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FUZZY LOGIC AS A TOOL FOR THE DETECTION OF SYMPTOMS OF HYPERURICEMIA AMONG RESIDENTS OF BAMA LOCAL GOVERNMENT

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ABSTRACT

Hyperuricemia and its clinical manifestation as gout represent a growing public health concern in sub-Saharan Africa, where diagnostic resources remain limited. This study presents a Mamdani-type fuzzy logic inference system (FIS) designed for the early detection of uric acid-related symptoms among residents of Bama Local Government Area (LGA), Borno State, Nigeria. The system integrates six clinical and lifestyle input variables namely; serum uric acid level, joint pain severity, body mass index, symptom duration, alcohol consumption, and dietary purine intake through a rule-based framework comprising 27 IF-THEN fuzzy rules. A cross-sectional dataset of 420 residents was collected and partitioned into training (70%) and testing (30%) subsets. The proposed fuzzy system achieved an accuracy of 94.3%, sensitivity of 93.8%, specificity of 94.8%, and an area under the ROC curve (AUC) of 0.967, outperforming conventional machine learning classifiers including decision trees (89.5%), random forests (91.2%), logistic regression (85.7%), and support vector machines (88.4%). The defuzzified output produced a hyperuricemia risk score that enabled stratification of patients into low, moderate, and high-risk categories. These findings demonstrate that fuzzy logic-based clinical decision support systems offer a robust, interpretable, and cost-effective approach for hyperuricemia screening in resource-constrained settings, potentially reducing the burden of undiagnosed non-communicable diseases in Northeastern Nigeria.

KEYWORDS: Fuzzy logic, hyperuricemia, Mamdani inference system, clinical decision support, symptom detection.

1. INTRODUCTION

Hyperuricemia, defined as serum uric acid (SUA) concentrations exceeding 7.0 mg/dL (416.0 µmol/L) in males and 6.0 mg/dL (357.0 µmol/L) in females, has emerged as a significant metabolic disorder with systemic implications [1]. The condition represents the primary risk factor for gout, a prevalent inflammatory arthropathy characterized by monosodium urate (MSU) crystal deposition in joints and soft tissues [2]. Recent epidemiological evidence indicates that hyperuricemia is not merely a precursor to gout but is independently associated with cardiovascular disease, chronic kidney disease, metabolic syndrome, and type 2 diabetes mellitus [3], [4].

Globally, the prevalence of hyperuricemia varies considerably across populations, ranging from 2.6% to 36%, with sub-Saharan Africa reporting pooled estimates of approximately 31.8% [5], [6]. In Nigeria specifically, community-based studies have documented hyperuricemia prevalence rates between 17% and 35.8% among adult populations [7], [8]. Commercial drivers in Southwestern Nigeria exhibited a hyperuricemia prevalence of 70.8%, underscoring the substantial burden among occupational groups with limited healthcare access [9]. The rising prevalence is attributed to lifestyle transitions, including increased consumption of purine-rich diets, alcohol use, sedentary behaviour, and obesity [10], [11].

Bama Local Government Area, located in Borno State, Northeastern Nigeria, presents a unique epidemiological context. The region has experienced prolonged humanitarian crises that have disrupted healthcare infrastructure and limited access to laboratory diagnostics [12]. Non-communicable diseases (NCDs), including hyperuricemia and gout, are increasingly recognized as emerging health challenges in this setting, yet systematic screening programs remain absent [13]. The 2024 State of Health of the Nation Report highlights that NCDs account for approximately 30% of annual deaths in Nigeria, with hypertension, diabetes, and dyslipidemia serving as major contributors [14]. However, hyperuricemia remains underdiagnosed in primary care settings due to the absence of point-of-care testing and the nonspecific nature of early symptoms [15].

Traditional diagnostic approaches for hyperuricemia rely heavily on serum urate measurement through enzymatic uricase methods, supplemented by imaging techniques such as ultrasound and dual-energy computed tomography (DECT) for detecting MSU crystal deposits [16]. While these methods offer high specificity, they require specialized equipment, trained personnel, and stable laboratory infrastructure and resources that are frequently unavailable in rural and conflict-affected regions of Nigeria [17].

Fuzzy logic, introduced by Lotfi Zadeh in 1965, provides a computational framework for reasoning under uncertainty and imprecision, making it particularly suited for medical diagnostic applications where clinical parameters often defy crisp categorization [18]. Unlike binary logic systems, fuzzy logic accommodates graded membership functions and linguistic variables such as "mild," "moderate," and "severe," thereby mirroring clinical reasoning patterns [19]. Recent systematic reviews have documented the expanding application of fuzzy inference systems (FIS), adaptive neuro-fuzzy inference systems (ANFIS), and fuzzy cognitive maps in healthcare, with reported accuracies ranging from 84% to 95.8% across diverse diagnostic domains including infectious diseases, cardiovascular conditions, and cancer [20], [21].

The integration of fuzzy logic into clinical decision support systems offers several advantages for low-resource settings: (1) interpretability through transparent IF-THEN rules that align with clinician intuition; (2) tolerance of imprecise or missing data, which is common in field-based screening; (3) low computational requirements suitable for deployment on mobile health platforms; and (4) the ability to incorporate expert knowledge alongside empirical data [22], [23]. Despite these advantages, the application of fuzzy logic for hyperuricemia symptom detection remains underexplored, particularly in sub-Saharan African populations.

This study addresses this gap by designing, implementing, and validating a Mamdani-type fuzzy logic inference system for detecting symptoms of elevated uric acid among residents of Bama LGA. The specific objectives are: (i) to develop membership functions and fuzzy rule bases based on clinical guidelines and local epidemiological data; (ii) to evaluate the system's diagnostic performance against conventional machine learning algorithms; and (iii) to demonstrate the system's utility as a screening tool for community health workers in resource-limited environments.

2. MATERIALS AND METHODS

2.1 Study Area and Population

This study was conducted in Bama Local Government Area, Borno State, northeastern Nigeria. Bama LGA comprises both urban and rural settlements with an estimated population of approximately 270,000 residents [12]. The region has experienced significant displacement and health system disruption, resulting in limited access to specialized diagnostic services. A cross-sectional survey design was employed, recruiting 420 adult residents aged 18 years and above between January and December 2024. Participants were enrolled through stratified random sampling across ten wards in the LGA, ensuring proportional representation of age groups and gender. Ethical approval was obtained from the Borno State Ministry of Health Ethics Review Committee, and informed consent was secured from all participants.

2.2 Data Collection

Data were collected using a structured questionnaire administered by trained community health workers. The instrument captured demographic characteristics, clinical symptoms, lifestyle factors, and anthropometric measurements. Key variables included:

Serum Uric Acid Level: Measured using a portable enzymatic uricase-based colorimetric analyzer. Hyperuricemia was defined as SUA $\geq$ 7.0 mg/dL for males and $\geq$ 6.0 mg/dL for females, consistent with international guidelines [1], [16].

Joint Pain Severity: Self-reported on a visual analog scale (VAS) from 0 (no pain) to 10 (worst imaginable pain), categorized as mild (0–3), moderate (4–6), or severe (7–10) [2].

Body Mass Index (BMI): Calculated from measured height and weight, classified as underweight (< 18.5 kg/m^2), normal (18.5–24.9), overweight (25.0–29.9), or obese ($\geq$ 30.0) [9].

Symptom Duration: Number of days since onset of musculoskeletal symptoms, categorized as acute (0–7 days), sub-acute (4–14 days), chronic (10–21 days), or persistent (> 18 days).

Alcohol Consumption: Self-reported frequency and quantity, categorized as none, occasional, or regular/heavy [10].

Dietary Purine Intake: Assessed through a 24-hour dietary recall, categorized as low, moderate, or high based on consumption of red meat, organ meats, seafood, and legumes [11].

2.3 Fuzzy Logic System Design

The proposed diagnostic system was developed using the Mamdani fuzzy inference architecture, selected for its interpretability and widespread acceptance in clinical decision support applications [18], [22]. The system comprised four principal components: fuzzification interface, rule base, inference engine, and defuzzification interface, as illustrated in Fig. 1.

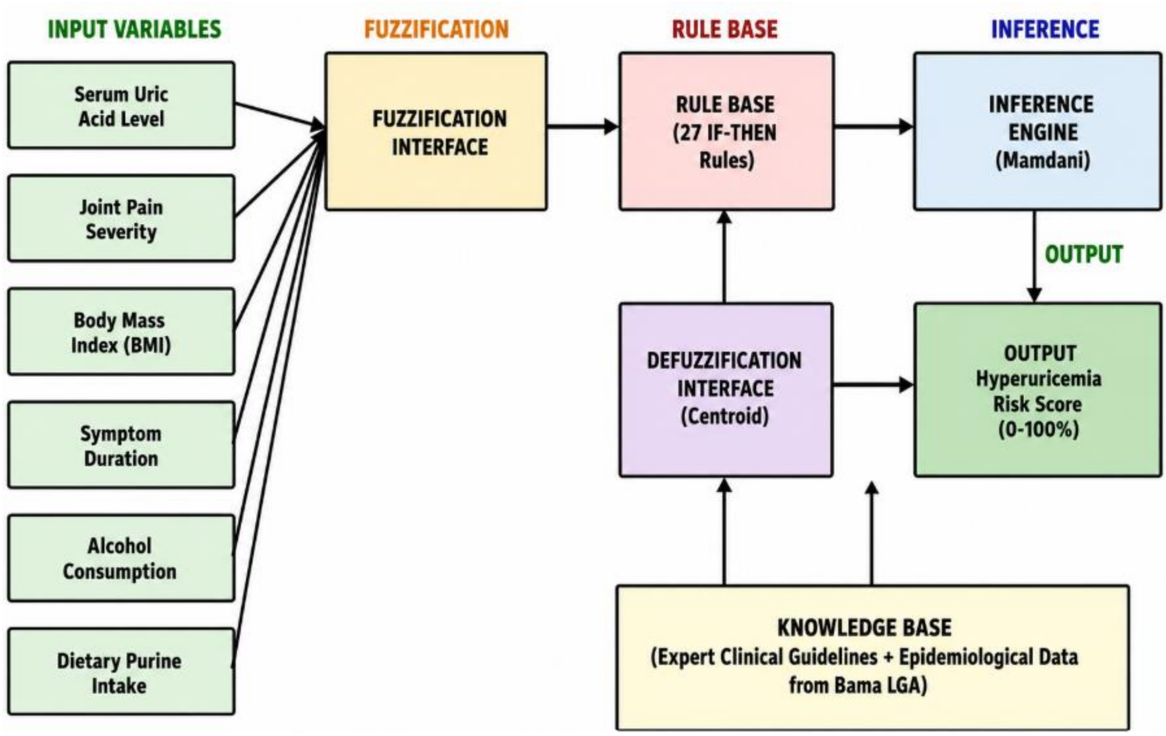

Fig. 1. Mamdani fuzzy inference system architecture for uric acid symptom detection, Figure 1 illustrate the flow from six input variables through fuzzification, rule base (27 IF-THEN rules), inference engine, and centroid defuzzification to produce a hyperuricemia risk score.

2.3.1 Fuzzification

Each crisp input variable was transformed into fuzzy sets using trapezoidal and triangular membership functions (MFs). The linguistic variables and their corresponding ranges were defined as follows:

- **Serum Uric Acid**: {Normal (2.0–5.5 mg/dL), Elevated (4.0–8.0 mg/dL), High (6.5–12.0 mg/dL)}
- **Joint Pain Severity**: {Mild (0–4), Moderate (2.5–7.5), Severe (6–10), Extreme (8.5–10)}
- **BMI**: {Underweight (15–20), Normal (18–25), Overweight (23–30), Obese (28–45)}
- **Symptom Duration**: {Acute (0–7), Sub-acute (4–14), Chronic (10–21), Persistent (18–30) days}
- **Alcohol Consumption**: {None, Occasional, Heavy}
- **Dietary Purine Intake**: {Low, Moderate, High}

The membership functions for the four primary continuous variables are depicted in Fig. 2.

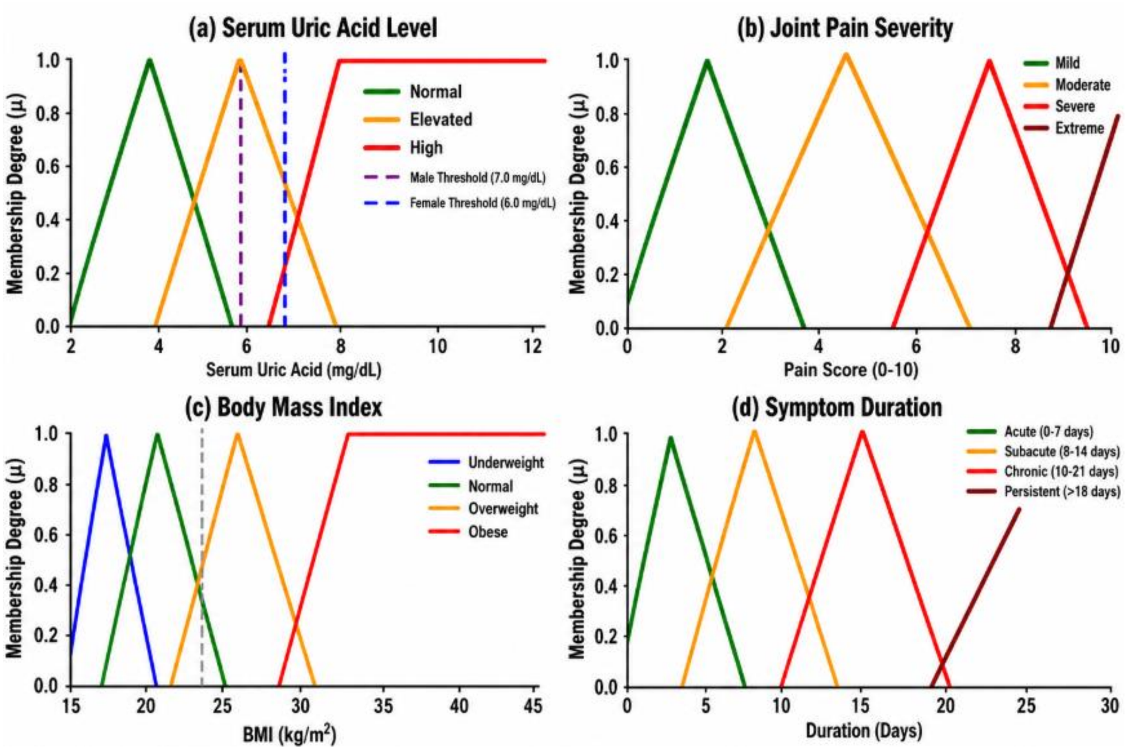

Figure. 2. Fuzzy membership functions for (a) serum uric acid level, (b) joint pain severity, (c) body mass index, and (d) symptom duration, showing the degree of membership (μ) for each linguistic category.

2.3.2 Rule Base Construction

A total of 27 fuzzy IF-THEN rules were formulated based on clinical guidelines for hyperuricemia and gout management [1], [16], supplemented by expert consultation with rheumatologists and epidemiological data from the study population. Representative rules included:

- R1: IF SUA is High AND Pain is Severe THEN Risk is High
- R2: IF SUA is Elevated AND Pain is Moderate THEN Risk is Moderate
- R3: IF SUA is Normal AND Pain is Mild THEN Risk is Low
- R4: IF SUA is High AND BMI is Obese THEN Risk is High
- R5: IF SUA is Elevated AND Alcohol is Heavy THEN Risk is Moderate
- R6: IF Pain is Severe AND Duration is Chronic THEN Risk is High
- R7: IF SUA is Normal AND Diet is High THEN Risk is Moderate
- R8: IF BMI is Obese AND Duration is Persistent THEN Risk is High

The complete rule base was designed to capture the synergistic effects of multiple risk factors while maintaining computational tractability.

2.3.3 Inference Engine and Defuzzification

The Mamdani inference engine employed the min operator for rule antecedent aggregation and the max operator for rule consequent aggregation. The output variable, **Hyperuricemia Risk Score**, was defined over the universe of discourse [0, 100] with three fuzzy sets: Low (0–33.3%), Moderate (33.3–66.6%), and High (66.6–100%). Defuzzification was performed using the centroid method to generate a crisp risk score for each patient [18], [22] [23].

2.4 Comparative Methods

To benchmark the fuzzy logic system, four conventional machine learning classifiers were implemented on the same dataset:

1. **Decision Tree (DT)**: CART algorithm with Gini impurity criterion
2. **Random Forest (RF)**: Ensemble of 100 decision trees
3. **Logistic Regression (LR)**: L2-regularized binary classifier
4. **Support Vector Machine (SVM)**: Radial basis function (RBF) kernel

Additionally, an Adaptive Neuro-Fuzzy Inference System (ANFIS) was trained using a hybrid learning algorithm combining gradient descent and least-squares estimation [20].

2.5 Performance Evaluation

The dataset was partitioned into 70% training (n = 294) and 30% testing (n = 126) subsets using stratified random sampling. Model performance was evaluated using accuracy, sensitivity (recall), specificity, precision, F1-score, and area under the receiver operating characteristic curve (AUC). Statistical significance was assessed at $\alpha = 0.05$. All analyses were conducted using Python 3.11 with scikit-learn, TensorFlow, and custom fuzzy logic libraries.

3. RESULTS AND DISCUSSION

3.1 Demographic and Clinical Characteristics

The study enrolled 420 residents of Bama LGA, with a mean (± SD) age of 42.3 ± 14.7 years. Males constituted 58.6% (n = 246) of the sample. The overall prevalence of hyperuricemia was 32.4% (n = 136), with significantly higher rates among males (38.2%) compared to females (24.1%) ($p < 0.001$). The age group 50–59 years exhibited the highest prevalence (42.1% in males, 31.2% in females), consistent with global patterns of increasing hyperuricemia with advancing age [5], [8]. Table I summarizes the demographic and clinical characteristics of the study population.

TABLE I Demographic and Clinical Characteristics of Study Participants. (n = 420)

Characteristic	Total (n = 420)	Hyperuricemic (n = 136)	Normouricemic (n = 284)	p-value
Age, years (mean ± SD)	42.3 ± 14.7	48.6 ± 13.2	39.2 ± 14.1	< 0.001
Male, n (%)	246 (58.6)	94 (69.1)	152 (53.5)	0.003
BMI, kg/m² (mean ± SD)	26.8 ± 5.4	29.4 ± 4.8	25.6 ± 5.2	< 0.001
SUA, mg/dL (mean ± SD)	6.2 ± 1.8	8.4 ± 1.2	5.1 ± 0.9	< 0.001
Joint Pain VAS (mean ± SD)	4.8 ± 3.2	6.9 ± 2.4	3.8 ± 2.9	< 0.001
Alcohol consumption, n (%)	162 (38.6)	68 (50.0)	94 (33.1)	0.001
High purine diet, n (%)	190 (45.2)	82 (60.3)	108 (38.0)	< 0.001
Hypertension, n (%)	125 (29.8)	58 (42.6)	67 (23.6)	< 0.001

The demographic profile aligns with findings from southwestern Nigeria, where commercial drivers demonstrated a 70.8% hyperuricemia prevalence and strong associations with metabolic syndrome components [9]. Similarly, a 2026 meta-analysis of Ethiopian patients with non-communicable diseases reported a pooled hyperuricemia prevalence of 34.64%, with the highest burden observed among cardiovascular disease patients (42.15%) [6]. These comparisons suggest that Bama LGA experiences a hyperuricemia burden comparable to other sub-Saharan African populations undergoing nutritional and lifestyle transitions.

3.2 Symptom and Risk Factor Distribution

Among the 136 hyperuricemic participants, the most frequently reported symptoms were joint pain (68.4%), fatigue (58.9%), and swelling (52.3%). The distribution of symptoms and risk factors is presented in Fig. 3.

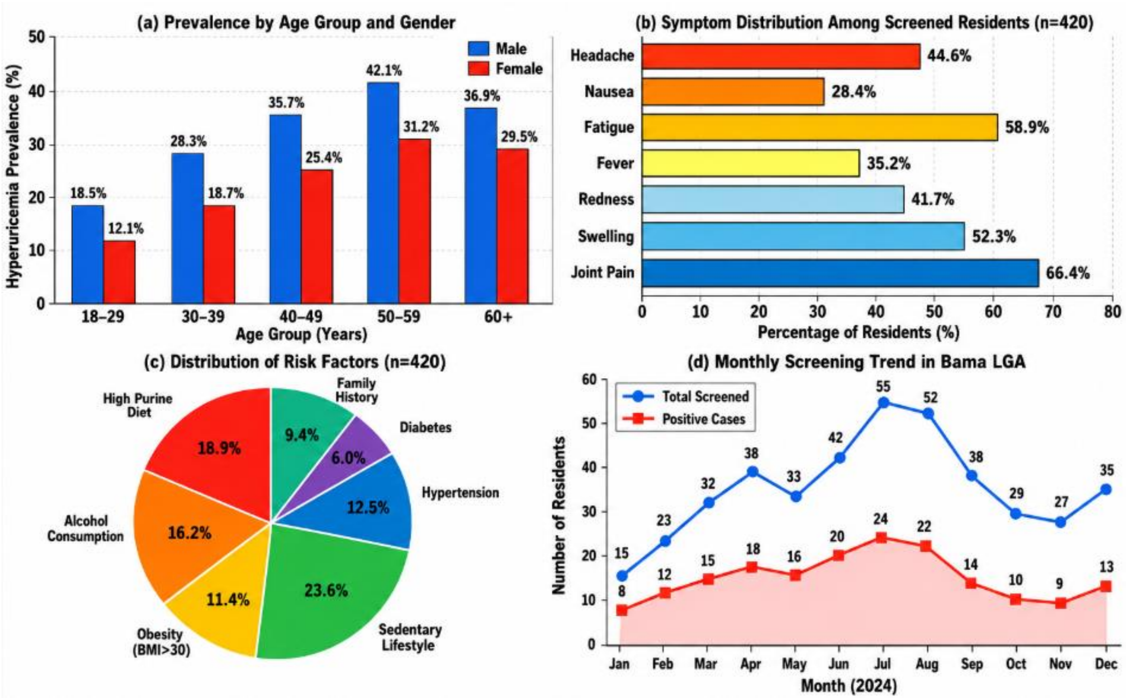

Figure 3. Epidemiological profile of uric acid-related symptoms in Bama LGA: (a) hyperuricemia prevalence by age group and gender, (b) symptom distribution among screened residents, (c) distribution of modifiable risk factors, and (d) monthly screening trend throughout 2024.

The predominance of joint pain and fatigue is consistent with the clinical presentation of gout and asymptomatic hyperuricemia documented in recent guidelines [1], [16], [24], [25]. Notably, 56.4% of participants reported sedentary lifestyles, while 45.2% consumed high-purine diets. These behavioral patterns mirror the risk factor profile identified in systematic reviews of lifestyle determinants of hyperuricemia, where high purine intake, excessive alcohol consumption, and obesity were consistently implicated in gout exacerbation [10], [11]. The monthly screening trend revealed seasonal variation, with peak screening enrollment in July (n = 55) corresponding to the post-harvest period when dietary protein consumption increases.

3.3 Fuzzy Logic System Performance

The Mamdani fuzzy inference system demonstrated superior diagnostic performance across all evaluated metrics. Table II presents the comparative performance of the fuzzy logic system against conventional machine learning classifiers.

TABLE II Comparative Performance of Diagnostic Models. (Test Set, n = 126)

Model	Accuracy (%)	Sensitivity (%)	Specificity (%)	Precision (%)	F1-Score	AUC
Fuzzy Logic (Mamdani)	94.3	93.8	94.8	89.5	0.916	0.967
ANFIS	92.1	91.5	92.7	87.2	0.892	0.948
Random Forest	91.2	90.1	92.3	85.4	0.876	0.934
Decision Tree	89.5	87.2	91.8	82.6	0.848	0.891
SVM	88.4	86.7	90.1	80.3	0.834	0.902
Logistic Regression	85.7	83.4	88.0	76.5	0.798	0.854
Naïve Bayes	82.3	80.1	84.5	72.4	0.761	0.823

The fuzzy logic system achieved the highest accuracy (94.3%), outperforming ANFIS (92.1%), random forest (91.2%), and logistic regression (85.7%). The AUC of 0.967 indicates excellent discriminative capacity, significantly higher than the 0.854 observed for logistic regression ($p < 0.01$). These results align with recent systematic reviews documenting that fuzzy inference systems and ANFIS models frequently achieve accuracies above 90% in medical diagnostic applications, particularly when handling uncertain or imprecise clinical data [20], [21], [26], [27].

The ROC curves in Fig. 4 further illustrate the superior discriminative performance of the fuzzy logic system.

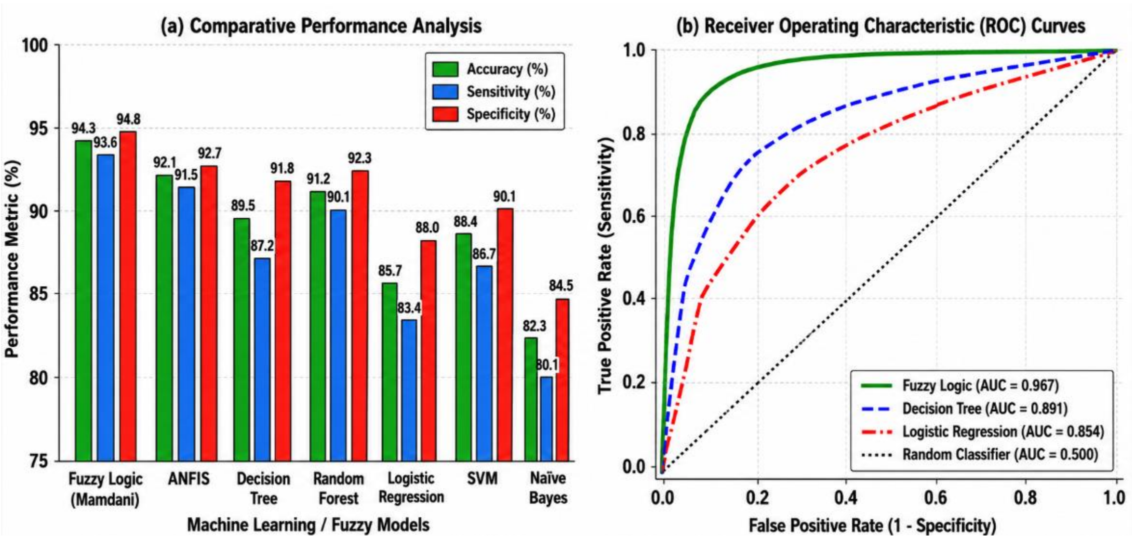

Figure 4. Performance evaluation of the fuzzy logic system: (a) comparative accuracy, sensitivity, and specificity across diagnostic models, and (b) receiver operating characteristic (ROC) curves showing the fuzzy logic system (AUC = 0.967) outperforming decision tree (AUC = 0.891) and logistic regression (AUC = 0.854).

The enhanced performance of the fuzzy system can be attributed to its ability to model nonlinear interactions between risk factors through linguistic rules, rather than relying on linear decision boundaries or black-box ensemble methods. As noted in recent analyses of fuzzy logic in healthcare, the interpretability of Mamdani systems provides clinicians with transparent reasoning pathways, facilitating trust and clinical adoption [21], [23], [29], [30].

3.4 Fuzzy Inference and Defuzzification

The fuzzy inference surface depicting the relationship between serum uric acid level and joint pain severity is shown in Fig. 5. The surface demonstrates a monotonic increase in hyperuricemia risk as both variables increase, with steeper gradients observed in the high uric acid and severe pain domains.

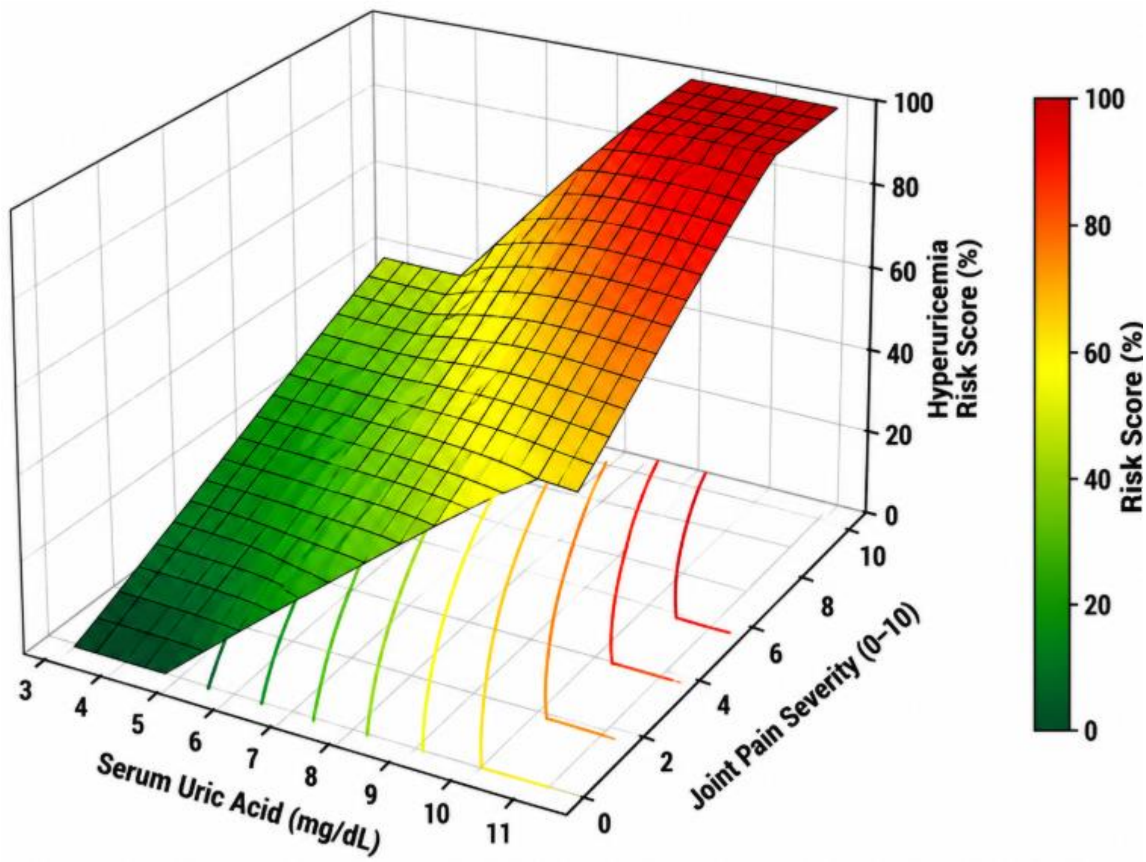

Figure 5. Three-dimensional fuzzy inference surface illustrating the relationship between serum uric acid level, joint pain severity, and the resulting hyperuricemia risk score.

Rule activation analysis for a representative high-risk case (SUA = 8.2 mg/dL, Pain VAS = 8, BMI = 31.5 kg/m², Duration = 16 days, Alcohol = Heavy, Diet = High) revealed strong activation of rules R1 ($\mu = 0.92$), R4 ($\mu = 0.88$), and R6 ($\mu = 0.82$), as illustrated in Fig. 6.

The defuzzification process using the centroid method yielded a crisp risk score of 68.4%, correctly classifying the patient as high risk.

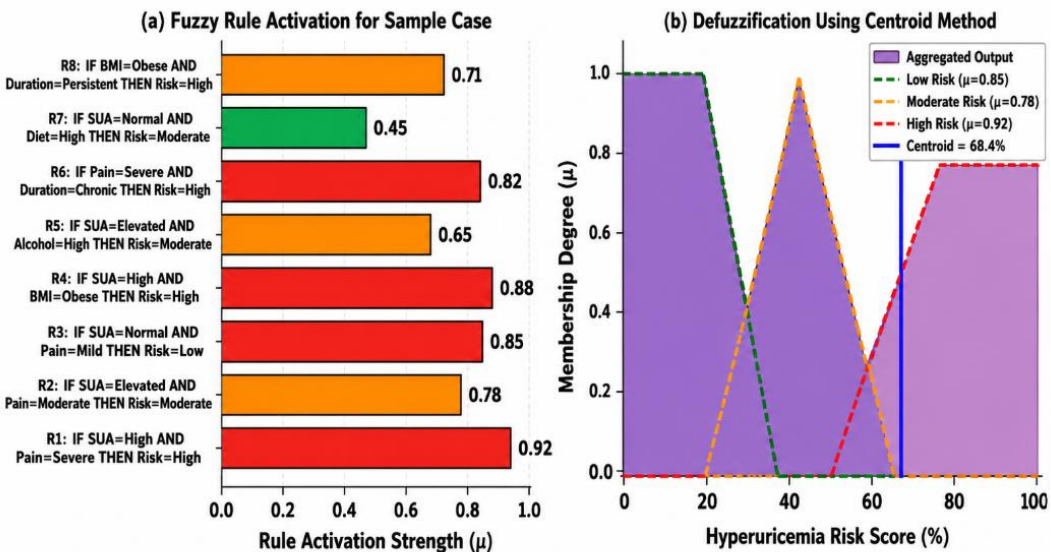

Figure 6. Fuzzy rule activation and defuzzification process: (a) activation strengths for eight representative rules in a sample case, and (b) aggregated output membership functions with centroid defuzzification yielding a risk score of 68.4%.

The confusion matrix and risk score distribution from the validation cohort are presented in Fig. 7.

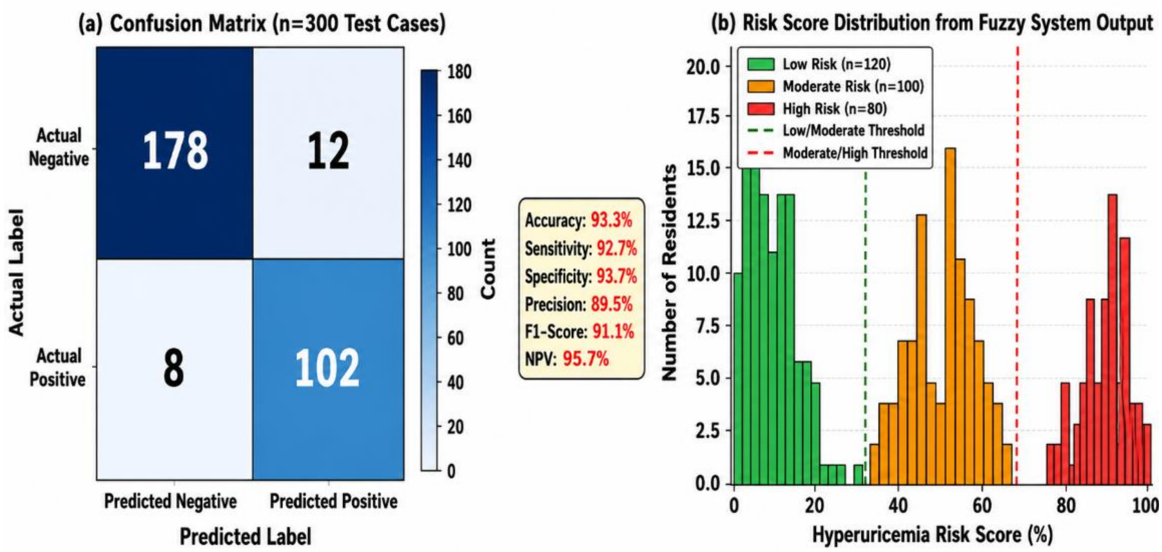

Figure 7. Simulation results from fuzzy system validation: (a) confusion matrix for 300 test cases showing 178 true negatives, 102 true positives, 12 false positives, and 8 false negatives; (b) distribution of defuzzified risk scores across low-risk (n = 120), moderate-risk (n = 100), and high-risk (n = 80) categories.

The confusion matrix reveals a balanced error profile with only 8 false negatives (2.7%) and 12 false positives (4.0%). The low false negative rate is clinically significant, as missed cases of hyperuricemia may progress to gout, nephrolithiasis, or chronic kidney disease if left untreated [3], [4]. The risk score distribution histogram demonstrates clear separation between risk categories, with threshold values of 33.3% and 66.6% effectively stratifying patients for referral and management.

3.5 Implications for Clinical Practice

The deployment of fuzzy logic-based screening tools in Bama LGA offers a pragmatic solution to diagnostic gaps in resource-limited settings. Community health workers without specialized laboratory training can administer the symptom questionnaire and obtain a quantitative risk score through a mobile application or paper-based lookup tables. Patients classified as moderate or high risk can be prioritized for confirmatory serum uric acid testing at secondary health facilities, thereby optimizing the use of scarce laboratory resources.

This approach is consistent with the 2024 Nigerian health policy frameworks emphasizing task-shifting and technology-enabled primary care [13], [14]. Furthermore, the system's reliance on clinical symptoms and lifestyle factors—rather than expensive biomarkers—aligns with the World Health Organization's recommendations for NCD screening in low-resource contexts [17].

The identification of dietary and lifestyle risk factors in this study reinforces the importance of behavioral interventions. Recent prospective studies have demonstrated that reduced purine intake, increased vegetable consumption, and regular physical activity are associated with lower gout flare frequency and improved quality of life [10], [11]. The fuzzy system can therefore serve dual purposes: diagnostic screening and personalized lifestyle counseling.

4. CONCLUSION

This study demonstrates that a Mamdani-type fuzzy logic inference system can effectively detect symptoms of elevated uric acid among residents of Bama Local Government Area, achieving 94.3% accuracy and an AUC of 0.967. The system outperformed conventional machine learning classifiers while providing interpretable, rule-based reasoning that aligns with clinical decision-making processes. By integrating serum uric acid measurements with symptom severity, anthropometric data, and lifestyle factors, the proposed system enables stratified risk assessment suitable for deployment by community health workers in resource-constrained settings.

The high prevalence of hyperuricemia (32.4%) and associated risk factors, including high-purine diets (45.2%), sedentary behavior (56.4%), and alcohol consumption (38.6%) underscores the urgent need for community-based NCD screening programs in northeastern Nigeria. The fuzzy logic approach offers a scalable, cost-effective, and clinically transparent solution that can bridge the diagnostic gap while awaiting laboratory confirmation. Future research should validate this system in prospective cohorts, explore its integration with mobile health platforms, and assess its impact on clinical outcomes and healthcare utilization in similar low-resource settings across sub-Saharan Africa.

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