Install and Import Required Libraries

```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
from google.colab import files
```

Load the Dataset

```
df = pd.read_csv('heart_disease_uci.csv')
```

Display first few rows

```
print(df.head(5))
```

```
   id  age     sex   dataset               cp  trestbps   chol    fbs  \
0   1   63    Male  Cleveland   typical angina     145.0  233.0   True
1   2   67    Male  Cleveland     asymptomatic     160.0  286.0  False
2   3   67    Male  Cleveland     asymptomatic     120.0  229.0  False
3   4   37    Male  Cleveland      non-anginal     130.0  250.0  False
4   5   41  Female  Cleveland  atypical angina     130.0  204.0  False

          restecg  thalch  exang  oldpeak        slope   ca  \
0  lv hypertrophy   150.0  False      2.3  downsloping  0.0
1  lv hypertrophy   108.0   True      1.5         flat  3.0
2  lv hypertrophy   129.0   True      2.6         flat  2.0
3          normal   187.0  False      3.5  downsloping  0.0
4  lv hypertrophy   172.0  False      1.4    upsloping  0.0

               thal  num
0      fixed defect    0
1            normal    2
```

```
2  reversable defect    1
3              normal    0
4              normal    0
```

Inspect Data

```
print("\nDataset Info:")
print(df.info())
print("\nMissing Values:")
print(df.isnull().sum())
```

```
Dataset Info:
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 920 entries, 0 to 919
Data columns (total 16 columns):
 #   Column    Non-Null Count  Dtype  
---  ------    --------------  -----  
 0   id        920 non-null    int64  
 1   age       920 non-null    int64  
 2   sex       920 non-null    object 
 3   dataset   920 non-null    object 
 4   cp        920 non-null    object 
 5   trestbps  861 non-null    float64
 6   chol      890 non-null    float64
 7   fbs       830 non-null    object 
 8   restecg   918 non-null    object 
 9   thalch    865 non-null    float64
 10  exang     865 non-null    object 
 11  oldpeak   858 non-null    float64
 12  slope     611 non-null    object 
 13  ca        309 non-null    float64
 14  thal      434 non-null    object 
 15  num       920 non-null    int64  
dtypes: float64(5), int64(3), object(8)
memory usage: 115.1+ KB
None
```

```
Missing Values:
id            0
age           0
sex           0
dataset       0
cp            0
trestbps     59
chol         30
fbs          90
restecg       2
thalch       55
exang        55
oldpeak      62
slope       309
ca          611
thal        486
num           0
dtype: int64
```

Rename target column and clean

```
df.rename(columns={'num': 'target'}, inplace=True)
df['target'] = (df['target'] > 0).astype(int)
```

Drop 'id' column (not useful)

```
df.drop(columns=['id'], inplace=True)
```

Handle Missing Values

```
df.replace({'': np.nan, '?': np.nan}, inplace=True)
```

Convert numeric columns to float where necessary

```
numeric_cols = ['age', 'trestbps', 'chol', 'thalch', 'oldpeak', 'ca']
for col in numeric_cols:
    df[col] = pd.to_numeric(df[col], errors='coerce')
```

Fill missing numeric values with median

```
for col in numeric_cols:
    df[col].fillna(df[col].median(), inplace=True)
```

```
/tmp/ipython-input-3154000584.py:2: FutureWarning: A value is trying to be set on a copy of a DataFrame or Series through c
The behavior will change in pandas 3.0. This inplace method will never work because the intermediate object on which we are

For example, when doing 'df[col].method(value, inplace=True)', try using 'df.method({col: value}, inplace=True)' or df[col]


  df[col].fillna(df[col].median(), inplace=True)
```

Categorical columns: fill with mode

```
categorical_cols = ['cp', 'fbs', 'restecg', 'exang', 'slope', 'thal', 'sex', 'dataset']
for col in categorical_cols:
    df[col].fillna(df[col].mode()[0], inplace=True)
```

```
/tmp/ipython-input-3512451438.py:3: FutureWarning: A value is trying to be set on a copy of a DataFrame or Series through c
The behavior will change in pandas 3.0. This inplace method will never work because the intermediate object on which we are

For example, when doing 'df[col].method(value, inplace=True)', try using 'df.method({col: value}, inplace=True)' or df[col]


  df[col].fillna(df[col].mode()[0], inplace=True)
/tmp/ipython-input-3512451438.py:3: FutureWarning: Downcasting object dtype arrays on .fillna, .ffill, .bfill is deprecated
```

```
    df[col].fillna(df[col].mode()[0], inplace=True)
```

Encode Categorical Variables

```
categorical_cols.remove('sex')  # We'll handle 'sex' separately as binary
df = pd.get_dummies(df, columns=categorical_cols, drop_first=True)
```

Encode 'sex': Male = 1, Female = 0

```
df['sex'] = df['sex'].map({'Male': 1, 'Female': 0})

print("Shape after encoding:", df.shape)
```

```
Shape after encoding: (920, 22)
```

Define Features and Target

```
X = df.drop('target', axis=1)
y = df['target']
```

Train-Test Split

```
from sklearn.model_selection import train_test_split
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=42, stratify=y)
```

Scale the Features

```
from sklearn.preprocessing import StandardScaler
scaler = StandardScaler()
X_train_scaled = scaler.fit_transform(X_train)
X_test_scaled = scaler.transform(X_test)
```

Train Models

```
from sklearn.linear_model import LogisticRegression
from sklearn.tree import DecisionTreeClassifier
from sklearn.ensemble import RandomForestClassifier
from sklearn.metrics import accuracy_score, precision_score, recall_score, f1_score, roc_auc_score, confusion_matrix, roc_curve
```

Dictionary to store results

```
models = {}
results = []
```

Logistic Regression

```
lr = LogisticRegression(max_iter=1000, random_state=42)
lr.fit(X_train_scaled, y_train)
y_pred_lr = lr.predict(X_test_scaled)
y_prob_lr = lr.predict_proba(X_test_scaled)[:, 1]
models['Logistic Regression'] = lr
results.append({
    'Model': 'Logistic Regression',
    'Accuracy': accuracy_score(y_test, y_pred_lr),
    'Precision': precision_score(y_test, y_pred_lr),
    'Recall': recall_score(y_test, y_pred_lr),
    'F1': f1_score(y_test, y_pred_lr),
```

```
    'ROC-AUC': roc_auc_score(y_test, y_prob_lr)
})
```

Decision Tree

```
dt = DecisionTreeClassifier(random_state=42, max_depth=8, min_samples_split=5)
dt.fit(X_train, y_train)  # No scaling needed
y_pred_dt = dt.predict(X_test)
y_prob_dt = dt.predict_proba(X_test)[:, 1]
models['Decision Tree'] = dt
results.append({
    'Model': 'Decision Tree',
    'Accuracy': accuracy_score(y_test, y_pred_dt),
    'Precision': precision_score(y_test, y_pred_dt),
    'Recall': recall_score(y_test, y_pred_dt),
    'F1': f1_score(y_test, y_pred_dt),
    'ROC-AUC': roc_auc_score(y_test, y_prob_dt)
})
```

Random Forest

```
rf = RandomForestClassifier(n_estimators=100, max_depth=7, min_samples_split=5,
                            random_state=42, class_weight='balanced')
rf.fit(X_train, y_train)
y_pred_rf = rf.predict(X_test)
y_prob_rf = rf.predict_proba(X_test)[:, 1]
models['Random Forest'] = rf
results.append({
    'Model': 'Random Forest',
    'Accuracy': accuracy_score(y_test, y_pred_rf),
    'Precision': precision_score(y_test, y_pred_rf),
    'Recall': recall_score(y_test, y_pred_rf),
    'F1': f1_score(y_test, y_pred_rf),
    'ROC-AUC': roc_auc_score(y_test, y_prob_rf)
```

```
})
```

Display Results

```
results_df = pd.DataFrame(results)
print("\n Model Performance Comparison:")
print(results_df.round(4))
```

```
 Model Performance Comparison:
                 Model  Accuracy  Precision  Recall      F1  ROC-AUC
0  Logistic Regression    0.8370     0.8273  0.8922  0.8585   0.9213
1        Decision Tree    0.7989     0.7876  0.8725  0.8279   0.8488
2        Random Forest    0.8533     0.8505  0.8922  0.8708   0.9219
```

Highlight best model

```
best_model = results_df.loc[results_df['F1'].idxmax()]['Model']
print(f"\n Best Model (by F1-score): {best_model}")
```

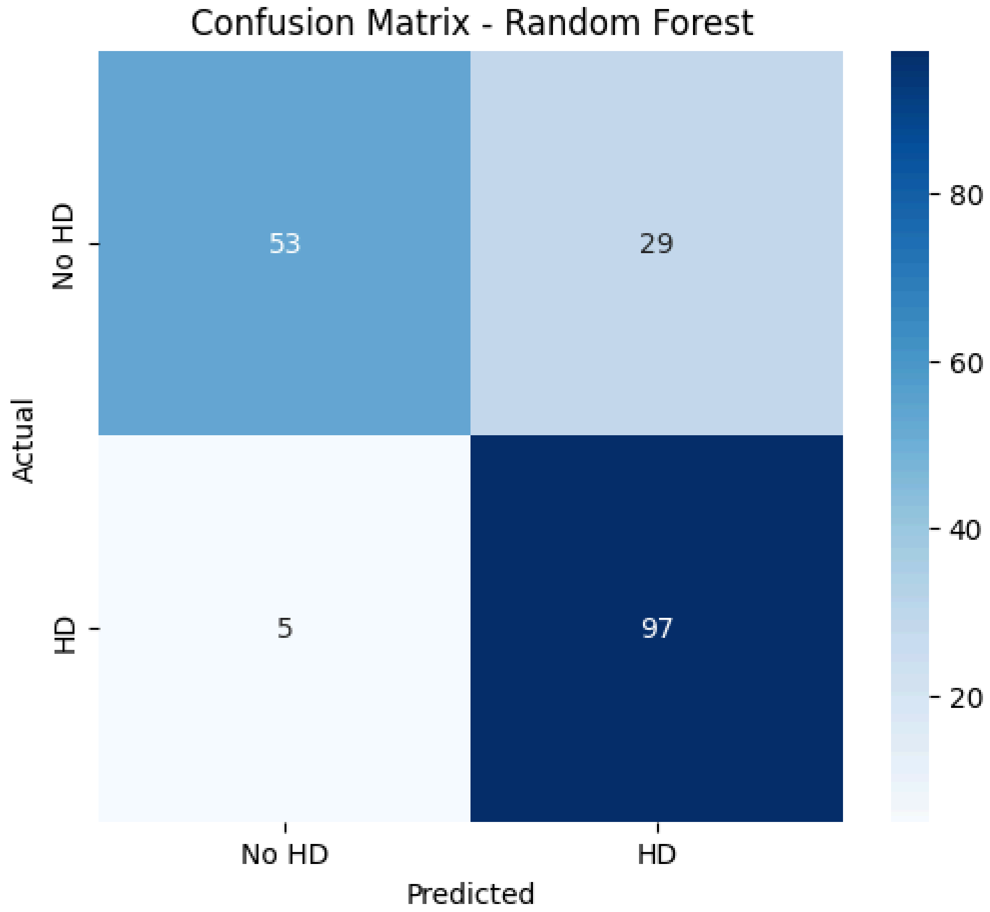
```
 Best Model (by F1-score): Random Forest
```

Confusion Matrix for Best Model

```
def plot_confusion_matrix(model_name):
    y_pred = models[model_name].predict(X_test if 'Tree' in model_name else X_test_scaled)
    cm = confusion_matrix(y_test, y_pred)
    plt.figure(figsize=(6,5))
    sns.heatmap(cm, annot=True, fmt='d', cmap='Blues', xticklabels=['No HD', 'HD'], yticklabels=['No HD', 'HD'])
    plt.title(f'Confusion Matrix - {model_name}')
    plt.ylabel('Actual')
```

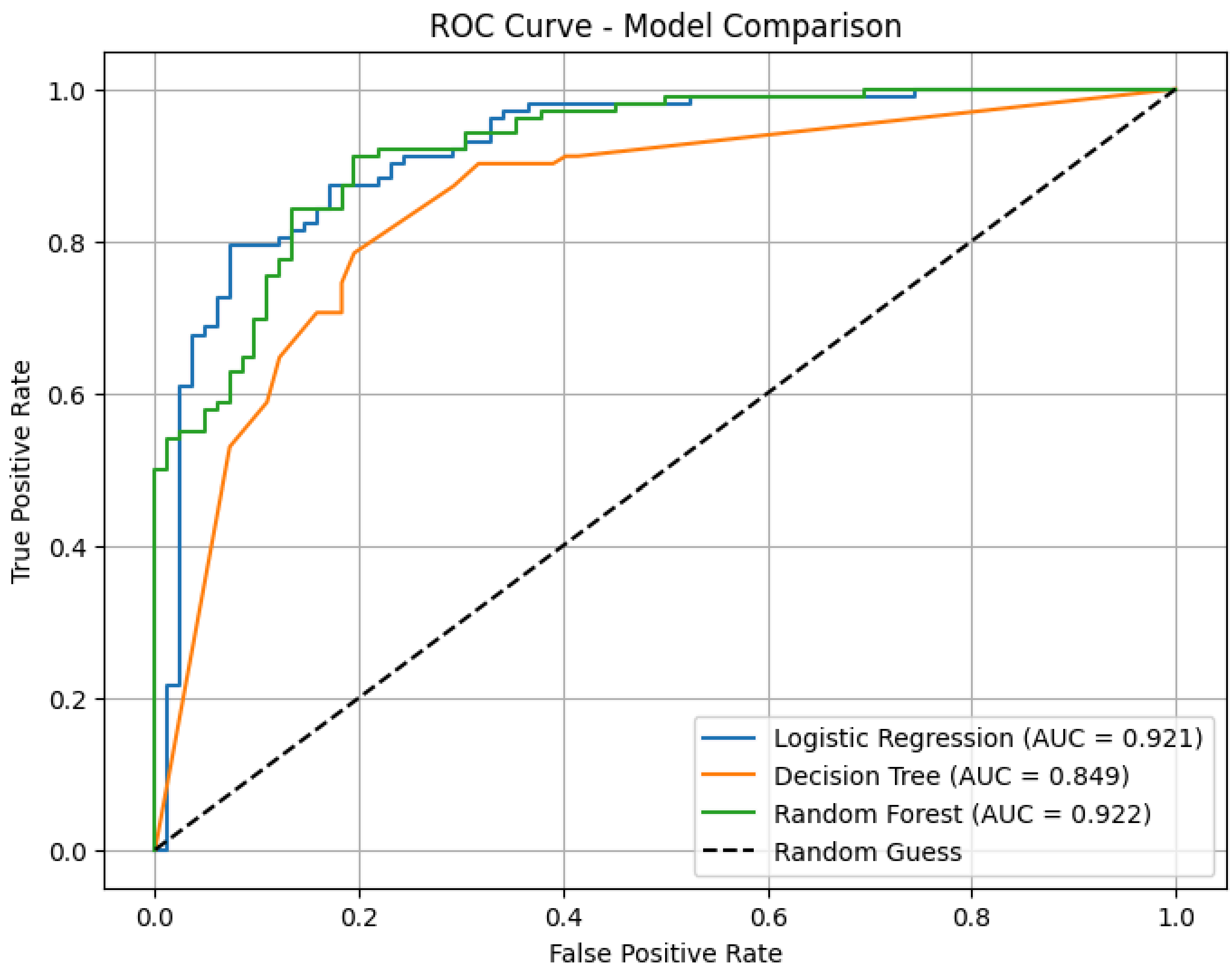
```
    plt.xlabel('Predicted')
    plt.show()

plot_confusion_matrix(best_model)
```

```
/usr/local/lib/python3.12/dist-packages/sklearn/utils/validation.py:2739: UserWarning: X does not have valid feature names,
  warnings.warn(
```



ROC Curve for All Models

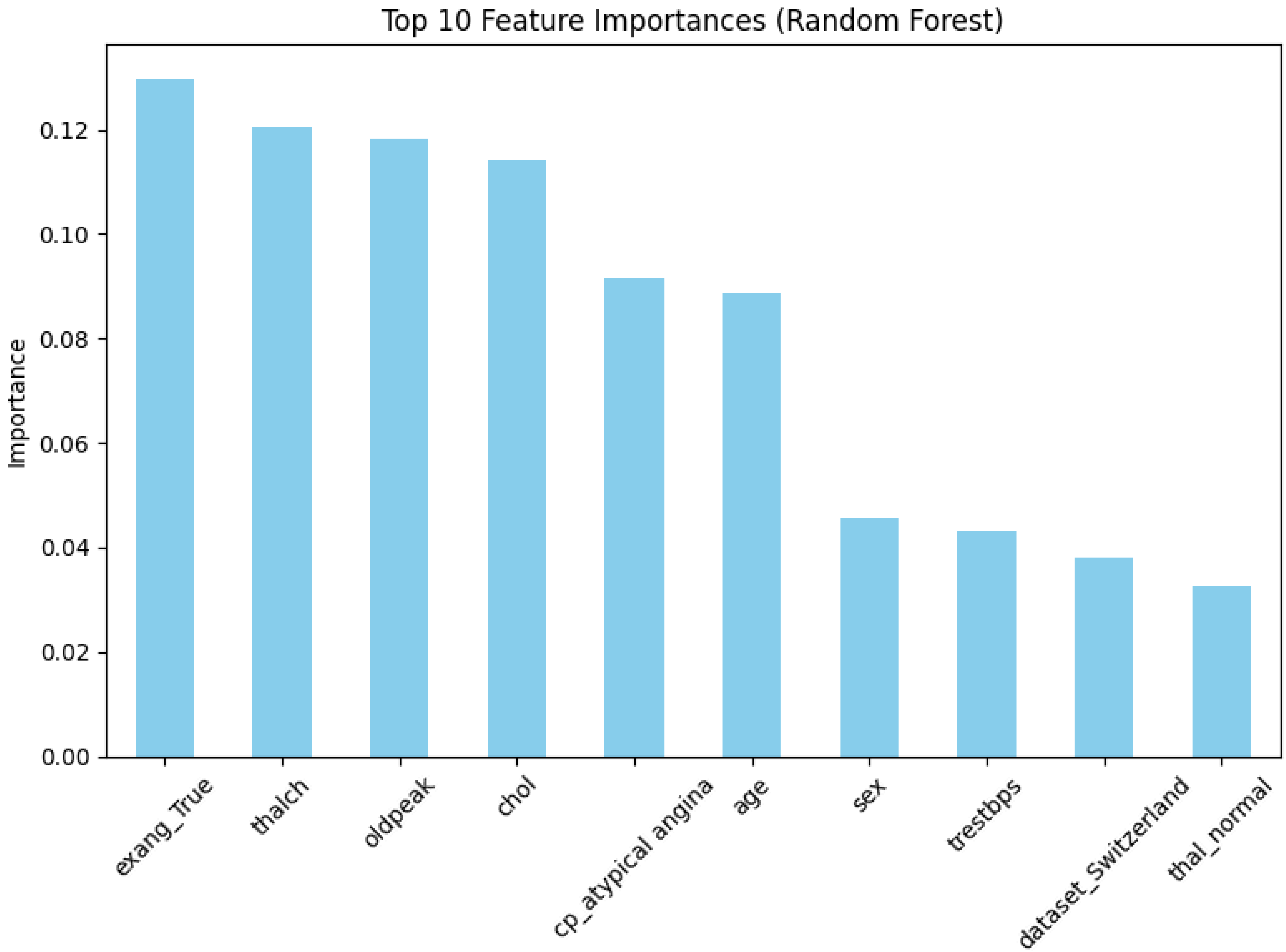
```python
plt.figure(figsize=(8,6))
for model_name in models.keys():
    if model_name == 'Logistic Regression':
        y_prob = lr.predict_proba(X_test_scaled)[:, 1]
        fpr, tpr, _ = roc_curve(y_test, y_prob)
        plt.plot(fpr, tpr, label=f"{model_name} (AUC = {roc_auc_score(y_test, y_prob):.3f})")
    elif model_name == 'Decision Tree':
        y_prob = dt.predict_proba(X_test)[:, 1]
        fpr, tpr, _ = roc_curve(y_test, y_prob)
        plt.plot(fpr, tpr, label=f"{model_name} (AUC = {roc_auc_score(y_test, y_prob):.3f})")
    elif model_name == 'Random Forest':
        y_prob = rf.predict_proba(X_test)[:, 1]
        fpr, tpr, _ = roc_curve(y_test, y_prob)
        plt.plot(fpr, tpr, label=f"{model_name} (AUC = {roc_auc_score(y_test, y_prob):.3f})")

plt.plot([0,1], [0,1], 'k--', label='Random Guess')
plt.xlabel('False Positive Rate')
plt.ylabel('True Positive Rate')
plt.title('ROC Curve - Model Comparison')
plt.legend()
plt.grid(True)
plt.show()
```



Feature Importance (Random Forest)

```
if best_model == 'Random Forest':
    feat_importance = pd.Series(rf.feature_importances_, index=X.columns).sort_values(ascending=False)
    plt.figure(figsize=(8,6))
    feat_importance.head(10).plot(kind='bar', color='skyblue')
```

```
plt.title('Top 10 Feature Importances (Random Forest)')
plt.ylabel('Importance')
plt.xticks(rotation=45)
plt.tight_layout()
plt.show()
```



save model

```
import joblib

# Select best model
best_model_instance = models[best_model]

# Save model and scaler
joblib.dump(best_model_instance, 'heart_disease_model.pkl')
joblib.dump(scaler, 'scaler.pkl')
joblib.dump(X.columns.tolist(), 'feature_columns.pkl')  # Save feature names for inference

print("\n✅ Best model and preprocessing objects saved!")
print("Files: 'heart_disease_model.pkl', 'scaler.pkl', 'feature_columns.pkl'")
```

```
✅ Best model and preprocessing objects saved!
Files: 'heart_disease_model.pkl', 'scaler.pkl', 'feature_columns.pkl'
```