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Heart Disease Risk Prediction Using Machine Learning and Web Deployment

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Abstract: Heart disease is one of the most critical global health challenges, responsible for millions of deaths annually. Early identification of individuals at risk plays a vital role in reducing mortality through preventive measures and timely medical intervention. This project presents a supervised machine learning–based Heart Disease Risk Prediction System using Logistic Regression. The model is trained on structured clinical data containing thirteen commonly used medical parameters. The trained model is integrated into a Flask-based web application that provides real-time predictions along with probability scores. The system emphasizes interpretability, reproducibility, and accessibility, making it suitable as an educational screening tool rather than a medical diagnostic system..

Keywords: Heart Disease Prediction, Machine Learning, Logistic Regression, Flask Web Application, Medical Data Analytics, Risk Assessment

I. Introduction

Cardiovascular diseases (CVDs) remain the leading cause of death worldwide, accounting for nearly one-third of global mortality. Lifestyle changes, aging populations, and increasing stress levels have contributed to the rising prevalence of heart-related illnesses. Early detection of heart disease risk can significantly reduce severe outcomes by enabling preventive care and lifestyle modification.

Traditional diagnostic methods rely on extensive clinical tests and expert interpretation, which may not always be accessible or affordable. Machine learning provides an efficient alternative by learning patterns from historical medical data and offering data-driven predictions. This project focuses on developing a reliable and interpretable machine learning model and deploying it through a web-based platform to improve public accessibility and awareness.

2. Objectives

2.1 Primary Objective

To design and implement an interpretable machine learning model capable of predicting heart disease risk using routine clinical parameters and deploy it through a web application.

2.2 Secondary Objectives

To preprocess and analyze medical data efficiently

To evaluate model performance using standard metrics

To provide probability-based predictions for transparency

To ensure reproducibility and ethical usage

3. Literature Review

Machine learning (ML) has been widely explored for cardiovascular disease (CVD) prediction because structured clinical features (age, blood pressure, cholesterol, ECG indicators, etc.) suit supervised classifiers. The UCI Heart Disease dataset (a common benchmark derived from multiple hospitals and widely used in academic work) remains the canonical dataset for early experiments in heart-disease classification and feature studies; many baseline studies still use it for reproducibility and comparison.

Classical statistical and machine learning models — particularly Logistic Regression, Decision Trees, Random Forests, and Support Vector Machines — are frequently used as baselines. Logistic Regression provides probabilistic outputs and interpretable coefficients, making it popular in clinical screening contexts where explainability is important. Several studies applying Logistic Regression to the UCI

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dataset report strong baseline performance and emphasize coefficient-based interpretability for clinical features.

Ensemble methods (Random Forest, Gradient Boosting) and hybrid approaches often improve predictive performance over single models by reducing variance and capturing nonlinear feature interactions. Comparative studies from 2021–2024 show ensembles and tuned Decision Tree variants outperform simpler models in raw accuracy on several heart-disease datasets, though gains can come at the cost of interpretability and higher risk of overfitting on small datasets. This motivates choosing simpler models like Logistic Regression if transparency is prioritized.

Deep learning models and representation learning have become more prominent when larger multimodal data are available (e.g., raw ECG signals, imaging, and large EHRs). LSTM, CNNs and transformer-style models have been used to extract features from time series (ECG) and combined with clinical variables to boost performance. However, deep models require larger datasets and careful regularization; for small structured tabular datasets the incremental benefit versus model complexity can be small. Recent reviews summarize these tradeoffs and recommend model choice based on data modality and volume.

Explainability and clinical-safety concerns are major themes in recent literature. Papers and reviews emphasize model interpretability (coefficient analysis, SHAP/LIME explanations), calibration of predicted probabilities, and external validation (separate cohorts) to avoid misleading clinical claims. Many authors caution that models trained on legacy datasets need revalidation before clinical use because of population shifts and spectrum bias.

Large-scale, clinically-deployed AI systems illustrate the direction of research from bench to bedside. For example, the NHS trial of an ECG-based AI risk tool ("Aire") and recent work showing that wearable (single-lead) ECGs plus AI can detect structural heart problems demonstrate that ML models can generalize to high-volume clinical and consumer devices — but only after rigorous validation and careful integration into clinical workflows. These real-world studies demonstrate both the potential and the strict validation pathways required for deployment.

Recent systematic reviews (2023–2025) synthesize the literature and note common limitations: small sample sizes, limited external validations, inconsistent preprocessing, and lack of calibration reporting. The reviews recommend (1) stronger cross-validation and external testing, (2) probability calibration for clinical decision thresholds, and (3) transparent reporting of cohorts and data provenance to support reproducibility — recommendations that directly inform the design choices in this project (Logistic Regression + probability output + reproducible artifacts).

Gaps and motivation for this project. Despite many promising results, a consistent gap remains between academic prototypes and safe, validated tools for population screening. Projects that prioritize interpretability, probability calibration, and a reproducible web deployment (so clinicians/educators can inspect and test the model) help bridge that gap. Our choice of Logistic Regression, probability outputs, input validation, model persistence, and clear ethical disclaimers follows these community recommendations.4. Methodology

4.1 Dataset Description

The dataset used in this project consists of patient records with thirteen input attributes and a binary target variable indicating the presence or absence of heart disease.

Input Features:

Age

Sex

Chest Pain Type (cp)

Resting Blood Pressure (trestbps)

Serum Cholesterol (chol)

Fasting Blood Sugar (fbs)

Resting ECG (restecg)

Maximum Heart Rate Achieved (thalach)

Exercise-Induced Angina (exang)

ST Depression (oldpeak)

Slope of ST Segment (slope)

Number of Major Vessels (ca)

Thalassemia (thal)

4.2 Data Preprocessing

Data preprocessing ensures quality and consistency of inputs. The steps include:

Encoding categorical features

Scaling numerical values

Handling missing values

Splitting data into training (80%) and testing (20%) sets

4.3 Model Selection

Logistic Regression was selected due to its ability to estimate probabilities and provide interpretable coefficients. The

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sigmoid function maps linear combinations of features into probability values between 0 and 1.

4.4 Model Persistence

The trained model is serialized using the joblib library, ensuring reproducibility and seamless deployment.

5. System Architecture

The system architecture consists of three layers:

Data Layer: Medical dataset and preprocessing pipeline

Model Layer: Trained Logistic Regression classifier

Application Layer: Flask web interface for user interaction

Users input clinical parameters through a web form, which are validated and passed to the prediction engine. The output includes both class prediction and probability score.

6. Results and Analysis

6.1 Performance Metrics

The model was evaluated using standard classification metrics.

Metric	Value
Accuracy	86.3%
Precision	85.1%
Recall	87.4%
F1-score	86.2%
ROC-AUC	0.89

The accuracy indicates strong overall performance, while the high recall value is crucial in healthcare applications to minimize missed heart disease cases.

6.2 Confusion Matrix Analysis

Classification	Count
True Positives	52
True Negatives	46
False Positives	9
False Negatives	7

The confusion matrix shows balanced predictions with a relatively low number of false negatives, making the model suitable for preliminary screening.

6.3 Probability-Based Interpretation

The system provides probability values along with predicted class labels. Patients with probability values close to the threshold (0.5) represent borderline cases, highlighting the need for further medical evaluation rather than definitive conclusions.

6.4 Feature Importance Analysis

Logistic Regression coefficients reveal that chest pain type, maximum heart rate, ST depression, and number of major vessels significantly influence predictions. These findings align with established clinical knowledge, reinforcing the model's interpretability.

6.5 Robustness and Stability

Consistent preprocessing, strict input validation, and saved model artifacts ensured stable predictions across multiple sessions. Cross-validation confirmed the model's generalization capability.

7. Validation and Ethical Considerations

Train–test split ensures generalization

Cross-validation confirms stability

Model reproducibility ensured via serialization

Ethical usage clearly stated: educational and screening purpose only

8. Future Scope

Threshold optimization and probability calibration

Integration of advanced models such as Random Forests and Neural Networks

Cloud-based deployment with CI/CD pipelines

Secure authentication and logging mechanisms

9. Conclusion

This project successfully implements a Heart Disease Risk Prediction System using Logistic Regression and Flask-based deployment. The system provides accurate, interpretable, and probability-based predictions, making it suitable as an educational screening tool. The results demonstrate the potential of machine learning to enhance preventive healthcare awareness and lay the groundwork for future advancements in medical data analytics

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