

AI-Based Medical Diagnosis Assistant Using Hybrid Rule-Based and Case-Based Reasoning

Mr. B. R. Vimal Aananth¹, Mr. S. R. Sudharsan¹, Ms. S. Vethaabinaya¹,
Ms. J. Sameeha¹, Mr. R. Roshan Joshua²

¹Department of Computer Science Engineering (Artificial Intelligence and Machine Learning), K. Ramakrishnan College of Technology, Tamil Nadu, India

²Assistant Professor, Department of Artificial Intelligence and Data Science, K. Ramakrishnan College of Technology, Tamil Nadu, India

Abstract

Accurate and explainable medical diagnosis remains a significant challenge due to overlapping symptoms, uncertainty in clinical data, and limited availability of medical experts. Conventional diagnostic systems based solely on rule-based reasoning lack adaptability, while purely data-driven models often fail to provide transparent justifications required for clinical trust. This paper presents a hybrid medical diagnosis assistant that integrates Rule-Based Reasoning (RBR), Case-Based Reasoning (CBR), and Naive Bayes probabilistic inference to deliver accurate and interpretable diagnostic recommendations. The proposed framework applies expert-defined clinical rules, retrieves relevant historical patient cases, and incorporates probabilistic reasoning to manage uncertainty in symptom patterns. Experimental evaluation on publicly available medical datasets demonstrates that the hybrid approach achieves an accuracy of 91.5%, outperforming standalone RBR and CBR systems. The system is designed as an explainable Clinical Decision Support System (CDSS) suitable for early-stage diagnosis and resource-constrained healthcare environments.

Keywords: Medical Diagnosis, Rule-Based Reasoning, Case-Based Reasoning, Naive Bayes, Clinical Decision Support System

1. Introduction

The growing complexity of modern healthcare has increased the difficulty of accurate medical diagnosis, particularly in cases where multiple diseases share similar symptom profiles. Timely and reliable diagnosis is critical for effective treatment; however, access to experienced medical specialists is often limited, especially in rural and under-resourced regions. Artificial Intelligence (AI) has emerged as a promising solution to support clinicians by automating diagnostic reasoning and decision-making processes.

Traditional medical expert systems primarily rely on predefined rules derived from expert knowledge. While such systems are transparent and interpretable, they are often rigid and unable to adapt to new or unseen clinical scenarios. Conversely, data-driven approaches such as machine learning models provide higher adaptability but frequently operate as black boxes, limiting their acceptance in clinical practice.

1.1 Problem Statement

Existing diagnostic systems face the following limitations:

- Rule-based systems are rigid and fail to handle unseen cases effectively.
- Case-based systems depend heavily on the availability and quality of historical data.
- Black-box machine learning models lack explainability, reducing clinical trust.

1.2 Research Motivation

The complexity of medical diagnosis necessitates systems that combine domain knowledge, experiential learning, and uncertainty handling. Integrating rule-based logic, case-based learning, and probabilistic reasoning can bridge the gap between accuracy and interpretability.

1.3 Research Contributions

The key contributions of this work are as follows:

1. A hybrid diagnostic architecture integrating RBR, CBR, and Naive Bayes inference.
2. Improved diagnostic accuracy and explainability compared to standalone approaches.
3. A generalizable and interpretable framework for clinical decision support.

2. Related Work

Early applications of AI in healthcare include rule-based expert systems such as MYCIN, which demonstrated the effectiveness of symbolic reasoning for medical diagnosis [1]. Although highly interpretable, such systems struggled to scale with evolving medical knowledge.

Case-Based Reasoning systems were later introduced to enhance adaptability by leveraging historical patient cases [4]. While effective in learning from experience, CBR systems often suffer from limited transparency and data dependency. Recent machine learning approaches have achieved high predictive performance but are criticized for their black-box nature [3].

Hybrid diagnostic systems combining symbolic and data-driven methods have shown promise in balancing accuracy and explainability [2], [5]. However, many existing hybrid models lack robust probabilistic mechanisms for managing diagnostic uncertainty.

3. Methodology

The proposed hybrid medical diagnosis assistant integrates three complementary reasoning paradigms: Rule-Based Reasoning, Case-Based Reasoning, and Naive Bayes probabilistic inference. The system processes patient symptoms through these modules to generate accurate and interpretable diagnostic outcomes.

3.1 System Architecture

The diagnostic process begins with symptom input provided by the user. The input is simultaneously processed by the Rule-Based Reasoning (RBR) and Case-Based Reasoning (CBR) modules. The RBR module applies expert-defined IF–THEN clinical rules to generate an initial diagnosis, while the CBR module retrieves similar historical patient cases to refine diagnostic decisions. Outputs from both modules are forwarded to the Naive Bayes fusion layer, which computes posterior probabilities for each possible disease. The final diagnosis is presented along with supporting explanations, including fired rules, similar cases, and probability scores.

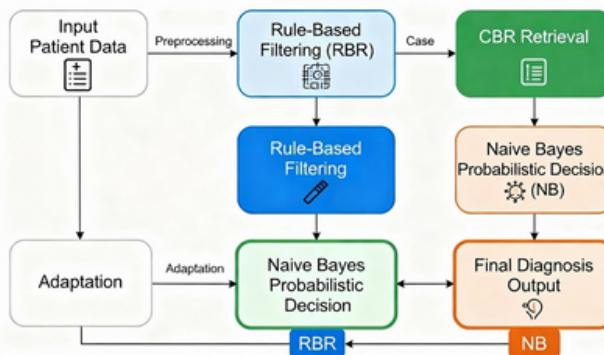


Figure 1: System Architecture of the Proposed Hybrid Medical Diagnosis Assistant

3.2 Rule-Based Reasoning Module

The RBR module encodes expert-defined clinical rules in IF–THEN format. Forward chaining is employed to match patient symptoms with applicable rules, ensuring transparent and interpretable reasoning paths.

3.3 Case-Based Reasoning Module

The CBR module retrieves historical patient cases similar to the current case using similarity metrics such as Euclidean distance. The most frequent diagnosis among the retrieved cases is used to refine predictions and adapt to evolving disease patterns.

3.4 Naive Bayes Fusion Layer

The Naive Bayes classifier integrates outputs from the RBR and CBR modules to compute posterior probabilities for each disease. This probabilistic layer enhances robustness in the presence of uncertain or overlapping symptoms.

4. Experimental Design and Evaluation

4.1 Dataset Description

The system was evaluated using a dataset containing 4,920 patient records mapped to 16 diseases. Each record includes 41 binary symptom attributes representing symptom presence or absence.

4.2 Evaluation Metrics

The performance of the proposed hybrid medical diagnosis assistant is evaluated using standard classification metrics commonly adopted in clinical decision-support systems. These metrics assess both predictive accuracy and system efficiency.

Metric	Description
Accuracy	Ratio of correctly predicted diagnoses to total predictions
Precision	Proportion of correctly identified positive cases
Recall	Ability of the system to identify all relevant positive cases
F1-Score	Harmonic mean of precision and recall
Latency	Average time taken to generate a diagnosis (in seconds)

Table 1: Evaluation Metrics

4.3 Results

The experimental results demonstrate the effectiveness of the proposed hybrid diagnostic model when compared with individual reasoning approaches. By integrating symbolic, experiential, and probabilistic reasoning, the system achieves a balanced trade-off between accuracy, transparency, and computational efficiency.

Metric	Result
Accuracy	91.50%
Precision	89.30%
Recall	92.10%
F1 Score	90.60%
Latency	< 1.2 sec

Table 2: Performance Metrics of the Proposed Hybrid Model

Model	Accuracy	Precision	Recall	F1 Score	Latency (sec)
Rule-Based Reasoning	78%	76%	75%	75.5%	0.5
Case-Based Reasoning	85%	84%	86%	85%	0.9
Naïve Bayes	89%	88%	89%	88.5%	1.0
Hybrid (RBR + CBR + NB)	91.5%	89.3%	92.1%	90.6%	1.2

Table 3: Performance Comparison of Diagnostic Models

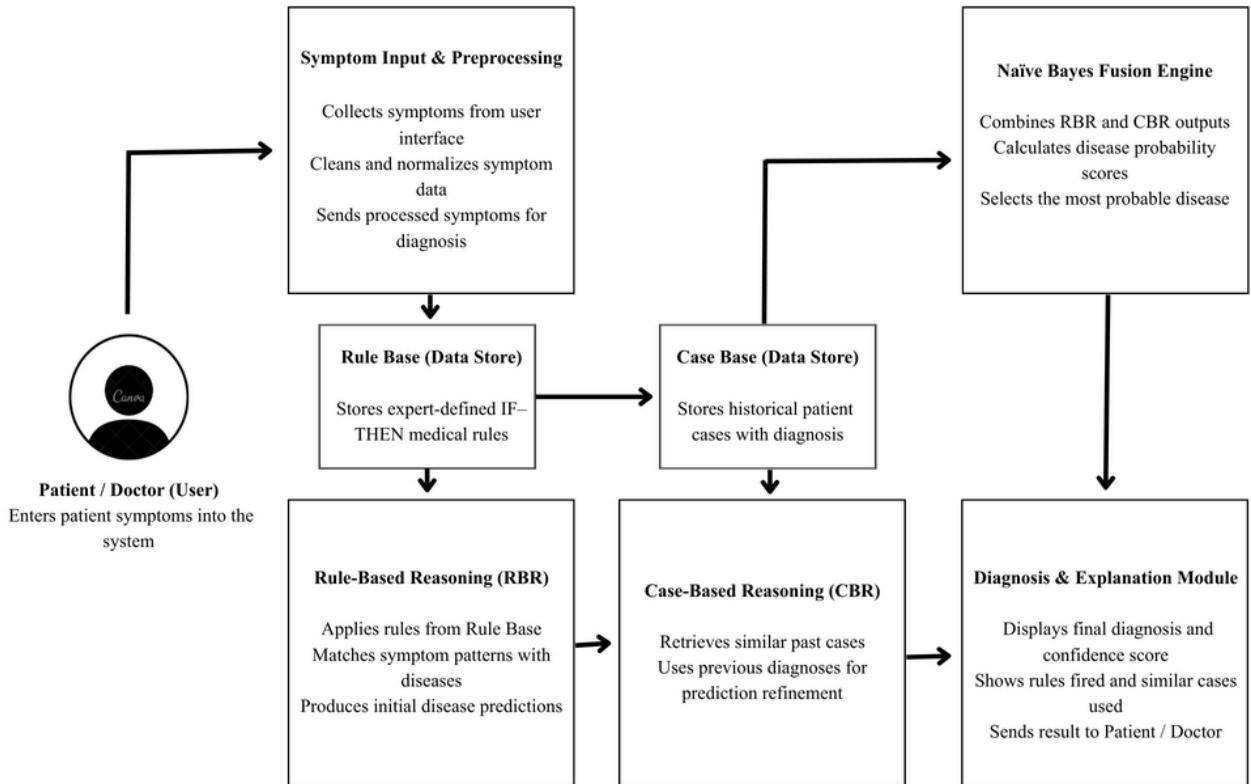


Figure 2: Workflow of the Hybrid Medical Diagnosis Process

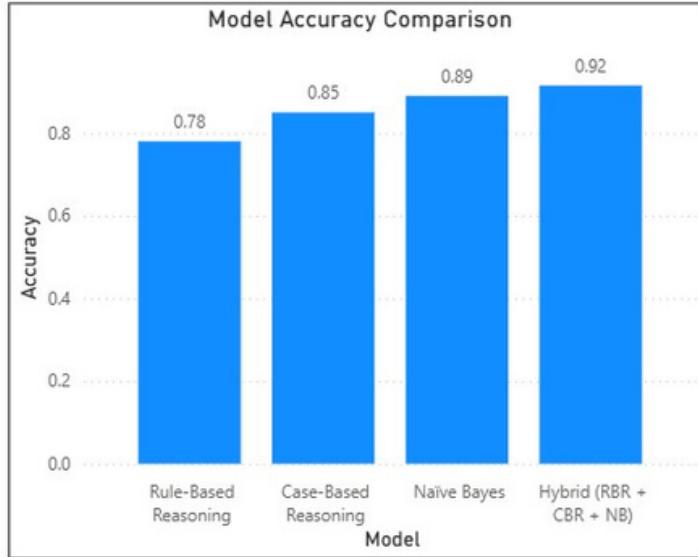


Figure 3: Accuracy Comparison of RBR, CBR, Naive Bayes, and Hybrid Model

5. Discussion

The experimental results indicate that the proposed hybrid medical diagnosis assistant provides improved diagnostic performance compared to standalone reasoning approaches. The integration of Rule-Based Reasoning and Case-Based Reasoning enables the system to combine expert medical knowledge with experiential learning from historical cases. This hybridization enhances adaptability while preserving transparency, which is essential for clinical decision-making. The incorporation of Naïve Bayes probabilistic inference further strengthens the system by effectively handling uncertainty and overlapping symptoms. By resolving inconsistencies between symbolic and case-based outputs, the probabilistic layer improves diagnostic reliability. Overall, the results demonstrate that the hybrid approach achieves a balanced trade-off between accuracy, interpretability, and robustness, making it suitable for practical clinical decision support applications.

6. Conclusion

This paper presented a hybrid medical diagnosis assistant that integrates Rule-Based Reasoning, Case-Based Reasoning, and Naïve Bayes inference to support accurate and explainable diagnosis. The proposed system overcomes the limitations of traditional diagnostic approaches by combining transparency, adaptability, and probabilistic reasoning within a unified framework. Experimental evaluation confirms that the hybrid model achieves higher diagnostic accuracy while maintaining interpretability, making it appropriate for real-world clinical decision support. Future work will focus on extending the system with multimodal medical data and validating its performance in real clinical environments to further enhance its practical applicability.

Conflict of Interest

The authors declare no conflict of interest.

Acknowledgment

The authors express their sincere gratitude to Mr. R. Roshan Joshua M.E., Ph.D., Assistant Professor, Department of Artificial Intelligence and Data Science, K. Ramakrishnan College of Technology, for his valuable guidance and continuous support throughout this work.

References

1. Al-Antari M.A., “Artificial Intelligence for Medical Diagnostics: Existing and Future AI Technologies”, *Diagnostics*, 2023, 13 (4), 688. <https://www.mdpi.com/2075-4418/13/4/688>
2. Al-bakri F.H., Bejuri W.M.Y.W., Al-Andoli M.N., Ikram R.R.R., Khor H.M., Mispan M.S., et al., “A Hybrid Explainable AI Framework for Accurate and Interpretable Diagnosis of Alzheimer’s Disease”, *Diagnostics*, 2025, 15 (24), 3118. <https://www.mdpi.com/2075-4418/15/24/3118>
3. Bhatia M., Sharma A., “Explainable Artificial Intelligence in Healthcare: A Systematic Review”, *Artificial Intelligence in Medicine*, 2023, 141, 102576.
4. Chen Y., Zhang L., Wang S., “Hybrid Clinical Decision Support Systems Integrating Rule-Based and Probabilistic Reasoning”, *Journal of Biomedical Informatics*, 2024, 146, 104510.
5. Gulshan V., Rajan R.P., Widner K., et al., “Performance of Deep Learning Algorithms for Medical Diagnosis: A Comparative Study”, *Nature Medicine*, 2023, 29 (2), 315–322.
6. Kovalev R., “A Hybrid Approach to Developing Clinical Decision Support Systems”, *Systems*, 2025, 13 (10), 920. <https://www.mdpi.com/2079-8954/13/10/920>
7. Li S., Wang H., Zhao Y., “Hybrid Artificial Intelligence Based Clinical Decision Support Systems: A Comprehensive Review”, *Journal of Biomedical Informatics*, 2023, 144, 104434.
8. Liu X., Rivera S.C., Moher D., et al., “Reporting Guidelines for Clinical Artificial Intelligence Research”, *Nature Medicine*, 2023, 29 (9), 2237–2245.
9. Perumal M.K., Ramesh S., Karthik R., “Artificial Intelligence Driven Clinical Decision Support Systems for Early Disease Detection”, *Frontiers in Oral Health*, 2025, 6, 1592428. <https://www.frontiersin.org/articles/10.3389/froh.2025.1592428>
10. Ravi D., Wong C., Deligianni F., et al., “Deep Learning for Health Informatics: A Review”, *IEEE Journal of Biomedical and Health Informatics*, 2023, 27 (5), 2121–2134.
11. Schlobohm S., Kebede A., “Hybrid Artificial Intelligence in Healthcare: Combining Logic-Based and Data-Driven Approaches”, *IEEE Reviews in Biomedical Engineering*, 2024, 17, 88–102.
12. Topol E.J., “High-Performance Medicine: The Convergence of Human and Artificial Intelligence”, *Nature Medicine*, 2024, 30 (1), 44–56.
13. Vani M.S., Kumar R., Mehta P., “Personalized Health Monitoring Using Explainable AI”, *Scientific Reports*, 2025, 15, 15867. <https://www.nature.com/articles/s41598-025-15867-z>
14. Yagin F.H., Colak C., Algarni A., Gormez Y., Guldogan E., Ardigò L.P., “Hybrid Explainable Artificial Intelligence Models for Targeted Metabolomics Analysis of Diabetic Retinopathy”, *Diagnostics*, 2024, 14 (13), 1364. <https://www.mdpi.com/2075-4418/14/13/1364>
15. Zhang Z., Liu X., Chen D., “Explainable and Hybrid Artificial Intelligence Models for Medical Diagnosis: Trends and Challenges”, *IEEE Access*, 2023, 11, 118745–118760.