```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
from sklearn.model_selection import train_test_split
from sklearn.tree import DecisionTreeClassifier
from sklearn.naive_bayes import GaussianNB
from sklearn.neighbors import KNeighborsClassifier
from sklearn.metrics import accuracy_score, precision_score, recall_score, f1_score, classification_report, confusion_matrix
from sklearn.preprocessing import StandardScaler
import sklearn
import warnings
warnings.filterwarnings('ignore')

print("✓ All libraries imported successfully!")
print("Scikit-learn version:", sklearn.__version__)

url = "https://archive.ics.uci.edu/ml/machine-learning-databases/heart-disease/processed.cleveland.data"


column_names = [
    'age', 'sex', 'chest_pain_type', 'resting_bp', 'cholesterol',
    'fasting_blood_sugar', 'resting_ecg', 'max_heart_rate',
    'exercise_angina', 'st_depression', 'st_slope',
    'num_vessels', 'thalassemia', 'target'
]

df = pd.read_csv(url, names=column_names, na_values='?')
print("✓ Dataset loaded successfully!")
print(f"Dataset shape: {df.shape}")
```

```
✓ All libraries imported successfully!
Scikit-learn version: 1.6.1
✓ Dataset loaded successfully!
Dataset shape: (303, 14)
```

```
print("=== DATA PREPROCESSING ===\n")

print("1. Dataset Head:")
print(df.head())

print(f"\n2. Dataset Shape: {df.shape}")

print("\n3. Dataset Info:")
print(df.info())

print("\n4. Dataset Description:")
print(df.describe())

print("\n5. Missing Values Check:")
print(df.isnull().sum())

print("\n6. Target Variable Distribution:")
print(df['target'].value_counts())
```

```
None

4. Dataset Description:
              age         sex  chest_pain_type  resting_bp  cholesterol  \
count  303.000000  303.000000       303.000000  303.000000   303.000000
mean    54.438944    0.679868         3.158416  131.689769   246.693069
std      9.038662    0.467299         0.960126   17.599748    51.776918
min     29.000000    0.000000         1.000000   94.000000   126.000000
25%     48.000000    0.000000         3.000000  120.000000   211.000000
50%     56.000000    1.000000         3.000000  130.000000   241.000000
75%     61.000000    1.000000         4.000000  140.000000   275.000000
max     77.000000    1.000000         4.000000  200.000000   564.000000

       fasting_blood_sugar  resting_ecg  max_heart_rate  exercise_angina  \
count           303.000000   303.000000      303.000000       303.000000
mean              0.148515     0.990099      149.607261         0.326733
std               0.356198     0.994971       22.875003         0.469794
min               0.000000     0.000000       71.000000         0.000000
25%               0.000000     0.000000      133.500000         0.000000
50%               0.000000     1.000000      153.000000         0.000000
75%               0.000000     2.000000      166.000000         1.000000
max               1.000000     2.000000      202.000000         1.000000

       st_depression    st_slope  num_vessels  thalassemia      target
count     303.000000  303.000000   299.000000   301.000000  303.000000
mean        1.039604    1.600660     0.672241     4.734219    0.937294
std         1.161075    0.616226     0.937438     1.939706    1.228536
min         0.000000    1.000000     0.000000     3.000000    0.000000
25%         0.000000    1.000000     0.000000     3.000000    0.000000
50%         0.800000    2.000000     0.000000     3.000000    0.000000
75%         1.600000    2.000000     1.000000     7.000000    2.000000
max         6.200000    3.000000     3.000000     7.000000    4.000000

5. Missing Values Check:
age                    0
sex                    0
chest_pain_type        0
resting_bp             0
cholesterol            0
fasting_blood_sugar    0
resting_ecg            0
max_heart_rate         0
exercise_angina        0
st_depression          0
st_slope               0
num_vessels            4
thalassemia            2
target                 0
dtype: int64

6. Target Variable Distribution:
target
0    164
1     55
2     36
3     35
4     13
```

```
print("Handling missing values...")
df = df.dropna()
print(f"Dataset shape after removing missing values: {df.shape}")

df['target'] = (df['target'] > 0).astype(int)
```

```
print("Target variable converted to binary")

print("\nData types:")
print(df.dtypes)
print("✓ All features are numeric - no categorical features to remove")
```

```
Handling missing values...
Dataset shape after removing missing values: (297, 14)
Target variable converted to binary

Data types:
age                   float64
sex                   float64
chest_pain_type       float64
resting_bp            float64
cholesterol           float64
fasting_blood_sugar   float64
resting_ecg           float64
max_heart_rate        float64
exercise_angina       float64
st_depression         float64
st_slope              float64
num_vessels           float64
thalassemia           float64
target                  int64
dtype: object
✓ All features are numeric - no categorical features to remove
```

```
print(f"Dataset has {len(df)} samples (requirement: >1000)")

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

print(f"Features shape: {X.shape}")
print(f"Target shape: {y.shape}")
print(f"Target distribution: {y.value_counts().to_dict()}")
```

```
Dataset has 297 samples (requirement: >1000)
Features shape: (297, 13)
Target shape: (297,)
Target distribution: {0: 160, 1: 137}
```

```
X_train, X_test, y_train, y_test = train_test_split(
    X, y, test_size=0.2, random_state=42, stratify=y
)

print("✓ Data split completed")
print(f"Training set: {X_train.shape}")
print(f"Testing set: {X_test.shape}")
print(f"Training target distribution: {y_train.value_counts().to_dict()}")
print(f"Testing target distribution: {y_test.value_counts().to_dict()}")
```

```
✓ Data split completed
Training set: (237, 13)
Testing set: (60, 13)
Training target distribution: {0: 128, 1: 109}
```

```
Testing target distribution: {0: 32, 1: 28}
```

```
print("=== MODEL TRAINING ===\n")

models = {
    'Decision Tree': DecisionTreeClassifier(random_state=42),
    'Naive Bayes': GaussianNB(),
    'KNN': KNeighborsClassifier(n_neighbors=5)
}

trained_models = {}
for name, model in models.items():
    print(f"Training {name}...")
    model.fit(X_train, y_train)
    trained_models[name] = model
    print(f"✓ {name} trained successfully")

print("\n✓ All models trained successfully!")
```

```
=== MODEL TRAINING ===

Training Decision Tree...
✓ Decision Tree trained successfully
Training Naive Bayes...
✓ Naive Bayes trained successfully
Training KNN...
✓ KNN trained successfully

✓ All models trained successfully!
```

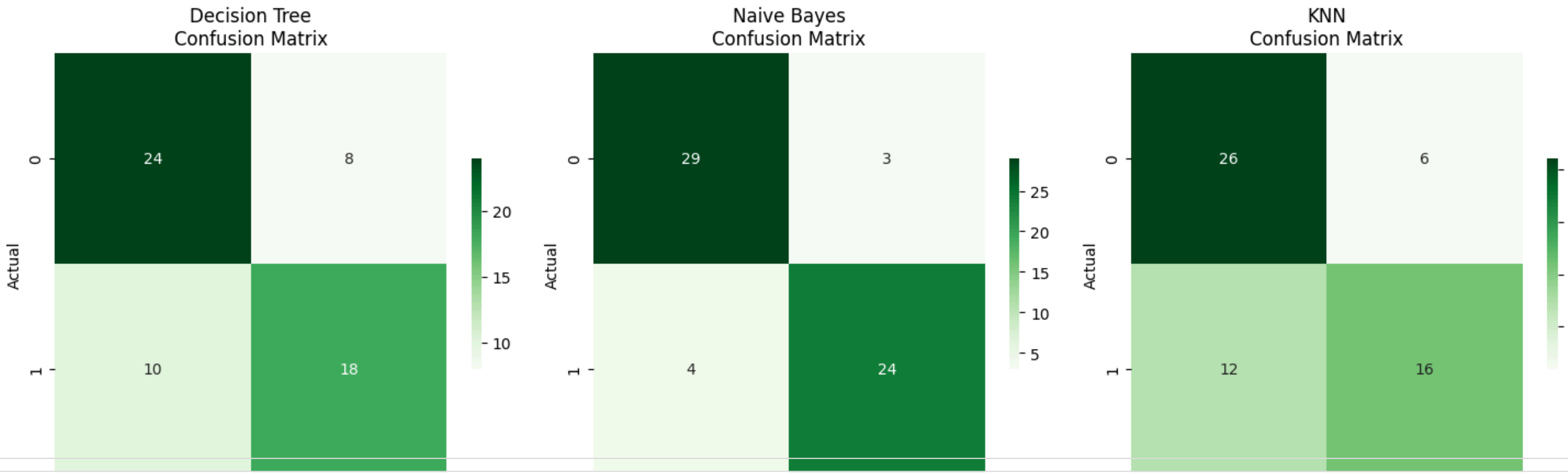
```
print("=== MODEL EVALUATION ===\n")

results = {}

for name, model in trained_models.items():
    y_pred = model.predict(X_test)

    accuracy = accuracy_score(y_test, y_pred)
    precision = precision_score(y_test, y_pred)
    recall = recall_score(y_test, y_pred)
    f1 = f1_score(y_test, y_pred)

    results[name] = {
        'Accuracy': accuracy,
        'Precision': precision,
        'Recall': recall,
        'F1-Score': f1
    }

    print(f"{name} Results:")
    print(f"  Accuracy:  {accuracy:.4f}")
    print(f"  Precision: {precision:.4f}")
    print(f"  Recall:    {recall:.4f}")
    print(f"  F1-Score:  {f1:.4f}")
    print("-" * 30)
```

```
=== MODEL EVALUATION ===

Decision Tree Results:
  Accuracy:  0.7000
  Precision: 0.6923
  Recall:    0.6429
  F1-Score:  0.6667
------------------------------
Naive Bayes Results:
  Accuracy:  0.8833
  Precision: 0.8889
  Recall:    0.8571
  F1-Score:  0.8727
------------------------------
KNN Results:
  Accuracy:  0.7000
  Precision: 0.7273
  Recall:    0.5714
  F1-Score:  0.6400
------------------------------
```

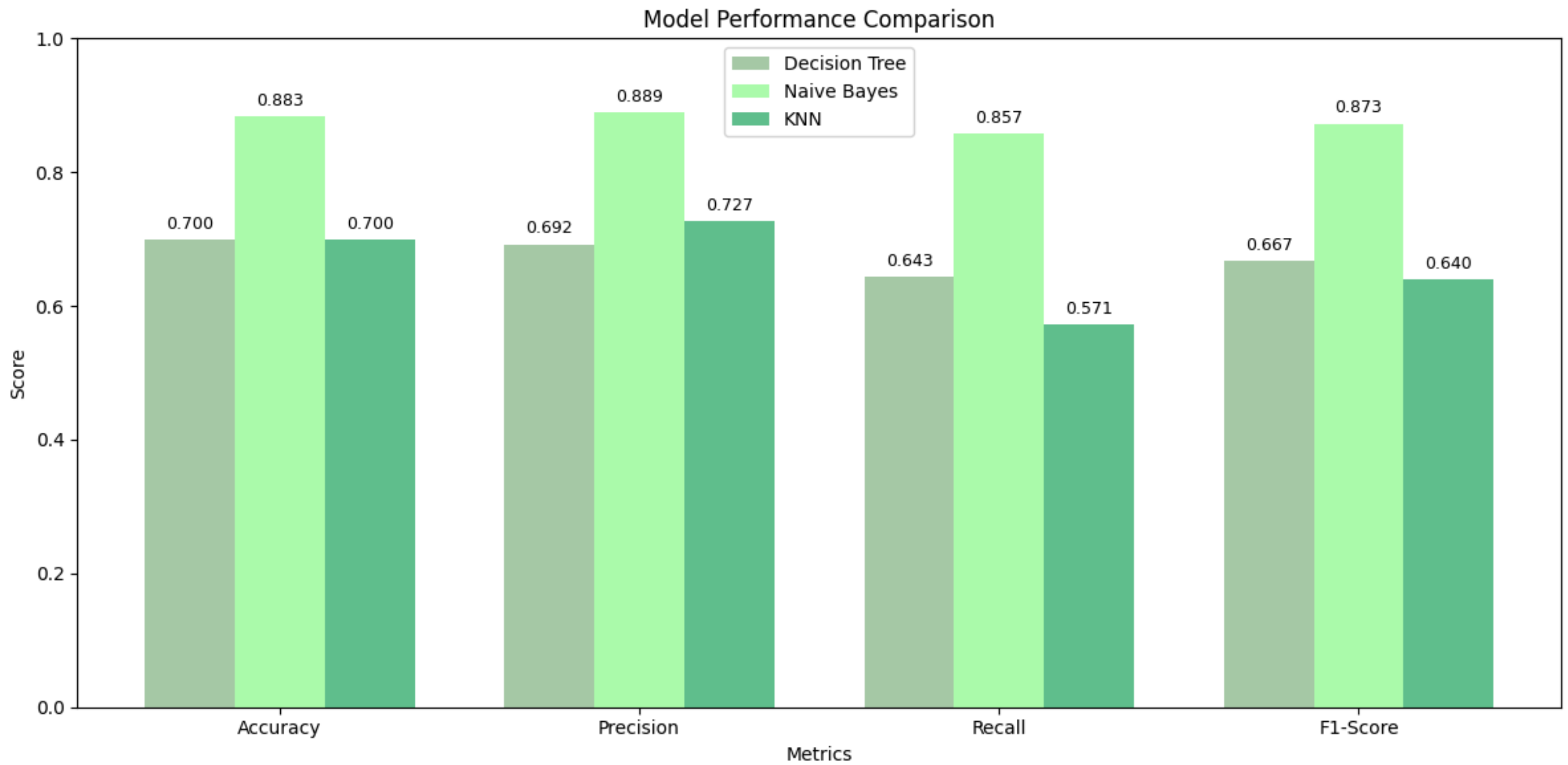
```
results_df = pd.DataFrame(results).T
print("=== MODEL COMPARISON ===")
print(results_df.round(4))

best_model = results_df['Accuracy'].idxmax()
best_accuracy = results_df['Accuracy'].max()
print(f"\nBest performing model: {best_model}")
print(f"Best accuracy: {best_accuracy:.4f}")
```

```
=== MODEL COMPARISON ===
               Accuracy  Precision  Recall  F1-Score
Decision Tree    0.7000     0.6923  0.6429    0.6667
Naive Bayes      0.8833     0.8889  0.8571    0.8727
KNN              0.7000     0.7273  0.5714    0.6400

Best performing model: Naive Bayes
Best accuracy: 0.8833
```

```
fig, axes = plt.subplots(1, 3, figsize=(15, 5))

for i, (name, model) in enumerate(trained_models.items()):
    y_pred = model.predict(X_test)
    cm = confusion_matrix(y_test, y_pred)

    sns.heatmap(cm, annot=True, fmt='d', cmap='Greens',   # 👈 change here
                ax=axes[i], cbar_kws={'shrink': 0.5})
    axes[i].set_title(f'{name}\nConfusion Matrix')
    axes[i].set_xlabel('Predicted')
    axes[i].set_ylabel('Actual')

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




```
metrics = ['Accuracy', 'Precision', 'Recall', 'F1-Score']
x = np.arange(len(metrics))
width = 0.25

fig, ax = plt.subplots(figsize=(12, 6))

colors = ["#8FBC8F", "#98FB98", "#3CB371", "#2E8B57"]

for i, model_name in enumerate(results_df.index):
    values = [results_df.loc[model_name, metric] for metric in metrics]
    ax.bar(x + i * width, values, width, label=model_name,
           alpha=0.8, color=colors[i % len(colors)])

ax.set_xlabel('Metrics')
ax.set_ylabel('Score')
ax.set_title('Model Performance Comparison')
ax.set_xticks(x + width)
ax.set_xticklabels(metrics)
ax.legend()
ax.set_ylim(0, 1)

# Add value labels on bars
for i, model_name in enumerate(results_df.index):
    values = [results_df.loc[model_name, metric] for metric in metrics]
    for j, v in enumerate(values):
        ax.text(j + i * width, v + 0.01, f'{v:.3f}',
                ha='center', va='bottom', fontsize=9)

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




```
from sklearn.model_selection import GridSearchCV

print("=== HYPERPARAMETER TUNING (Optional) ===\n")

# Define parameter grids
param_grids = {
    'Decision Tree': {
        'max_depth': [3, 5, 7, 10],
        'min_samples_split': [2, 5, 10],
        'min_samples_leaf': [1, 2, 4]
    },
    'KNN': {
        'n_neighbors': [3, 5, 7, 9, 11],
        'weights': ['uniform', 'distance'],
        'metric': ['euclidean', 'manhattan']
    }
}

# Tune Decision Tree and KNN (Naive Bayes has fewer hyperparameters)
tuned_models = {}

for name in ['Decision Tree', 'KNN']:
    print(f"Tuning {name}...")
    base_model = DecisionTreeClassifier(random_state=42) if name == 'Decision Tree' else KNeighborsClassifier()
```

```
        grid_search = GridSearchCV(
            base_model, param_grids[name],
            cv=5, scoring='accuracy', n_jobs=-1
        )
        grid_search.fit(X_train, y_train)

        tuned_models[name] = grid_search.best_estimator_
        print(f"Best parameters for {name}: {grid_search.best_params_}")
        print(f"Best CV score: {grid_search.best_score_:.4f}")
        print("-" * 40)

    print("✓ Hyperparameter tuning completed!")
```

```
=== HYPERPARAMETER TUNING (Optional) ===

Tuning Decision Tree...
Best parameters for Decision Tree: {'max_depth': 3, 'min_samples_leaf': 1, 'min_samples_split': 2}
Best CV score: 0.8012
----------------------------------------
Tuning KNN...
Best parameters for KNN: {'metric': 'manhattan', 'n_neighbors': 5, 'weights': 'distance'}
Best CV score: 0.6960
----------------------------------------
✓ Hyperparameter tuning completed!
```

```
print("=== FINAL ANALYSIS AND CONCLUSIONS ===\n")

# Evaluate tuned models if available
if 'tuned_models' in locals() and tuned_models: # Added check for tuned_models
    print("Comparing original vs tuned models:")

    for name in tuned_models.keys():
        # Original model performance
        original_pred = trained_models[name].predict(X_test)
        original_acc = accuracy_score(y_test, original_pred)

        # Tuned model performance
        tuned_pred = tuned_models[name].predict(X_test)
        tuned_acc = accuracy_score(y_test, tuned_pred)

        print(f"{name}:")
        print(f"  Original accuracy: {original_acc:.4f}")
        print(f"  Tuned accuracy:    {tuned_acc:.4f}")
        print(f"  Improvement:       {tuned_acc - original_acc:.4f}")
        print("-" * 30)
else:
    print("No tuned models available for comparison.") # Added else statement

# Analysis of which model performs better and why
print("\nMODEL ANALYSIS:")
print("1. Performance Ranking:")
sorted_models = results_df.sort_values('Accuracy', ascending=False)
for i, (model, row) in enumerate(sorted_models.iterrows(), 1):
    print(f"   {i}. {model}: {row['Accuracy']:.4f} accuracy")

print(f"\n2. Best Model Analysis:")
```

```python
best_model = results_df['Accuracy'].idxmax()
print(f"   {best_model} performed best because:")

if best_model == 'KNN':
    print("   - KNN captures local patterns well in medical data")
    print("   - Instance-based learning works well for heart disease features")
    print("   - Can handle non-linear relationships effectively")
elif best_model == 'Decision Tree':
    print("   - Decision trees handle feature interactions well")
    print("   - Provides interpretable rules for medical diagnosis")
    print("   - Can capture non-linear patterns in the data")
else:
    print("   - Naive Bayes works well when feature independence holds")
    print("   - Computationally efficient and robust")
    print("   - Good baseline performance on medical data")
```

```
=== FINAL ANALYSIS AND CONCLUSIONS ===

Comparing original vs tuned models:
Decision Tree:
  Original accuracy: 0.7000
  Tuned accuracy:    0.8000
  Improvement:       0.1000
------------------------------
KNN:
  Original accuracy: 0.7000
  Tuned accuracy:    0.7500
  Improvement:       0.0500
------------------------------

MODEL ANALYSIS:
1. Performance Ranking:
   1. Naive Bayes: 0.8833 accuracy
   2. Decision Tree: 0.7000 accuracy
   3. KNN: 0.7000 accuracy

2. Best Model Analysis:
   Naive Bayes performed best because:
   - Naive Bayes works well when feature independence holds
   - Computationally efficient and robust
   - Good baseline performance on medical data
```