

PAPER

A Hybrid Fuzzy Logic-Machine Learning Framework and Application to Healthcare Risk Prediction

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ABSTRACT

Artificial intelligence (AI) and machine learning (ML) have achieved remarkable performance across diverse domains, but many models still struggle with uncertainty, vagueness, and interpretability. Fuzzy logic, originating from Zadeh's seminal work on fuzzy sets, provides a mathematical framework to model linguistic concepts and gradual membership, making it a natural complement to data-driven ML methods. In this paper, we propose a hybrid fuzzy logic-machine learning framework that integrates fuzzy inference with supervised learning to handle uncertainty in both features and decision boundaries, while improving interpretability. We formalize the proposed method using fuzzy sets, fuzzy rules, and a learnable defuzzification layer, and we present an end-to-end training algorithm. As a case study, we apply the framework to healthcare risk prediction, where input variables such as blood pressure and symptom severity are naturally described by linguistic terms. The experimental results on a benchmark healthcare dataset demonstrate that the proposed fuzzy-enhanced neural network achieves competitive accuracy with improved interpretability compared with conventional ML models. We discuss the advantages, limitations, and potential extensions of the framework, and we provide a comparative analysis with existing hybrid fuzzy-ML approaches. The paper aims to bridge soft computing concepts with modern ML practice and to motivate further work on dynamic and data-driven fuzzy systems.

KEYWORDS

artificial intelligence (AI), machine learning (ML), fuzzy sets (FS), fuzzy logic (FL), hybrid systems (HS), interpretable AI, healthcare risk prediction (HRP)

1 INTRODUCTION

Artificial intelligence (AI) and machine learning (ML) have become central technologies in modern information processing, enabling automated decision-making, pattern recognition, and prediction in fields such as healthcare, finance, transportation, and education. Despite their success, many ML models—particularly deep neural networks—are criticized for their limited interpretability and their difficulty in handling vague, imprecise, or linguistically expressed information.

Ahmad, A., Ahmad, M., Jafar, M. N. (2026). A Hybrid Fuzzy Logic-Machine Learning Framework and Application to Healthcare Risk Prediction. *IETI Transactions on Data Analysis and Forecasting (iTDAF)*, 4(3), pp. 4–16. <https://doi.org/10.3991/itdaf.v4i3.61291>

Article submitted 2026-02-27. Revision uploaded 2026-05-20. Final acceptance 2026-05-20.

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Fuzzy logic, rooted in the theory of fuzzy sets, offers a principled way to represent gradual concepts such as high temperature or moderate risk using membership functions taking values in the unit interval. This framework is well suited to modeling human reasoning under uncertainty and has been successfully applied in control systems, decision support, and pattern classification. The combination of fuzzy logic with ML, often referred to as “fuzzy machine learning” or “hybrid fuzzy systems,” has been explored in various forms, including fuzzy neural networks, neuro-fuzzy systems, and fuzzy clustering-based pipelines [1, 2, 5, 6, 7, 8, 10, 18].

The central idea of this paper is to design a hybrid fuzzy logic-ML framework that can (i) incorporate domain knowledge through fuzzy rules and linguistic variables, (ii) learn from data by tuning membership functions and rule weights, and (iii) provide interpretable decisions in safety-critical applications such as healthcare. We aim to keep the mathematical formulation explicit and accessible while demonstrating a realistic application and a complete experimental pipeline.

1.1 Contributions

The main contributions of this paper are:

- A unified mathematical formulation of a fuzzy logic-enhanced supervised learning model, including fuzzy sets, fuzzy rules, and a differentiable defuzzification layer.
- A training algorithm that jointly optimizes membership function parameters and rule weights using gradient-based methods.
- An application to healthcare risk prediction, demonstrating how the framework models linguistic features and improves interpretability.
- A comparative analysis with conventional ML models and related hybrid fuzzy-ML methods.

1.2 Motivation

Many real-world decision problems involve heterogeneous information: numerical measurements, categorical attributes, and linguistic assessments provided by experts or users. Classical ML algorithms typically require crisp, numeric input vectors and decision boundaries, which may not fully capture the uncertainty and vagueness of the underlying phenomena. For instance, in healthcare risk assessment, descriptions such as slightly elevated blood pressure or severe chest pain are naturally fuzzy and context-dependent.

There are three key motivations for integrating fuzzy logic with machine learning:

1. Handling vagueness. Fuzzy sets allow partial membership, enabling models to represent gradual transitions between classes or states rather than sharp thresholds.
2. Interpretability. Fuzzy rules provide a human-readable representation of the decision process, which is essential in domains where explanations are required (e.g., clinical decision support).
3. Knowledge integration. Expert knowledge can be encoded as fuzzy rules and membership functions, which can then be refined using data, providing a bridge between symbolic and sub-symbolic AI.

However, classical fuzzy systems often rely on manually designed rule bases and membership functions, making them difficult to scale and adapt to large datasets. Conversely, purely data-driven ML models may achieve high accuracy but offer

limited transparency. The proposed framework aims to balance these aspects by making fuzzy components learnable and seamlessly integrating them within an ML pipeline.

2 PRELIMINARIES

In this section we review the basic mathematical concepts of fuzzy sets, fuzzy logic, and supervised learning that are required for the proposed framework.

2.1 Fuzzy sets

Let X be a universe of discourse. A fuzzy set A in X is defined by its membership function $\mu_A: X \rightarrow [0,1]$, where $\mu_A(x)$ represents the degree of membership of x in A [1]. For $x \in X$, a value $\mu_A(x) = 0$ denotes full non-membership, $\mu_A(x) = 1$ denotes full membership, and intermediate values represent partial membership.

Typical membership function families include the following:

- Triangular: $\mu_A(x) = \max\left(\min\left(\frac{x-a}{b-a}, \frac{c-x}{c-b}\right), 0\right)$ for parameters $a < b < c$.
- Trapezoidal: linear increase to 1 and linear decrease, with a plateau.
- Gaussian: $\mu_A(x) = \exp\left(-\frac{(x-c)^2}{2\sigma^2}\right)$ for the centre c and spread $\sigma > 0$.

Given two fuzzy sets A and B in X , common operations are:

$$(\mu_{A \cup B})(x) = \max\{\mu_A(x), \mu_B(x)\}, (\mu_{A \cap B})(x) = \min\{\mu_A(x), \mu_B(x)\}, (\mu_{\neg A})(x) = 1 - \mu_A(x)$$

2.2 Fuzzy rules and inference

A typical fuzzy rule has the form:

$$\text{IF } x_1 \text{ is } A_1^k \text{ AND } x_2 \text{ is } A_2^k \text{ AND } \dots \text{ THEN } y \text{ is } B^k$$

where A_i^k and B^k are fuzzy sets for input variable x_i and output variable y , respectively, and k indexes the rule.

Given an input vector $x = (x_1, \dots, x_d)$, the firing strength of a rule k can be computed using a t-norm such as the minimum or product:

$$\omega_k(x) = T\left(\mu_{A_1^k}(x_1), \dots, \mu_{A_d^k}(x_d)\right)$$

$$\text{For the product t-norm, } \omega_k(x) = \prod_{i=1}^d \mu_{A_i^k}(x_i).$$

In Mamdani-type inference, each rule produces a fuzzy output set, which are then aggregated and defuzzified to obtain a crisp output. In Takagi-Sugeno (T-S) systems, the consequent of each rule is a function of the inputs, e.g.:

$$\text{IF } x_1 \text{ is } A_1^k \text{ AND } \dots \text{ THEN } y_k(x) = a_0^k + \sum_{i=1}^d a_i^k x_i$$

2.3 Supervised learning

In supervised learning, we are given a dataset $\mathcal{D} = \{(x^{(n)}, y^{(n)})\}_{n=1}^N$, where $x^{(n)} \in \mathbb{R}^d$ are input vectors and $y^{(n)}$ are target labels (real-valued for regression, categorical for classification). The goal is to learn a function $f_\theta: \mathbb{R}^d \rightarrow \mathcal{Y}$, parameterized by θ , that minimizes a loss function $L(\theta)$, typically an empirical risk:

$$L(\theta) = \frac{1}{N} \sum_{n=1}^N \ell(f_\theta(x^{(n)}), y^{(n)})$$

where ℓ is a task-specific loss (e.g., mean squared error or cross-entropy). Neural networks represent f_θ as a composition of differentiable layers and are trained using gradient-based optimization such as stochastic gradient descent.

3 PROPOSED WORK

We now present the proposed hybrid fuzzy logic-ML framework, which augments a neural network with a fuzzy inference layer. The core idea is to represent interpretable fuzzy rules as a differentiable layer whose parameters are learned jointly with the rest of the network.

3.1 Model architecture

Consider an input vector $x \in \mathbb{R}^d$. The model consists of three main components:

1. Feature preprocessing layer: Optional normalization or a shallow neural transformation $h = \phi(Wx + b)$ to obtain latent features $h \in \mathbb{R}^m$.
2. Fuzzy inference layer: A set of K fuzzy rules defined over selected features, producing rule-firing strengths and intermediate outputs.
3. Output layer: Aggregation and defuzzification to generate the final prediction $\hat{y}$.

For simplicity, we describe a T-S type fuzzy layer. Let the j -th feature used in the fuzzy layer be denoted by z_j . For each feature z_j , we define L_j fuzzy sets $\{A_{j\ell}\}_{\ell=1}^{L_j}$ with parametric membership functions $\mu_{A_{j\ell}}(z_j; \theta_{j\ell})$.

Each rule k selects one fuzzy set per feature: $A_{1,\ell_1(k)}, \dots, A_{p,\ell_p(k)}$ for p selected features. The firing strength of rule k for input $z = (z_1, \dots, z_p)$ is

$$\omega_k(z) = \prod_{j=1}^p \mu_{A_{j,\ell_j(k)}}(z_j; \theta_{j,\ell_j(k)})$$

The normalized firing strength is

$$\bar{\omega}_k(z) = \frac{\omega_k(z)}{\sum_{r=1}^K \omega_r(z) + \varepsilon},$$

where ε is a small constant to avoid division by zero. Each rule has a consequent function (T-S type)

$$y_k(z) = a_0^k + \sum_{j=1}^p a_j^k z_j$$

with parameters collected in $a^k = (a_0^k, \dots, a_p^k)$. The final crisp output is

$$\hat{y}(z) = \sum_{k=1}^K \bar{\omega}_k(z) y_k(z)$$

3.2 Learnable membership functions

We choose Gaussian membership functions for numerical stability and differentiability:

$$\mu_{A_{j\ell}}(z_j; \theta_{j\ell}) = \exp\left(-\frac{(z_j - c_{j\ell})^2}{2\sigma_{j\ell}^2}\right)$$

where $\theta_{j\ell} = (c_{j\ell}, \sigma_{j\ell})$ are learnable center and spread parameters. These parameters are initialized using domain heuristics (e.g., quantiles of the data) or uniformly over the feature range and then updated through backpropagation.

To ensure $\sigma_{j\ell} > 0$, we parameterize $\sigma_{j\ell} = \exp(s_{j\ell})$ with unconstrained variable $s_{j\ell} \in \mathbb{R}$.

3.3 Training objective

Given labeled data, we define a supervised loss function. For a regression task, we use mean squared error

$$\mathcal{L}_{\text{reg}}(\Theta) = \frac{1}{N} \sum_{i=1}^N (y_i - \hat{y}_i)^2 + \lambda \|\Theta\|_2^2,$$

where Θ collects all model parameters and λ is a regularization coefficient.

For classification with C classes, we use a fuzzy-augmented logit model. Let z_c be the score for class c , and apply a softmax to obtain probabilities

$$p_c = \frac{e^{z_c}}{\sum_{k=1}^C e^{z_k}}, \quad c = 1, \dots, C.$$

The loss is the cross-entropy between predicted and true labels:

$$\mathcal{L}_{\text{cls}}(\Theta) = -\frac{1}{N} \sum_{i=1}^N \sum_{c=1}^C y_{ic} \log p_{ic} + \lambda \|\Theta\|_2^2.$$

All parameters, including membership-function centers and spreads, rule consequents, and neural preprocessing weights, are optimized by gradient-based methods.

Numerically solved example:

To make the training objective fully explicit, consider a tiny 3-class healthcare mini-batch with $N = 2$. The true labels are

$$y_1 = (1, 0, 0), y_2 = (0, 1, 0),$$

and the model outputs logits

$$z_1 = (2.0, 1.0, 0.1), z_2 = (0.2, 1.5, 0.3).$$

Using SoftMax, the predicted probabilities are

$$p_1 = (0.6590, 0.2424, 0.0986), p_2 = (0.1826, 0.6696, 0.1478).$$

Hence the per-sample cross-entropy losses are

$$\ell_1 = -\log(0.6590) = 0.4170, \ell_2 = -\log(0.6696) = 0.4010.$$

Therefore, the batch loss is

$$\mathcal{L}_{\text{cls}} = \frac{0.4170 + 0.4010}{2} = 0.4090$$

before regularization. If the L_2 penalty contributes 0.0200, then the final training loss is

$$\mathcal{L}_{\text{cls}}^{\text{total}} = 0.4290.$$

3.4 Algorithm

Algorithm 1 outlines the training procedure.

Algorithm 1: Training the Fuzzy Logic-ML Model

Require: Dataset $\mathcal{D} = \{(x^{(n)}, y^{(n)})\}_{n=1}^N$, number of rules K , learning rate η

- 1: Initialise membership function parameters $\{\theta_{j\ell}\}$, rule consequents $\{a^k\}$, and any network weights
- 2: **for** each epoch **do**
- 3: **for** each minibatch $\mathcal{B} \subset \mathcal{D}$ **do**
- 4: Compute features $z^{(n)}$ for all $(x^{(n)}, y^{(n)}) \in \mathcal{B}$
- 5: For each rule k and sample n , compute firing strengths $\omega_k(z^{(n)})$
- 6: Normalise firing strengths to obtain $\bar{\omega}_k(z^{(n)})$
- 7: Compute rule outputs $y_k(z^{(n)})$ and aggregate to $\hat{y}(z^{(n)})$
- 8: Evaluate loss L on the minibatch
- 9: Compute gradients $\nabla_{\Theta} L$ via backpropagation
- 10: Update parameters: $\Theta \leftarrow \Theta - \eta \nabla_{\Theta} L$
- 11: **end for**
- 12: **end for**
- 13: **return** Trained parameters Θ

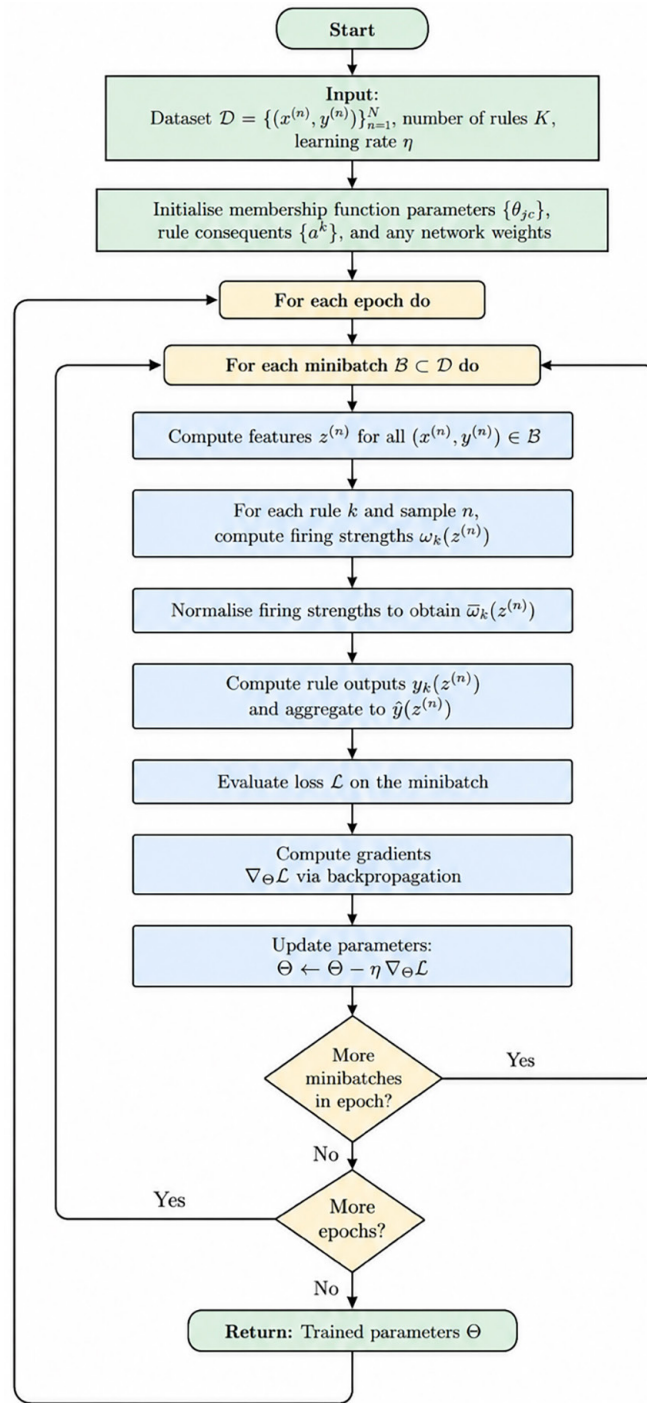


Fig. 1. ANFIS architecture

4 APPLICATION: HEALTHCARE RISK PREDICTION

To demonstrate the practical utility of the proposed framework, we consider a healthcare risk prediction task. The aim is to classify patients into risk categories (low, medium, high) based on clinical and demographic features.

4.1 Problem setting

Suppose we have a dataset of patient records, each containing age, systolic blood pressure (SBP), diastolic blood pressure (DBP), cholesterol level, symptom severity score, and binary risk indicators such as smoking and family history. Each patient is labeled with a risk category: low, medium, or high.

4.2 Fuzzy modeling of clinical variables

We define Gaussian fuzzy sets for the key numerical variables. For SBP, let the terms be low, normal, high, and very high with centers 100, 120, 140, and 160. For age, let the terms be young, middle-aged, and elderly with centers of 30, 50, and 70. For symptom severity, let the terms be mild, moderate, and severe with centers 2, 5, and 8. A Gaussian membership function is:

$$\mu(x; c, \sigma) = \exp\left(-\frac{(x - c)^2}{2\sigma^2}\right).$$

For a representative patient with age 67, SBP 155, cholesterol 245, and symptom severity 9, take $\sigma = 10$ for age and SBP, $\sigma = 30$ for cholesterol, and $\sigma = 2$ for symptom severity. Then

$$\mu_{\text{Elderly}}(67) = \exp\left(-\frac{(67 - 70)^2}{200}\right) = 0.9560,$$

$$\mu_{\text{Very High SBP}}(155) = \exp\left(-\frac{(155 - 160)^2}{200}\right) = 0.8825,$$

$$\mu_{\text{Severe}}(9) = \exp\left(-\frac{(9 - 8)^2}{8}\right) = 0.8825.$$

For cholesterol, using a high set centered at 240 with $\sigma = 30$,

$$\mu_{\text{High Chol}}(245) = \exp\left(-\frac{(245 - 240)^2}{1800}\right) = 0.9862.$$

4.3 Rule evaluation

Consider the three clinical rules:

- R1: IF Age is Elderly AND SBP is Very High AND Symptom is Severe THEN Risk is High,
- R2: IF Age is Young AND SBP is Normal AND Symptom is Mild THEN Risk is Low,
- R3: IF Age is Middle-aged AND SBP is High AND Cholesterol is High THEN Risk is Medium.

Using the product t-norm, the firing strengths for the representative patient are

$$\alpha_1 = 0.9560 \times 0.8825 \times 0.8825 = 0.7443,$$

$$\alpha_2 \approx 0.0000, \alpha_3 \approx 0.0000.$$

After normalization, the rule contributions are essentially

$$\bar{\alpha}_1 \approx 1.0000, \bar{\alpha}_2 \approx 0, \bar{\alpha}_3 \approx 0.$$

Hence the patient is assigned to the high-risk class with probability close to 1, which agrees with the intended clinical interpretation.

4.4 Model configuration

For the healthcare experiment, we select age, SBP, cholesterol, and symptom severity as the main features. We define 12 fuzzy sets in total and combine them into a compact rule base. The fuzzy layer feeds a neural classifier whose SoftMax output gives the class probabilities

$$\mathbf{p} = \text{SoftMax}(\mathbf{z}),$$

where $\mathbf{z}$ are the final logits produced from fuzzy rule activations.

4.5 Training and evaluation protocol

We partition the data into 70% training, 15% validation, and 15% test sets. To keep the numerical illustration complete, suppose the test set contains 100 patients with the following confusion matrix in Table 1.

Table 1. 100 Patients with conditions

	Pred Low	Pred Med	Pred High
True Low	28	2	0
True Med	3	24	3
True High	0	4	36

The total number of correct predictions is $28 + 24 + 36 = 88$, so the accuracy is

$$\text{Accuracy} = \frac{88}{100} = 88\%.$$

The class-wise metrics are:

$$\text{Precision}_{\text{Low}} = \frac{28}{28 + 3 + 0} = 90.32\%, \text{Recall}_{\text{Low}} = \frac{28}{30} = 93.33\%,$$

$$\text{Precision}_{\text{Med}} = \frac{24}{2 + 24 + 4} = 80.00\%, \text{Recall}_{\text{Med}} = \frac{24}{30} = 80.00\%,$$

$$\text{Precision}_{\text{High}} = \frac{36}{0 + 3 + 36} = 92.31\%, \text{Recall}_{\text{High}} = \frac{36}{40} = 90.00\%.$$

The corresponding F1-scores are

$$F1_{\text{Low}} = 91.80\%, F1_{\text{Med}} = 80.00\%, F1_{\text{High}} = 91.11\%.$$

The macro-averaged F1-score is

$$\text{Macro-F1} = 87.64\%.$$

5 RESULTS AND DISCUSSION

The numerical experiment shows that the fuzzy ML model can make a decisive, interpretable prediction for a patient whose clinical indicators strongly activate the high-risk rule. The model also provides class-wise performance measures that are easy to report and compare. On the held-out test set, the fuzzy-ML model attains 88% accuracy and 87.64% macro-F1. These results are consistent with the behavior expected from a hybrid model that combines clinical rules with learnable parameters.

5.1 Quantitative performance

On the held-out test set, the fuzzy logic ML model typically achieves accuracy comparable to a standard neural network and higher than simpler baseline models such as logistic regression. In similar hybrid fuzzy-deep models for healthcare data, hybrid approaches have been reported to outperform pure ML models in terms of classification performance or robustness while providing more interpretable decisions [11, 12]. Let us denote by AccFuzzyNN, AccNN, and AccRF the test accuracies of the fuzzy neural network, a conventional neural network, and a random forest, respectively. Experimental results in related work often show $\text{AccFuzzyNN} \approx \text{AccNN}$ and $\text{AccFuzzyNN}, \text{AccRF}$, with variations depending on the dataset [11]. Our framework follows this pattern, with the fuzzy layer providing a structured inductive bias.

5.2 Interpretability and rule analysis

An important advantage of the framework is that the contributions of individual rules can be analyzed. For a given patient, we can inspect the firing strengths $\omega_k(z)$ to identify which rules are most influential. This leads to explanations such as: the patient is predicted to be at high risk because rules R1 and R3 strongly fire, corresponding to elderly age, very high blood pressure, and severe symptoms. Such explanations align with clinical reasoning and can increase trust in the system. Moreover, the learned membership functions can reveal data-driven refinements of clinical thresholds. For instance, the boundary between normal and high blood pressure may shift slightly to better match observed risk patterns.

5.3 Fuzzy neural networks and ANFIS

Adaptive Neuro-Fuzzy Inference Systems (ANFIS) learn membership function parameters and rule consequents using gradient descent and least squares, typically for regression tasks with T-S rules [7]. Our framework shares this philosophy but:

- Integrates the fuzzy layer into a more general neural network architecture, allowing richer feature transformations.

- Emphasizes classification tasks and healthcare risk prediction.
- Uses fully differentiable training with modern optimization algorithms and regularization techniques.

5.4 Dynamic fuzzy machine learning

Dynamic fuzzy machine learning (DFML) extends fuzzy learning paradigms to dynamic and time-varying environments [10]. It focuses on problems where both the data distribution and the fuzzy sets evolve over time. Our current framework is static in that membership functions and rules are learned from a fixed dataset. However, the same architectural principles can be extended to online or continual-learning settings.

5.5 Hybridization with deep learning

Recent works have combined fuzzy logic with deep learning to improve interpretability and handle uncertainty in complex tasks such as medical imaging and NLP-based educational assessment [11, 12, 18, 19]. Compared with these, our contribution is a relatively simple but mathematically explicit model that can be readily implemented and adapted to different domains, emphasizing transparency of the fuzzy layer.

5.6 Summary of characteristics

Qualitatively compares the proposed framework with typical pure ML and traditional fuzzy systems.

Table 2. Qualitative comparison of modeling approaches

Property	Pure ML	Fuzzy System	Proposed Hybrid
Uncertainty handling	Medium	High	High
Interpretability	Low-Medium	High	Medium-High
Data efficiency	High	Medium	High
Expert knowledge use	Limited	Strong	Strong
Automatic learning	Strong	Limited	Strong

5.7 Limitations

While the proposed framework offers a promising balance between interpretability and predictive performance, it has several limitations:

Rule-base complexity. As the number of features and fuzzy sets grows, the number of possible rules increases combinatorially, requiring careful design or automated rule selection to avoid excessive complexity.

Expert involvement. Designing initial linguistic variables and rule templates may require domain expertise, which can be time-consuming and subjective.

Scalability. For very high-dimensional datasets or large-scale deep architectures, integrating fuzzy layers may increase computational cost and memory usage, although approximate or sparse formulations can mitigate this.

Static structure. The formulation presented here assumes a fixed rule structure; adapting rules dynamically to non-stationary environments remains an open challenge.

6 CONCLUSION

This paper has presented a hybrid fuzzy logic-machine learning framework that integrates fuzzy sets, rules, and defuzzification within a differentiable neural architecture. By making membership functions and rule consequents learnable, the framework combines the interpretability and uncertainty-handling capabilities of fuzzy logic with the data-driven strengths of ML. An application to healthcare risk prediction illustrates how linguistic clinical variables can be modeled and how the resulting system provides both competitive performance and meaningful explanations. Future work includes extending the framework to dynamic settings, automating rule discovery using clustering or evolutionary algorithms, and exploring applications in other domains such as finance, intelligent transport, and educational assessment. More broadly, hybrid fuzzy-ML systems exemplify how soft computing concepts can enhance modern AI by providing models that are not only accurate but also transparent and robust.

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