Classifying Heart Disease Status using Clinical and Demographic Data

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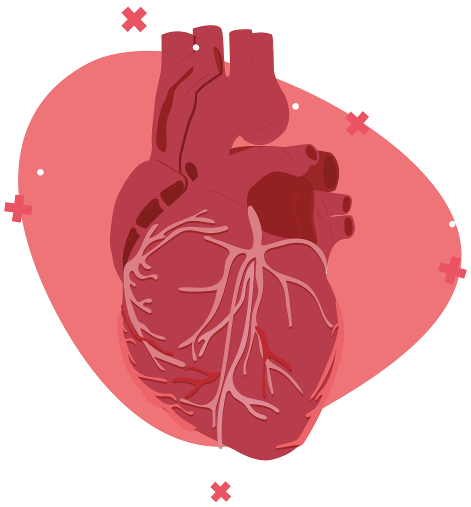
Context and Background

Introduction



Heart disease is the **leading cause of death worldwide**

Responsible for about **18 million** deaths annually

Source: WHO, 2024

The Question:

Based on a patient's demographics and clinical data, can we reliably predict if they have heart disease?

Dataset Overview

Why This Dataset?

Dynamic Demographic

Reputable & Rich Clinical Data

Access to Multi Factor Analysis

Source

This dataset represents the largest available resource for heart disease research, created by integrating five well-known datasets.

Dataset Composition

The final dataset was compiled from the following sources:

- Cleveland: 303 observations
- Hungarian: 294 observations
- Switzerland: 123 observations
- Long Beach VA: 200 observations
- Statlog (Heart): 270 observations

Pre-Cleaned Data

- Initial Combined Records: 1,190
- Identified & Eliminated Duplicates: 272
- Final Unique Records: 918
- Missing Values: 0

Variables

Explanatory Variables (Predictors)

- **Age** – Patient age (years)
- **Sex** – Male (M) / Female (F)
- **ChestPainType** – TA (Typical Angina), ATA (Atypical Angina), NAP (Non-Anginal Pain), ASY (Asymptomatic)
- **RestingBP** – Resting blood pressure (mm Hg)
- **Cholesterol** – Serum cholesterol (mg/dl)
- **FastingBS** – Fasting blood sugar > 120 mg/dl (1 = Yes, 0 = No)
- **RestingECG** – Normal, ST (ST-T wave abnormality), LVH (ventricular hypertrophy)
- **MaxHR** – Maximum heart rate achieved (60–202 bpm)
- **ExerciseAngina** – Exercise-induced angina (Y = Yes, N = No)
- **Oldpeak** – ST depression (numeric value)
- **ST_Slope** – Up (upsloping), Flat, Down (downsloping)

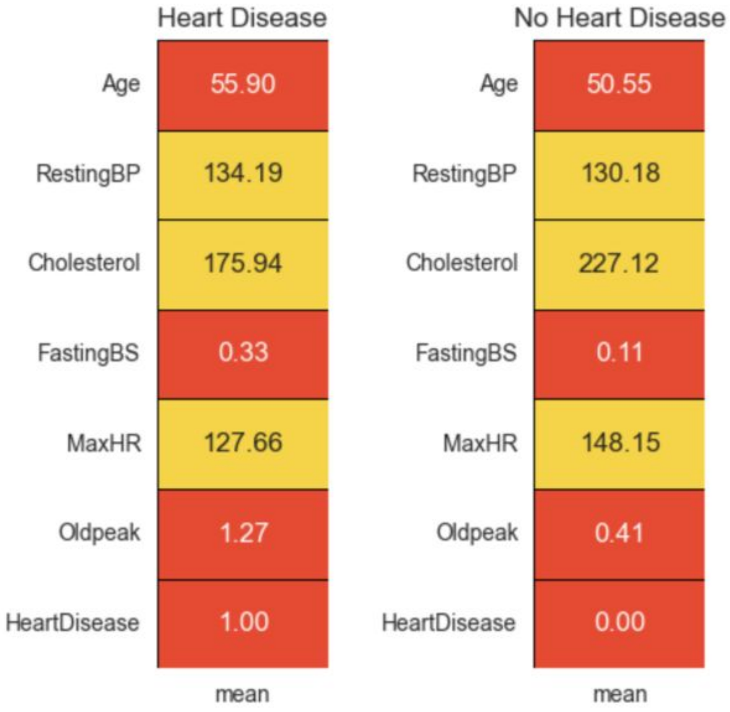
Response Variable (Target)

HeartDisease

[1: Heart Disease, 0: Normal]

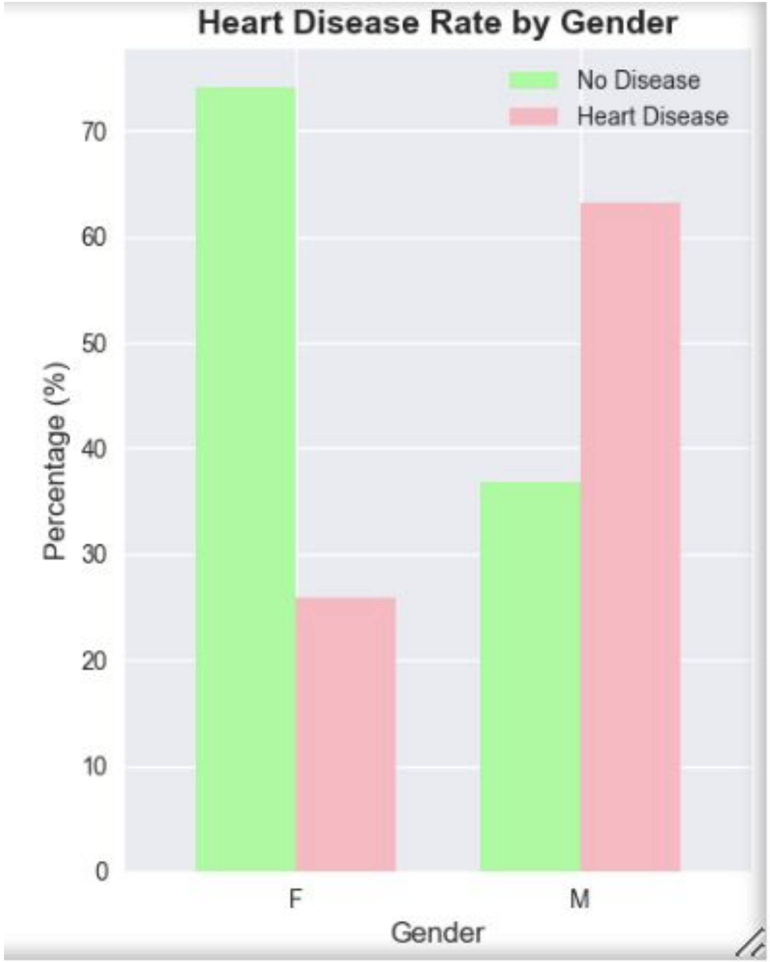
Dataframe Info & Summary Statistics

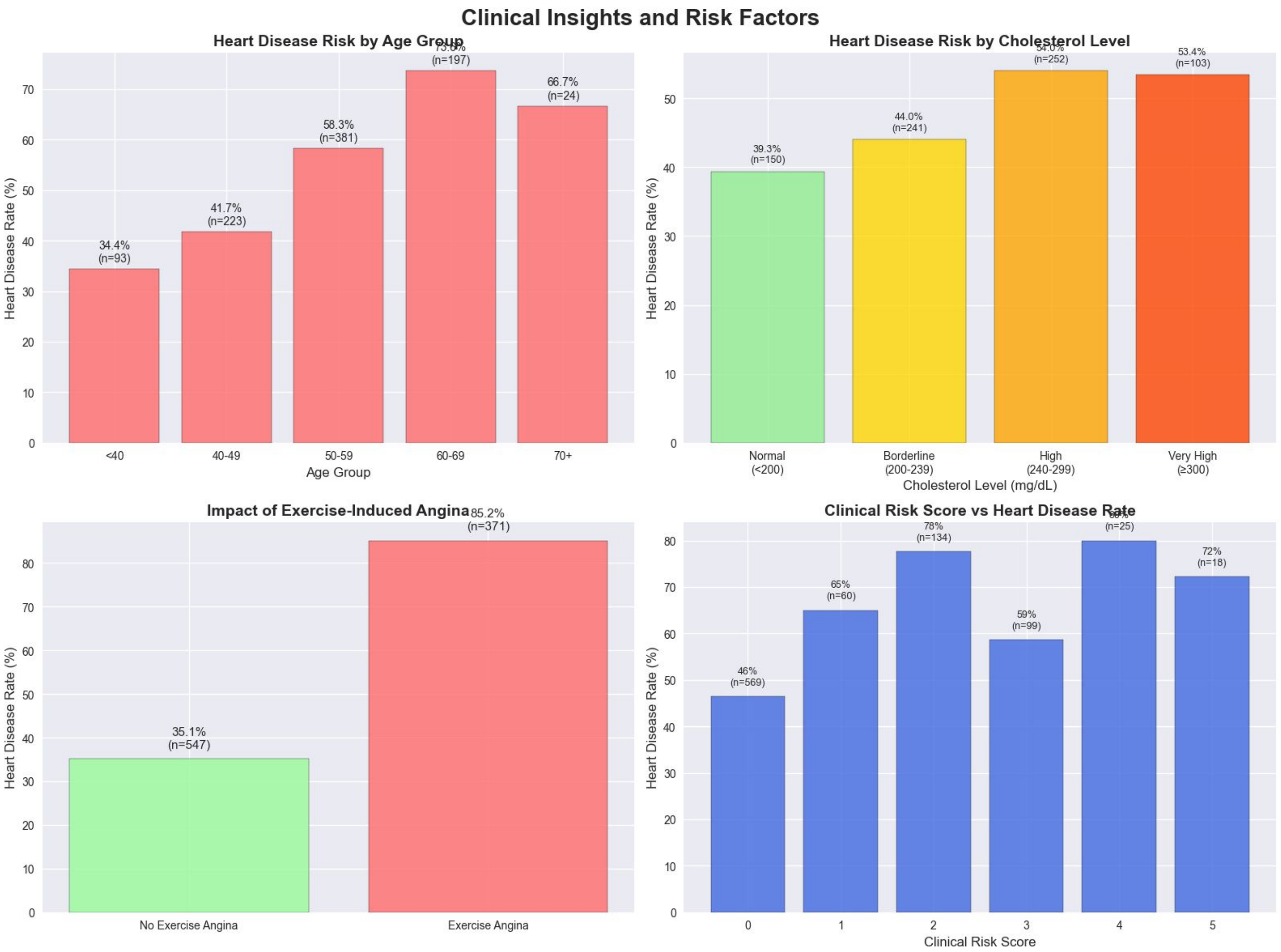
```
------------------ Dataframe Info ------------------
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 918 entries, 0 to 917
Data columns (total 12 columns):
 #   Column          Non-Null Count  Dtype
---  ------          --------------  -----
 0   Age             918 non-null    int64
 1   Sex             918 non-null    object
 2   ChestPainType   918 non-null    object
 3   RestingBP       918 non-null    int64
 4   Cholesterol     918 non-null    int64
 5   FastingBS       918 non-null    int64
 6   RestingECG      918 non-null    object
 7   MaxHR           918 non-null    int64
 8   ExerciseAngina  918 non-null    object
 9   Oldpeak         918 non-null    float64
 10  ST_Slope        918 non-null    object
 11  HeartDisease    918 non-null    int64
dtypes: float64(1), int64(6), object(5)
memory usage: 86.2+ KB
None

---------- Dimnensions (rows, columns) ----------
(918, 12)
```



Categorical Variables

Variable	Category	Percentage
Sex	M	79.0%
Sex	F	21.0%
ChestPainType	ASY	54.0%
ChestPainType	NAP	22.1%
ChestPainType	ATA	18.8%
ChestPainType	TA	5.0%
RestingECG	Normal	60.1%
RestingECG	LVH	20.5%
RestingECG	ST	19.4%
ExerciseAngina	N	59.6%
ExerciseAngina	Y	40.4%
ST_Slope	Flat	50.1%
ST_Slope	Up	43.0%
ST_Slope	Down	6.9%




Clinical Insights and Risk Factors
Heart Disease Risk by Age Group
Heart Disease Rate (%)
34.4%
(n=93)
41.7%
(n=223)
58.3%
(n=381)
73.6%
(n=197)
66.7%
(n=24)
<40
40-49
50-59
60-69
70+
Age Group
Heart Disease Risk by Cholesterol Level
Heart Disease Rate (%)
39.3%
(n=150)
44.0%
(n=241)
54.0%
(n=252)
53.4%
(n=103)
Normal
(<200)
Borderline
(200-239)
High
(240-299)
Very High
(≥300)
Cholesterol Level (mg/dL)
Impact of Exercise-Induced Angina
Heart Disease Rate (%)
35.1%
(n=547)
85.2%
(n=371)
No Exercise Angina
Exercise Angina
Clinical Risk Score vs Heart Disease Rate
Heart Disease Rate (%)
46%
(n=569)
65%
(n=60)
78%
(n=134)
59%
(n=99)
(n=25)
72%
(n=18)
Clinical Risk Score

Dataset Preparation for ML Models

Feature Engineering & Preprocessing

Step 1 — Feature Engineering

- Created **new, more informative columns** by converting raw values (e.g., cholesterol, age) into clinical flags and descriptive categories
- Purpose to **boost model accuracy** by making key patterns and relationships easier for the models to learn

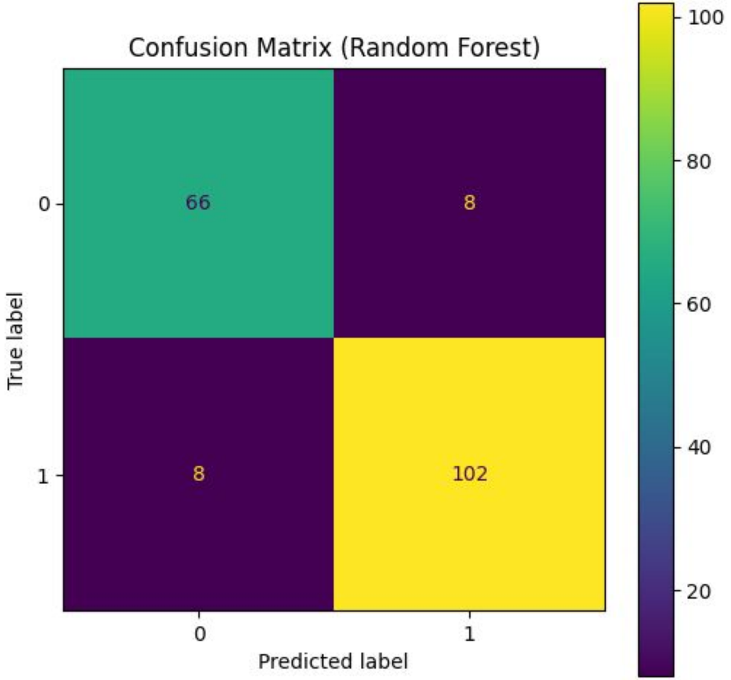
Step 2 — Preprocessing

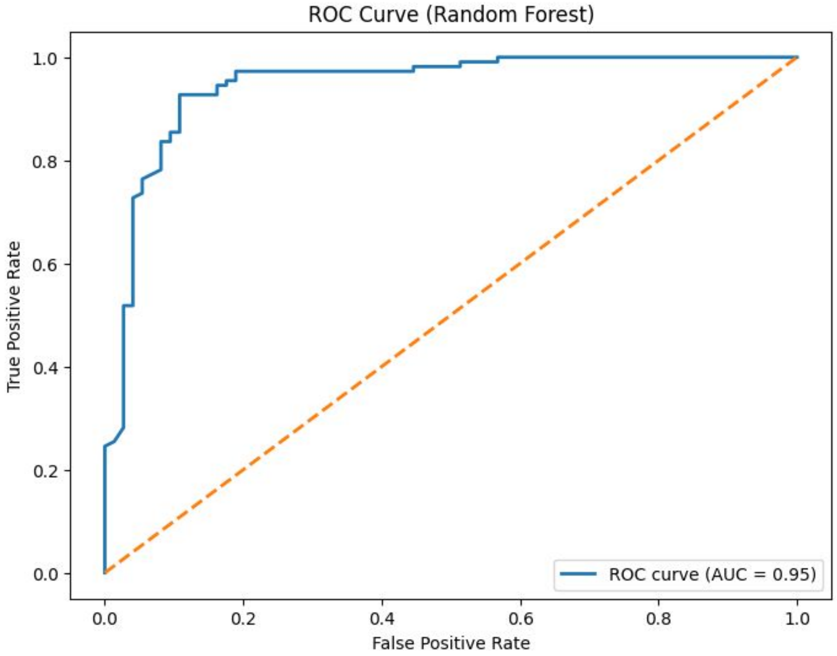
- Built a pipeline using scikit-learn which encoded categorical variables
- Purpose to ensure data was **totally clean and model-ready**, improving consistency and models' ability to learn

Our Models

Random Forest Classifier

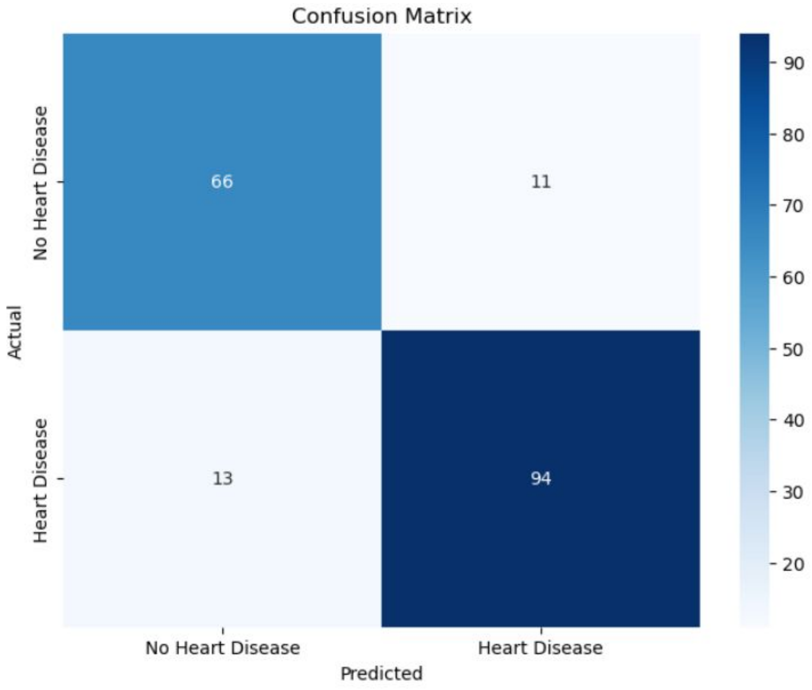
- AUC: 0.95

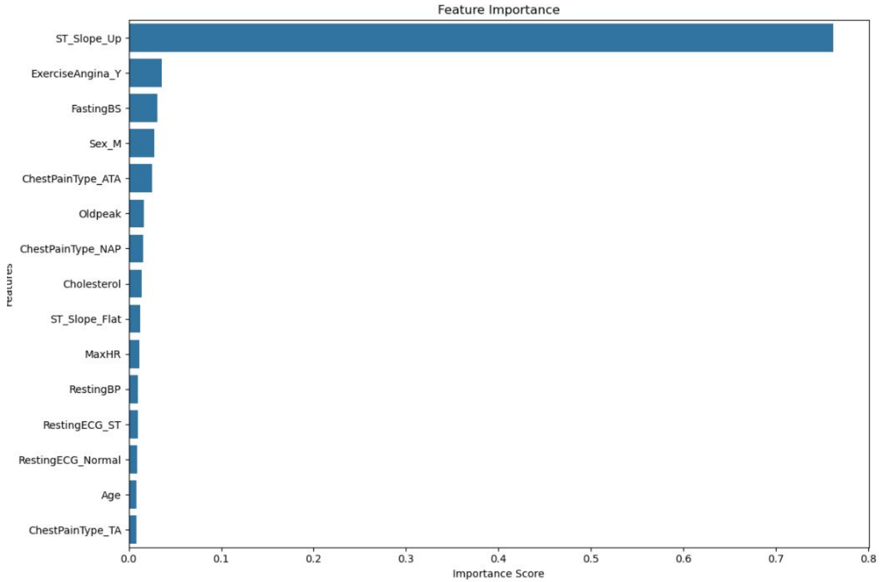




- Accuracy: 91.3%
- Recall (True Positive Rate): 92.7%
- Precision: 92.7%

Gradient Boosting





- **Accuracy: 87%**
- **Recall (True Positive Rate): 88.04%**
- **Precision: 88.04%**

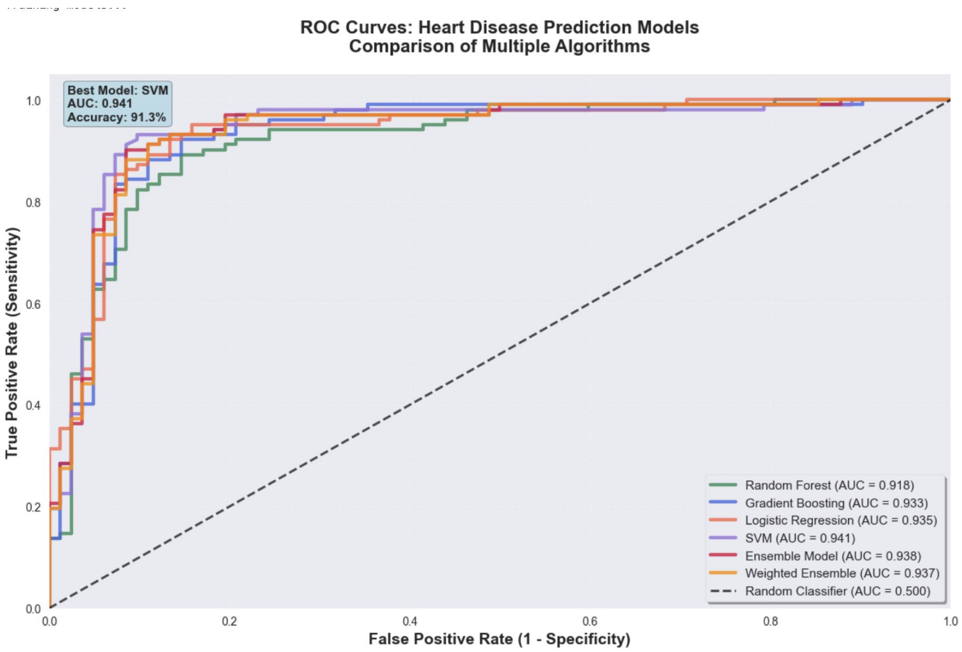
Ensemble Method

Accuracy: 90.22%

Recall: 90%

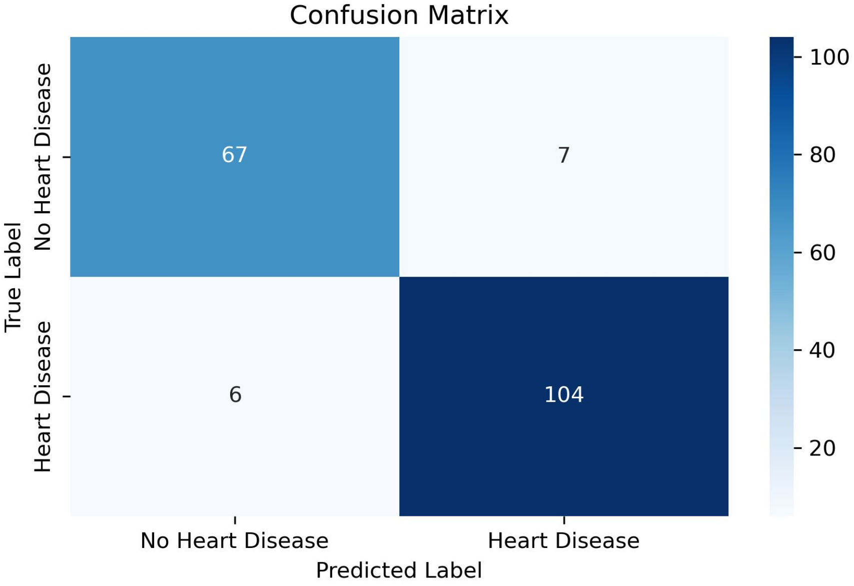
AUC: 0.935

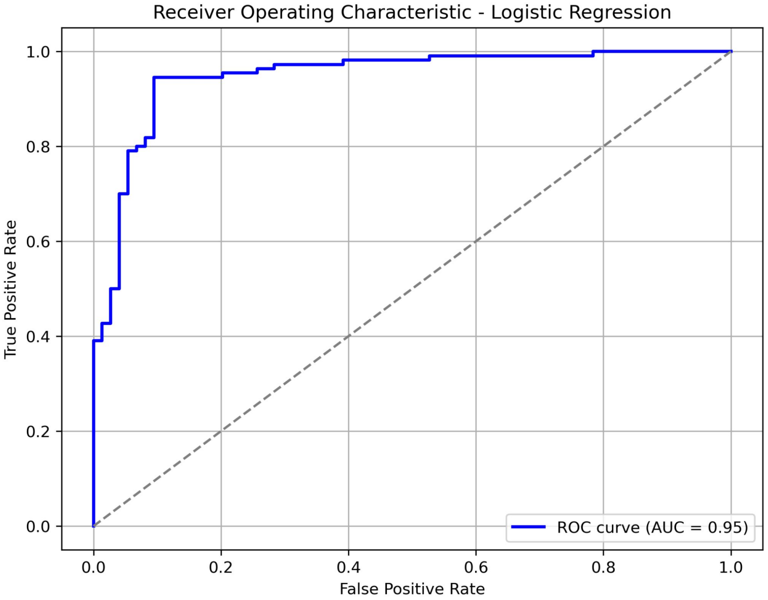
```
Individual Model Test Accuracies:
RandomForest: 84.78%
GradientBoosting: 88.04%
SVM: 89.13%
LogisticRegression: 88.59%
Neural Network: 84.78%
Voting Ensemble: 89.67%
Final Weighted Ensemble: 90.22%
```



Best Model: Logistic Regression

- **AUC: 0.95**





- **Accuracy: 92.9%**
- **Recall (True Positive Rate): 94.5%**
- **Precision: 93.7%**

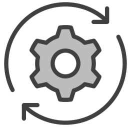
Conclusion

Real Time Impact

- Empowers Preventive Healthcare
- Reduces Healthcare Costs
- Lowers Hospitalization Rates
- Promotes Health Equity

Improvements / Future Work

Hyperparameter Tuning



Cost - Sensitive Learning

External Validation

Deployment Readiness - Real Time

Continuous Learning Pipeline

Thank You