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Uncertainty-Aware Decision Support for Hiv/Aids Treatment Using Fuzzy Logic

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Abstract
The treatment of HIV/AIDS presents significant challenges due to uncertainties in clinical data, patient adherence variability, and evolving medical guidelines. Traditional crisp decision models often fail to capture these uncertainties, leading to abrupt and sometimes unrealistic treatment recommendations. This study proposes an uncertainty-aware decision support system based on a Mamdani Fuzzy Inference System (FIS) to enhance clinical decision-making for HIV/AIDS treatment. The system incorporates three input variables—CD4 count, viral load, and adherence level and generate an output variable representing treatment urgency. Membership functions and a comprehensive rule base of 27 rules enable the system to process uncertain or imprecise inputs, while the centroid defuzzification method provides a crisp urgency score. Simulation results demonstrate that the fuzzy model yields nuanced and clinically interpretable recommendations, balancing biological and behavioral factors to produce smooth transitions across urgency levels. By addressing the limitations of crisp threshold models, the proposed system provides a robust, transparent, and flexible tool for improving treatment prioritization in HIV/AIDS care.
Keywords: *Fuzzy Inference System (FIS); HIV/AIDS Treatment; Decision Support System; Uncertainty Handling; Mamdani Model; Centroid Defuzzification; Patient Adherence; Clinical Decision-Making*

1. INTRODUCTION

HIV/AIDS remains one of the most pressing global health concerns, requiring lifelong treatment and continuous monitoring. Clinical decision-making in HIV/AIDS care is inherently uncertain, as it depends on a combination of biological indicators, such as CD4 count and viral load, and behavioral factors, such as patient adherence to therapy. These variables are often imprecise or subject to fluctuation, making rigid, threshold-based decision models inadequate for nuanced patient care. For example, while a CD4 count below 200 cells/mm^3 may indicate urgency in traditional models, patients with slightly higher counts but poor adherence or elevated viral loads may still face significant risks. This highlights the limitations of crisp models that rely on strict cutoffs without accounting for overlapping or interacting factors. Fuzzy logic, with its ability to model uncertainty and partial truths, offers a powerful alternative. By translating quantitative medical data into qualitative linguistic terms such as Low, Medium, and High, fuzzy inference systems bridge the gap between numerical analysis and clinical reasoning. This study introduces a Mamdani-type fuzzy inference system for HIV/AIDS treatment prioritization, designed to integrate biological and behavioral factors, handle uncertainty effectively, and generate transparent, clinically relevant recommendations.

Gupta et al. (2011) explored data mining classification techniques applied to breast cancer diagnosis and prognosis. Their work provided a comparative evaluation of classification algorithms such as decision trees, neural networks, and Bayesian methods for analyzing medical datasets. The study highlighted how data mining approaches could aid in detecting cancer at early stages and predicting patient outcomes. Although not directly related to fuzzy logic, the research emphasized the significance of computational intelligence in healthcare diagnostics, setting the groundwork for later applications of soft computing and hybrid methods in disease detection and management. **Igodan et al. (2013)** proposed an online fuzzy-logic knowledge warehousing and mining model tailored for the diagnosis and therapy of HIV/AIDS. Their approach combined fuzzy logic with knowledge warehousing to manage large datasets, while providing rule-based decision support for patient treatment. The study demonstrated how fuzzy inference systems could reduce uncertainty in HIV/AIDS therapy by modeling patient data and offering adaptable recommendations. This work is notable as one of the earlier applications of fuzzy logic specifically for HIV/AIDS management, showing how uncertainty-aware systems could complement traditional clinical practice. **Kora et al. (2019)** applied fuzzy inference to ECG data, transforming continuous signals into linguistic terms for diagnosis. The model effectively managed noise and variability in cardiac signals, illustrating the strength of fuzzy systems in handling uncertainty in physiological data. While focused on arrhythmia rather than HIV/AIDS, the research validated the adaptability of fuzzy models in medical diagnostics, reinforcing their potential in decision support systems across diverse health domains. **Oye and Isah (2019)** considered variables such as CD4 count, viral load, and treatment adherence to guide clinical decision-making. The research emphasized the ability of fuzzy logic to handle imprecise and fluctuating medical indicators, offering recommendations for treatment adjustments and patient monitoring. Unlike rigid threshold systems, the model allowed gradual transitions between urgency levels, making it directly relevant to uncertainty-aware decision support for HIV/AIDS care. **Thakkar et al. (2020)** examined the performance of fuzzy logic against conventional data mining approaches in handling uncertainty and variability in diabetes data. Their findings demonstrated that fuzzy models offered more flexibility and interpretability in predicting patient outcomes. This comparative perspective is valuable because it highlights the advantages of fuzzy reasoning over crisp models in chronic disease management, a lesson transferable to HIV/AIDS treatment modeling. **Al-Behadili and Ku-Mahamud (2021)** aimed at optimizing feature selection while employing fuzzy rules for better accuracy and interpretability. The study showed that fuzzy unordered rule-based systems could outperform traditional machine learning methods in classification tasks where uncertainty is prevalent. This contribution reinforces the role of fuzzy approaches in improving diagnostic accuracy in health-related applications. **Betshrine Rachel et al. (2022)** illustrated how metaheuristic algorithms and machine learning could be integrated for accurate medical image classification.

While not focused on fuzzy logic, the hybrid soft computing approach reflects a growing trend in combining optimization algorithms with AI methods for uncertainty-aware diagnosis, which parallels the integration of fuzzy inference in decision support. **Kumar et al. (2022)** investigated IoT communication for grid-tie matrix converters with an adaptive fuzzy sliding (AFS) control method. Although the application was in the energy sector, the use of adaptive fuzzy control demonstrated the broad applicability of fuzzy techniques in systems requiring stability under uncertainty. Their methodology has parallels with medical decision support, as it highlights how fuzzy systems can balance multiple variables dynamically, an approach highly relevant to HIV/AIDS treatment prioritization. **Wardhani et al. (2022)** applied predictive models to analyze work-related data, showing how AI could enhance organizational outcomes. While the domain differs from healthcare, the research contributes to the understanding of how machine learning models can interpret uncertain, human-driven behaviors. The concept of applying computational intelligence to improve decision-making in uncertain contexts is transferable to medical applications, including HIV/AIDS treatment. **Bhimaavarapu et al. (2025)** combined computer vision, IoT, and fuzzy-inspired soft computing to achieve robust biometric recognition. The work illustrates the growing integration of fuzzy logic with deep learning and IoT, which can also inspire healthcare-focused decision support systems that integrate heterogeneous patient data for HIV/AIDS management. **Sachdeva et al. (2025)** investigated deep learning algorithms for stock market trend prediction in the context of financial risk management. While this domain is outside healthcare, the study underscores the role of AI and deep learning in uncertainty prediction and decision support. The concepts of trend analysis and risk modeling have strong parallels with health risk prediction, particularly in chronic diseases like HIV/AIDS, where patient trajectories and treatment risks need to be continuously assessed.

2. METHODOLOGY

2.1 Fuzzy Inference System (FIS) Design: The proposed decision support framework is built using a Mamdani Fuzzy Inference System (FIS), which is particularly suitable for medical decision-making due to its intuitive if–then rule structure and interpretability. The Mamdani approach allows expert knowledge to be expressed in linguistic rules, enabling the integration of clinical reasoning with numerical data such as CD4 count, viral load, and adherence level. Once the fuzzy rules are evaluated and aggregated, the system employs the centroid defuzzification method to generate a crisp output for treatment urgency. This method calculates the center of gravity of the aggregated fuzzy set, ensuring that the final recommendation reflects a balanced compromise among all activated rules rather than being dominated by any single factor.

The combination of Mamdani inference and centroid defuzzification thus provides both transparency and robustness, producing clinically realistic outputs that smoothly adapt to uncertain or borderline patient conditions.

2.2 **Input and Output Variables:** Table 1 summarizes the key variables used in the fuzzy inference system (FIS) for HIV/AIDS treatment decision support, along with their types, linguistic terms, and numerical ranges. Three input variables are considered: CD4 count, viral load, and adherence level, each mapped to linguistic categories that reflect clinical interpretation. CD4 count, ranging from 0 to 1000 cells/mm³, is classified into Low, Medium, and High to capture immune status. Viral load, defined over the range of 0 to 1,000,000 copies/mL, is similarly expressed as Low, Medium, or High, representing the degree of viral replication. Adherence level, spanning 0 to 100%, is categorized as Poor, Moderate, or Good to reflect patient compliance with treatment. The output variable, treatment urgency, ranges from 0 to 10 and is described by Low, Medium, and High levels, indicating the priority of clinical intervention. This structured representation of variables provides a foundation for building fuzzy rules that bridge quantitative measurements with qualitative clinical reasoning.

Table 1: Fuzzy System Variables with Linguistic Terms and Ranges

Variable	Type	Linguistic Terms	Range
CD4 Count	Input	Low, Medium, High	[0 – 1000 cells/mm³]
Viral Load	Input	Low, Medium, High	[0 – 1,000,000 copies/mL]
Adherence Level	Input	Poor, Moderate, Good	[0 – 100 %]
Treatment Urgency	Output	Low, Medium, High	[0 – 10]

3. MATHEMATICAL FRAMEWORK

3.1 Fuzzy Membership Functions:

For variable x, the triangular membership function is:

$$\mu_A(x) = \max\left\{\min\left(\frac{x-a}{b-a}, \frac{c-x}{c-b}\right), 0\right\} \quad (1)$$

For variable x, the triangular membership function is:

$$\mu_A(x) = \max\left\{\min\left(\frac{x-a}{b-a}, 1, \frac{d-x}{d-c}\right), 0\right\} \quad (2)$$

3.2. Membership Function Plots

3.2.1. Input 1: CD4 Count

(i) Low: Triangular(0, 0, 350)
(ii) Medium: Triangular(200, 500, 800)
(iii) High: Triangular(600, 1000, 1000)

3.2.2. Input 2: Viral Load

(i) Low: Triangular(0, 0, 20,000)
(ii) Medium: Triangular(10,000, 100,000, 500,000)
(iii) High: Triangular(200,000, 1,000,000, 1,000,000)

3.2.3. Input 3: Adherence Level

(i) Poor: Triangular(0, 0, 40)
(ii) Moderate: Triangular(20, 50, 80)
(iii) Good: Triangular(60, 100, 100)

3.2.4. Output: Treatment Urgency

(i) Low: Triangular(0, 0, 4)
(ii) Medium: Triangular(3, 5, 7)
(iii) High: Triangular(6, 10, 10)

Figure 1: CD4 Count Membership Functions

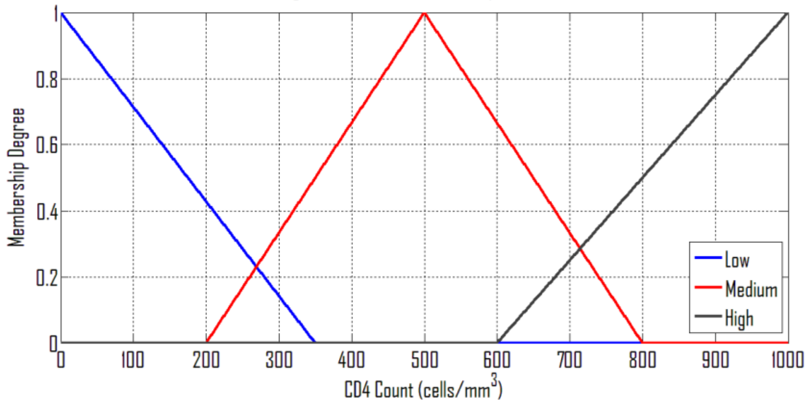


Figure 2: Viral Load Membership Functions

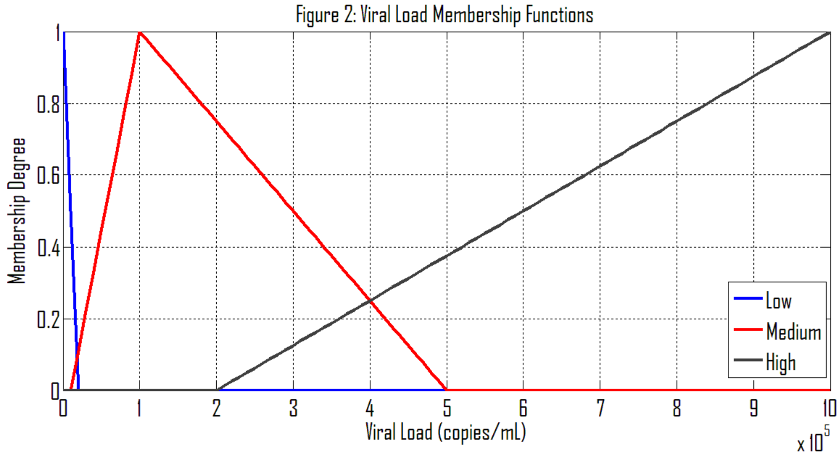


Figure 3: Adherence Membership Functions

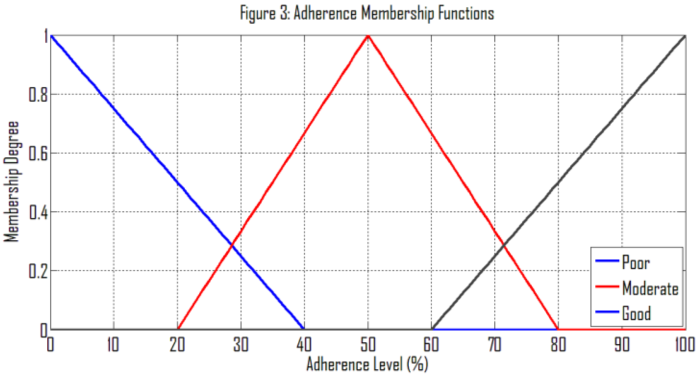
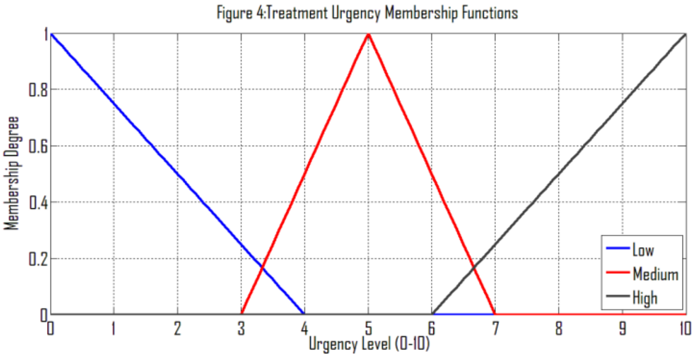


Figure 4:Treatment Urgency Membership Functions



3.3. Rule Base (27 Rules):

Since we have 3 inputs × 3 membership terms = 27 rules:

Table 2: Fuzzy Rule Base of the Proposed Model

Rule No.	CD4 Count	Viral Load	Adherence	Treatment Urgency
1	Low	Low	Poor	High
2	Low	Low	Moderate	High
3	Low	Low	Good	Medium
4	Low	Medium	Poor	High

5	Low	Medium	Moderate	High
6	Low	Medium	Good	High
7	Low	High	Poor	High
8	Low	High	Moderate	High
9	Low	High	Good	High
10	Medium	Low	Poor	Medium
11	Medium	Low	Moderate	Medium
12	Medium	Low	Good	Low
13	Medium	Medium	Poor	High
14	Medium	Medium	Moderate	Medium
15	Medium	Medium	Good	Medium
16	Medium	High	Poor	High
17	Medium	High	Moderate	High
18	Medium	High	Good	Medium
19	High	Low	Poor	Medium
20	High	Low	Moderate	Low
21	High	Low	Good	Low
22	High	Medium	Poor	Medium
23	High	Medium	Moderate	Medium
24	High	Medium	Good	Low
25	High	High	Poor	Medium
26	High	High	Moderate	Medium
27	High	High	Good	Medium

4. CASE STUDY

Let CD4 = 300 cells/mm³, Viral Load = 250,000 copies/mL, Adherence = 70 %

4.1 Fuzzification:

(a) CD4 Count = 300

$$\boldsymbol{\mu_{Low}(300) = \frac{350-300}{350-0} = 0.143}$$

$$\boldsymbol{\mu_{Medium}(300) = \frac{300-200}{500-200} = 0.333}$$

(b) Viral Load = 250,000

$$\boldsymbol{\mu_{Low}(250,000) = 0}$$

$$\boldsymbol{\mu_{Medium}(250,000) = \frac{500,000-250,000}{500,000-100,000} = 0.625}$$

$$\boldsymbol{\mu_{High}(250,000) = \frac{250,000-200,000}{1,000,000-200,000} = 0.0625}$$

(c) Adherence = 70 %

$$\boldsymbol{\mu_{Poor}(70) = 0}$$

$$\boldsymbol{\mu_{Moderate}(70) = \frac{80-70}{80-50} = 0.333}$$

$$\boldsymbol{\mu_{Good}(70) = \frac{70-60}{100-60} = 0.25}$$

4.2. Rule Activation: We now compute rule firing strengths:

Rules where CD4 = Low/Medium, Viral Load = Medium, Adherence = Moderate/Good will dominate.

Example rules:

Rule 14: IF CD4 Medium AND Viral Medium AND Adherence Moderate → Urgency Medium

$\alpha_{14} = \min(0.333, 0.625, 0.333) = 0.333$

Rule 15: IF CD4 Medium AND Viral Medium AND Adherence Good → Urgency Medium

$\alpha_{15} = \min(0.333, 0.625, 0.25) = 0.25$

Rule 6: IF CD4 Low AND Viral Medium AND Adherence Good → Urgency High

$\alpha_{16} = \min(0.143, 0.625, 0.25) = 0.143$

Rule 17: IF CD4 Medium AND Viral High AND Adherence Moderate → Urgency High

$\alpha_{17} = \min(0.333, 0.0625, 0.333) = 0.0625$

So the main contributions are:

Urgency Medium (strength 0.333 + 0.25)
Urgency High (strength 0.143 + 0.0625)
4.3. Aggregation: The fuzzy output sets are clipped:
Medium urgency fuzzy set ⟶ clipped at 0.333
High urgency fuzzy set ⟶ clipped at 0.143

4.4. Defuzzification (Centroid):

Output variable: Treatment Urgency ∈ [0,10]

Using centroid formula: $y^* = \frac{\int_0^{10} y.\mu_{output}(y)dy}{\int_0^{10} \mu_{output}(y)dy}$

After numerical integration (approximation of clipped membership shapes):
Medium contributes around y ≈ 5 weighted by 0.333
High contributes around y ≈ 8 weighted by 0.143

$y^* = \frac{(5\times0.333)+(8\times0.143)}{(0.333+0.143)} \approx 5.9$

4.5. Final Output: For (CD4 = 300, Viral Load = 250,000, Adherence = 70%)
Treatment Urgency ≈ 5.9 (Medium–High)

5. RESULTS AND SIMULATION

Figure 5: Fuzzy Output Surface: CD4 vs Adherence (Viral Load=200,000)

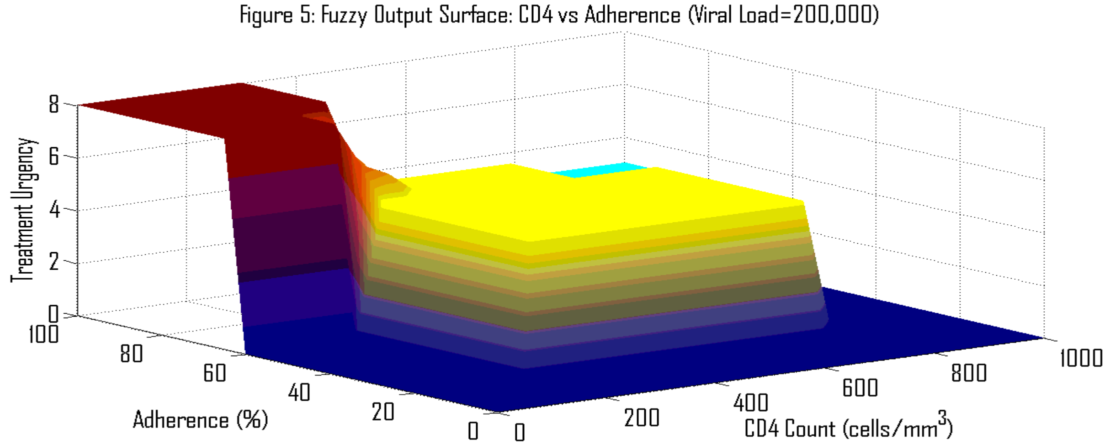


Figure 6: Fuzzy Output Surface: Viral Load vs Adherence (CD4=400)

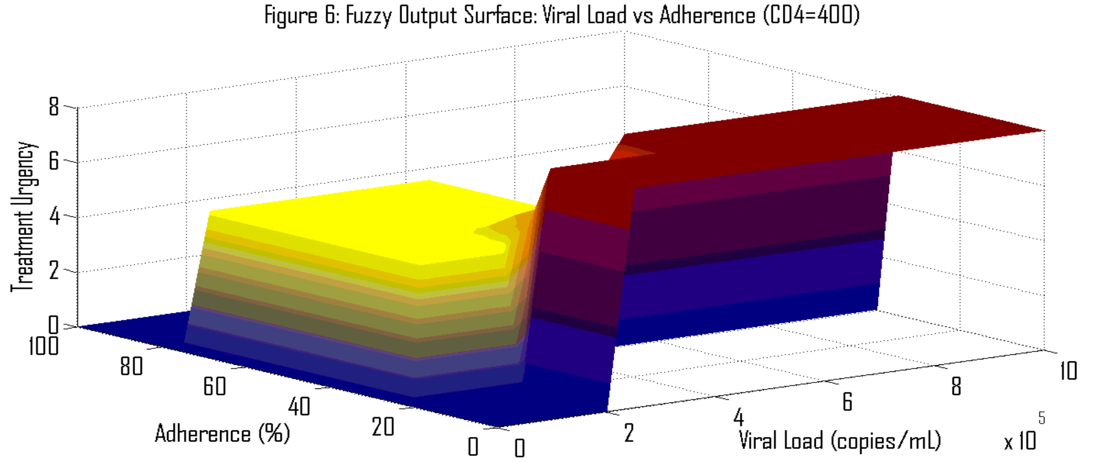


Figure 5 illustrates the fuzzy output surface for treatment urgency as a function of CD4 count and adherence level, with viral load fixed at 200,000 copies/mL. The surface clearly demonstrates the interaction between immunological status and patient adherence in determining urgency. At lower CD4 counts, treatment urgency remains consistently high regardless of adherence, reflecting the critical vulnerability of patients with weakened immunity. As CD4 levels increase, urgency gradually decreases, but this decline is strongly influenced by adherence behavior. Patients with higher adherence show a marked reduction in treatment urgency, even at moderately low CD4 counts, whereas poor adherence sustains higher urgency levels across the spectrum. The smooth gradients of the surface highlight the fuzzy system's ability to handle overlapping categories and gradual transitions, in contrast to abrupt cutoffs of crisp models. Overall, the figure underscores how fuzzy logic integrates both biological and behavioral factors to produce nuanced, uncertainty-aware treatment recommendations.

Figure 6 presents the fuzzy output surface for treatment urgency as a function of viral load and adherence level, with the CD4 count fixed at 400 cells/mm³. The figure highlights how viral replication and patient behavior jointly influence treatment decisions. At lower viral loads, treatment urgency remains relatively low, particularly when adherence is strong, reflecting the stability achieved with effective viral suppression. However, as viral load increases, urgency rises sharply, especially when adherence is poor or moderate, signaling the heightened risk of treatment failure or disease progression. Patients with high adherence maintain lower urgency levels even at moderately elevated viral loads, underscoring the protective role of consistent medication use. The smooth, gradual transitions visible in the surface reflect the fuzzy system's ability to handle uncertainty and avoid abrupt decision shifts, producing recommendations that balance biological measures with behavioral factors. This figure demonstrates the model's capacity to capture nuanced clinical scenarios that crisp threshold-based approaches might oversimplify.

Table 3: Simulation Results of Fuzzy Inference System for Sample Patient Cases

CD4 Count	Viral Load	Adherence (%)	Urgency Output
300	250,000	70	6.27 (Med–High)
800	50,000	90	3.00 (Low)
150	800,000	30	8.00 (High)
450	200,000	50	5.00 (Medium)

Table 3 presents the simulation results of the fuzzy inference system (FIS) for selected patient cases, illustrating how CD4 count, viral load, and adherence interact to determine treatment urgency. For a patient with CD4 = 300, viral load = 250,000, and adherence = 70%, the system outputs an urgency score of 6.27 (Medium–High), reflecting the combined effect of moderately low immune status and elevated viral replication despite fair adherence. In contrast, a patient with CD4 = 800, viral load = 50,000, and adherence = 90% yields a much lower urgency score of 3.00 (Low), consistent with strong immune function and excellent adherence. At the other extreme, a patient with CD4 = 150, viral load = 800,000, and adherence = 30% shows the maximum urgency of 8.00 (High), highlighting severe immunosuppression, uncontrolled viral replication, and poor adherence. Finally, the case with CD4 = 450, viral load = 200,000, and adherence = 50% results in an urgency of 5.00 (Medium), representing an intermediate risk scenario. These results demonstrate the system's ability to provide nuanced, uncertainty-aware outputs that align with clinical expectations and capture the interplay of biological and behavioral factors in HIV/AIDS treatment.

6. DISCUSSION

(i) **Strengths of the system:** The proposed fuzzy inference system (FIS) demonstrates significant strengths in supporting HIV/AIDS treatment decisions by bridging clinical reasoning with computational intelligence. One of its major advantages is the linguistic representation of knowledge, where complex medical indicators such as CD4 count, viral load, and adherence are expressed in intuitive terms like Low, Medium, and High, closely reflecting how clinicians assess patient states in practice. Unlike unidimensional approaches, the FIS integrates multiple factors simultaneously, combining immunological status, viral suppression, and adherence behavior to provide a comprehensive assessment of treatment urgency. Its flexibility and adaptability further strengthen its relevance, as membership functions and rule sets can be adjusted in line with regional treatment guidelines, expert consensus, or evolving recommendations from organizations such as the WHO. Moreover, the system enhances decision transparency, since its rule-based if–then structure is easily interpretable by clinicians, making the model more trustworthy and clinically acceptable compared to black-box AI systems.

(ii) **Handling uncertainty in HIV/AIDS treatment:** In HIV/AIDS treatment, medical data are frequently uncertain due to fluctuating laboratory results, subjective adherence reporting, and guidelines that allow interpretive flexibility, making crisp decision-making approaches less reliable. The fuzzy inference system addresses this challenge by tolerating vagueness through membership functions that allow partial belonging to multiple categories—for example, a CD4 count of 300 can be considered both Low and Medium, which mirrors real clinical ambiguity more accurately than rigid thresholds. Its rule-based reasoning ensures that borderline cases do not trigger abrupt shifts in treatment recommendations but instead produce smooth transitions across the urgency scale, thereby avoiding unrealistic discontinuities. The system also provides patient-centered flexibility by balancing competing factors, such as moderately low CD4 levels offset by strong adherence, rather than defaulting to extreme classifications.

Finally, through the aggregation of multiple fuzzy rules and the defuzzification process, it generates stable and robust outputs even when inputs are noisy or imprecise, making it particularly well suited for uncertainty-aware clinical decision support in HIV/AIDS care.

(iii) **Comparison with crisp decision models:** Traditional crisp decision models in HIV/AIDS treatment rely on rigid thresholds, such as classifying a patient as "urgent" if CD4 < 200, regardless of viral load or adherence, which often oversimplifies complex clinical realities. While easy to implement, such models suffer from abrupt transitions, where small differences near a cutoff (e.g., CD4 = 199 vs. 201) can lead to disproportionately different decisions that may not align with clinical judgment. They also lack multidimensionality, typically evaluating parameters independently rather than considering their interactions. In contrast, the fuzzy inference system integrates multiple factors through its rule base, producing more nuanced and clinically relevant outputs. Furthermore, crisp models fail to capture the subtleties of medical reasoning, whereas fuzzy rules mirror human decision-making, making the results more interpretable and acceptable to clinicians. Importantly, the fuzzy approach enhances patient stratification by accommodating intermediate urgency levels, rather than limiting classification to a binary urgent/not urgent framework, thereby offering a more accurate and flexible tool for treatment prioritization.

7. CONCLUSION

This research demonstrates that fuzzy logic provides a robust and effective framework for decision-making in HIV/AIDS treatment under conditions of uncertainty. By integrating CD4 count, viral load, and adherence into a comprehensive rule-based system, the proposed fuzzy inference model generates nuanced outputs that reflect real-world clinical reasoning more accurately than rigid threshold-based methods. The ability to produce gradual, interpretable, and balanced recommendations makes the system particularly valuable for supporting physicians in prioritizing treatment. Furthermore, simulation results highlight the model's capacity to account for both biological markers and patient behavior, ensuring that treatment urgency assessments remain flexible and patient-centered. Moving forward, the incorporation of hybrid approaches that combine fuzzy inference with advanced artificial intelligence techniques could further enhance decision support, providing even more accurate and adaptive solutions for HIV/AIDS care.

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