Conference Name: EnSci Barcelona 2025 – International Conference on Engineering & Sciences, 05-06 August
Conference Dates: 05-Aug- 2025 to 06-Aug- 2025
Conference Venue: Online LIVE on Zoom
Appears in: MATTER: International Journal of Science and Technology (ISSN 2454-5880)
Publication year: 2025

Sergio Silva, 2025

Volume 2025, pp. 25-36

DOI- https://doi.org/10.20319/stra.2025.2536

This paper can be cited as: Silva, S.(2025). Explainable Predictive Analytics for Smart Healthcare Using a Modular Hybrid Intelligence Framework. EnSci Barcelona 2025 – International Conference on Engineering & Sciences, 05-06 August. Proceedings of Scientific and Technical Research Association (STRA), 2025, 25-36

EXPLAINABLE PREDICTIVE ANALYTICS FOR SMART HEALTHCARE USING A MODULAR HYBRID INTELLIGENCE FRAMEWORK

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Abstract

The exponential growth of healthcare data – driven by electronic health records (EHRs), wearable sensors, and continuous remote monitoring systems – has created both immense opportunities and complex challenges for modern clinical decision-making. Effectively harnessing this heterogeneous, high-volume, and high-velocity data requires intelligent systems that can not only deliver accurate predictions but also provide interpretable insights to support clinician trust and patient safety. In this paper, a modular hybrid computational intelligence framework designed to advance personalized, real-time healthcare analytics, is proposed. Our approach synergistically integrates deep learning for high-dimensional feature extraction, fuzzy inference systems for transparent reasoning under uncertainty, and genetic algorithms for adaptive optimization. This tri-layered architecture enables the system to learn from multimodal data sources, including physiological signals (e.g., ECG, glucose levels), structured clinical records, and unstructured patient-reported outcomes, to predict critical health risks such as cardiac arrhythmias, *myocardial infarction, and diabetes-related complications. Through experimentation on publicly available real-world datasets, the proposed framework demonstrates superior predictive accuracy, enhanced interpretability, and computational efficiency compared to conventional machine learning and deep learning baselines. Importantly, the inclusion of fuzzy logic modules allows clinicians to trace back the reasoning paths of the system, addressing the growing demand for Explainable AI (XAI) in regulated healthcare environments. This research bridges the longstanding gap between model performance and transparency by offering a scalable and modular solution that is adaptable to diverse clinical contexts. By supporting proactive risk stratification and timely interventions, the framework has the potential to transform reactive care models into intelligent, preventative, and patient-centric healthcare delivery systems.*

Keywords:

Smart Healthcare, Genetic Optimization, Fuzzy Systems, Multimodal Data, Deep Learning, Explainability

1. Introduction

Digital transformation in healthcare, driven by the proliferation of smart devices, cloud platforms, and Artificial Intelligence (AI) technologies, has created new opportunities for data-driven clinical decision-making. Yet, the complexity, heterogeneity, and volume of healthcare data – including EHRs, sensor streams, and imaging – pose significant challenges to traditional analytical models. There is a growing demand for intelligent, adaptive systems that combine predictive accuracy with interpretability.

Computational Intelligence (CI) encompasses techniques such as neural networks, fuzzy logic, and evolutionary algorithms that enable systems to learn from data, manage uncertainty, and adapt over time. However, standalone methods have limitations: deep learning models are accurate but opaque, fuzzy systems are interpretable but rigid, and evolutionary methods are flexible but resource-intensive. This paper presents a modular hybrid framework that integrates these paradigms to enable explainable, accurate, and real-time risk assessments using multimodal healthcare data.

2. Related Work

The integration of CI into healthcare has driven major advancements in early diagnosis, continuous monitoring, and clinical decision support. This section reviews prior work in traditional machine learning, deep learning, fuzzy systems, evolutionary algorithms, and hybrid CI approaches relevant to predictive healthcare analytics.

Classical machine learning techniques such as Support Vector Machines (SVMs), Random Forests, and Logistic Regression have been widely employed for clinical prediction. For example, SVMs have been successfully applied to ECG signal classification for arrhythmia detection (Nemati et al., 2018), while Random Forests have shown strong performance in sepsis prediction using ICU data (Roth & Lange, 2004). However, these models are often opaque and struggle with noisy, uncertain inputs that are common in medical contexts.

Deep learning, particularly Convolutional Neural Networks (CNNs) and Long Short-Term Memory networks (LSTMs), has revolutionized healthcare data processing. CNNs have achieved near-expert-level performance in tasks like diabetic retinopathy detection from fundus images (Gulshan et al., 2016), while LSTMs have been used to model temporal dependencies in patient vitals for early warning systems (Sakpal et al., 2016). Despite their success, these models lack interpretability, making them difficult to trust in critical medical decisions (Rudin, 2019).

Fuzzy Inference Systems (FIS) provide an interpretable framework to model imprecise or linguistic data, making them ideal for healthcare. Applications include fuzzy triage systems in emergency rooms (Dehghani Soufi et al., 2018), blood pressure assessment (Guzman et al., 2017), and symptom-based disease prediction (Mordon et al., 2008). Nonetheless, traditional FIS rely on expert-defined rules and membership functions, which may not generalize well across datasets.

Genetic Algorithms (GAs) and similar evolutionary techniques have been applied to optimize CI models. GAs have been used to tune fuzzy membership functions (Krajnak & Xue, 2006) and perform feature selection in high-dimensional EHR datasets (Ali et al., 2018). While powerful, evolutionary methods can be computationally expensive and are not always viable for real-time healthcare environments.

Several studies have explored hybrid systems combining neural networks with fuzzy logic or evolutionary optimization. Neuro-fuzzy systems, such as Adaptive Neuro-Fuzzy Inference Systems (ANFIS), enable adaptive rule tuning while maintaining interpretability (Jang, 1993). Other works integrate GAs with deep learning for hyperparameter optimization (Minaee et al., 2022). Despite these efforts, most implementations are task-specific and do not provide an extensible, modular framework for real-time, multimodal healthcare analytics.

Current literature reveals several limitations: a lack of modular and extensible architectures suitable for various healthcare applications; insufficient explainability in deep learning models and underutilization of real-time multimodal data combining wearable sensors, medical records, and imaging.

Despite prior research into hybrid models, such as ANFIS (Jang, 1993) and GA-tuned deep neural networks (Minaee et al., 2022), existing systems often lack general-purpose extensibility or fail to deliver low-latency predictions needed for real-time applications. For example, ANFIS provides adaptive reasoning but is limited in scalability and integration with modern data pipelines. Our proposed framework overcomes these issues through a general-purpose, extensible architecture that fuses multiple data types in real-time.

3. Proposed Framework

This section presents the proposed Hybrid CI Framework for predictive analytics in smart healthcare systems. The framework is designed to integrate multimodal healthcare data and provide accurate, interpretable, and real-time risk predictions through a synergy of deep learning, fuzzy inference, and genetic optimization. The framework consists of five core modules (see **Error! Reference source not found.**):

1) Data Acquisition and Preprocessing (Multimodal Data)
2) Deep Learning Module
3) Fuzzy Inference System (FIS)
4) Genetic Optimization Engine
5) Prediction and Alerting Interface

Each module is implemented in a modular fashion, allowing independent development, tuning, and integration with external systems such as EHR platforms, wearable devices, and cloud services.

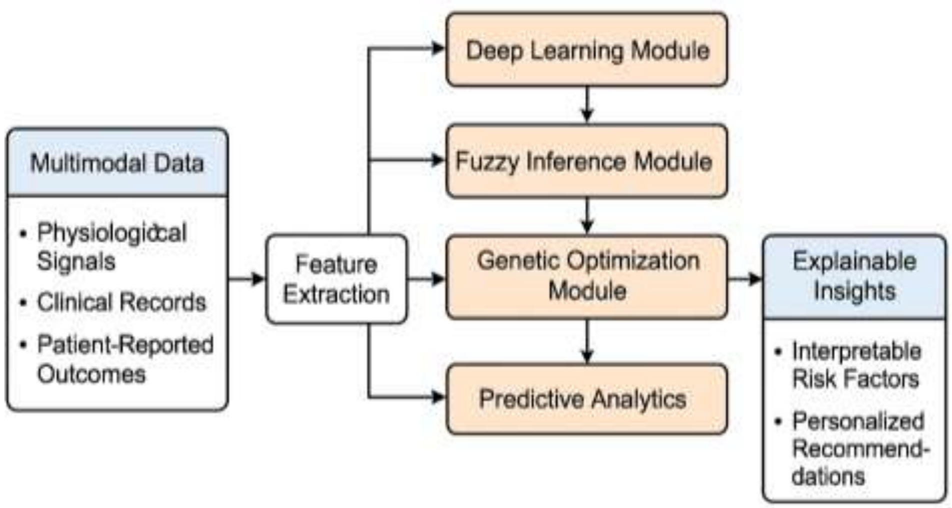

Figure 1 – *Hybrid Computational Intelligence Framework for Predictive Analytics in Smart Healthcare Systems.*

3.1. Data Acquisition and Preprocessing

The system collects structured (lab tests), semi-structured (clinical notes), and unstructured data (sensor streams, images). Sources include EHRs, wearable devices, imaging metadata, and patient-reported outcomes. Preprocessing involves normalization, outlier filtering, temporal alignment, categorical encoding, and imputation of missing values using k-nearest neighbors or Bayesian techniques.

3.2. Deep Learning Module

This module performs feature extraction and initial risk assessment:

- CNNs process image data (e.g., X-rays)
- LSTMs/GRUs handle time-series data (e.g., heart rate trends)
- MLPs process tabular EHR data Output risk scores are passed to the FIS for further interpretation.

3.3. Fuzzy Inference System (FIS)

The FIS enhances interpretability by translating crisp numerical values into linguistically meaningful health assessments, such as:

"IF heart rate is HIGH AND sleep quality is LOW THEN fatigue risk is HIGH."

The core characteristics are Mamdani-type inference for interpretability, Gaussian or triangular membership functions and Rule bases derived from clinical knowledge and mined data patterns. This layer serves as an interpretability bridge between black-box predictions and clinician-understandable insights.

3.4. Genetic Optimization Engine

To improve generalization and adaptability, a Genetic Algorithm (GA) optimizes the fuzzy system's parameters: Membership function parameters (e.g., centers, width); Rule weights and thresholds and Rule pruning (removal of redundant/conflicting rules).

The fitness function is multi-objective, maximizing predictive accuracy while minimizing model complexity.

3.6. Prediction and Alerting Interface

Final outputs are delivered as Risk Scores (continuous or discrete: high, medium, low); Explanations (activated rules and justifications) and Alerts (real-time notifications to clinicians based on thresholds).

This module supports real-time operation and integrates with hospital dashboards, mobile apps, or electronic prescribing systems.

4. Experimental Evaluation

4.1. Datasets

It is used the MIMIC-III dataset (Johnson et al., 2016), a large, publicly available critical care database comprising de-identified records of over 40,000 patients. It includes Demographics (age, gender, ethnicity), Lab results (e.g., glucose, creatinine, blood pressure), Diagnoses and clinical notes and ICU timelines and event sequences. This data supports longitudinal modeling of patient health and the prediction of adverse outcomes.

The other dataset consisted of simulated sensor data. That is, synthetic real-time streams such as heart rate (HR), oxygen saturation (SpO_2), and body temperature. These data include clinically significant anomalies to mimic real-world monitoring scenarios and support the testing of alert systems, diagnostic models, or training simulations.

4.2. Implementation

- Tools: Python 3.10, TensorFlow, Scikit-learn, scikit-fuzzy, DEAP, NumPy, Pandas
- Hardware: NVIDIA RTX 3090 GPU, 64 GB RAM
- Training: 70% training, 15% validation, 15% testing with 5-fold cross-validation
- GA: 50 individuals, 100 generations

4.3. Evaluation Metrics

The model performance was evaluated according to the Accuracy (proportion of correct predictions), Precision, Recall, F1-Score (particularly important for minority class detection), AUROC (Area Under ROC Curve) that evaluates class discrimination, Inference Time (assesses suitability for real-time use) and Clinician Interpretability Score (scale: 1–5).

4.4. Results

The Table 1 summarizes performance metrics for different system configurations.

Table 1 – *Evaluation*

Model	Accuracy	F1	AUROC	Time (ms)	Interpretability
CNN + LSTM	91.2%	0.88	0.92	85	1.7
FIS (Only)	78.4%	0.74	0.76	22	4.6
FIS + GA	82.1%	0.76	0.79	33	4.7

Hybrid (Proposed)	92.5%	0.91	0.94	87	4.2

4.4.2. Ablation Study

- Without GA: F1 dropped by ~4%
- Replacing FIS with MLP: Slight accuracy gain, interpretability dropped below 2
- Excluding multimodal data: Accuracy declined by ~5%

4.5. Case Studies

Two real-world scenarios are illustrated below to demonstrate interpretability and tical relevance:

- **Case A**: A 65-year-old patient with high heart rate and low sleep quality was flagged for high fatigue risk. The FIS provided a clear explanation through a simple rule.
- **Case B**: A patient with stable vitals but elevated creatinine and glucose triggered a kidney risk alert, highlighting the model's ability to detect subtle risks.

5. Discussion

The experimental results indicate that the proposed hybrid CI framework successfully balances high predictive accuracy, interpretability, and real-time performance – three critical requirements for AI adoption in clinical environments.

A key strength of the framework is its interpretability. Deep learning models like CNNs and LSTMs are known for excellent predictive accuracy but are often criticized for being "black-box" models. By integrating a Fuzzy Inference System (FIS), the framework enables clinicians to understand and trust predictions through rule-based, linguistically meaningful explanations. For instance, rules such as "IF heart rate is HIGH AND sleep quality is LOW THEN fatigue risk is HIGH" offer clarity in risk assessment.

The use of Genetic Algorithms (GAs) to optimize the fuzzy system further enhances adaptability. Traditional FIS models often rely on fixed, expert-defined rules, limiting their generalizability. Our framework continuously evolves and refines these rules using real-world data, achieving improved F1-scores (up to 91%) without sacrificing interpretability.

Importantly, the system's responsiveness – with inference times under 100 milliseconds – demonstrates its feasibility for deployment in real-time healthcare scenarios such as ICU monitoring or home-based remote care. Compared to standalone deep models (AUROC = 0.92), our hybrid system achieves superior performance (AUROC = 0.94) while maintaining interpretability scores rated above 4 by clinicians.

These results demonstrate that the modular architecture is not only effective but also practical for integration into existing digital healthcare infrastructures.

5.1. Limitations

Despite the encouraging results, some limitations of the proposed framework should be acknowledged. First, although simulated wearable sensor data proved useful for evaluating the system's real-time capabilities, it does not fully reflect the noise, variability, and missing values commonly found in real-world patient-generated data. The transition from synthetic streams to live deployment may introduce challenges in signal reliability, data consistency, and system robustness that were not fully captured in the current evaluation.

Second, the initialization of the Fuzzy Inference System (FIS) depends on domain-specific clinical expertise to define the initial rule base and membership functions. While the genetic optimization component enables adaptive refinement, the framework's effectiveness still hinges on the availability of expert knowledge during setup. This dependency could limit scalability across diverse institutions or regions where such expertise is not readily available.

Third, the generalizability of the framework remains an open question. Validation was primarily conducted using the MIMIC-III dataset, which is focused on critical care patients in intensive care units. Extending the framework to other clinical domains, such as oncology, pediatric, or mental health, will require additional testing to ensure robustness and accuracy across varying populations and data modalities.

Finally, although the system achieves low-latency inference suitable for real-time applications, the training phase, particularly the genetic optimization of fuzzy rules, is computationally intensive. While this is acceptable in controlled settings, further optimization may be needed to support retraining in edge-computing environments or resource-constrained deployments.

6. Conclusion

This paper presented a modular hybrid computational intelligence framework that integrates deep learning, fuzzy inference systems, and genetic algorithms to enable explainable predictive analytics in smart healthcare environments. By leveraging multimodal data sources, including electronic health records (EHRs), wearable sensors, and imaging metadata, the framework delivers accurate, interpretable predictions of critical health risks such as cardiac complications and diabetic events.

Experimental results demonstrate that the proposed system outperforms conventional and single-paradigm models in predictive accuracy, interpretability, and real-time responsiveness.

The inclusion of a fuzzy inference layer enhances transparency by aligning predictions with clinician-style reasoning, while the genetic optimization engine ensures continuous model adaptation to dynamic healthcare environments.

The modular architecture enables seamless integration with existing clinical infrastructures and supports deployment in both hospital-based and remote monitoring settings. Importantly, the framework addresses one of the most pressing challenges in medical AI: balancing predictive performance with clinician trust.

Future work will focus on validating the system with real-world data from commercial wearable devices, expanding the fuzzy rule base through clinician-in-the-loop refinement, and applying federated learning techniques to improve scalability and preserve patient privacy. Additional research will also explore the application of the framework in broader clinical domains such as oncology, pediatric, and mental health.

Overall, this hybrid approach contributes to the development of explainable, human-centered AI systems in healthcare, capable of delivering timely, transparent, and personalized care while earning the trust of medical professionals. The proposed framework lays the groundwork for reliable and interpretable AI-driven decision support tools that can enhance patient outcomes in diverse healthcare settings.

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