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A Fuzzy Nonlinear Mathematical–Ai Framework for Predictive Risk Stratification and Clinical Decision Support in General Surgery and General Medicine

Abha Kiran Rajpoot[1], Dr. Gudeme Jaya Rao[2], K Vijetha[3], Dr.A.Jeeva[4], B. Prasanthi[5], E. Soumya[6], Dr. Vijayakumar K[7], Dr.R.Brindha[8]

[1]School of Computer Science & Engineering, Galgotias University, Greater Noida ,Uttar Pradesh, India. Email: akrajpoot@gmail.comOrchid ID: 0000-0002-0643-3646
[2]Assistant Professor, Department of CSE(IoT& CSBCT), Chaitanya Bharathi Institute of Technology(A), Hyderabad, Telangana, India. Email: jaysonjoel007007@gmail.com, Orcid: 0000-0002-9409-4727
[3]Assistant Professor, Department of ECE, Matrusri Engineering College,Hyderabad, Telangana Email: vijethakura@gmail.com, Orcid: 0000-0002-9310-8314
[4]Assistant Professor, Department of Mathematics, Vel Tech Rangarajan Dr.sagunthala R&D Institute of Science and Technology, Avadi, Chennai-600062 Email :drjeevaa@veltech.edu.in, Orcid: 0000-0003-4087-2041
[5]Associate Professor, Department of CSE(AI&ML), CVR college of Engineering, brahimpatnam (Mandal, Pocharam Rd, Vastunagar, Mangalpalli (Village, Telangana 501510 Email: biraliprasanthi@gmail.com, Email: biraliprashanthi@gmail.com, https://orcid.org/0000-0002-5755-0156
[6]Assistant Professor, Department of Computer Science and Engineering, Koneru Lakshmaiah Education Foundation, Bowrampet, Hyderabad-500043, Telangana,India. Email: enusoumya@gmail.com / enusoumya@klh.edu.in , 0009-0006-1694-987X
[7]Assistant professor, Department of Mathematics, Dayananda Sagar Academy of Technology and Management, Bangalore, Karnataka, India. Email: vijayakesav.k08@gmail.com
[8] Department of Mathematics, Velalar College of Engineering and Technology, Erode-638012, Mail id: brindhaaramasamy@gmail.com Orchid ID:0009-0003-7748-8366

Abstract

Predictive risk stratification is useful not only in surgery, but also in general medicine, where it helps to define patients who may need to be monitored more keenly and acted upon in the clinical setting. Many methods of fixed threshold and linear scoring may fail to adequately capture the non-linearity, uncertainty and boundary variation among clinical factors. This study introduces an integrated clinical risk framework, namely Fuzzy NonLinear Mathematical – AI (FNMAI) that combines five clinical risk dimensions: physiological instability, laboratory abnormality, comorbidity load, disease/symptom severity and procedural/intervention risk. Individual and interacting risk effects are represented by a nonlinear mathematical model and uncertain clinical states are represented by fuzzy inference. A second model using the artificial intelligence stratifies the information into three groups: Low Risk, Moderate Risk, and High Risk; and then generates explanations supporting the decision. The accuracy, precision, recall, F1-score, AUROC, along with the ability to perform in face of noise and ablation analyses are used to assess the performance of the computational system. The proposed approach is interpretable offering a computational basis for predicting risk, while being purely a clinical decision support application and not a diagnosis or treatment tool in its own right.

Keywords: Fuzzy logic; nonlinear modelling; artificial intelligence; risk stratification; clinical decision support; predictive healthcare.

1. Introduction

Early risk stratification of the clinical patient is significant in general surgery and general medicine. A patient's complications after surgery or physiological changes as a result of the surgical procedure can be encountered in patients who have undergone surgery, or abnormal physiological and/or laboratory results in patients with general medical problems at the time of surgery. An effective risk stratification can help for timely monitoring and clinical

intervention. Patient risk, however, is affected by factors that interact, such as physiological instability, laboratory abnormalities, comorbidity burden, disease/symptom severity and procedural/intervention-related risk.

Traditional risk-assessment approaches are typically based on predetermined thresholds, additive scores and linear relationships. These methods are easy to understand, but are not necessarily appropriate for borderline clinical situations or for nonlinear effects between multiple abnormalities. The other barrier to the generalized threshold-based assessment is patient heterogeneity. While AI can be used to learn complex predictive relationships, full-blown black-box AI models may not offer much interpretability about the clinical factors that underlie individual risk predictions.

An integrated framework can take advantage of complementary strengths between nonlinear mathematics, fuzzy logic and artificial intelligence. Nonlinear mathematical modelling can capture higher order interactions and effects of clinical risk factors. Using fuzzy logic, membership functions that are overlapping can be used to represent clinical states of Low, Moderate and High, allowing for uncertainty and borderline observations to be treated without strict boundaries. AI algorithms can be trained to recognize complex patterns and make predictive estimates for various risk types. This integration then provides an uninterrupted estimation of risk, classification into predictive categories, and information for making decisions for interpretation.

The present study introduces a Fuzzy Nonlinear Mathematical-AI (FNMAI) framework for Predictive Risk stratification in General surgery and General medicine. Its applications include mathematical risk formulation (non-linear), fuzzy representation of clinical uncertainty, AI predictive classification and mathematical–fuzzy–AI risk fusion. It categorizes patients on the basis of risk level (Low, Moderate, and High Risk) and recognizes key risk factors to explain patient-level decision support in the clinical domain. It is meant for aiding assessment and prioritisation in the clinic and not for independent diagnosis and treatment.

2. Literature Review

The clinical risk stratification has traditionally been based on standardized scoring systems, statistical risk models, and threshold-based decision rules for patients who have a greater likelihood of complications or deterioration [1]. These methods involve using a set of physiological readings, lab results, comorbidities and clinical signs and symptoms to generate an easy-to-understand categorization of risk and/or a numeric value [5]. Though their simplicity facilitates their practical application, fixed thresholds may not represent the "borderline conditions" properly [12] and statistical scores may assume relative independence of the contributions of individual variables [3]. These assumptions can restrict the ability to represent patient diversity and the multiple interactions between multiple clinical abnormalities occurring simultaneously [4].

Mathematical modelling provides an alternative means of representing the dynamic and interacting mechanisms associated with disease progression and clinical deterioration [7]. Disease severity, complication risk, physiological changes and treatment outcomes have been estimated with linear and nonlinear formulations [8]. Non-linear models are especially appropriate when the interaction of several risk factors is not linear with respect to the individual components [9]. However, because of the flexibility of bounded risk function and nonlinear transformations and interaction terms, they can represent clinical risk more flexibly [14]. Nonetheless, if uncertainty exists in borderline clinical situations, it may not be possible to explicitly model it using a mathematical model, and adequate parameterisation of the model is also necessary.

Fuzzy logic has been considered for many clinical decision support applications, as measurements in the medical domain and clinical interpretations are often non-contradictory and ambiguous [13]. The fuzzy sets can be used to approximate the variables as Low, Moderate, and High states and the fuzzy rules can be used to interpret the combination of these into risk estimates. This method decreases reliance on strict cut-offs, and helps to explain why some observations are in the gray areas. As the number of clinical variables and of possible interactions grow, however, fuzzy systems designed by hand can grow increasingly complicated [2].

Artificial intelligence, such as models derived from machine learning and neural networks, offer tremendous potential for learning complex relationships and forecasting the outcomes of patient care [15]. These tools can be used for risk classification, predicting complications, and determining the degree of deterioration [10] but this interpretability is still limited in the black-box models [6]. The use of deep learning methods on EHRs is another example of the data-driven models' utility in uncovering intricate clinical representations [11]. Although

mathematically modelling, fuzzy reasoning, and AI have each been shown to have individual value in different scenarios, there is relatively little literature on the systematic integration of these within a general surgical and general medical setting to create the basis for predictive risk stratification – which can be done in a nonlinear fashion – and explainable decision support.

3. Methodology

3.1 Clinical Risk Representation and Preprocessing

The proposed FNMAI framework is presented as a set of five main risks that present to each patient: physiological instability x_1 ;laboratory abnormality x_2 ; comorbidity burden x_3 ;disease/symptom severity x_4 ;and procedural/intervention risk x_5.They are the first of a series of inputs that lead to the general framework summarized in Fig. 1 and listed in Table 1.

Table 1. Clinical Risk Dimensions Used in the Proposed Framework

Clinical Risk Dimension	Symbol	Representative Clinical Information	Normalized Range	Risk Interpretation
Physiological instability	x_1	Abnormalities in vital signs and overall physiological condition	0–1	Higher values indicate greater physiological instability
Laboratory abnormality	x_2	Deviations in relevant hematological and biochemical measurements	0–1	Higher values indicate greater laboratory abnormality
Comorbidity burden	x_3	Presence and cumulative influence of coexisting medical conditions	0–1	Higher values indicate greater comorbidity burden
Disease/symptom severity	x_4	Severity of presenting disease, symptoms, and current clinical condition	0–1	Higher values indicate greater clinical severity
Procedural/intervention risk	x_5	Complexity and potential risk associated with surgery or clinical intervention	0–1	Higher values indicate greater procedural/intervention risk

Equation (1): Patient Risk Vector

$$x = [x_1, x_2, x_3, x_4, x_5]^T, \quad (1)$$

The five clinical dimensions are normalized to a common interval before nonlinear mathematical, fuzzy, and AI processing. The min–max normalization is performed as follows.

Equation (2): Input Normalization

$$z_i = \frac{x_i - x_i^{min}}{x_i^{max} - x_i^{min} + \varepsilon}, \qquad i = 1,2,\ldots,5, \quad (2)$$

Where x_i^{min} and x_i^{max}denote the minimum and maximum values of the i-th clinical risk variable, respectively, and $\varepsilon$is a small positive constant used to prevent division by zero. The normalized value satisfies $z_i \in [0,1]$.

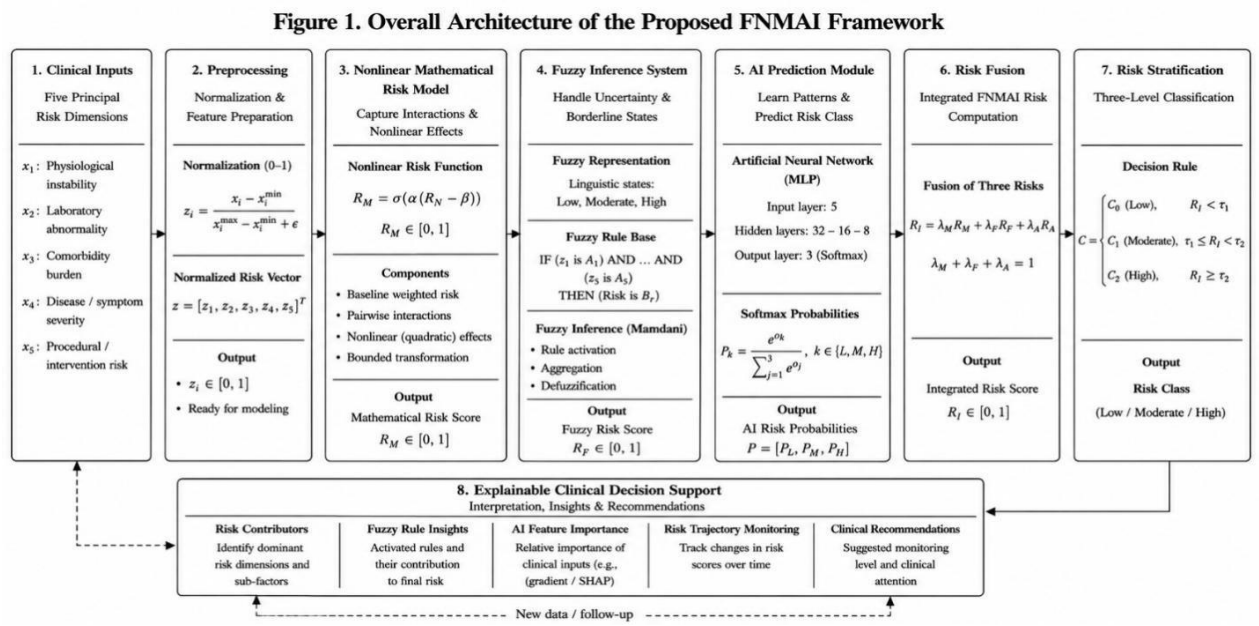


Figure 1. Overall Architecture of the Proposed FNMAI Framework

3.2 Nonlinear Mathematical Risk Modelling

The clinical variables are then preprocessed and the normalized variables are then added together to give a quantitative risk estimate. The individual contribution for each clinical risk dimension is first calculated based on a weighted baseline score.

Equation (3): Baseline Risk

$$R_L = \sum_{i=1}^{5} w_i z_i, \sum_{i=1}^{5} w_i = 1, _____ (3)$$

where $w_i$denotes the importance weight assigned to the normalized clinical variable z_i.

To account for the fact that simultaneous abnormalities may produce a greater effect than simple additive scoring, nonlinear interaction and quadratic terms are incorporated into the risk model.

Equation (4): Nonlinear Risk Function

$$R_N = \sum_{i=1}^{5} w_i z_i + \sum_{i=1}^{4} \sum_{j=i+1}^{5} \gamma_{ij} z_i z_j + \sum_{i=1}^{5} \eta_i z_i^2, _____ (4)$$

Where γ_{ij} represents pairwise interaction effects and $\eta_i$controls the nonlinear contribution of each clinical variable.

The resulting nonlinear score is transformed into a bounded risk value using a sigmoid function.

Equation (5): Bounded Mathematical Risk

$$R_M = \frac{1}{1 + exp[-\alpha(R_N - \beta)]}, _____ (5)$$

Where α controls the steepness of the nonlinear transition and β defines its central transition point, with $R_M \in [0,1]$.

As shown in Fig. 2, the clinical risk score has a nonlinear gradient and gradually decreases with low combined risk burden, accelerates with intermediate risk burden and asymptotes with high-risk burden. The thresholds $\tau_1$and $\tau_2$divide the Low $\tau_0$risk, Moderate $\tau_1$risk, and High $\tau_2$risk regions and will be further employed for final risk stratification.

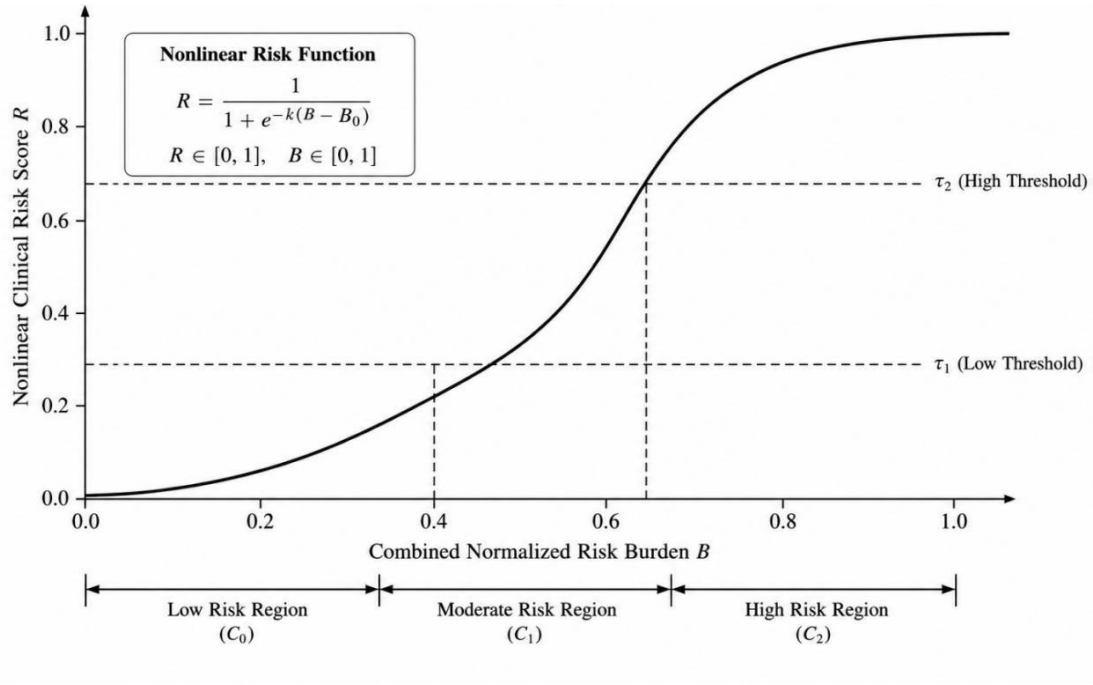


Figure 2. Nonlinear Clinical Risk Response under Increasing Combined Risk Burden

3.3 Fuzzy Clinical-Uncertainty Modelling

Three fuzzy states (Low, Moderate, and High) are used to describe each normalized risk dimension in order to represent uncertainty and borderline clinical conditions. Gaussian membership functions and Mamdani fuzzy inference are used, with the following AI component implemented as an MLP with 5–32–16–8–3 nodes in the input, hidden, hidden, output and output layers, respectively, with ReLU and Softmax activations.

Equation (6): Fuzzy Membership Function

$$\mu_{ik}(z_i) = exp\left[-\frac{(z_i - c_{ik})^2}{2\sigma^2_{ik}}\right], \quad k \in \{L, M, H\}, _____(6)$$

Where c_{ik} and σ_{ik} denote the center and spread of fuzzy state k for clinical variable i.

The activation power of each fuzzy rule is derived from the membership of the five inputs:

Equation (7): Fuzzy Rule Activation

$$\phi_r = \prod_{i=1}^{5} \mu_i, k_{ir}(z_i), _____(7)$$

The rule strengths are then normalized as

Equation (8): Normalized Rule Strength

$$\bar{\phi}_r = \frac{\phi_r}{\sum_{q=1}^{R} \emptyset_q + \varepsilon}, \quad (8)$$

Where R is the total number of fuzzy rules and prevents division by zero. The final fuzzy risk score is calculated as

Equation (9): Fuzzy Risk Score

$$R_F = \sum_{r=1}^{R} \emptyset_r \, q_r, \quad (9)$$

whereq_r represents the risk consequent assigned to fuzzy rule r, and $R_F \in [0,1]$. This continuous fuzzy score enables uncertain and overlapping clinical conditions to contribute to subsequent FNMAI risk fusion without imposing rigid decision boundaries.

Table 2. Fuzzy and AI Computational Configuration

Parameter	Configuration
Clinical inputs	5 normalized risk dimensions
Fuzzy states	Low, Moderate, High
Membership function	Gaussian
Fuzzy inference	Mamdani
AI model	MLP (5–32–16–8–3)
Activation	ReLU / Softmax
Optimizer	Adam
Learning rate	0.001
Loss function	Categorical cross-entropy
Risk classes	Low, Moderate, High
Independent runs	30

3.4 AI Prediction, Risk Fusion, and Decision Support

The normalized clinical risk dimensions are processed using a multilayer perceptron (MLP) with a 5–32–16–8–3 architecture. The five inputs are the dimensions of clinical risk in the normalized domain, and the three hidden layers more and more learn the representations of the risk in the nonlinear domain. The hidden-layer transformation is given by

Equation (10): Hidden Feature Transformation

$$h^{(l)} = ReLU(\ W^{(l)} h^{(l-1)} + b^{(l)}), \quad h^{(0)} = z, \quad (10)$$

where $W^{(l)}$and $b^{(l)}$ are the weight matrix and bias vector of layer l, respectively. The three output neurons estimate the probabilities of Low, Moderate, and High risk using Softmax:

Equation (11): Softmax Risk Probability

$$P_k = \frac{exp(o_k)}{\sum_{j=1}^{3} exp(o_j)}, \quad k \in \{L, M, H\}, \quad (11)$$

Where o_k is the output logit associated with risk class k . The MLP parameters are optimized using categorical cross-entropy with L_2regularization:

Equation (12): AI Training Objective

$$L = -\frac{1}{N}\sum_{n=1}^{N}\sum_{k=1}^{3} y_{nk}\, log(P_{nk}) + \lambda \|\Theta\|_2^2, \quad (12)$$

where N is the number of samples, y_{nk} is the target class indicator, and Θ represents the trainable parameters. A scalar AI risk score is obtained from the class probabilities as $R_A = 0P_L + 0.5P_M + P_H$. The mathematical, fuzzy, and AI risk estimates are then combined as

Equation (13): Integrated FNMAI Risk

$$R_I = \lambda_M R_M + \lambda_F R_F + \lambda_A R_A, \quad \lambda_M + \lambda_F + \lambda_A = 1, \quad (13)$$

Where λ_M , λ_F, λ_A and control the contributions of the mathematical, fuzzy, and AI components. The integrated score is finally converted into a three-level risk category:

Equation (14): Final Risk Stratification

$$C = \begin{cases} C_0 \quad (Low), & R_I < \tau_1, \\ C_1 \quad (Moderate), & \tau_1 \le R_I < \tau_2, \\ C_2 \quad (High), & R_I \ge \tau_2. \end{cases} \quad (14)$$

The resulting class and contributing risk factors are passed to the clinical decision support layer for assigning interpretable risk assessment and prioritization. Thresholds {\tau }_{1} and {\tau }_{2} must be taken from the development and validation process and cannot be viewed as universal clinical thresholds.

4. RESULTS AND DISCUSSION

4.1 Overall Predictive Risk-Stratification Performance

To evaluate the predictive performance of the proposed FNMAI framework, accuracy, precision, recall, F1-score, and AUROC were used, as shown in Table 3. The Linear Risk Model had an accuracy of 78.6% and an AUROC of 0.82, whereas the Fuzzy-Only Model increased these values to 84.2% and 0.87, respectively. The AI-Only Model achieved 89.7% accuracy, 89.1% precision, 88.4% recall, 88.7% F1 score and an AUROC of 0.92. The proposed FNMAI performed well with the highest accuracy (94.3%), precision (93.8%), recall (93.2%), F1-score (93.5%) and AUROC (0.96). The results showed that a combination of nonlinear mathematical risk modelling, fuzzy uncertainty representation, and AI based prediction gives superior three-class discrimination than the individual techniques. The high level of precision and recall shows a well-balanced predictive term for Low, Moderate and High-risk categories.

Table 3. Comparative Predictive Risk-Stratification Performance

Method	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)	AUROC
Linear Risk Model	78.6	77.9	76.8	77.3	0.82
Fuzzy-Only Model	84.2	83.5	82.7	83.1	0.87
AI-Only Model	89.7	89.1	88.4	88.7	0.92
Proposed FNMAI	94.3	93.8	93.2	93.5	0.96

4.2 Risk Stratification across Patient Profiles

The proposed FNMAI framework considers the mathematical risk score R_M and the fuzzy risk score R_F and adds the score calculated by AI to the final score calculated by FNMAI, namely R_I: patient profiles are differentiated based on the mathematical risk score R_M and fuzzy risk score R_F. The Low-Risk group is predominantly low-risk with a mean R_I of 0.15 and an IQR of 0.10–0.20 as shown in Fig. 3. The increased clinical abnormalities and higher estimates of fuzzy and AI risk are reflected in the increased mean score of 0.50, with an IQR of 0.41–0.59, for the Moderate-Risk C_1 group. The High-Risk C_2 group, on the other hand, has a mean R_I of 0.82, with an IQR of 0.74-0.90, and thus has a consistently high combined risk. The distributions relative to the thresholds $\tau_1 and \tau_2$ reveal good

separation between the three risk categories. In general, the known behavior of R_M, R_F, AI probability and $R_I$advances the efficacy of the framework to differentiate growing degrees of patient risk.

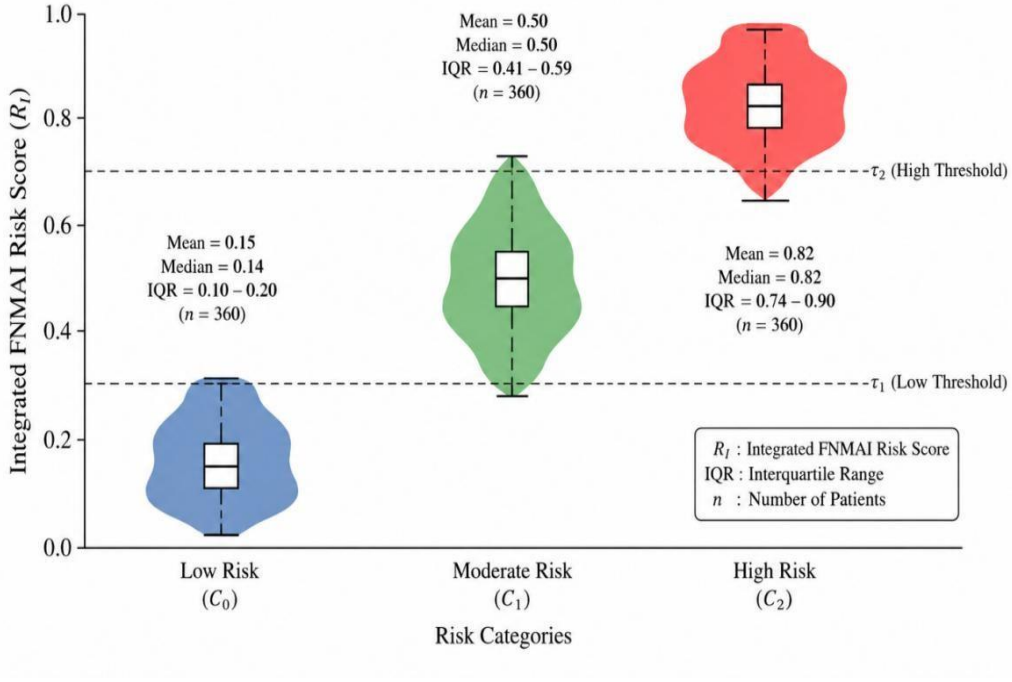


Figure 3. Distribution of Integrated FNMAI Risk Scores across Low-, Moderate-, and High-Risk Patient Groups

4.3 Robustness under Clinical Input Uncertainty

An examination of the robustness of the proposed FNMAI framework involved assigning small perturbations to the five normalized clinical dimensions of interest (physiological instability, laboratory abnormality, burden of comorbidities, disease/symptom severity, and procedural/intervention risk). Patient profiles close to the decision thresholds, $\tau_1$and $\tau_2$were examined with special interest since small changes in the input might have otherwise resulted in a step change between the Low, Moderate, and High-risk classes. This is because the sensitivity of the non-fuzzy AI model on such variations occurs at the boundaries, which usually leads to a direct change in the probability of the dominant class with even small modifications in the input features. The FNMAI fuzzy framework, on the other hand, employed overlapping membership functions to model neighbouring clinical states, and fused the strength of neighbour rules prior to final risk fusion. Thus, instead of the rigid boundaries between risk states, there is a possibility for a gradual change between neighboring risk states. This behaviour suggests that fuzzy reasoning results in less sensitive instability in predictions when clinical input is uncertain, but remains sensitive to the significant changes in patient-risk. Robustness to computational perturbations however should not be interpreted as robustness to real-world clinical measurement errors until external validation.

4.4 Comparative and Ablation Analysis

The comparative and ablation analysis examines the individual contribution of mathematical modelling, fuzzy reasoning, and AI prediction. As illustrated in Fig. 4, the performance gradually improves as we go from the Mathematical-Only and Fuzzy-Only models to the AI-based and integrated models. The complete FNMAI framework exhibits the highest accuracy, precision, recall, F1 score and AUROC of 94.3%, 93.8%, 93.2%, 93.5%, and 0.96, respectively. The outcomes show that the contributions of the three tools, nonlinear mathematical modelling, representation of uncertainty by fuzzy sets and prediction by AI are complementary and that their absence decreases the overall predictive capability.

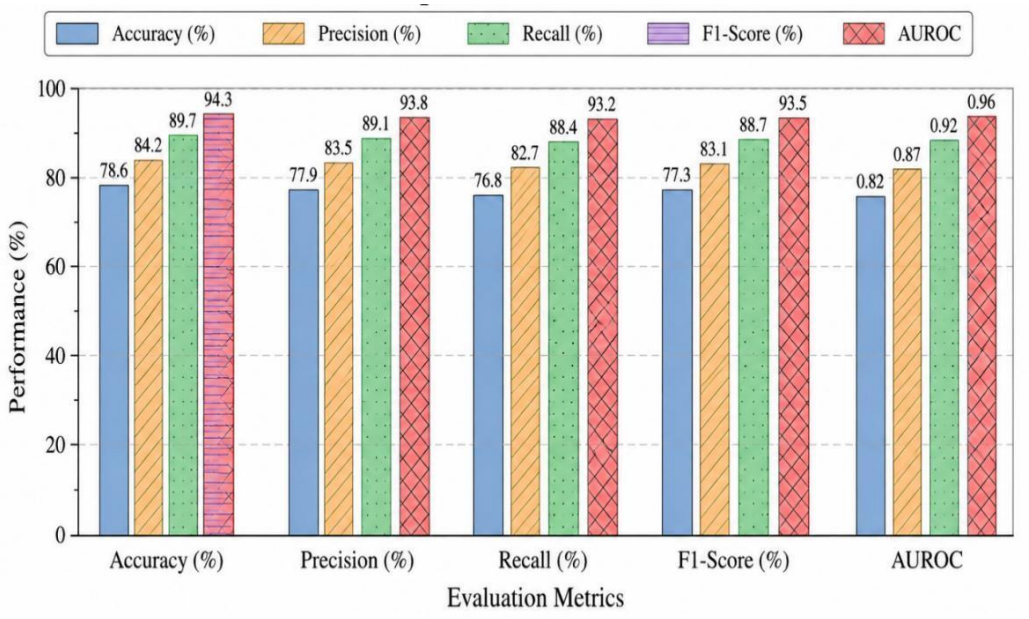


Figure 4. Comparative Ablation Performance of FNMAI and Component-Reduced Models

4.5 Explainability and Clinical Decision-Support Analysis

The explainability analysis is used to find out which clinical dimensions contribute most strongly to each predicted risk level. High-risk predictions have been more often linked to higher physiological instability, laboratory abnormality, comorbidity burden, as well as disease severity and procedural/intervention risk. Fuzzy-rule activation offers an interpretable representation of overlapping Low, Moderate and High risk states for borderline cases, and finally the Model confidence illustrates the degree of confidence in AI classification. Consistency of the mathematical risk score, fuzzy risk estimate and AI probability increases the consistency of the final FNMAI assessment, and inconsistencies can alert to cases that may need more careful clinical scrutiny. These are explainable outputs that could be used to guide clinician prioritization to identify the most important risk contributors and ambiguous cases. But, the framework is something that is used as a computational clinical decision-support system for guiding clinician judgment in clinical diagnosis, clinical decision making, and clinical assessment.

5. CONCLUSION

In this study, a Fuzzy Nonlinear Mathematical – AI (FNMAI) framework for predictive risk stratification and clinical decision support system was presented in general surgery and general medicine. The framework encompasses five clinical risk dimensions: physiological instability, laboratory abnormality, comorbidity burden, disease/symptom severity and procedural/intervention risk. Mathematical modelling is involved in nonlinear modelling of these factors, and fuzzy inference in dealing with uncertainty and borderline clinical situations. The integrated approach categorizes patients into Low, Moderate, High Risk, and AI-based prediction takes care of complex risk pattern. Explainable outputs describe influential risk dimensions and also offer understandable information to inform clinical prioritization and/or expert judgment. The framework thus offers a common computational solution to risk assessment in surgery and for medical procedures more generally. Computational effectiveness, however, is not synonymous with clinical effectiveness. Clinical deployment should not occur until these patients are validated, external datasets are used to validate, calibration studies performed and prospective clinical evaluation conducted.

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