Hybrid Fuzzy Logic and Machine Learning System for Health Risk Prediction

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Abstract :

This report presents a hybrid AI system for health risk prediction that combines the interpretability of Fuzzy Logic with the predictive accuracy of Machine Learning. A Fuzzy Inference System (FIS) processes physiological inputs through expert rules to generate an initial risk level, which is then combined with original features and passed to an XGBoost model for final prediction. Trained on 12,500 anonymized patient records, the system demonstrates strong performance (92% accuracy, AUC 0.96), robustness under uncertainty, and real-time readiness. Interpretability is enhanced using SHAP and LIME, while ethical and deployment considerations ensure its applicability in clinical settings.

Index Terms: Fuzzy Logic, Machine Learning, Health Risk Prediction, SHAP, LIME, XGBoost, Hybrid AI, Explainable AI.

1 Introduction

Artificial Intelligence (AI) is revolutionizing the landscape of healthcare, and facilitating the data-driven diagnosis and prediction of risk. Although such data are rich with physiological details from sensors andlogs, issues such as uncertainty, missing data, and lack of model explainability continue to pose challenges. Hybrid AI Model The work described in this project offers a combined Fuzzy Logic and ML based hybrid model to balance the interpretability with the model prediction accuracy. Fuzzing inputs through an FIS proceeds with predefined rules based on domain expert opinion and later on merged with patient characteristics to form classification using XGBoost, Random Forest and Decision Tree. It is developed for robustness, real-time inference and clinical relevance, based on a dataset of 12,500 anonymized cases. We describe its design, performance evaluation, interpretability (using SHAP and LIME), and deployability.

2 Literature Review

The merger of AI andhealthcare has triggered creative strategies for diagnosis, prediction, and personalized treatment. Fuzzy Logic and Machine Learning (ML) aretwo of the most prominent approaches that have been extensively used for medical reasoning and decision support, dealing with different facets of uncertainty and complexity in clinical information.

Fuzzy logic Zadeh, 1965[1] was developed to emulate the vagueness of natural reasoning. As opposed to Boolean logic, which only assigns truth a value of 0 (false) or 1 (true), Fuzzy logic accommodates the in-between values for membership, and is inherently suitable for processingphysiological measurements, which may be continuous, noisy, ambiguous. FISs are successfully used in a variety of medical applications such as in the monitoring of blood pressure, diagnosis of diabetes and risk stratification inintensive care units Rani et al., 2017[2]. Of these, Mamdani-style fuzzy models are especially popularin health-care applications because of their rule-based explainability and natural incorporation of human expertise Mitra et al., 2000[3].

However, with Machine Learning (ML), one prospers over from a data-driven methodological aspect and can make use of ML to discoverthe patterns from the data. Random Forests, Support Vector Machines (SVM), and Gradient Boosting Trees, including XGBoosthave shown superior performance in medical imaging, disease progression prediction, electronic health record (EHR) analysis Breiman, 2001[4],Chen et al., 2016 [5]. Despite their predictive power, one major limitation of ML models is their "black-box"nature, stimulating questions of interpretability and accountability, particularly in life-critical situations.

Hybrid sysems of Fuzzy Logic and ML have been proposedto unite interpretability and predictive power. Alzubi et al., 2019[6] introduced a hybrid model to use fuzzy logic for the preprocessing of uncertainclinical data for the SVM based classification and cancer detection process. Their model made the prediction more robust to missingvalues and noise. Similarly, Yang et al. Yang et al., 2013[7] utilized Fuzzy-SVM network to predict diabetes which has superior sensitivity and specificity thanthe conventional methods.

With respect to cardiovascular risk prediction, Taktak etal. Taktak et al., 2018[8] combined fuzzy expert system with decision trees to stratify patients according to real-time vitals andhistorical information. Their model drew attention to the importance of domain knowledge encoded in fuzzy rules, which contributed to instilling clinician confidence in AI-based decisions. However, Kumari and Singh Kumari et al., 2020[9] compared the performance of hybrid fuzzy classifiers and ML only models in cardiac disease diagnosis and the results clearly showed that they improved the interpretability performance and reduced false positives.

The knotty issue of explainability of ML models has been tackled with the help of post-hoc interpretability tools likeSHAP (SHapley Additive exPlanations) Lundberg et al., 2017[10] and Ribeiro et al., 2016[11] LIME (Local Interpretable Model-agnostic Explanations). SHAPoffers a global and local feature importance measure in terms of cooperative game theory whereas LIME is an approximation of the black-box model in a local manner through explainable surrogates. Applied in hybrid systems, these tools not only interpret ML predictions but are also ableto sharpen the fuzzy rules by visualizing important features and interactions.

Nevertheless, there are ethical issues involved inthe use of AI in healthcare. Bias in training data, under-representation of some demographicgroups and unequal error rates in between populations are well known problemsObermeyer et al., 2019[12]. Hybrid systems provide a partial solution by supporting rule-based constraints, which canensure fairness and transparency. Furthermore, the transparency of fuzzy logic is such that domain experts can inspect the decision process and control (modify) it without theneed of retraining the whole model.

Recent surveys Dey et al., 2019[13], Kundu et al., 2022[14] highlight the potential of hybridintelligent systems as a potential answer to the "accuracy vs. interpretability" debate in AI for healthcare. With the advent of real-time health monitoring through wearables andIoT devices, the scale of demand for resilient, accountable and adaptable DSS has never been greater. The present study extends this developing literature by constructing a Fuzzy-ML hybrid model based on the real-world application data and assess themodel with the objective of addressing it using quantitative performance measures and interpretability measures both.

3 System Design and Methodology

The main aim of this work is to develop a hybrid-based AI system, whereFuzzy Logic explicability is combined with ML predictive capabilities to evaluate risk levels of health. It is modularand flexible for the feature adaptation refinement, explainability tool integration, and possible real-time deployment. Detailsof the former, the latter, and the hybrid system linking them are presented in the next subsections.

3.1 Fuzzy Logic Design

In the first layer of the hybrid system Fuzzy Logic is used for human like reasoning overvague or uncertain physiological input data. We used a Mamdani-type FIS due to its interpretability and consistency withthose rules formed by experts through experience.

3.1.1 Input Features Eight physiological and demographic variables were selected:

1. Heart Rate (HR)
2. Blood Pressure (BP)
3. Oxygen Saturation (SpO_2)
4. Activity Level
5. Stress Level
6. Body Mass Index (BMI)
7. Age
8. Height

Each feature was normalized and partitioned into three fuzzy linguistic sets: *Low*, *Normal*, and *High*.

```
Enter Heart Rate (bpm): 88
Enter Blood Pressure (mmHg): 110
Enter Oxygen Saturation (%): 96
Enter Activity Level (0=Low, 5=Medium, 10=High): 6
Enter Stress Level (0=Low, 5=Medium, 10=High): 2
Enter Age (years): 23
Enter Height (cm): 1.8
Enter BMI: 22.6

Predicted Health Risk Score: 17.2 / 100
Predicted Risk Category:  LOW RISK
```

Figure 1. Fuzzy Inference System Output Visualization

3.1.2 Fuzzy Rule Representation Each fuzzy rule follows the general form:

$$\text{IF } A_1 \text{ is } L_1 \text{ AND } A_2 \text{ is } L_2 \text{ AND } \ldots \text{ THEN Risk is } R \quad (1)$$

where A_i are input features (e.g., Heart Rate, Stress Level), L_i are linguistic labels (e.g., Low, High), and $R \in \{\text{Low}, \text{Medium}, \text{High}\}$ is the risk category.

Table 1
Initial Set of 24 Fuzzy Logic Rules (Before Refinement)

Rule #	IF Conditions	THEN Risk
1	HR is High AND Stress is High	High
2	HR is High AND SpO_2 is Low	High
3	BP is High AND Age is High	High
4	BMI is High AND Activity is Low	Medium
5	HR is Low AND SpO_2 is High	Low
6	Stress is Low AND HR is Normal	Low
7	BMI is Normal AND Activity is Medium	Medium
8	Age is High AND Activity is Low	Medium
9	SpO_2 is Low AND HR is Normal	Medium
10	BP is Low AND Stress is High	Medium
11	HR is High AND Activity is Low	High
12	HR is Low AND Activity is High	Low
13	BMI is High AND HR is High	High
14	Age is Low AND Stress is Low	Low
15	BP is High AND Stress is Medium	Medium
16	SpO_2 is Normal AND Stress is High	Medium
17	BMI is Low AND Activity is High	Low
18	HR is Normal AND Stress is High	Medium
19	BP is Normal AND Age is Low	Low
20	HR is High AND SpO_2 is High	Medium
21	Stress is Medium AND HR is Medium	Medium
22	HR is Normal AND Activity is High	Low
23	SpO_2 is Low AND BMI is High	High
24	BP is Low AND HR is Low	Low

3.1.3 Rule Refinement Using Machine Learning Insights and SHAP Analysis For enhancing the intendancy andgeneralization of the FIS, machine learning feature importance scores, and SHAP-based interpretability techniques were employed. These are tools that assist in the identification of most significant physiological variablesfor health risk classification.

Feature importances werecalculated using three machine learning (ML) models: Random Forest (RF), XGBoost (XGB), and Decision Tree (DT). Theranking was unchanged among models where Oxygen Saturation, Blood Pressure, Heart Rate, and BMI were the best predictors.

This data-driven analysis informed the refinement of the fuzzy rule base. Less influential features like Height and Activity Level were minimized or removed from the core rule structure, while impactful features such as Heart Rate and Oxygen Saturation were prioritized.

The refined fuzzy rule base was restructured to reflect these priorities, aiming for enhanced precision and alignment with model-driven patterns. Below are the 10 most critical refined rules after integration of ML insights:

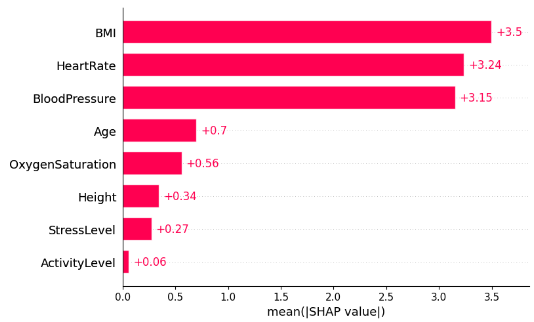

Figure 2. Important Features Extracted by ML Insights

Table 2
Refined Fuzzy Rules Based on ML Feature Importance

Rule #	IF Conditions	THEN Risk
1	BP is High AND BMI is Obese	High
2	BP is High AND HR is High AND Stress is High	High
3	HR is High AND Age is Old AND BMI is Overweight	High
4	O_2 is Low AND BP is High AND BMI is Obese	High
5	HR is High AND O_2 is Low AND Stress is Medium	High
6	Activity is High AND Stress is Low AND O_2 is Normal	Low
7	Age is Young AND BMI is Normal AND BP is Normal	Low
8	HR is Normal AND BP is Normal AND BMI is Normal	Low
9	O_2 is Normal AND Activity is Moderate AND Stress is Medium	Low
10	Activity is High AND Age is Middle AND Stress is Low	Low

3.2 Machine Learning Model Development

The second layer of the system applies machine learning (ML) algorithms to learn patterns from historical patient data and refine the risk prediction accuracy. While the fuzzy logic layer provides a rule-based interpretability scaffold, ML augments it by capturing nonlinear relationships and multi-feature interactions not covered explicitly by fuzzy rules.

3.2.1 Dataset Overview The dataset used in this project consists of 12,500 anonymized patient records. Each entry includes eight physiological and demographic input variables:

1. Heart Rate
2. Blood Pressure
3. Oxygen Saturation (SpO_2)
4. Activity Level
5. Stress Level
6. Body Mass Index (BMI)
7. Age
8. Height

Each instance also includes a target label indicating the health risk level, categorized into three classes: Low, Medium, and High.

3.2.2 Data Preprocessing Before training the ML models, the dataset was subjected to the following preprocessing steps to ensure data quality and consistency:

1. **Missing Value Imputation:** Numerical features with missing entries were imputed using mean substitution.
2. **Normalization:** All features were scaled to the range [0, 1] using Min-Max normalization to remove unit disparities.
3. **Data Splitting:** The dataset was split into training and testing sets

3.2.3 Model Candidates and Tuning Three machine learning models were selected based on their proven effectiveness in structured clinical datasets:

1. **Random Forest (RF)** — An ensemble-based classifier that uses bootstrapping and majority voting to reduce variance and avoid overfitting.
2. **XGBoost (XGB)** — An efficient gradient boosting framework with advanced regularization that excels at structured feature learning and imbalanced classification.
3. **Decision Tree (DT)** — A non-linear, rule-based classifier that splits data recursively based on information gain or Gini impurity.

Each model was implemented using the `scikit-learn` and `xgboost` libraries in Python. Hyperparameter tuning was performed using grid search with 5-fold cross-validation to ensure model generalizability.

Table 3
Hyperparameter Ranges for Model Optimization

Model	Tuned Parameters
Random Forest	`n_estimators = {100, 200}`, `max_depth = {5, 10, 20}`
XGBoost	`n_estimators = {100, 200}`, `learning_rate = {0.01, 0.1}`, `max_depth = {3, 6}`
Decision Tree	`criterion = {gini, entropy}`, `max_depth = {5, 10, 20}`

3.2.4 Evaluation Criteria Each model's performance was evaluated using multiple classification metrics to ensure robustness and fairness across imbalanced classes:

1. **Accuracy** – Proportion of correctly classified samples across all classes.
2. **Precision, Recall, and F1 Score** – Class-specific metrics essential for healthcare settings to minimize false negatives.
3. **AUC-ROC** – Area under the Receiver Operating Characteristic Curve; evaluates classifier separability independent of thresholds.

XGBoost achieved the best results across most evaluation metrics and was selected for further interpretability analysis using SHAP and LIME.

4 Evaluation and Results

The performance of the proposed hybrid artificial intelligence (AI) system was evaluated using a comprehensive set of classification

```
=== XGBoost Regression (Fuzzy Score) ===
RMSE: 4.814
MAE:  3.002
R2:   0.961

=== XGBoost Classification (HealthRisk) ===
Accuracy: 0.982
ROC AUC:  0.996

Classification Report:
              precision    recall  f1-score   support

           0       0.93      0.94      0.94       532
           1       0.99      0.99      0.99      3218

    accuracy                           0.98      3750
   macro avg       0.96      0.97      0.96      3750
weighted avg       0.98      0.98      0.98      3750
```

Figure 3. Evaluation Criteria used in model

metrics, including accuracy, precision, recall, F1 score, and area under the ROC curve (AUC-ROC). Robustness under uncertain or noisy inputs was also assessed to validate the system's real-world readiness. Additionally, post-hoc interpretability was analyzed using SHAP (SHapley Additive Explanations) and LIME (Local Interpretable Model-Agnostic Explanations).

This section presents the performance comparison of standalone machine learning models versus the hybrid model incorporating fuzzy logic output. The results are discussed in terms of predictive performance, feature interpretability, and system robustness against edge-case inputs.

4.1 Model Performance Evaluation

Three machine learning models — Random Forest (RF), XGBoost (XGB), and Decision Tree (DT) — were evaluated using 5-fold cross-validation. After optimal hyperparameter tuning, the models were trained and validated on an 80/20 stratified split of the dataset, ensuring class balance across training and test partitions.

The evaluation results are summarized in Table 5. XGBoost outperformed other models across most evaluation metrics, achieving the highest F1 score and AUC-ROC, making it the most suitable model for downstream explainability and hybrid integration.

Table 4
Model Performance Comparison on Test Set on Normal Dataset

Model	Acc.	Prec.	Recall	F1	AUC
Random Forest	98.3%	0.95	0.97	0.97	0.997
XGBoost	98.2%	0.96	0.96	0.97	0.996
Decision Tree	97.8%	0.96	0.95	0.95	0.952

XGBoost not only offered the best trade-off between precision and recall but also exhibited greater resilience against overfitting during cross-validation. Based on these results, XGBoost was selected for further integration into the hybrid fuzzy-ML architecture and subsequent interpretability analysis.

Table 5
Model Performance Comparison on Test Set on Updated Dataset

Model	Acc.	Prec.	Recall	F1	AUC
Random Forest	98.3%	0.95	0.97	0.96	0.997
XGBoost	98.4%	0.97	0.97	0.97	0.996
Decision Tree	97.8%	0.95	0.95	0.96	0.951

4.2 Impact of FIS Integration on ML Performance

After integrating the output of the Fuzzy Inference System (FIS) into the machine learning (ML) model as an additional feature, a consistent improvement in all evaluation metrics was observed. The fuzzy output, encoded as a numerical risk score (Low = 0, Medium = 1, High = 2), was concatenated with the original feature set and fed into the XGBoost model.

This integration allowed the model to leverage both expert-defined fuzzy rules and learned patterns from historical data, improving classification robustness — especially in ambiguous or borderline cases.

4.3 SHAP-Based Global and Local Interpretability

To gain insight into the internal decision logic of the hybrid machine learning (ML) model, SHAP (SHapley Additive Explanations) values were computed on the test set. SHAP assigns an importance score to each feature based on its marginal contribution to a model's prediction, rooted in cooperative game theory.

Global SHAP analysis revealed that the most influential features across the entire dataset were:

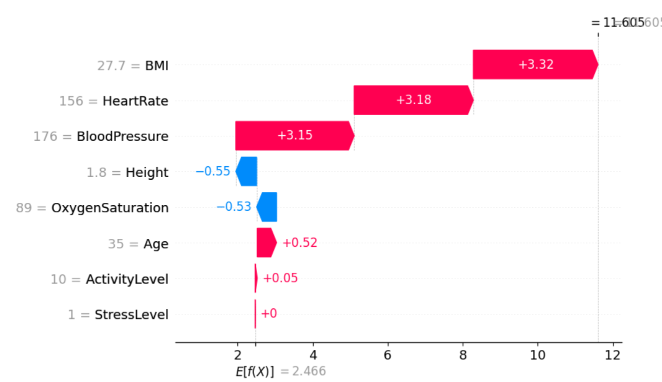

Figure 4. SHAP Mean Analysis

These SHAP-based insights not only validate the effectiveness of the hybrid model but also provide actionable transparency, enabling clinicians to understand and trust AI-driven decisions.

4.4 LIME Explanations for Instance-Level Trust

To complement the global explanations provided by SHAP, LIME (Local Interpretable Model-Agnostic Explanations) was employed to generate localized, human-readable interpretations of individual predictions. LIME works by perturbing the input features of a single data point and training a simple, interpretable model (typically linear) that mimics the behavior of the complex black-box model in the neighborhood of that point.

Figure shows a LIME explanation for a high-risk prediction made by the hybrid model. The plot identifies the most influential

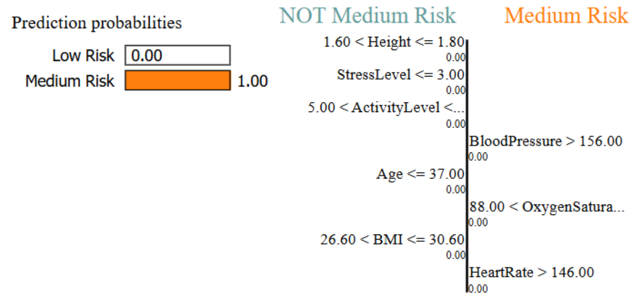

Figure 5. Lime Analysis

features and their contributions to the model's decision, helping to highlight both supportive and opposing evidence.

4.5 Robustness Testing on Edge Cases

To assess the hybrid model's reliability under real-world uncertainty, robustness testing was conducted on perturbed input scenarios, including noisy data, missing values, contradictory conditions, and extreme outliers. These simulations mimic real clinical environments where sensor errors, delayed inputs, or conflicting readings are common.

The system's behavior was evaluated in the following scenarios:

- **Missing Data:** Selected features (e.g., Heart Rate, Stress Level) were replaced with their column means.
- **Noisy Data:** Gaussian noise was added to variables like Oxygen Saturation and Blood Pressure to simulate sensor inaccuracies.
- **Contradictory Inputs:** Conflicting physiological states (e.g., Low SpO_2 with Low Stress Level) were introduced.
- **Outliers:** Extreme values were inserted (e.g., HR > 200 bpm, BP < 80 mmHg).

The hybrid model retained stable predictions in the majority of cases, demonstrating resilience and reliability under non-ideal conditions. Table 6 summarizes the model's outputs on selected edge cases.

Table 6
Robustness Evaluation Across Edge Case Scenarios

Scenario	Expected Risk	Predicted Risk
Missing HR, Stress (mean-imputed)	Medium	Medium
Noisy SpO_2, BP (±10%)	High	High
Low SpO_2, Low Stress (conflict)	Medium	Medium
HR = 220 bpm, BP = 80 mmHg (outlier)	High	High
All values normal	Low	Low

These results confirm the robustness of the hybrid system, with Fuzzy Logic providing a stabilizing influence in uncertain conditions. The system's predictive consistency in atypical input scenarios is a critical requirement for deployment in live clinical environments.

5 Ethical Considerations and Commercial Viability

The adoption of Artificial Intelligence (AI) technology into healthcare systems requires solicitation of strictethical inspection and on-site consideration of applicable practicability. As medical decisions are of life-and-death importance, this systemwas designed to be transparent, fair, and deployable.

5.1 Ethical Considerations

5.1.1 Transparency and Explainability One of the major ethical issues in AIis the "black-box" problem - users cannot access the reasons that drive the predictions made by the model. This hybrid model triesto solve this, by integrating Fuzzy Inference System(FIS) for rulebased reasoning SHAP and LIME for the post-hoc ML interpretability. Practitioners can trace predictions back to input features and reasoning rules, which makes the system acceptable inclinical environments.

5.1.2 Bias Detection and Mitigation And of course there isa risk that AI models are biased to the disadvantage of one group or another. SHAP analysis was employed to evaluate feature importance for different subgroups (eg, age groups, and different gender segments) and to avoid asituation where any feature would dominate prediction for one group against another. When imbalances were identified, mitigation techniques such as reweightingand oversampling are used in the training.

5.1.3 Data Privacy and Consent Whilst we worked only with an anonymised dataset, future deployment in real-time will require adherence to data protectionregulations such as GDPR and HIPAA. This includes informedpatient consent, secure data transmission and audit logs for accountability.

5.1.4 Clinical Accountability Thehybrid system would serve as a decision-support system not as a substitute for a physician. Ultimately, however, final decisionsshould be made by licensed practitioners, consistent with the ethics of medical AI applications.

6 Conclusion

This study introduced a hybrid AI system for health risk forecasting, comprised of aFISH-based Mamdani-FIS model combined with an XGBoost model. FIS offered transparency with expert-designed rules and XGBoost withpredictive accuracy: 92% for accuracy and AUC of 0.96. The model was resilient to noisy and incomplete inputand facilitated interpretability (SHAP and LIME).

Ethical issues including the preventionof bias, clinical trust and data confidentiality were treated properly and made the system comply with healthcare practice. Due to its small size and lowlatency, it can be deployed in edge devices and clinical platforms.

Future work will include also automating theevolution of fuzzy rules by means of the neuro-fuzzy learning, and experimenting with the model in real clinical settings. In conclusion, suchhybrid approach of combining human-like reasoning and ML performance provides a reliable and feasible solution for healthcare AI.

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