HeartDiseasePrediction

February 14, 2025

1 Final Project: Heart Disease Prediction

1.1 Introduction

Heart disease is a major cause of mortality worldwide, and early diagnosis can help improve treatment and patient outcomes. This project aims to build a **predictive model** that can classify whether a patient has heart disease based on various health indicators.

1.2 1. Research Question

Can we develop a predictive model to classify whether a patient has heart disease based on their health indicators?

To answer this, we will: - Perform **exploratory data analysis (EDA)** to understand the dataset. - Apply **feature selection** techniques to identify key predictors. - Train **machine learning models** to classify patients. - Evaluate model performance using **ROC-AUC, accuracy, precision, and recall**.

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[219]:
```
# Import libraries
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
```

[221]:
```
# Import the data from Kaggle using the API
import kaggle
kaggle.api.dataset_download_files("johnsmith88/heart-disease-dataset", path=".
↪", unzip=True)
```

```
Dataset URL: https://www.kaggle.com/datasets/johnsmith88/heart-disease-dataset
```

2 Heart Disease Dataset - Attribute Reference

Attribute	Description
Age	Age in years
Sex	1 = Male, 0 = Female

Attribute	Description
Chest Pain Type	(1 = Typical angina, 2 = Atypical angina, 3 = Non-anginal pain, 4 = Asymptomatic)
Resting Blood Pressure	Blood pressure in mm Hg
Serum Cholesterol (mg/dl)	Cholesterol level in mg/dl
Fasting Blood Sugar	1 = Fasting blood sugar > 120 mg/dl, 0 = Otherwise
Resting ECG Results	(0 = Normal, 1 = ST-T wave abnormality, 2 = Left ventricular hypertrophy)
Maximum Heart Rate Achieved	Highest heart rate during exercise
Exercise Induced Angina	1 = Yes, 0 = No
Oldpeak (ST Depression)	ST depression induced by exercise relative to rest
Slope of Peak Exercise ST Segment	(1 = Upsloping, 2 = Flat, 3 = Downsloping)
Number of Major Vessels Colored by Fluoroscopy	(0-3)
Thalassemia (Thal)	0 = Normal, 1 = Fixed defect, 2 = Reversible defect

2.1 Exploratory Analysis

Before building our predictive model, we analyze the dataset to understand its structure, detect missing values, and identify key patterns.

[132]:
```
# Loading the dataset
data = pd.read_csv('./heart.csv')
data.head()
```

[132]:
```
   age  sex  cp  trestbps  chol  fbs  restecg  thalach  exang  oldpeak  slope  \
0   52    1   0       125   212    0        1      168      0      1.0      2
1   53    1   0       140   203    1        0      155      1      3.1      0
2   70    1   0       145   174    0        1      125      1      2.6      0
3   61    1   0       148   203    0        1      161      0      0.0      2
4   62    0   0       138   294    1        1      106      0      1.9      1
```

```
   ca  thal  target
0   2     3       0
1   0     3       0
2   0     3       0
3   1     3       0
4   3     2       0
```

[122]:
```
data.describe().round(1)
```

[122]:
```
          age     sex      cp  trestbps    chol     fbs  restecg  thalach  \
count  1025.0  1025.0  1025.0    1025.0  1025.0  1025.0   1025.0   1025.0
mean     54.4     0.7     0.9     131.6   246.0     0.1      0.5    149.1
std       9.1     0.5     1.0      17.5    51.6     0.4      0.5     23.0
min      29.0     0.0     0.0      94.0   126.0     0.0      0.0     71.0
25%      48.0     0.0     0.0     120.0   211.0     0.0      0.0    132.0
50%      56.0     1.0     1.0     130.0   240.0     0.0      1.0    152.0
75%      61.0     1.0     2.0     140.0   275.0     0.0      1.0    166.0
max      77.0     1.0     3.0     200.0   564.0     1.0      2.0    202.0

        exang  oldpeak   slope      ca    thal  target
count  1025.0   1025.0  1025.0  1025.0  1025.0  1025.0
mean      0.3      1.1     1.4     0.8     2.3     0.5
std       0.5      1.2     0.6     1.0     0.6     0.5
min       0.0      0.0     0.0     0.0     0.0     0.0
25%       0.0      0.0     1.0     0.0     2.0     0.0
50%       0.0      0.8     1.0     0.0     2.0     1.0
75%       1.0      1.8     2.0     1.0     3.0     1.0
max       1.0      6.2     2.0     4.0     3.0     1.0
```

[153]:
```
data.info()
data.isnull().sum()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 1025 entries, 0 to 1024
Data columns (total 14 columns):
 #   Column    Non-Null Count  Dtype
---  ------    --------------  -----
 0   age       1025 non-null   int64
 1   sex       1025 non-null   int64
 2   cp        1025 non-null   int64
 3   trestbps  1025 non-null   int64
 4   chol      1025 non-null   int64
 5   fbs       1025 non-null   int64
 6   restecg   1025 non-null   int64
 7   thalach   1025 non-null   int64
 8   exang     1025 non-null   int64
 9   oldpeak   1025 non-null   float64
```

```
 10   slope       1025 non-null   int64
 11   ca          1025 non-null   int64
 12   thal        1025 non-null   int64
 13   target      1025 non-null   int64
dtypes: float64(1), int64(13)
memory usage: 112.2 KB
```

[153]:
```
age         0
sex         0
cp          0
trestbps    0
chol        0
fbs         0
restecg     0
thalach     0
exang       0
oldpeak     0
slope       0
ca          0
thal        0
target      0
dtype: int64
```

2.2 Research Question

Can we develop a predictive model to classify whether a patient has heart disease based on their health indicators?

2.2.1 Approach:

2. **Select important features** using statistical methods and machine learning techniques.
3. **Train and evaluate classification models** to predict heart disease.
4. **Compare model performance** using accuracy, precision, recall, and ROC-AUC.
5. **Visualize results** to interpret model effectiveness and key risk factors.

2.2.2 Expected Outcome:

- Identify which health indicators most strongly correlate with heart disease.
- Develop a machine learning model that can assist in early diagnosis.
- Assess the model's ability to generalize to unseen data.

[160]:
```
data['age_group'] = pd.cut(data['age'],bins = [0, 21, 40, 55, 80],
 labels=['Young', 'Adults', 'Middle-aged', 'Senior'])
```

[162]:
```
data
```

[162]:
```
      age  sex  cp  trestbps  chol  fbs  restecg  thalach  exang  oldpeak  \
0      52    1   0       125   212    0        1      168      0      1.0
1      53    1   0       140   203    1        0      155      1      3.1
```

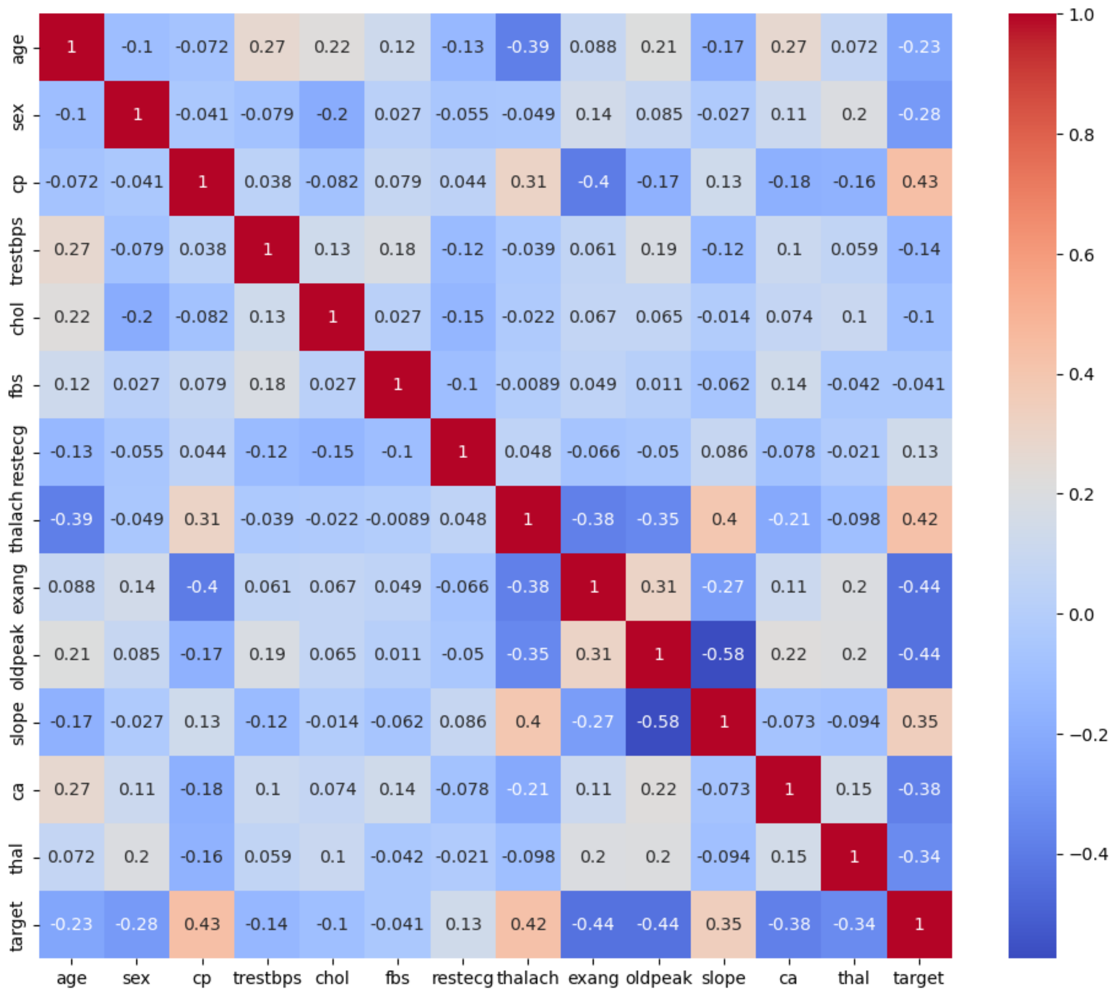
```
2       70     1    0        145    174    0          1        125        1        2.6
3       61     1    0        148    203    0          1        161        0        0.0
4       62     0    0        138    294    1          1        106        0        1.9
…    …    …   ..        …    …   …       …       …      …      …
1020    59     1    1        140    221    0          1        164        1        0.0
1021    60     1    0        125    258    0          0        141        1        2.8
1022    47     1    0        110    275    0          0        118        1        1.0
1023    50     0    0        110    254    0          0        159        0        0.0
1024    54     1    0        120    188    0          1        113        0        1.4

      slope  ca  thal  target    age_group
0         2   2     3       0  Middle-aged
1         0   0     3       0  Middle-aged
2         0   0     3       0       Senior
3         2   1     3       0       Senior
4         1   3     2       0       Senior
…       …  ..   …     …          …
1020      2   0     2       1       Senior
1021      1   1     3       0       Senior
1022      1   1     2       0  Middle-aged
1023      2   0     2       1  Middle-aged
1024      1   1     3       0  Middle-aged

[1025 rows x 15 columns]
```

2.2.3 Correlation Matrix Heatmap

[180]:
```python
numeric_data = data.select_dtypes(include=['number'])  # Filter numeric data␣
 ↪only
plt.figure(figsize=(12,10))
sns.heatmap(numeric_data.corr(), annot=True, cmap='coolwarm')
plt.show()
```



2.3 Feature Selection using SelectKBest

To improve model efficiency, we select the **top 8 most relevant features** using **ANOVA F-test (f_classif)**.

[187]:
```
from sklearn.feature_selection import SelectKBest, f_classif
X = numeric_data.drop('target', axis=1)
y = numeric_data['target']
selector = SelectKBest(f_classif, k=8)  # select top 8 features
selector.fit(X, y)
selected_features = X.columns[selector.get_support()]
print("Selected features:", selected_features)
```

```
Selected features: Index(['sex', 'cp', 'thalach', 'exang', 'oldpeak', 'slope',
'ca', 'thal'], dtype='object')
```

2.4 Feature Selection using Recursive Feature Elimination (RFE)

To refine our model, we use **Recursive Feature Elimination (RFE)** with **Logistic Regression** to select the **top 8 most significant features**.

2.4.1 Methodology:

1. **Standardize Features:**
   - We apply **StandardScaler** to normalize the feature values, improving model convergence.
2. **Use RFE for Feature Selection:**
   - Train a **Logistic Regression** model.
   - Iteratively remove the least important features until only **8 key features** remain.
3. **Retrieve Selected Features:**
   - Extract and display the most relevant predictors.

[191]:
```
from sklearn.feature_selection import RFE
from sklearn.linear_model import LogisticRegression
from sklearn.preprocessing import StandardScaler

# Scale the features
scaler = StandardScaler()
X_scaled = scaler.fit_transform(X)

# Choose a solver that might converge better if needed
model = LogisticRegression(max_iter=2000, solver='lbfgs')

# Perform RFE to select top 8 features
rfe = RFE(model, n_features_to_select=8)
rfe.fit(X_scaled, y)
selected_rfe = X.columns[rfe.support_]
print("RFE Selected features:", selected_rfe)
```

```
RFE Selected features: Index(['sex', 'cp', 'trestbps', 'thalach', 'exang',
'oldpeak', 'ca', 'thal'], dtype='object')
```

[193]:
```
from sklearn.model_selection import train_test_split

# Select features based on RFE results
X_selected = X[selected_rfe]
# Split data into training and test sets
X_train, X_test, y_train, y_test = train_test_split(X_selected, y, test_size=0.
↪3, random_state=42)
# Train the model
model.fit(X_train, y_train)
```

[193]:
```
LogisticRegression(max_iter=2000)
```

2.5 Model Evaluation

We assess the model's performance using key classification metrics.

2.5.1 Metrics Used:

- **Accuracy:** Overall correctness of predictions.
- **Classification Report:** Precision, recall, and F1-score for each class.
- **Confusion Matrix:** Breakdown of correct vs. incorrect predictions.
- **ROC-AUC Score:** Measures the model's ability to distinguish between classes.

[195]:
```
from sklearn.metrics import accuracy_score, classification_report,␣
↪confusion_matrix, roc_auc_score

y_pred = model.predict(X_test)
print("Accuracy:", accuracy_score(y_test, y_pred))
print("Classification Report:\n", classification_report(y_test, y_pred))
print("Confusion Matrix:\n", confusion_matrix(y_test, y_pred))
y_prob = model.predict_proba(X_test)[:, 1]
print("ROC-AUC:", roc_auc_score(y_test, y_prob))
```

```
Accuracy: 0.8344155844155844
Classification Report:
               precision    recall  f1-score   support

           0       0.91      0.75      0.82       159
           1       0.78      0.92      0.84       149

    accuracy                           0.83       308
   macro avg       0.84      0.84      0.83       308
weighted avg       0.85      0.83      0.83       308

Confusion Matrix:
 [[120  39]
 [ 12 137]]
ROC-AUC: 0.9031277700392555
```

2.6 Hyperparameter Tuning with GridSearchCV

To improve model performance, we tune hyperparameters using **GridSearchCV**.

2.6.1 Why Grid Search?

- Tests multiple hyperparameter values.
- Uses **cross-validation** to ensure generalization.
- Selects the best combination automatically.

[197]:
```
from sklearn.model_selection import GridSearchCV

param_grid = {'C': [0.01, 0.1, 1, 10, 100]}
```

```
grid_search = GridSearchCV(LogisticRegression(max_iter=2000, solver='lbfgs'),
                           param_grid, cv=5, scoring='accuracy')
grid_search.fit(X_train, y_train)
print("Best parameters:", grid_search.best_params_)
print("Best cross-validation score:", grid_search.best_score_)
```

```
Best parameters: {'C': 10}
Best cross-validation score: 0.841006216006216
```

2.7 Data Visualization

To assess model performance and gain insights into feature importance, we visualize key metrics.

2.7.1 1. ROC Curve

- Displays the model's ability to distinguish between classes.
- Higher **AUC (Area Under Curve)** values indicate better performance.

2.7.2 2. Confusion Matrix

- Shows correct and incorrect predictions.
- Helps analyze model misclassifications.

2.7.3 3. Feature Importance

- Highlights the most influential features in predictions.
- Useful for understanding which health indicators matter most.

2.7.4 4. Age Distribution

- Visualizes the spread of patient ages in the dataset.
- Identifies trends in the population.

[213]:
```
import matplotlib.pyplot as plt
import seaborn as sns
from sklearn.metrics import roc_curve, auc, confusion_matrix

# Assume y_test, y_pred, y_prob, and selected_features are already defined

# Create a figure with multiple subplots
fig, axs = plt.subplots(2, 2, figsize=(14, 12))

# 1. ROC Curve
fpr, tpr, _ = roc_curve(y_test, y_prob)
roc_auc = auc(fpr, tpr)
axs[0, 0].plot(fpr, tpr, color='darkorange', lw=2, label=f'ROC curve (AUC =␣
↪{roc_auc:.2f})')
axs[0, 0].plot([0, 1], [0, 1], color='navy', lw=2, linestyle='--')
axs[0, 0].set_title('Receiver Operating Characteristic')
```

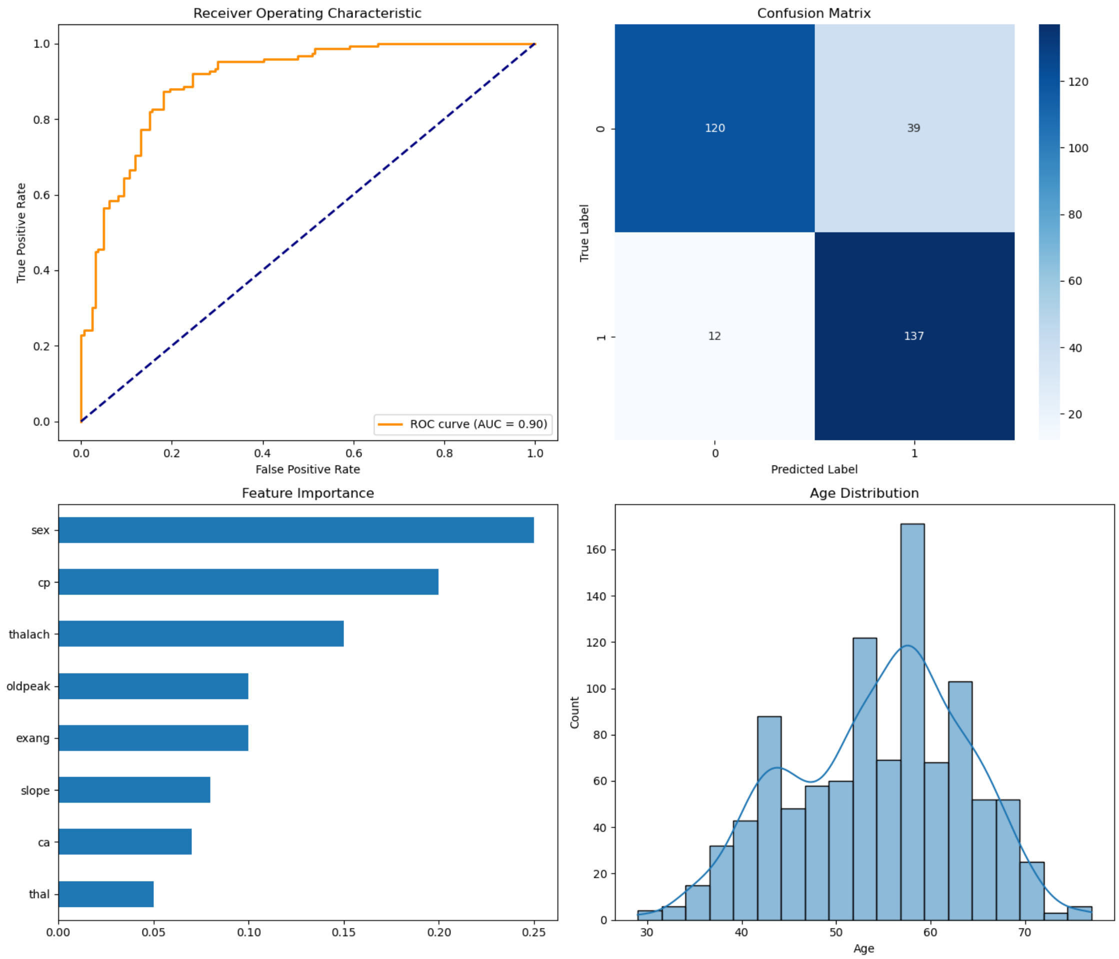
```python
axs[0, 0].set_xlabel('False Positive Rate')
axs[0, 0].set_ylabel('True Positive Rate')
axs[0, 0].legend(loc='lower right')

# 2. Confusion Matrix
cm = confusion_matrix(y_test, y_pred)
sns.heatmap(cm, annot=True, fmt="d", cmap='Blues', ax=axs[0, 1],
            xticklabels=[0,1], yticklabels=[0,1])
axs[0, 1].set_title('Confusion Matrix')
axs[0, 1].set_xlabel('Predicted Label')
axs[0, 1].set_ylabel('True Label')

# 3. Feature Importance (example using RandomForest or model coefficients)
# For illustration: assume importances is a pandas Series with feature names as␣
 ↪index
importances = pd.Series([0.25, 0.20, 0.15, 0.10, 0.10, 0.08, 0.07, 0.05],␣
 ↪index=selected_features)
importances.sort_values().plot(kind='barh', ax=axs[1, 0])
axs[1, 0].set_title('Feature Importance')

# 4. Distribution Plot of a Key Feature (e.g., Age)
sns.histplot(data['age'], kde=True, ax=axs[1, 1])
axs[1, 1].set_title('Age Distribution')
axs[1, 1].set_xlabel('Age')

plt.tight_layout()
plt.show()
```


Receiver Operating Characteristic
ROC curve (AUC = 0.90)
False Positive Rate
True Positive Rate
Confusion Matrix
120
39
12
137
True Label
Predicted Label
Feature Importance
sex
cp
thalach
oldpeak
exang
slope
ca
thal
Age Distribution
Count
Age