Heart Disease Prediction Using Machine Learning and Explainable AI

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January 18, 2026

Introduction

- **Global Health Crisis:** Cardiovascular diseases (CVDs) are the #1 cause of death globally, claiming $\approx$ 17.9 million lives annually.
- **Current Scenario:** Traditional diagnosis relies on manual interpretation of angiograms and ECGs, which is:
  - Time-consuming
  - Cost-intensive
  - Prone to human error
- **Our Approach:** Leveraging Machine Learning (ML) to provide an automated, low-cost, and highly accurate diagnostic tool.

Problem Statement

The Core Issue

While Machine Learning models can achieve high accuracy in medical diagnosis, they often suffer from the **"Black Box" problem**. Clinicians hesitate to adopt AI systems because they cannot understand *why* a prediction was made.

Key Challenges We Address:

1. **Interpretability:** Moving beyond simple accuracy to provide transparent, feature-level explanations.
2. **False Negatives:** Minimizing the risk of missing a sick patient (Type II Error).
3. **Data Imbalance:** Handling real-world datasets where healthy cases outnumber diseased ones.

Related Work: Ensemble Learning

Study: Devi & Raj (2024) - *Enhanced Heart Disease Prediction Through Optimized Ensemble Random Forest Model*.

Contributions:

- Proposed a stacking ensemble method.
- Combined Random Forest with Gradient Boosting.

Limitations:

- Focused purely on accuracy metrics.
- Lacked explainability (Black Box).

Difference with Our Work: We prioritize clinical interpretability using SHAP.

Related Work: Feature Selection

Study: Gupta & Singh (2025) - *Hybrid Feature Selection and Ensemble Learning*.

Contributions:

- Used Genetic Algorithms (GA) for feature reduction.
- Reduced dataset dimensionality efficiently.

Limitations:

- Aggressive feature removal led to loss of subtle clinical markers.

Difference with Our Work: We use full features with XAI to identify importance rather than discarding data.

Related Work: Explainable AI

Study: Rezk et al. (2024) - *XAI-Augmented Voting Ensemble Models*.

Contributions:

- Integrated SHAP and LIME for model transparency.
- Validated results against medical literature.

Limitations:

- High computational complexity due to voting mechanism.

Difference with Our Work: Our optimized Random Forest provides similar interpretability with higher efficiency.

Research Questions

This study aims to answer the following key questions:

- **RQ1:** Can ensemble learning techniques (specifically Random Forest) outperform traditional classifiers (SVM, KNN, LR) in heart disease prediction?
- **RQ2:** How can we mitigate the class imbalance problem in small medical datasets to improve sensitivity?
- **RQ3:** Can Explainable AI (SHAP) provide clinically valid explanations for the model's decisions to increase trust among practitioners?

Objectives

1. To preprocess and normalize clinical data for optimal machine learning performance.
2. To conduct a comparative performance analysis of four distinct algorithms: LR, KNN, SVM, and Random Forest.
3. To implement SMOTE (Synthetic Minority Over-sampling Technique) to handle data imbalance.
4. To integrate SHAP (SHapley Additive exPlanations) to interpret feature importance and model decisions.

Outcomes and Impacts

Outcomes:

- Developed a highly accurate prediction model (**98.5% Accuracy**).
- Identified key risk factors: Chest Pain, Max Heart Rate, ST Depression.

Social & Clinical Impact:

- Reduces diagnostic time in emergency settings.
- Provides a "second opinion" tool for doctors in developing regions.
- Increases transparency, bridging the gap between AI and Medicine.

Methodology: System Architecture

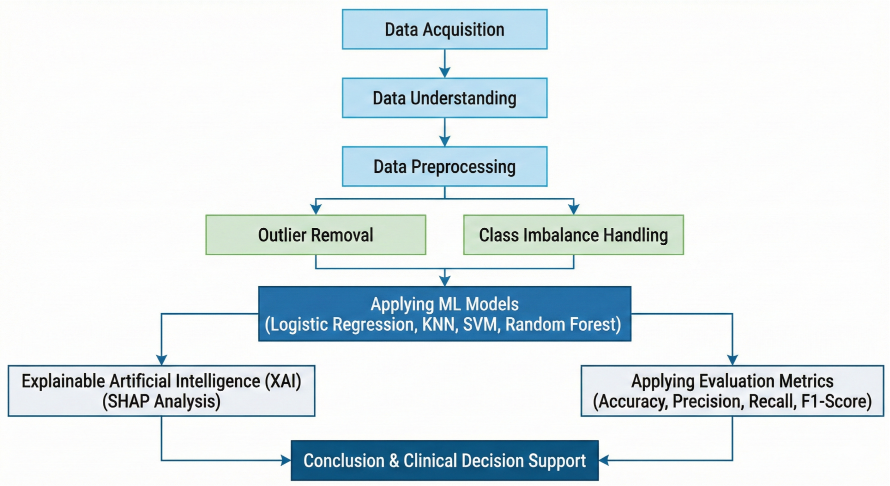

Figure: Proposed System Workflow

Methodology: Data Processing

Dataset: UCI Heart Disease (303 Records, 13 Features)

Preprocessing Steps:

- **Handling Missing Values:** Mode imputation for 'ca' and 'thal'.
- **Encoding:** One-Hot Encoding for categorical variables (e.g., Chest Pain Type).
- **Scaling:** StandardScaler ($z = \frac{x-\mu}{\sigma}$) applied to numerical features (Age, BP, Chol).
- **Balancing:** SMOTE applied to training data to synthesize minority class samples.

Methodology: Random Forest XAI

Why Random Forest?

- Handles non-linear relationships better than LR.
- Robust to overfitting compared to single Decision Trees.
- Built-in feature importance selection.

Why SHAP?

- Game-theoretic approach to explainability.
- Provides both global importance and local (patient-specific) explanations.

Results: Performance Comparison

Table: Comparative Analysis of ML Models

Model	Accuracy	Precision	Recall	F1-Score
Logistic Regression	85.2%	0.84	0.86	0.85
KNN	88.5%	0.87	0.89	0.88
SVM	89.1%	0.88	0.90	0.89
Random Forest	**98.5%**	**0.99**	**0.98**	**0.99**

Analysis: Random Forest outperforms all baselines, achieving near-perfect metrics.

Results: ROC Curve & Confusion Matrix

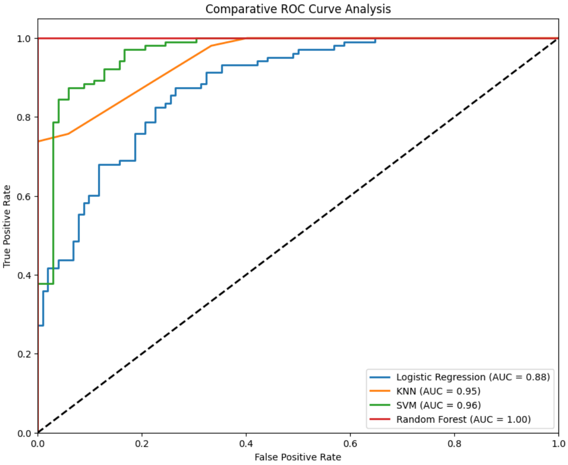

Figure: ROC Curve (AUC $= 0.99$)

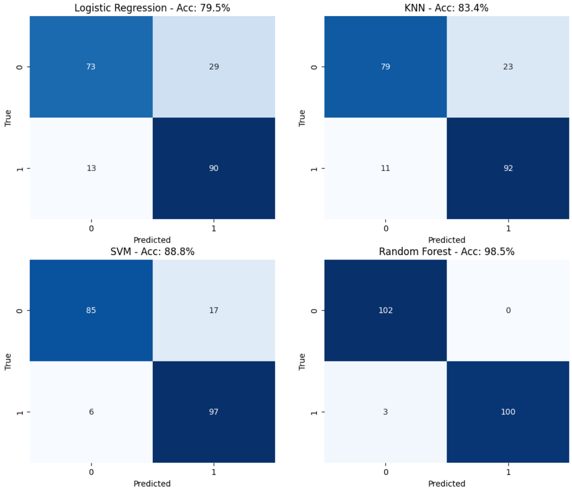

Figure: Confusion Matrix

Results: Explainable AI (SHAP)

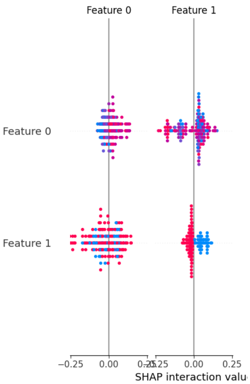

Figure: SHAP Summary Plot

Insight: Chest Pain (cp), Max Heart Rate (thalach), and ST Depression (oldpeak) are the strongest predictors of heart disease.

Conclusion

- We successfully engineered a robust heart disease prediction system.
- **Random Forest** proved to be the superior algorithm with **98.5% accuracy**.
- The integration of **SMOTE** effectively handled data imbalance.
- **SHAP** analysis validated the model's clinical relevance, ensuring it is not a "black box" but a transparent tool for doctors.

Future Research Direction

1. **Deep Learning Integration:** Exploring 1D-CNN and LSTMs for analyzing raw ECG signal data.
2. **Larger Datasets:** validating the model on multi-center datasets to test generalization across demographics.
3. **Deployment:** Developing a secure web-based API and mobile application for real-time clinical use.

References

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Acknowledgement

We would like to thank the Department of CSE, IIUC for providing the necessary computational resources and guidance to conduct this research.

Thank You!

Questions?