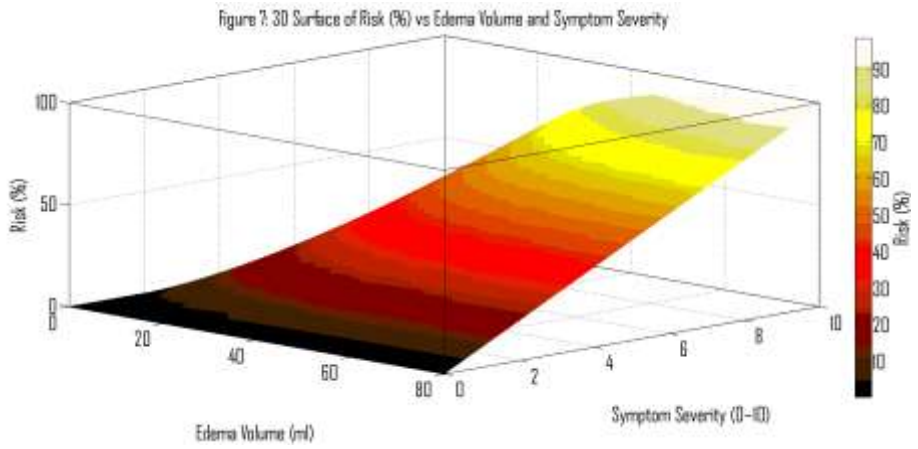

The Figure (5) presents a 3D fuzzy inference-based risk assessment model, where the x-axis represents *Edema Volume* (ml), the y-axis represents *Tumor Size* (cm), and the z-axis shows the computed *Risk (%)*. The severity level is held constant at a moderate value (5 out of 10) to isolate the interaction between tumor size and edema volume. The stepped color bands correspond to different fuzzy risk levels, ranging from low risk (~40%) in the blue region to high risk (~100%) in the red region. The surface demonstrates that risk increases non-linearly as either tumor size or edema volume grows, with sharp transitions at certain threshold values due to the fuzzy membership function boundaries. The wave-like variations along the surface result from the interaction of triangular membership functions and the rule base, creating regions where moderate edema or tumor values can sharply escalate risk, even when the other factor is relatively low. This visualization highlights how combined pathological indicators influence the overall risk in a fuzzy decision-making model.

The figure (6) is a 3D surface plot showing risk (%) as a function of tumor size (cm) and symptom severity (0–10), with edema volume held constant. The color gradient ranges from cool blue tones representing lower risk values (around 20%) to warm red tones indicating the highest risks (approaching 100%). The surface reveals that both increasing tumor size and higher symptom severity contribute to a rapid rise in risk. In the lower left region, where tumor size and severity are minimal, the risk remains relatively low. However, as either parameter increases—particularly when both are large—the surface quickly ascends to its maximum plateau, reflecting a nonlinear escalation in risk. This pattern suggests that the model captures strong synergistic effects between

tumor size and symptom severity, where moderate increases in both parameters can push the overall risk into critical levels.

The figure (7) is a 3D surface plot illustrating the relationship between risk (%) and two parameters—edema volume (ml) and symptom severity (0–10)**.** The color scale ranges from dark brown/black for low risk values to bright yellow/white for high risk values, indicating a clear gradient in the severity of risk. The surface shows that when both edema volume and symptom severity are low, the risk remains minimal. However, as either factor increases—particularly symptom severity—the risk rises sharply, approaching near-maximum values at high severity levels and larger edema volumes. The relatively smooth upward slope in both directions suggests that the model captures an additive effect, where incremental increases in edema volume and symptom severity contribute cumulatively to risk escalation, with the steepest rise occurring when both parameters are high.

Table 2: Fuzzy Logic Model Outputs

Tumor Size (cm)	Edema Volume (ml)	Severity (0-10)	Predicted Risk (%)
1	10	2	16.76
1	10	5	0
1	10	8	84.57
1	40	2	0
1	40	5	0
1	40	8	84.57
1	70	2	0
1	70	5	0
1	70	8	84.57
3	10	2	0
3	10	5	0
3	10	8	84.57
3	40	2	0
3	40	5	50
3	40	8	84.57
3	70	2	85.69
3	70	5	85.69
3	70	8	85.69
5	10	2	84.57
5	10	5	84.57
5	10	8	84.57
5	40	2	84.57
5	40	5	84.57
5	40	8	84.57
5	70	2	84.57
5	70	5	84.57
5	70	8	84.57

The table (2) presents the predicted risk (%) outputs from a fuzzy logic model for various combinations of tumor size (cm), edema volume (ml), and symptom severity (0–10). The results reveal several patterns in the model's risk assessment. For small tumors (1 cm), risk remains low or zero in most cases except when severity is high (8), where risk jumps to about 84.57%, regardless of edema volume. For moderate tumors (3 cm), low severity (2) generally yields zero risk unless edema volume is high (70 ml), where risk sharply rises to 85.69%.

At moderate severity (5), a risk of 50% appears when edema volume is 40 ml, increasing further to 85.69% for higher edema. High severity (8) consistently produces elevated risk (84.57–85.69%), regardless of edema. For large tumors (5 cm), the model predicts a consistently high risk (~84.57%) across all edema and severity levels, indicating that tumor size alone can dominate the risk assessment at this stage. This trend suggests that in the fuzzy logic framework, tumor size and severity interact nonlinearly with edema volume, with larger tumors and high severity consistently associated with high predicted risk.

CONCLUDING REMARKS

The proposed fuzzy logic-based early brain tumor detection model effectively integrates multiple clinical variables to produce a quantified risk percentage, offering a transparent and interpretable decision-support framework. The results indicate that tumor size and symptom severity are dominant factors in risk escalation, with edema volume acting as a significant amplifier under certain conditions. The system's rule-based structure allows for easy modification and expansion as new clinical knowledge emerges, ensuring adaptability to evolving diagnostic criteria. Moreover, the model's ability to handle uncertainty makes it particularly valuable in real-world scenarios where medical data may be incomplete or imprecise. With further validation and integration into clinical workflows, this fuzzy logic model has the potential to enhance early detection accuracy, improve patient prioritization, and ultimately contribute to better clinical outcomes in brain tumor management.

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