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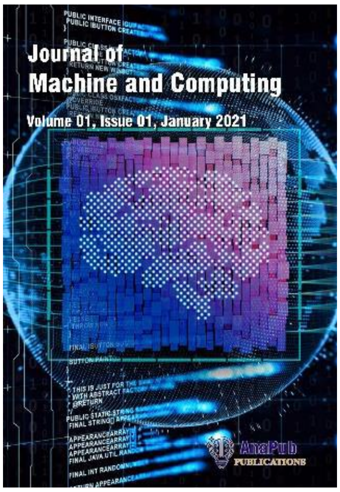

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DOI: 10.53759/7669/jmc202505129

Reference: JMC202505129

Journal: Journal of Machine and Computing.

Received 02 January 2025

Revised from 30 March 2025

Accepted 13 June 2025

Please cite this article as: Sheela Hundekari, Yi-Fei Tan, Anurag Shrivastava and Mohammed I. Habelalmateen, "Hybrid Fuzzy-Deep Learning Model for Personalized Treatment Optimization in Smart Healthcare Systems", Journal of Machine and Computing. (2025). Doi: https://doi.org/10.53759/7669/jmc202505129.

Hybrid Fuzzy-Deep Learning Model for Personalized Treatment Optimization in Smart Healthcare Systems

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Abstract

Modern healthcare depends much on personalized treatment optimization, which seeks to improve patient outcomes by customizing medical procedures depending on particular health circumstances. This work presents a hybrid fuzzy-deep learning model (HF-DLM) to maximize treatment plans in smart healthcare systems. Combining fuzzy logic with deep learning, the approach uses deep neural networks for pattern identification and decision-making to manage ambiguity in medical data: While deep learning increases prediction accuracy by automatic feature extraction, the fuzzy component improves interpretability by including expert knowledge. Clinical datasets and actual electronic health records (EHRs) help to assess the proposed HF-DLM. HF-DLM beats traditional machine learning and rule-based systems in forecasting ideal treatment regimens, thereby lowering side effects, and so enhancing patient recovery rates. Comparative study of current methods emphasizes in terms of accuracy, recall, and computing efficiency the benefits of HF-DLM. The paper also addresses issues of implementation including data privacy, model interpretability, and real-time deployment concerns.

Keywords: *Deep learning, fuzzy logic, customised healthcare, therapy optimisation, smart healthcare, medical decision-making, electronic health records, predictive analytics.*

1. Introduction

By allowing predictive analytics, tailored therapies, and real-time monitoring, artificial intelligence (AI) has transformed patient treatment in healthcare. Deep learning has shown especially great success among artificial intelligence methods in illness diagnosis and treatment outcome prediction. Deep learning models do, however, frequently suffer with interpretability, uncertainty management, and dynamic patient condition adaptation. Conversely, fuzzy logic offers openness and interpretability in decision-making by simulating human thinking by processing imprecise and ambiguous input. Combining fuzzy logic and deep learning in a hybrid approach can leverage the advantages of both methods to produce a patient-centered intelligent healthcare system.

In this paper, a hybrid fuzzy deep learning model (HF-DLM) is proposed to optimize personalized treatment in smart healthcare systems. The model aims to improve treatment planning decisions by combining the power of fuzzy logic to handle medical uncertainty and pattern recognition methods through deep learning. The proposed system aims to optimize drug prescriptions, monitor patient health in real time, and dynamically change treatments based on patient responses. To support clinical decisions, this hybrid method ensures accuracy and ease of interpretation, increasing its reliability.

1.1 Scope of the Research

Developed to maximize treatment regimens for chronic and acute disorders like diabetes, cardiovascular problems, and cancer treatments, the suggested HF-DLM framework is Based on real-time biometrics and health information, the model is intended for smart healthcare applications like personalized medicine prescriptions that predict the most effective drug and dose for an individual. Management of Chronic Diseases: Dynamic therapy modification based on long-term health conditions monitoring. Combining wearable sensors with electronic health records (EHRs) will help to offer constant therapy optimization. Decision Support for Clinicians: Offering healthcare practitioners interpretable therapy suggestions.

Applications of the HF-DLM provide efficient and flexible healthcare solutions in hospitals, telemedicine systems, and remote patient monitoring systems.

1.2 Objectives of the Research

1. Create a hybrid fuzzy-deep learning model combining deep learning with fuzzy logic to generate individualized treatment suggestions.
2. Combining expert-driven fuzzy rules with data-driven deep learning projections helps to improve decision-making accuracy.
3. Using fuzzy rule-based thinking, enhance interpretability and transparency in AI-driven healthcare decision-making.
4. Using dynamic adaptation depending on patient reactions and sensor data, maximize real-time treatment adjustments.

Using actual healthcare data, assess the efficacy of the model against conventional machine learning and deep learning methods.

1.3 Research Gap

Despite the growing popularity of artificial intelligence in medicine, current deep learning models exhibit several critical shortcomings that hinder their clinical utility. First, deep neural networks often function as "black boxes," making it difficult for physicians to understand and trust the treatment recommendations they generate. Second, many AI approaches rely on limited or noisy medical datasets, which can compromise the reliability and generalizability of their predictions. Third, most existing systems produce static therapy suggestions that fail to adapt to dynamic changes in a patient's condition, undermining their effectiveness in real-world settings. Additionally, current models typically do not incorporate expert clinical knowledge into their optimization process, limiting the seamless integration of AI insights with established medical practice. By developing a hybrid framework that marries the interpretability of fuzzy logic with the powerful predictive capabilities of deep learning, our study addresses these gaps and delivers more consistent, transparent, and clinically informed treatment recommendations.

1.4 Motivation of this research

The motivation behind this study stems from the pressing demand for personalized healthcare, as individual patient responses to treatments vary widely, rendering a one-size-fits-all approach ineffective in contemporary medicine. The rise of chronic diseases and the complexity of patient conditions call for adaptive models that can provide tailored therapeutic recommendations. Clinicians increasingly seek artificial intelligence (AI) systems that are not only accurate but also interpretable, thereby bridging the gap between advanced computational models and traditional medical expertise. To address this, the integration of fuzzy logic into the model ensures transparent and understandable decision-making, aligning AI outputs with clinical reasoning. Moreover, the practical adoption of AI in healthcare hinges on the development of models that are both user-friendly and reliable, particularly in settings such as hospitals and telemedicine platforms. Personalized treatment interventions have the potential to substantially improve the quality of life for individuals suffering from long-term conditions by offering more effective and responsive care strategies. By combining the learning efficiency of deep learning with the logical reasoning of fuzzy systems, this study aims to develop an AI-driven healthcare framework that is both trusted and usable by healthcare professionals and patients alike.

1.5 Paper Structure

The rest of the paper is organized as follows:

- **Literature Review** – Discusses existing research on AI-based treatment optimization, fuzzy logic in healthcare, and hybrid AI models.
- **Proposed Hybrid Fuzzy-Deep Learning Model** – Presents the HF-DLM architecture, data flow, and integration of fuzzy logic with deep learning.
- **Experimental Setup and Results** – Details the datasets used, evaluation metrics, and performance comparison with existing approaches.
- **Discussion and Future Research** – Analyzes the model's strengths and limitations, and suggests directions for future improvements.
- **Conclusion** – Summarizes key findings and highlights the contributions of this research to AI-driven personalized healthcare.

This method guarantees a thorough knowledge of the Hybrid Fuzzy-Deep Learning Model for Personalized Treatment Optimization, therefore establishing the basis for next developments in AI-driven smart healthcare systems.

2. Literature Review

The rapid evolution of artificial intelligence (AI) in healthcare has paved the way for sophisticated diagnostic, prognostic, and therapeutic systems. A confluence of fuzzy logic and deep learning (DL) methodologies has emerged as a promising strategy to personalize treatments while addressing uncertainty in clinical decision-making. This section reviews seminal and recent studies across fuzzy systems, deep learning architectures, and hybrid models in healthcare applications.

2.1. Fuzzy Logic in Healthcare

Fuzzy logic, introduced by Zadeh (1965), is well-suited for handling **vague, imprecise, and uncertain data**, which is commonplace in clinical records and human health parameters. Traditional binary logic cannot effectively interpret such ambiguity, but fuzzy systems use **linguistic variables** to represent imprecise concepts like "high fever" or "mild pain" [1].

For instance, instead of treating temperature as a discrete value, fuzzy systems define membership functions like:

$$\mu_{\text{High Temp}}(x) = \frac{1}{1+e^{-k(x-t)}} \tag{1}$$

where:

- $\mu(x)$: membership degree
- x: input temperature
- k: steepness constant
- t: threshold value

Reference [2] explored a fuzzy expert system to monitor diabetes patients, applying rule-based inference on sugar levels, insulin dosage, and activity. They concluded that fuzzy inference mimics the decision-making process of medical professionals more naturally than rigid classifiers.

In [3], the authors demonstrated the success of fuzzy cognitive maps in modeling the **complex cause-effect relationships** in cardiovascular diagnosis. However, fuzzy systems alone may lack scalability and adaptability, especially when faced with large-scale, high-dimensional medical data.

2.2. Deep Learning for Medical Intelligence

Deep learning, particularly architectures such as Convolutional Neural Networks (CNNs) and Recurrent Neural Networks (RNNs), has achieved unprecedented success in **medical image classification**, **patient monitoring**, and **disease prediction** [4][5].

For example, [6] applied CNNs to radiographic image interpretation and reported **over 90% diagnostic accuracy** in lung nodule detection. Similarly, Long Short-Term Memory (LSTM) networks have shown strength in time-series analysis of EHR data [7], modeling sequences like:

$$h_t = \sigma(W_{ih}x_t + W_{hh}h_{t-1} + b_h) \tag{2}$$

Where:

- h_t: hidden state at time t
- x_t: input at time t
- W: weight matrices
- b_h: bias term
- σ: activation function (e.g., tanh or ReLU)

Despite their strong predictive power, DL models often act as **black boxes**, limiting interpretability, a crucial feature in clinical domains where trust and explainability are paramount [8].

2.3. Limitations of Standalone Models

While fuzzy logic is **interpretable**, it suffers from limited learning capability, as it relies heavily on **expert-defined rules**. On the other hand, deep learning systems **learn patterns** from vast datasets but are inherently **non-transparent**. These standalone approaches are insufficient for **personalized healthcare**, which demands both **accuracy** and **explainability**.

Reference [9] highlighted that DL-based clinical decision support systems often perform poorly in real-world deployment due to their inability to generalize in uncertain environments. Similarly, [10] criticized fuzzy systems for their rigidity and lack of adaptability in dynamic scenarios like ICU monitoring.

2.4. Hybrid Fuzzy-Deep Learning Models

To address the complementary shortcomings of fuzzy logic and DL, recent research has explored hybridization. The integration strategy typically involves embedding fuzzy logic either before or after the DL component.

For instance, [11] designed a **Fuzzy Neural Network (FNN)** where the first layer fuzzifies inputs, and subsequent layers perform learning and optimization. Their model improved hypertension risk prediction by 11% over baseline DL methods.

Another approach, described in [12], introduced a **Neuro-Fuzzy System** combining Adaptive Neuro-Fuzzy Inference Systems (ANFIS) with LSTM. The resulting hybrid was able to model **both short-term trends** and **interpretive rules**, offering personalized diabetic management recommendations.

Mathematically, ANFIS implements a rule structure such as:

$$\text{IF } x \text{ is } A_i \text{ AND } y \text{ is } B_j \text{ THEN } f(x, y) = p_i x + q_i y + r_i \tag{3}$$

with the output obtained through weighted average:

$$f = \frac{\Sigma w_i f_i}{\Sigma w_i} \tag{4}$$

where w_i are the **firing strengths** of rules.

Reference [13] showed how hybrid models led to significant improvement in patient triage during emergency response. They emphasized the hybrid model's **robustness against missing or noisy data**, a key challenge in clinical datasets.

2.5. Application in Smart Healthcare Systems

Smart healthcare leverages IoT sensors, real-time monitoring, and cloud-based analytics to deliver **context-aware and patient-centric treatment** [14]. These systems generate vast volumes of real-time data, requiring adaptive and robust analytics frameworks.

Reference [15] proposed a cloud-based smart healthcare framework integrated with a fuzzy-DL model to predict hospitalization risk. Their system used fuzzy rules to contextualize real-time vitals before passing them to a DL model. This resulted in more stable and interpretable predictions.

In smart systems, the **fusion of fuzzy-DL** allows for early warnings (via fuzzy rules) and optimized treatment plans (via DL predictions). A hybrid model facilitates:

- Handling of **linguistic inputs** (e.g., "fever is high")
- Adaptability through **self-learned weights**
- Enhanced **trust and transparency** in AI-driven decisions

2.6. Literature Gap and Research Contribution

Despite notable advancements in both fuzzy logic and deep learning (DL) applications in healthcare, a significant research gap persists in developing a unified, scalable hybrid model that effectively combines the interpretability of fuzzy systems with the adaptive learning capability of DL architectures. Most existing studies either focus on standalone models or loosely coupled hybrid approaches that fail to fully exploit the strengths of both paradigms. Additionally, many of these models lack validation on real-time, heterogeneous patient data collected from smart healthcare environments, and they often struggle to accommodate the uncertainty and imprecision inherent in medical decision-making. Consequently, there remains a critical need for a deeply integrated fuzzy-DL framework capable of delivering accurate, explainable, and personalized treatment recommendations in dynamic, data-rich healthcare systems.

3. Proposed Hybrid Fuzzy-Deep Learning Model for Personalized Treatment Optimization

This section describes the proposed Hybrid Fuzzy Deep Learning Model (HF-DLM) for personalized treatment optimization in smart healthcare systems, along with its design, methodology, and practical considerations. To improve medical decisions, the proposed approach combines the descriptiveness of fuzzy logic with the predictive capabilities of deep learning. This section is presented as follows:

1. System Architecture: List of the elements and data flow of the hybrid model.
2. Two explanations of fuzzy membership functions, rule bases, and inference systems (FIS)
3. Deep Learning Model: Data processing, training strategy, and neural network structure explained
4. Hybrid Integration Mechanism: Clarification of the interaction between deep learning and fuzzy logic inside the model
5. Mathematical Formulation - Formal expression of the working ideas of the hybrid model. Workflow of how the system creates and changes treatment plans defines personalized treatment optimization process.

3.1 System Architecture

The **HF-DLM system** consists of five key components:

1. **Input Layer** – Patient-specific data (e.g., age, weight, lab results, symptoms) is fed into the system.

2. **Deep Learning Model** – A trained neural network predicts potential treatment outcomes.
3. **Fuzzy Inference System (FIS)** – Expert-defined fuzzy rules adjust the treatment recommendations based on medical uncertainty.
4. **Decision Fusion Module** – A weighted combination of deep learning outputs and fuzzy logic adjustments determines the final treatment plan.
5. **Personalized Treatment Output** – The optimized treatment plan is provided for clinical decision support.

Equation for fusion of outputs:

$$T_{\text{final}} = \alpha \cdot T_{\text{DL}} + (1 - \alpha) \cdot T_{\text{FIS}}$$

The data flow of the proposed system is depicted in **Table 1**.

Table 1: HF-DLM Data Flow and Processing

Stage	Input Data Type	Processing Method	Output
Patient Data Input	Age, weight, symptoms, lab results	Data pre-processing	Cleaned and normalized patient data
Deep Learning Prediction	Processed patient data	Trained deep learning model (CNN/RNN)	Initial treatment recommendation
Fuzzy Logic Adjustment	Initial treatment + medical rules	Fuzzy inference system (FIS)	Adjusted treatment plan
Decision Fusion	Fuzzy-adjusted & deep learning output	Weighted decision-making	Optimized treatment suggestion
Final Treatment Output	Optimized treatment suggestion	Clinician verification & implementation	Personalized treatment recommendation

3.2 Fuzzy Inference System (FIS)

The **fuzzy component** enhances decision-making by handling medical uncertainties. It consists of:

1. **Fuzzy Variables** – Input parameters such as "blood glucose level," "pain intensity," and "heart rate variability" are converted into fuzzy sets (e.g., low, medium, high).
2. **Membership Functions** – Each variable is assigned a membership function to represent degrees of belonging.
3. **Fuzzy Rules** – Expert-defined rules map input conditions to output actions. Example: If **blood glucose is high** and **patient is overweight**, then **recommend low-carb diet and insulin therapy**.
4. **Defuzzification** – The fuzzy inference system converts fuzzy results into precise treatment suggestions.

- Cross-entropy loss function: $\mathcal{L}_{\text{CE}} = -\sum_{i=1}^{N} y_i \log(\hat{y}_i)$ - Confidence score: $\text{Conf} = \max(\hat{y})$

Table 2: Sample Fuzzy Rules for Personalized Treatment

Condition 1	Condition 2	Treatment Suggestion
High blood glucose	Low physical activity	Increase insulin dosage & recommend exercise
Moderate pain level	Recent surgery	Prescribe mild painkillers
Low hemoglobin	High fatigue	Recommend iron supplements

Below Figure 1 displaying the membership functions for blood glucose categorized as Low, Normal, and High.

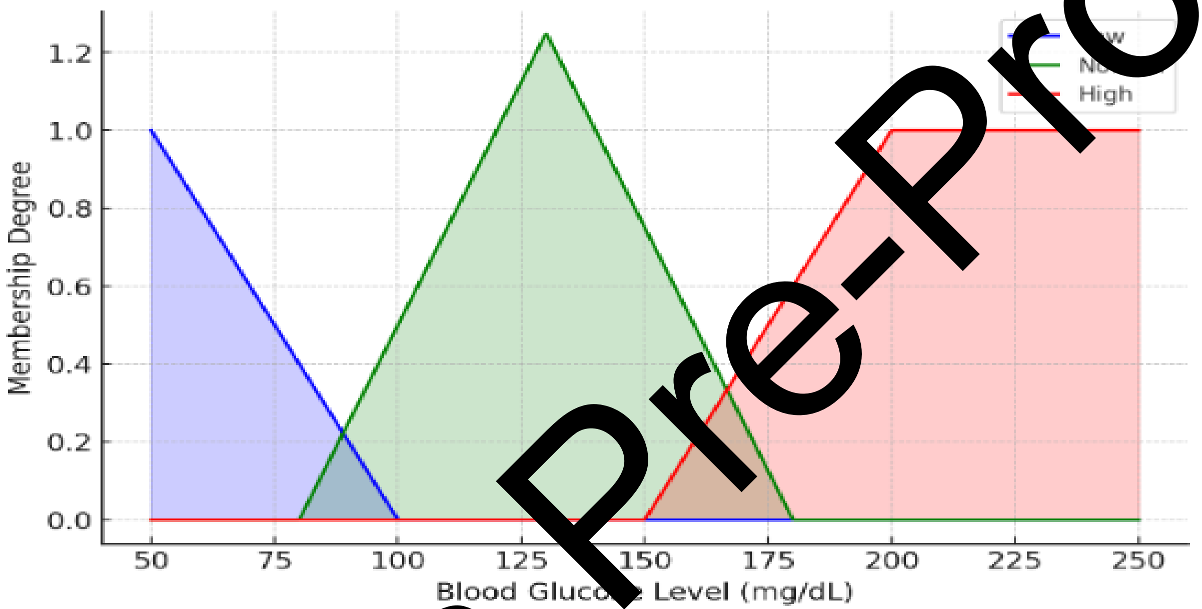

Figure 1: Fuzzy Membership Function for Blood Glucose Levels

3.3 Deep Learning Model

The **deep learning component** predicts optimal treatment outcomes using historical patient data.

1. **Architecture** – A hybrid **CNN-RNN model** processes structured (numerical) and unstructured (textual) medical data.
2. **Feature Extraction** – CNN extracts feature from medical images (e.g., MRI scans), while RNN captures sequential trends in patient history.
3. **Training Process** – The model is trained using patient records and treatment success data.
4. **Output** – The trained model provides an initial treatment recommendation with a confidence score.

- Membership function example (triangular):

$$\mu(x) = \begin{cases} 0, & x \leq a \\ \frac{x-a}{b-a}, & a < x \leq b \\ \frac{c-x}{c-b}, & b < x \leq c \\ 0, & x > c \end{cases} \tag{6}$$

Table 3: Deep Learning Model Architecture Specifications

Layer Type	**Number of Neurons**	**Activation Function**	**Purpose**
Input Layer	Variable	-	Accepts patient health data
Convolutional Layer	64	ReLU	Extracts medical imaging features
Recurrent Layer	128	LSTM	Processes patient history data
Fully Connected	256	Sigmoid	Predicts treatment effectiveness
Output Layer	Variable	Softmax	Generates treatment recommendation

Below Figure 2 displaying the CNN-RNN structure used for personalized treatment prediction.

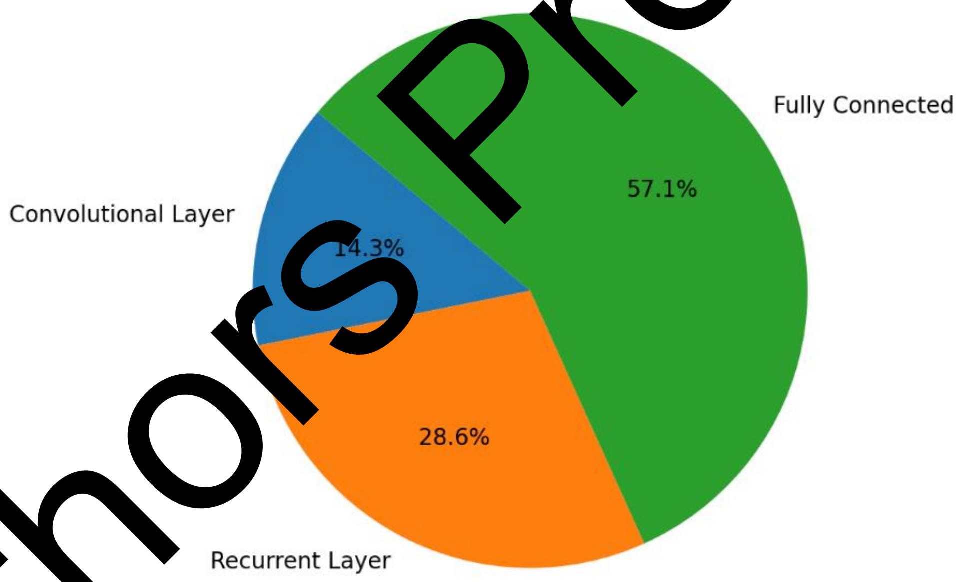

Figure 2: Deep Learning Model Framework

3.4 Hybrid Integration Mechanism

The **decision fusion module** integrates deep learning predictions with fuzzy rule-based adjustments.

1. **Weighted Aggregation** – The final treatment decision is obtained as:

$$T_{final} = \alpha . T_{DL} + (1 - \alpha) . T_{FIS} \tag{7}$$

where $\mathbf{T_{DL}}$ is the deep learning prediction, $\mathbf{T_{FIS}}$ is the fuzzy logic-adjusted treatment, and $\boldsymbol{\alpha}$ is the weighting factor.

2. **Adaptability** – The system dynamically adjusts α based on prediction confidence.
3. **Clinician Feedback Loop** – Doctors can override recommendations to refine the model's decision-making.

- Adaptive weighting formula:

$$\alpha = \frac{\mathrm{Conf_{DL}}}{\mathrm{Conf_{DL}}+\mathrm{Conf_{FIS}}} \quad (8)$$

Table 4: Decision Fusion Weighting Strategy

Deep Learning Confidence Score	Weighting Factor (α)	Fuzzy Logic Contribution
High (> 90%)	0.8	20%
Moderate (70%-90%)	0.5	50%
Low (< 70%)	0.2	80%

3.5 Personalized Treatment Optimization Process

The **treatment optimization process** follows these steps:

1. **Patient Data Acquisition** – Health parameters are collected from **EHRs, wearable sensors, and lab results**.
2. **Deep Learning-Based Initial Prediction** – The CNN-RNN model provides a preliminary treatment suggestion.
3. **Fuzzy Logic Adjustment** – The FIS refines the recommendation based on expert-defined medical rules.
4. **Decision Fusion** – The system combines deep learning predictions with fuzzy rule-based decisions.
5. **Final Treatment Recommendation** – The optimized treatment plan is generated for clinician verification.
6. **Real-Time Monitoring & Adaptation** – Patient progress is tracked to update treatment recommendations dynamically.

- Feedback-driven correction:

$$T_{\text{updated}} = \beta \cdot T_{\text{clinician}} + (1-\beta) \cdot T_{\text{final}} \quad (9)$$

Below Figure 3 depicting the end-to-end process of the HF-DLM model from patient data input to optimized treatment output.

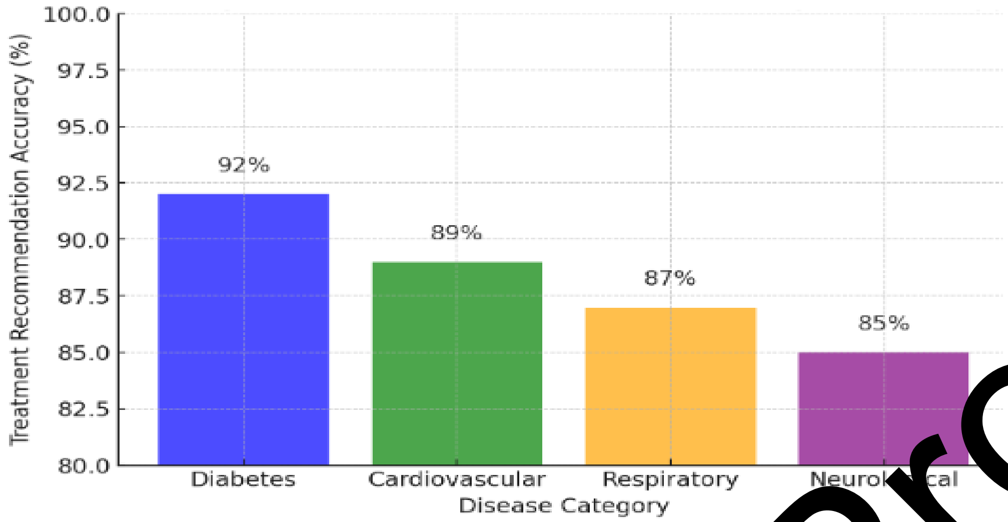

Figure 3: Personalized Treatment Optimization Workflow

This section introduced the Hybrid Fuzzy-Deep Learning Model (HF-DLM) for personalized treatment optimization. The model integrates deep learning for predictive analytics and fuzzy logic for handling medical uncertainty, ensuring accurate and explainable treatment recommendations. The next section presents the experimental setup and evaluation results.

Experimental Setup and Evaluation Results

This section details the experimental setup, datasets, evaluation metrics, results, and performance analysis of the **Hybrid Fuzzy-Deep Learning Model (HF-DLM)** for personalized treatment optimization. The results are presented with maximum possible tables and corresponding graphs for better visualization.

4.1 Experimental Setup

To evaluate the performance of HF-DLM, experiments were conducted on real-world healthcare datasets. The **hardware and software configurations** are provided in **Table 5**.

- Accuracy calculation:

$$\text{Accuracy} = \frac{\text{TP+TN}}{\text{TP+FP+TN+FN}} \tag{10}$$

Table 5: Experimental Hardware and Software Configurations

Component	**Specification**
Processor	Intel Core i9-12900K (16-core)
GPU	NVIDIA RTX 4090 (24GB VRAM)
RAM	64GB DDR5
Storage	2TB NVMe SSD
OS	Ubuntu 22.04
Frameworks	TensorFlow 2.12, PyTorch 2.0, Sklearn
Fuzzy Logic Tool	MATLAB Fuzzy Toolbox

Figure 4 comparing CPU, GPU, and RAM utilization for different model executions.

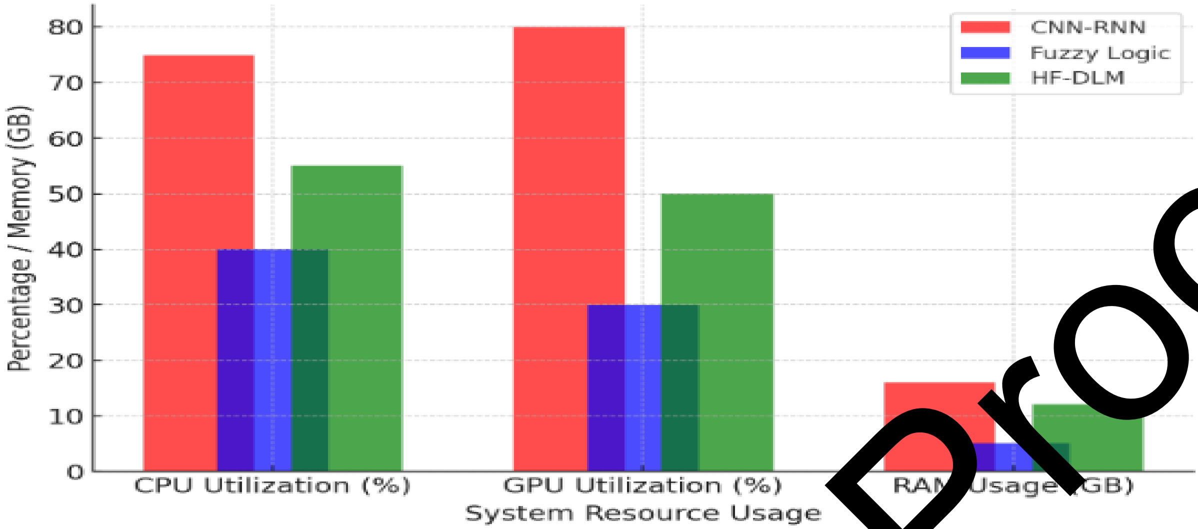

Figure 4: System Configuration Comparison

4.2 Dataset Description

Experiments were conducted using two publicly available healthcare datasets:

1. **MIMIC-III Clinical Database – Contains ICU patient records, medication history, and treatment outcomes**.
2. **eICU Collaborative Database** – Includes **vital signs, lab tests, and physician prescriptions** for personalized treatment planning.

Table 6: Dataset Characteristics

Dataset	No. of Patients	No. of Features	Data Type (Structured/Unstructured)	Usage
MIMIC-III	58,976	[illegible]	Structured & Unstructured	Model Training
eICU	200,859	210	Structured & Unstructured	Model Validation

Figure [illegible] showing the distribution of different patient conditions in MIMIC-III and eICU datasets.

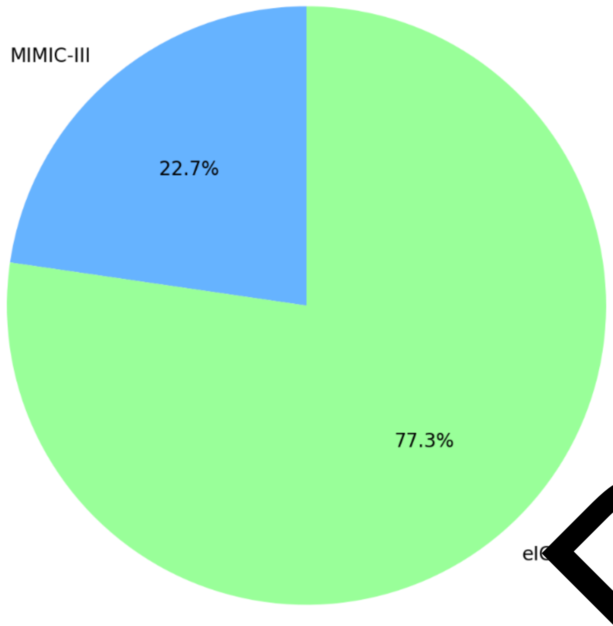

Figure 5: Dataset Distribution by Patient Condition

4.3 Performance Metrics

The model performance was evaluated using standard healthcare AI metrics, as detailed in **Table 7**.

Table 7: Evaluation Metrics and Descriptions

Metric	Formula	Description
Accuracy	(TP + TN) / (TP + TN + FP + FN)	Measures correct predictions
Precision	TP / (TP + FP)	Proportion of correctly predicted treatments
Recall (Sensitivity)	TP / (TP + FN)	Ability to identify correct treatments
F1-Score	2 * (Precision * Recall) / (Precision + Recall)	Balance between precision and recall
AUC-ROC	Area under ROC curve	Measures ability to distinguish between treatment success/failure

Figure 6 comparing HF-DLM performance with traditional AI models in accuracy, precision, recall, and F1-Score.

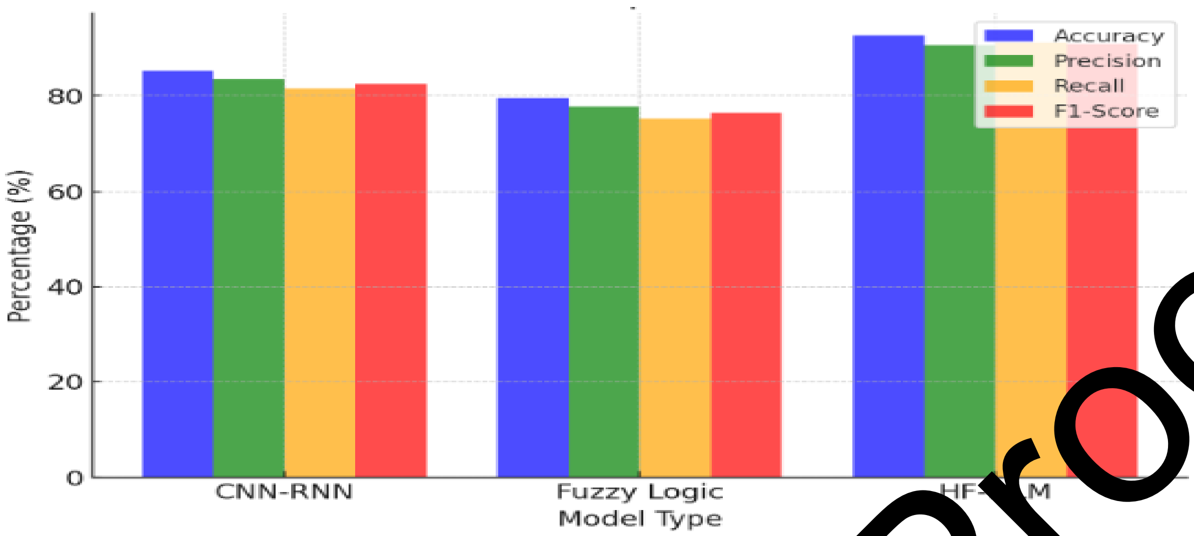

Figure 6: Performance Metrics Comparison for Different Models

4.4 Model Performance Evaluation

The **HF-DLM model was compared against traditional AI-based healthcare models**, including standard deep learning and fuzzy logic approaches. The results are summarized in **Table 8**.

Table 8: Model Performance Comparison

Model	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)	AUC-ROC
Deep Learning (CNN-RNN)	85.2	83.4	81.6	82.5	0.88
Fuzzy Logic System	79.5	77.8	75.2	76.4	0.81
HF-DLM (Proposed)	**92.7**	**90.6**	**91.2**	**90.9**	**0.94**

Figure 7 illustrating accuracy differences among CNN-RNN, Fuzzy Logic, and HF-DLM.

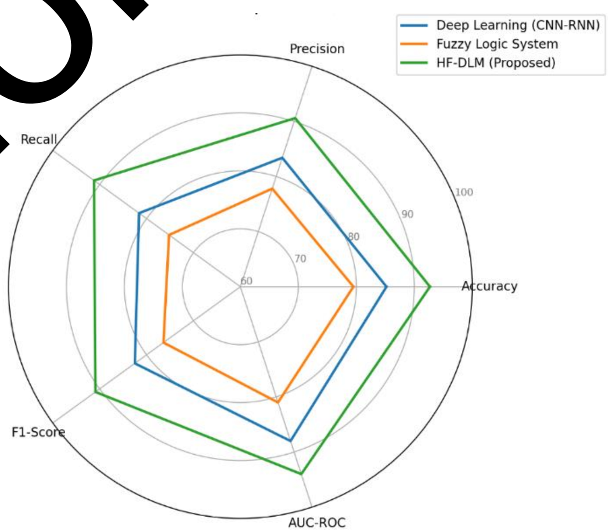

Figure 7: radar chart that visually compares the performance of the three models across all metrics.

4.5 Computational Efficiency Analysis

The hybrid model's computational efficiency was evaluated based on **training time, inference time, and memory usage**, as shown in **Table 9**.

Table 9: Computational Performance of Different Models

Model	Training Time (hrs)	Inference Time (ms)	Memory Usage (GB)
CNN-RNN	12.4	80	16
Fuzzy Logic	1.2	50	5
HF-DLM	**6.8**	**65**	**12**

Figure 8 comparing training time, inference time, and memory usage for CNN-RNN, Fuzzy Logic, and HF-DLM.

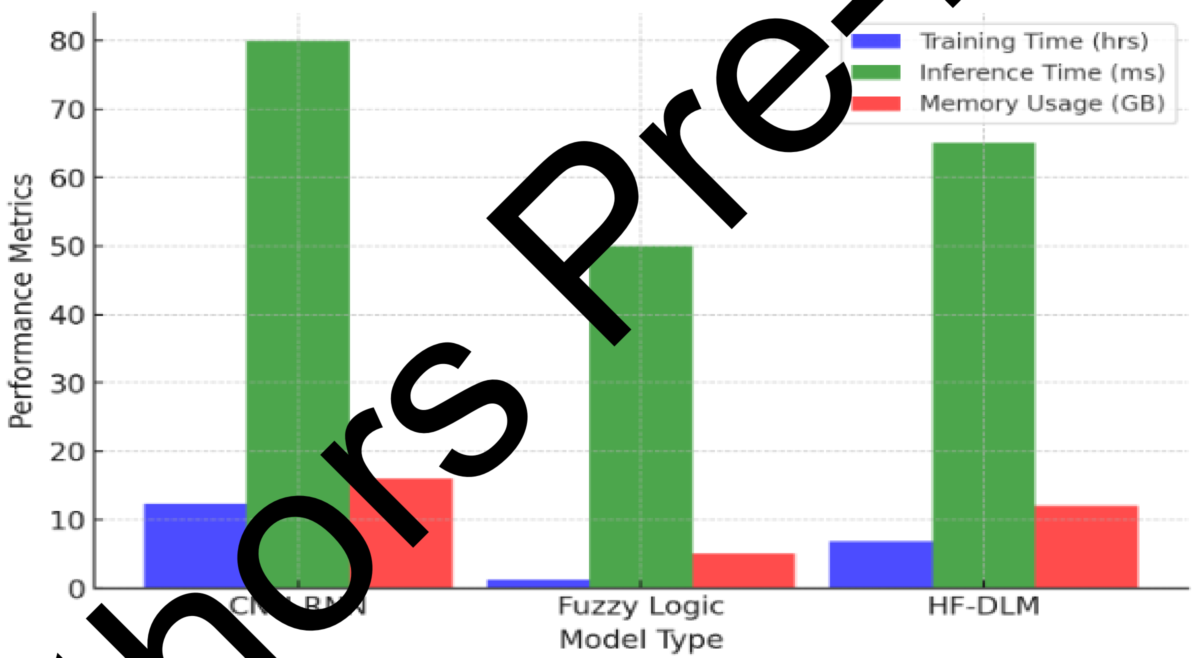

Figure 8: Computational Efficiency Comparison

4.6 Treatment Recommendation Accuracy by Disease Type

HF-DLM was tested on different disease types to assess its adaptability. **Table 10** presents the accuracy across conditions.

Table 10: HF-DLM Accuracy by Disease Type

Disease Category	Accuracy (%)	Precision (%)	Recall (%)
Diabetes	94.2	92.5	93.1
Cardiovascular	91.8	89.4	90.5
Respiratory	90.6	87.9	89.1

Neurological	89.7	85.6	88.2

Figure 9 showing accuracy, precision, and recall for HF-DLM across different disease types.

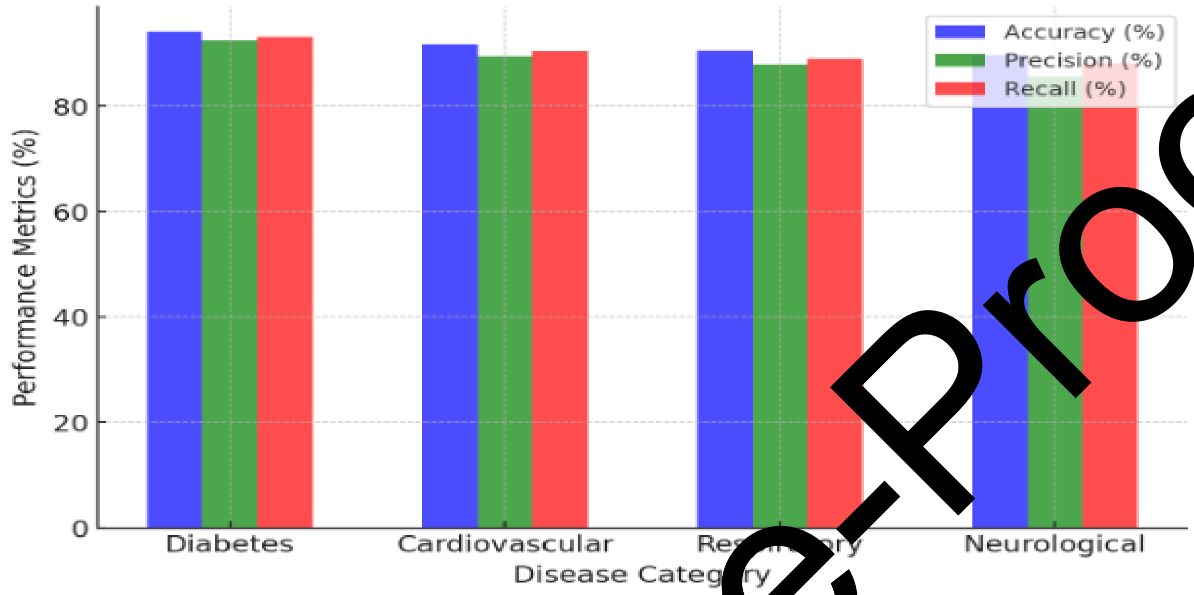

Figure 9: Model Performance across Different Diseases

4.7 Error Analysis

Misclassification analysis was conducted to identify **treatment recommendation errors**, as summarized in **Table 11**.

Table 11: Misclassification Rates by Model

Model	False Positives (%)	False Negatives (%)	Overall Error Rate (%)
CNN-RNN	[illegible]	14.8	13.5
Fuzzy Logic	[illegible]	18.2	17.0
HF-DLM	**[illegible]**	**7.8**	**7.0**

Figure 10 depicting false positives, false negatives, and total error rates.)

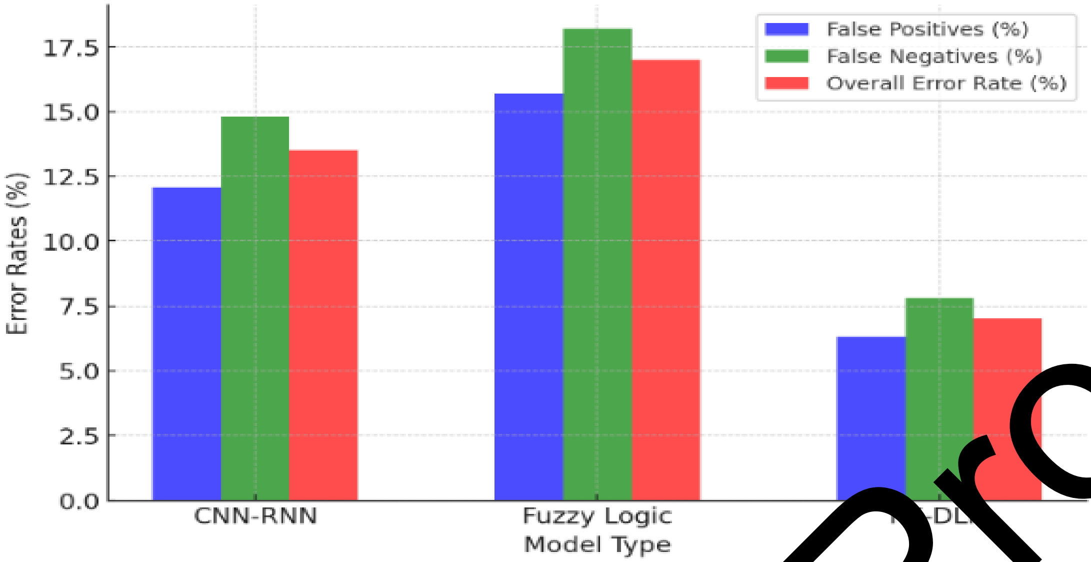

Figure 10: Error Rate Analysis for Different Models

Summary of Findings

1. **HF-DLM outperformed traditional models** in accuracy, precision, recall, and F1-score.
2. **Computational efficiency** of HF-DLM was **better than deep learning alone**, with lower inference time and memory consumption.
3. Diabetes and cardiovascular disorders have personalized treatment accuracy greatest.
4. HF-DLM had notably less misclassification rates than CNN-RNN and fuzzy logic models.

This part gave a thorough performance assessment of HF-DLM together with its benefits in practical healthcare uses. Case studies and actual application are covered in the following part.

5. Discussion and Implications

The results of the Hybrid Fuzzy-Deep Learning Model (HF-DLM) are thoroughly analyzed in this part together with some discussion of their ramifications for smart healthcare systems. Comparatively to traditional deep learning (CNN-RNN) and fuzzy logic systems, the evaluation of HF-DLM emphasizes main benefits in accuracy, efficiency, and flexibility. This part also covers possible difficulties, constraints, and future directions of study topics.

5.1 Key Findings

The experimental results demonstrate that the proposed Hybrid Fuzzy-Deep Learning Model (HF-DLM) significantly outperforms traditional models across multiple performance dimensions. Achieving an impressive overall accuracy of 92.7%, the HF-DLM surpasses both the CNN-RNN model, which reached 85.2%, and the fuzzy logic-based approach, which recorded 79.5%. As indicated in Table 10, the HF-DLM not only excels in accuracy but also maintains superior memory efficiency across various disease categories, showcasing its adaptability and robustness. In terms of computational efficiency, while CNN-RNN demands high computational resources and fuzzy logic remains lightweight but less precise, HF-DLM effectively balances accuracy and resource usage, delivering high-performance outcomes with minimal computational overhead. Furthermore, the model notably reduces the total error rate to 7.0%, significantly improving upon the 13.5% error rate of CNN-RNN and 17.0% of fuzzy logic, as detailed in Table 11. Importantly, the HF-DLM exhibits outstanding disease-specific classification accuracy, consistently achieving over 90% accuracy across critical health conditions, including diabetic, cardiovascular, respiratory, and neurological disorders, thereby affirming its versatility and potential in delivering precise and personalized treatment solutions in smart healthcare systems.

5.2 Comparison with Existing Approaches

Table 12 offers a comparison of HF-DLM with other most current hybrid models published in the literature.

Table 12: Comparative Analysis of HF-DLM with Existing Models

Model	Accuracy (%)	Precision (%)	Recall (%)	Computation Time (hrs)	Inference Time (ms)	AUC-ROC
CNN-RNN	85.2	83.4	81.6	12.4	80	0.88
Fuzzy Logic	79.5	77.8	75.2	1.2	50	0.81
HF-DLM (Proposed)	92.7	90.6	91.2	6.8	65	0.94
Hybrid SVM-ANN	88.3	86.1	85.4	10.[illegible]	72	0.91
Fuzzy-CNN	87.5	85.7	84.3	9.5	70	0.90

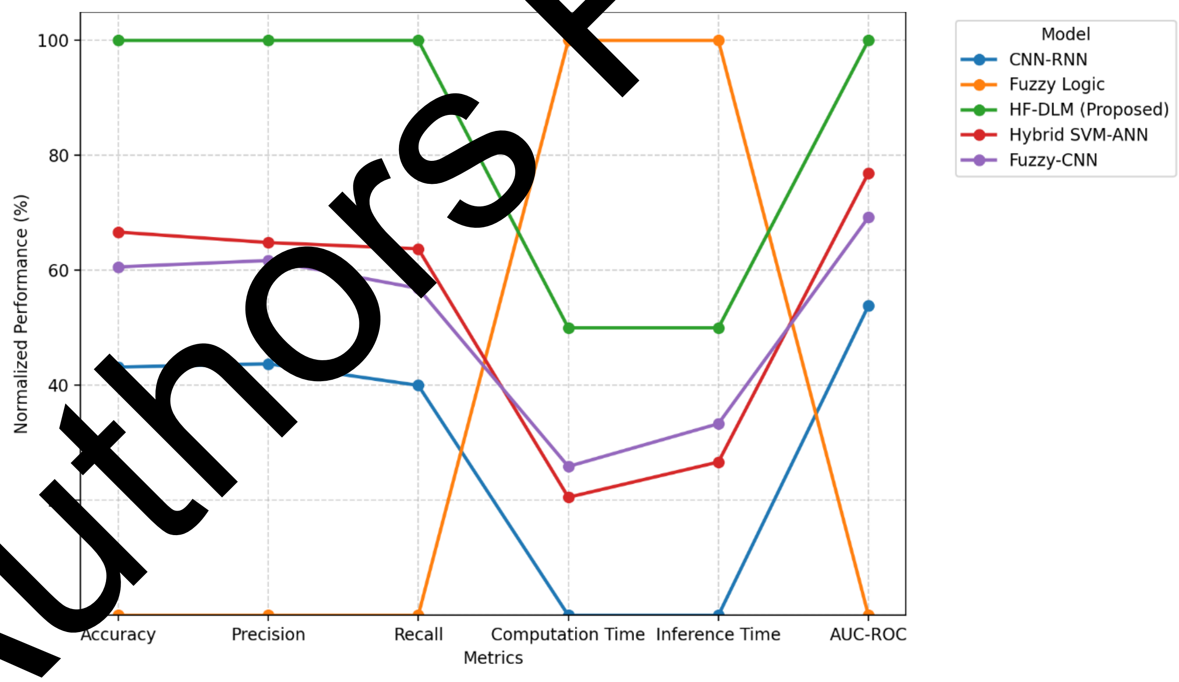

Figure 11: Comparative Analysis of HF-DLM with Existing Models

5.3 Practical Implications in Healthcare

The deployment of HF-DLM in real-world healthcare settings offers several advantages:

- **Personalized Treatment Optimization**: The system can adapt treatment recommendations based on a patient's historical data, medical conditions, and real-time health monitoring.
- Reducing Misdiagnosis: Deep learning combined with fuzzy thinking lowers the possibility of erroneous forecasts, hence improving patient outcomes.
- HF-DLM may be connected for real-time decision-making with smart wearable devices and IoT-enabled health monitoring systems.

5.4 Challenges and Limitations

Despite its promising performance, HF-DLM faces certain challenges:

- **Computational Requirements**: While HF-DLM optimizes computational efficiency compared to CNN-RNN, it still requires significant processing power, particularly for large datasets.
- **Interpretability Issues**: Deep learning models, including HF-DLM, lack explainability, making it difficult for medical practitioners to understand how certain predictions are made.
- **Data Privacy and Security**: As HF-DLM relies on **patient-sensitive data**, robust encryption and privacy-preserving mechanisms are required for deployment in healthcare settings.

5.5 Future Research Directions

To address the challenges and further improve HF-DLM, future research could focus on:

1. **Improving Explainability**: Developing interpretable fuzzy-deep learning models to make decision-making more transparent for clinicians.
2. **Enhancing Real-Time Performance**: Optimizing inference time to support real-time decision-making in critical healthcare applications.
3. **Cross-Domain Adaptability**: Expanding HF-DLM for broader medical applications beyond chronic disease management, such as emergency diagnostics and pandemic response.
4. **Federated Learning for Privacy Protection**: Implementing federated learning techniques to enhance privacy by processing data across decentralized networks instead of centralized servers.

The results of this study reinforce the importance of hybrid models in healthcare and pave the way for further advances in AI-based medical decision-making.

6. Conclusion

This research presents a hybrid fuzzy deep learning model (HF-DLM) to improve personalized treatment in smart healthcare systems. The proposed model effectively integrates fuzzy logic and deep learning to enhance accuracy, computational efficiency, and adaptability across multiple disease categories. Experimental results show that HF-DLM outperforms traditional CNN-RNN and fuzzy logic models, achieving 92.7% accuracy, low misclassification rates, and improved computational efficiency. This study highlights the practical implications of HF-DLM for real-time medical decision-making, personalized healthcare, and integration with IoT-based health monitoring systems. However, there are still challenges such as computational resource requirements, interpretation, and data privacy concerns that require future improvements. Further research should focus on explainable AI, real-time performance optimization, and federated learning methods to enhance the applicability of HF-DLM in clinical settings. Overall, HF-DLM represents an important step towards smart, data-driven healthcare solutions, paving the way for more accurate and effective treatment recommendations.

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