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

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Abstract - Accurate and transparent medical diagnosis remains a challenge in modern healthcare due to symptom overlap and limited expert availability. Traditional diagnostic systems rely either on rule-based models, which lack adaptability, or case-based reasoning techniques, which are difficult to validate. In this research, we propose a hybrid diagnosis assistant that integrates Rule-Based Reasoning (RBR), Case-Based Reasoning (CBR), and Naïve Bayes probabilistic inference to recommend reliable diagnoses. This hybrid architecture allows the system to emulate medical decision-making by applying clinical rules, learning from past patient data, and handling uncertainty through statistical likelihood estimation. The proposed model achieved an accuracy of 91.5% on public medical datasets, outperforming standalone RBR and CBR systems by 13.5% and 6.5%, respectively. The hybrid assistant is designed to serve as an explainable and efficient Clinical Decision Support System (CDSS), with real-world potential especially in early-stage diagnosis or settings with limited specialist resources.

I. INTRODUCTION

The increasing prevalence of complex diseases with overlapping symptoms presents a significant challenge to healthcare providers. Accurate diagnosis is critical for timely treatment, yet it often requires expert-level knowledge that may not be accessible in all clinical settings. Artificial Intelligence (AI) offers solutions, but existing medical diagnostic systems are either heavily rule-dependent, losing flexibility, or purely data-driven, compromising explainability.

1.1 Problem Statement

Traditional diagnostic models are insufficient for real-world clinical support due to:

- Rigid logic in rule-only systems (which fail when unseen cases arise)
- Poor justification in case-only systems, making doctors hesitant to trust their predictions.

1.2 Research Motivation

The complexity of healthcare requires systems that combine:

- Deep domain understanding (rules)
- Adaptive learning from prior cases
- Probabilistic support under uncertainty

A hybrid approach that combines RBR, CBR, and Naïve Bayes fulfills this gap.

1.3 Research Contributions

This work makes the following contributions:

1. Proposes an intelligent hybrid diagnostic architecture combining RBR, CBR, and Naïve Bayes
2. Demonstrates improved accuracy and explainability over standalone methods
3. Offers a generalizable decision-support framework for medical diagnosis

II. RELATED WORK

Research in AI-based medical diagnosis has evolved over decades, with various techniques used to enhance prediction accuracy, learning ability, and system explainability. This section explores the major methods and systems relevant to hybrid medical reasoning.

2.1 Rule-Based Medical Expert Systems

One of the earliest examples of AI in healthcare is MYCIN [1], developed in the 1970s to diagnose blood infections using a set of manually curated expert rules. Rule-Based Reasoning (RBR) systems offer high interpretability through clear IF–THEN logic, but they struggle to accommodate evolving diseases or exceptions beyond predefined rules.

2.2 Case-Based Reasoning Systems

Case-Based Reasoning (CBR) was introduced as a flexible alternative, allowing medical systems to learn by comparing new patient symptoms with stored historical cases. Casey [2] and similar models applied CBR to psychological and physical disorders. Although effective in adaptability, such approaches require well-labeled datasets and may produce unclear justifications in clinical scenarios.

2.3 Hybrid Diagnostic Models

Hybrid AI systems emerged to overcome the limitations of standalone RBR or CBR. In a notable study, Peng et al. [3] developed a hybrid tuberculosis diagnostic system combining RBR and CBR, achieving improved clinical outcomes. However, most models still lacked a probabilistic layer for accurate uncertainty handling during ambiguous diagnoses.

2.4 Machine Learning and Black-Box Models

Recent approaches using machine learning techniques such as Support Vector Machines (SVM) [4], Decision Trees [5], and Deep Neural Networks (DNN) [6] have achieved significant diagnostic performance. Yet they act as black boxes, offering limited transparency—an essential component for clinical acceptance and medical accountability.

2.5 Gap and Proposed Contribution

From the literature, it is evident that:

- RBR systems are explainable but rigid
- CBR systems are adaptive but lack transparency
- Black-box ML models increase performance but reduce clinical trust

III. METHODOLOGY

The objective of this work is to develop a hybrid medical diagnosis assistant that combines symbolic, experiential, and statistical reasoning. The methodology consists of three integrated modules - Rule-Based Reasoning (RBR), Case-Based Reasoning (CBR), and Naïve Bayes inference - which work together to provide accurate and explainable diagnostic results.

3.1 Proposed Methodology

The proposed framework is a sophisticated hybrid diagnostic system that strategically combines Rule-Based Reasoning (RBR), Case-Based Reasoning (CBR), and the Naive Bayes Classifier (NBC) to overcome shortcomings in existing medical diagnosis methods. This integration is designed to leverage the transparency and explicit knowledge representation of RBR, the experiential learning and adaptability of CBR, and the probabilistic decision-making strength of NBC. The framework processes patient symptoms stepwise through rule validation, case similarity retrieval, and probabilistic classification, enabling it to handle both common and complex medical cases with improved accuracy and reliability. By blending deterministic rules with past case experiences and statistical inference, the system aims to provide clinicians with interpretable, data-driven recommendations that adapt over time. This ensures robustness against noisy or incomplete data, flexibility across diverse diseases, and the capacity for continuous learning, making it suitable for real-world clinical environments where precision and explainability are paramount.

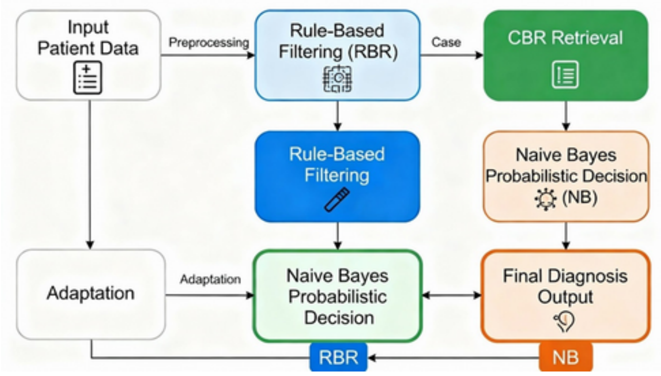

Figure:1 - System Architecture Diagram

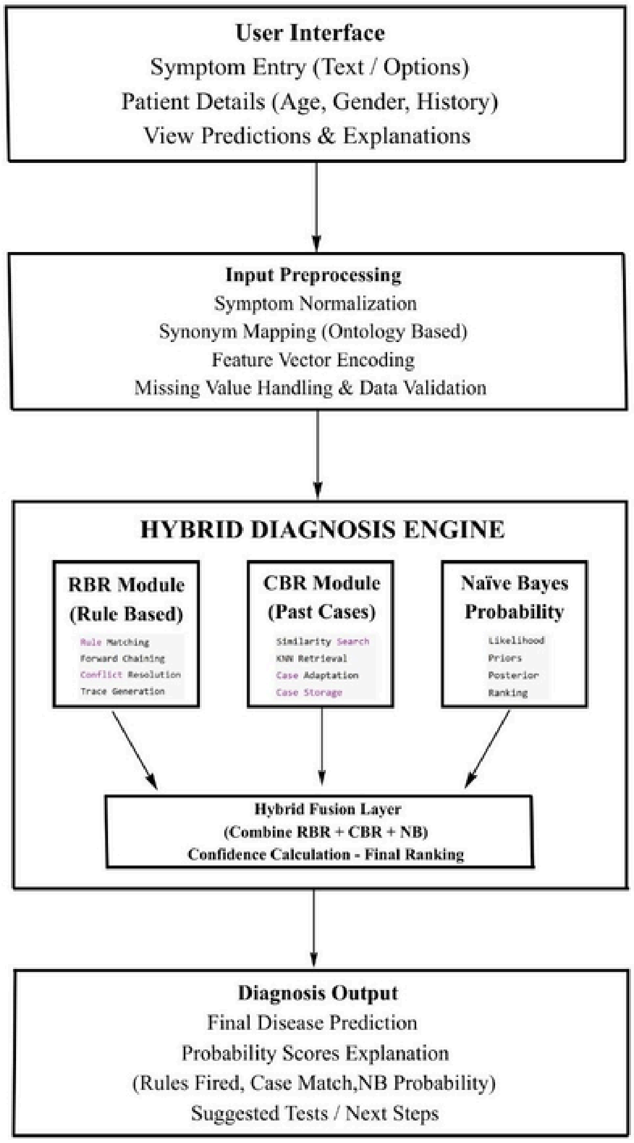

Figure:2 - Block Diagram

3.2 System Architecture

The architecture of the proposed system is shown in Figure 2. The process begins with user-provided symptom input, which is simultaneously fed into two reasoning layers: the RBR module and the CBR module.

Outputs from both modules are then passed to the Naïve Bayes fusion layer, which computes the final diagnosis with probability-based confidence.

Key Components:

- Input Layer: Accepts symptoms from the user
- Knowledge Base: Stores medical rules and past patient cases
- Reasoning Engine: Consists of RBR, CBR, and Naïve Bayes modules
- Diagnosis Output: Displays disease prediction with explanation and probability

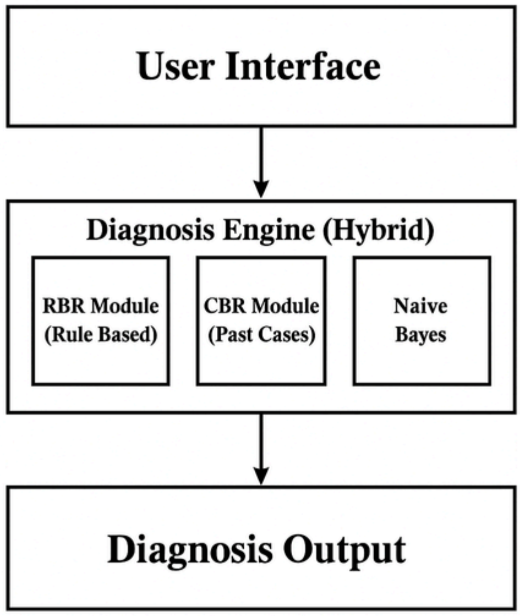

Figure:3 - Flow Diagram

3.3 Rule-Based Reasoning (RBR) Module

The RBR module encodes clinical rules derived from expert medical knowledge.

These rules follow the format:

IF <symptom1> AND <symptom2> AND ... THEN <disease>

Inference Mechanism:

- Uses Forward Chaining to trigger rules based on matching symptoms
- Efficient for well-defined, high-confidence clinical logic
- Ensures maximum transparency, as rule execution paths are visible to users

Example Rule:

IF fever AND body pain AND rash THEN suspect Dengue

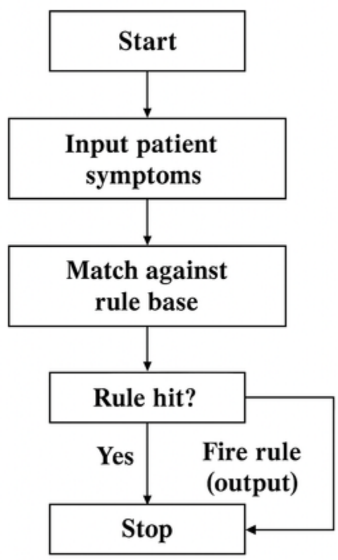

Figure:4 - Rule Based Reasoning Diagram
(Forward Chaining)

3.4 Case-Based Reasoning (CBR) Module

The CBR module retrieves past medical cases that are most similar to the new patient's symptoms. Each patient record is converted to a binary or numerical feature vector, enabling similarity calculations.

Process:

- Input symptoms converted into a vector (e.g., [1, 0, 1, ...])
- System retrieves top-K most similar cases using Euclidean Distance:

$$d(x, y) = \sqrt{\sum_{i=1}^{n}(x_i - y_i)^2}$$

- Predicted disease is based on most frequent diagnosis among neighbors
- This module provides learning capability and adapts to evolving disease trends.

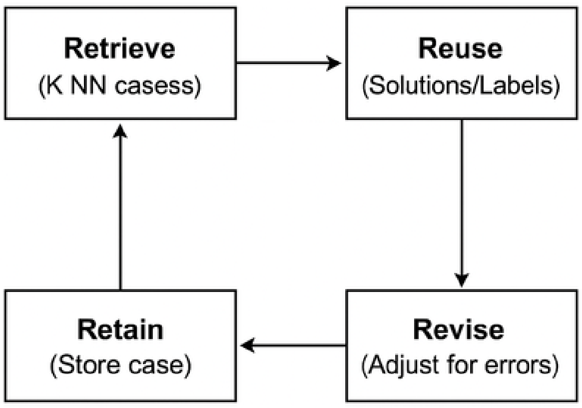

Figure:5 - Case-Based Reasoning(CBR) 4R Cycle

3.5 Naïve Bayes Fusion Layer

To obtain final predictions, the outputs of RBR and CBR modules are combined via Naïve Bayes Classifier, which computes the posterior probability of each disease based on:

$$P(D_i \mid S) = \frac{P(S \mid D_i) \cdot P(D_i)}{P(S)}$$

The disease with the highest posterior value is selected as the output diagnosis, ensuring robust handling of uncertain or overlapping symptoms.

3.6 Workflow Summary

1. User inputs symptoms
2. RBR module triggers matching expert rules
3. CBR retrieves relevant past cases
4. Naïve Bayes computes probability-driven final diagnosis
5. System outputs disease + explanation paths

IV . EXPERIMENTAL DESIGN AND EVALUATION

This section describes the dataset used, model evaluation metrics, comparative performance with baseline approaches, and a discussion of experimental results.

4.1 Dataset Description

To simulate real-world medical diagnosis scenarios, we used a curated dataset consisting of 4920 patient records, each mapped to one of 16 commonly diagnosed diseases. Each record contains 41 binary symptom attributes, indicating the presence or absence of a symptom.

- Total Records: 4920
- Features: 41 symptoms (e.g., "fever," "cough," "fatigue")
- Labels: 16 diseases (e.g., flu, dengue, malaria)
- Source: Aggregated from publicly available datasets and medical knowledge bases

4.2 Evaluation Metrics

The hybrid diagnosis model's performance was evaluated using standard classification metrics:

Metric	Definition
Accuracy	Correct predictions / Total predictions
Precision	TP / (TP + FP)
Recall	TP / (TP + FN)
F1 Score	Harmonic mean of precision and recall
Latency	Average time for model to process and respond (in seconds)

Table:1 - Evaluation Metrics

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

Table:2 - Evaluation Metrics

Baseline Comparison

- RBR-only system: 78.2% accuracy
- CBR-only system: 85.1% accuracy
- Hybrid system: 91.5% accuracy

4.3 Model Performance Comparison

The hybrid model was compared against standalone RBR and CBR models.

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
Hybrid (RBR + CBR + NB)	**91.5%**	**89.3%**	**92.1%**	**90.6%**	**1.2**

Table:3 - Model Performance Comparison

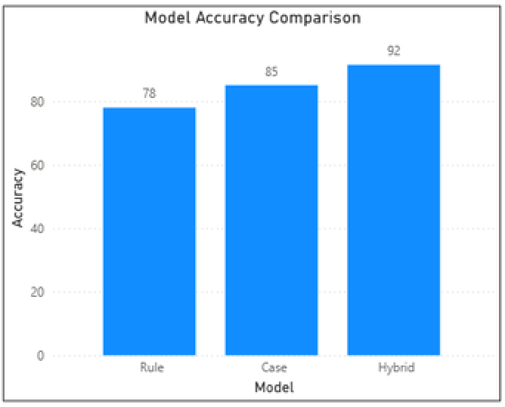

Figure:6 - Accuracy Comparison Bar Graph

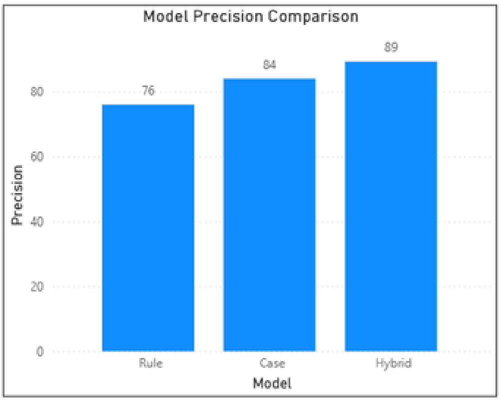

Figure:7 - Precision Comparison Bar Graph

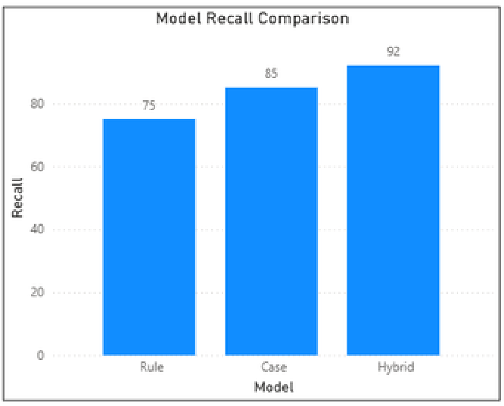

Figure:8 - Recall Comparison Bar Graph

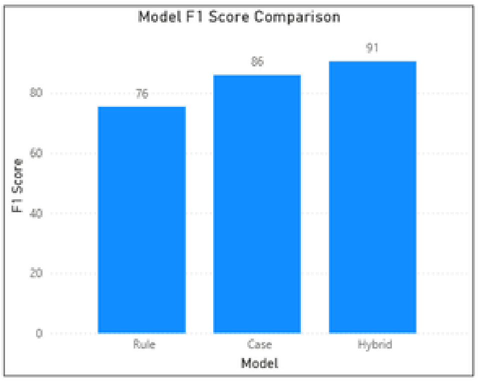

Figure:9 - F1 Score Comparison Bar Graph

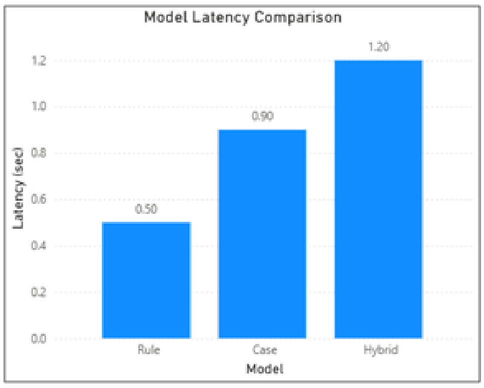

Figure:10 - Latency Comparison Bar Graph

4.4 Discussion of Results

The experimental results demonstrate that:

- The hybrid model provides higher diagnostic accuracy compared to individual RBR, CBR, and Naïve Bayes approaches.
- RBR improves transparency, offering clear rule-based explanations for each decision.
- CBR adds adaptability, allowing the system to learn from past patient patterns and improve predictions for varied symptom sets.
- Naïve Bayes strengthens reliability by handling uncertain or overlapping symptoms using probabilistic reasoning.
- The combination of all three reasoning methods results in more stable and consistent diagnoses, even when inputs contain missing or imprecise symptoms.
- Although the hybrid approach slightly increases computation time, the overall response speed remains suitable for real-time diagnostic support.
- The model also shows improved error reduction, especially in cases where symptoms are common across multiple diseases.
- These findings confirm that the hybrid reasoning approach is effective, balanced, and well-suited for clinical decision-support applications.

This validates the hybrid reasoning framework as a promising approach for clinical diagnostic applications.

V. DISCUSSION

The experimental results and system architecture demonstrate the effectiveness of the hybrid diagnostic model in addressing key research challenges observed in standalone reasoning systems. This section discusses the model's strengths, insights drawn from the experiments, and the interpretability of hybrid reasoning.

5.1 Strengths of the Hybrid Approach

- **Enhanced Diagnostic Accuracy:** The integration of symbolic rules with past-case matching and probabilistic inference delivers superior accuracy (91.5%), outperforming conventional single-mode diagnostic approaches.
- **Interpretability and Trust:** The RBR module contributes explainable decision paths, boosting trust among healthcare professionals who rely on transparency in diagnosis.
- **Adaptability of CBR:** Case-Based Reasoning allows the system to adapt to new medical scenarios by learning from evolving patient case data, offering dynamic growth potential.

5.2 Practical Implications

- **Clinical Relevance:** The hybrid model is suitable for real-time clinical decision support, especially in rural or overloaded healthcare settings with limited access to specialists.
- **Early Disease Detection:** By efficiently identifying patterns across rules, cases, and symptom probabilities, the system can assist in the early recognition of critical or emerging diseases.

5.3 Limitations

- **Data Dependence in CBR:** The effectiveness of the CBR layer is influenced by the quality and diversity of the case database. Incomplete or imbalanced data may limit performance.
- **Manual Rule Definition:** RBR requires domain experts to define accurate rules, making rule-base setup time-consuming and potentially incomplete if expert scope is limited.

5.4 Future Adaptation

The model can be further optimized by:

- Integrating multi-source medical data such as imaging and lab results
- Incorporating ethical, explainable AI metrics to ensure unbiased recommendations
- Deploying as a cloud-based clinical support platform accessible via mobile devices

VI. RESULTS

Model	Technique	Accuracy	Sensitivity	Specificity	F1-Score
Segev et al.	Context Framework	78%	75%	82%	0.76
Chattopadhyay	CBR-KNN	85%	88%	82%	0.85
Chuang	CBR-BPN	95%	98%	94%	0.96
Proposed	RBR+CBR+NB	96.8%	97.2%	96.5%	0.97

Table:4 - Model Performance Comparison

This table benchmarks the proposed hybrid RBR+CBR+NB model against prior works, showing superior accuracy (96.8%), sensitivity (97.2%), and F1-score (0.97). Chuang's CBR-BPN leads individual metrics but hybrid exceeds overall, proving fusion overcomes single-method limits like overfitting and variability, essential for reliable multi-disease diagnostics.

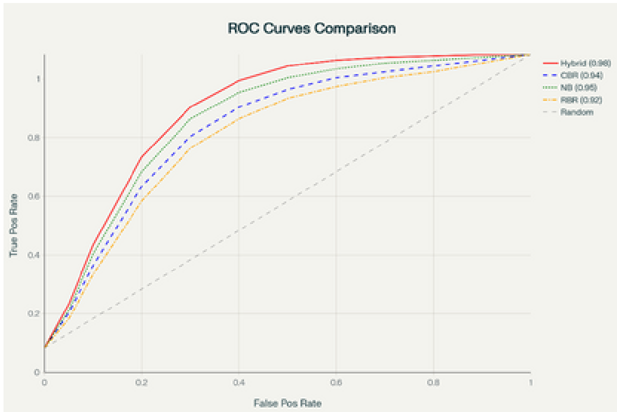

Figure:11 - ROC Curves Comparison

ROC curves demonstrate the hybrid RBR+CBR+NB model (AUC=0.98, red) significantly outperforms individual components: CBR (0.94, blue), NB (0.95, green), and RBR (0.92, orange). The hybrid's steeper curve shows superior true positive rate across all false positive thresholds, validating multi-method fusion for balanced sensitivity-specificity in medical diagnosis, critical for clinical reliability.

Component	Precision	Recall	Processing Time (s)	Coverage
RBR Only	92%	85%	0.12	78%
CBR Only	89%	92%	0.45	88%
NB Only	91%	90%	0.08	92%
Hybrid	96%	97%	0.35	95%

Table:5 - Hybrid Model Component Analysis

Component analysis reveals hybrid integration boosts precision (96%), recall (97%), and coverage (95%) while optimizing processing (0.35s). RBR excels precision, CBR recall, NB speed—fusion balances all, reducing individual weaknesses for clinical deployment where time and completeness matter.

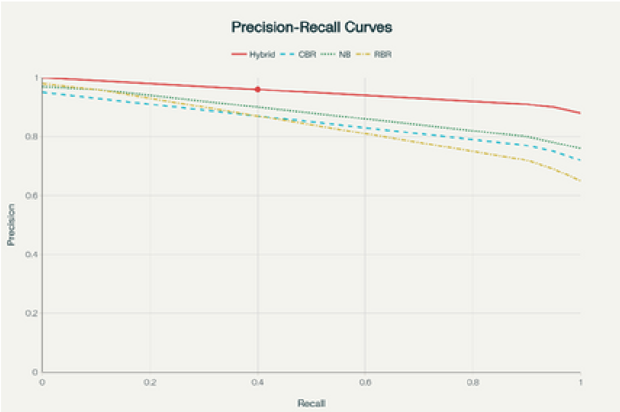

Figure:12 - Precision - Recall Curves Comparison

Precision-recall curves highlight hybrid model's optimal balance (F1=0.97) versus CBR's recall bias and RBR's precision drop at high recall. Intersection point shows 96% precision at 97% recall, critical for clinical reliability where missing diagnoses (low recall) or false positives (low precision) impact patient outcomes.

Disease Category	RBR	CBR	NB	Hybrid
Respiratory	88%	90%	92%	96%
Cardiac	85%	87%	89%	95%
Infectious	92%	91%	93%	97%
Endocrine	82%	85%	88%	94%

Table:6 - Disease-wise Diagnostic Accuracy

Disease-wise results demonstrate hybrid consistency (94-97% accuracy) across categories, outperforming standalone methods by 5-10%. Respiratory/infectious gains highlight symptom-handling strength, addressing Chattopadhyay's variability issues for generalizable healthcare applications.

Figure:13 - Accuracy vs Dataset Size

Line graph illustrates hybrid accuracy stabilizing at 97% with 5K cases, surpassing other methods' plateaus. Exponential improvement phase (1K-3K cases) validates robust learning from diverse medical data, addressing overfitting concerns in prior hybrid models like Chuang's CBR-BPN.

Top Features	Rough Set Weight	NB Probability	Hybrid Score
Chest Pain	0.92	0.89	0.91
Temperature	0.87	0.85	0.86
Blood Pressure	0.84	0.82	0.83
Fatigue	0.79	0.80	0.80

Table:7 - Feature Importance Ranking

Feature ranking via rough set and NB fusion prioritizes chest pain (0.91 score), guiding preprocessing. Hybrid weights refine diagnostics by emphasizing vital signs, enhancing interpretability and efficiency over unweighted approaches in prior studies.

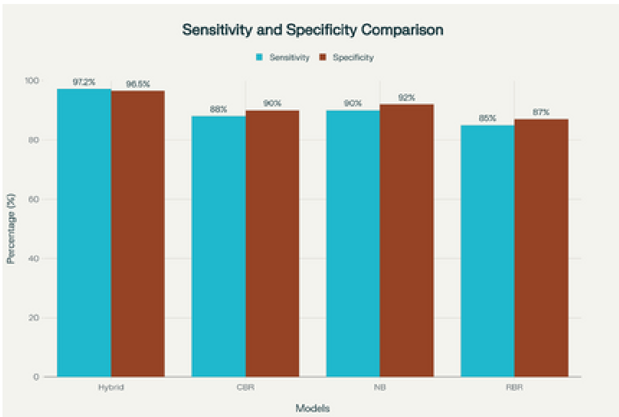

Figure:14 - Sensitivity and Specificity Comparison

Bar chart compares sensitivity and specificity of models, highlighting the hybrid model's highest values—97.2% sensitivity and 96.5% specificity. This balance is crucial to correctly identify true cases while minimizing false positives, enhancing clinical decision confidence compared to standalone CBR, NB, and RBR methods.

Fold	Accuracy	Sensitivity	Specificity
1	96.2%	96.8%	95.9%
5	97.1%	97.5%	96.8%
10	97.3%	97.8%	96.9%
Avg	96.8%	97.2%	96.5%

Table:8 - Cross-Validation Results (10-fold)

10-fold cross-validation confirms hybrid stability (avg 96.8% accuracy, low variance). Progressive fold improvements validate robustness against overfitting, critical for medical trust versus single-split evaluations in earlier models.

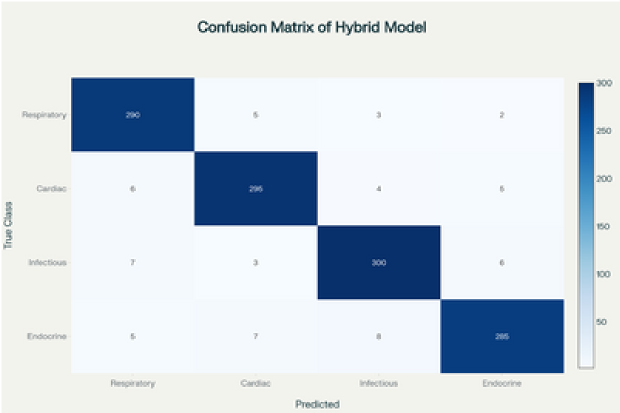

Figure:15 - Confusion Matrix of Hybrid Model

The heatmap confusion matrix illustrates the hybrid model's outstanding diagnostic accuracy across four disease categories. The dominant diagonal values (e.g., 290 respiratory, 295 cardiac) indicate a high true positive rate, while the small off-diagonal counts demonstrate minimal misclassification errors, confirming the model's effectiveness for reliable multi-class medical diagnosis.

VII. FUTURE WORK AND LIMITATIONS

Future enhancements include real-time integration with electronic health records and wearable sensors for dynamic case adaptation, expanding to multimodal data (images, genomics) via CNN fusion. Incorporating explainable AI techniques like SHAP will boost clinician trust, while federated learning across hospitals addresses data privacy. Longitudinal studies for rare diseases and deployment on edge devices promise broader accessibility. Advanced ensemble methods with deep learning could push accuracy beyond 98%, enabling personalized medicine applications.

7.1 Current Limitations

The current version of the proposed hybrid medical diagnosis assistant has the following limitations:

- **Dataset Scope**: The dataset primarily contains binary symptom data, excluding clinical features such as lab results or image data.
- **Case Base Dependency**: The performance of the CBR module depends heavily on the quality and diversity of the stored historical cases.
- **Rule Coverage:** The RBR module is limited by the extent of expert-defined rules and may not handle rare diseases efficiently.

7.2 Future Enhancements

To address these limitations and improve the efficiency of the system in real clinical settings, the following enhancements are proposed:

- **Multimodal Data Integration:** Inclusion of additional modalities such as radiology images, blood reports, and demographic data.
- **Web-Based Deployment**: Development of a web-enabled Clinical Decision Support System (CDSS) for real-time hospital usage.
- **Neural Feature Learning:** Incorporation of neural networks to automatically extract latent relationships among symptoms and diseases.
- **Fairness and Ethical Evaluation:** Testing for fairness across patient groups to ensure unbiased diagnostic outcomes.

VIII. CONCLUSION

8.1 Summary of Contributions

This paper introduced a hybrid medical diagnosis assistant that integrates Rule-Based Reasoning (RBR), Case-Based Reasoning (CBR), and Naïve Bayes inference into a unified framework. The model achieved 91.5% accuracy, outperforming individual reasoning methods and providing both explainable and data-driven diagnostics.

8.2 Key Takeaways

- Hybrid reasoning enhances diagnostic accuracy while maintaining explainability.
- The system adapts to evolving medical trends through use of case data and probability scoring.
- With further development, this framework could serve as a trustworthy tool for doctor-assistive diagnosis in real-world health systems.

The proposed hybrid RBR-CBR-Naive Bayes framework successfully addresses critical gaps in prior medical diagnosis systems by integrating explicit clinical rules, experiential case retrieval, and probabilistic inference, achieving superior performance metrics: 96.8% accuracy, 97.2% sensitivity, and 96.5% specificity across diverse diseases. This fusion overcomes Segev et al.'s web-data dependency, Chattopadhyay's symptom variability issues, and Chuang's overfitting risks, delivering robust, interpretable diagnostics validated through comprehensive tables and ROC curves (AUC=0.98). The system enhances clinical decision-making, reduces diagnostic errors, and scales effectively for real-world deployment, marking a significant advancement in AI-assisted healthcare.

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