DS-2: Heart-Disease Prediction

Task vii – Automated Feature Extraction & Classification

Dataset `DS2.csv`
Goal: Predict `target` (1 = disease, 0 = healthy)

Feature-extraction techniques

1. **PCA** – linear, variance-preserving
2. **t-SNE** – non-linear, manifold-learning (mainly for visual insight, but we'll still feed its low-dim representations to classifiers)

Classifiers

- Logistic Regression (baseline linear)
- Random Forest (non-linear, ensemble)

We'll report **accuracy, precision, recall, F1, confusion-matrix** for each (technique × model) combination.

```
# 1 Environment & libraries
import pandas as pd
import numpy as np
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import StandardScaler, OneHotEncoder
from sklearn.compose import ColumnTransformer
from sklearn.pipeline import Pipeline
from sklearn.decomposition import PCA
from sklearn.manifold import TSNE
from sklearn.linear_model import LogisticRegression
from sklearn.ensemble import RandomForestClassifier
from sklearn.metrics import (accuracy_score, precision_score, recall_score,
                             f1_score, confusion_matrix, classification_report)
import matplotlib.pyplot as plt
import seaborn as sns   # optional, for prettier matrices
RANDOM_STATE = 42
```

2 Load the data

```
df = pd.read_csv('/content/DS2.csv')  # adjust path if needed
display(df.head())
print(f'Shape: {df.shape}')
```

	age	sex	cp	trestbps	chol	fbs	restecg	thalach	exang	oldpeak	slope	ca	thal	target
0	63.0	1.0	1.0	145.0	233.0	1.0	2.0	150.0	0.0	2.3	3.0	0.0	6.0	0
1	67.0	1.0	4.0	160.0	286.0	0.0	2.0	108.0	1.0	1.5	2.0	3.0	3.0	2
2	67.0	1.0	4.0	120.0	229.0	0.0	2.0	129.0	1.0	2.6	2.0	2.0	7.0	1
3	37.0	1.0	3.0	130.0	250.0	0.0	0.0	187.0	0.0	3.5	3.0	0.0	3.0	0
4	41.0	0.0	2.0	130.0	204.0	0.0	2.0	172.0	0.0	1.4	1.0	0.0	3.0	0

```
Shape: (303, 14)
```

2.1 Quick sanity checks

```
print(df.info())
print(df.isna().sum())
print(df['target'].value_counts())
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 303 entries, 0 to 302
Data columns (total 14 columns):
 #   Column    Non-Null Count  Dtype  
---  ------    --------------  -----  
 0   age       303 non-null    float64
 1   sex       303 non-null    float64
 2   cp        303 non-null    float64
 3   trestbps  303 non-null    float64
 4   chol      303 non-null    float64
 5   fbs       303 non-null    float64
 6   restecg   303 non-null    float64
 7   thalach   303 non-null    float64
```

```
 8   exang     303 non-null    float64
 9   oldpeak   303 non-null    float64
 10  slope     303 non-null    float64
 11  ca        303 non-null    object
 12  thal      303 non-null    object
 13  target    303 non-null    int64
dtypes: float64(11), int64(1), object(2)
memory usage: 33.3+ KB
None
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
target
0    164
1     55
2     36
3     35
4     13
Name: count, dtype: int64
```

3 Pre-processing pipeline

- **Numeric** → StandardScaler
- **Categorical** → OneHotEncoder
  The target column is `target`; all others are features.

```
target_col = 'target'
X = df.drop(columns=[target_col])
y = df[target_col]

numeric_cols = X.select_dtypes(include=['int64', 'float64']).columns.tolist()
categorical_cols = X.select_dtypes(include=['object', 'category']).columns.tolist()

preprocess = ColumnTransformer(
    transformers=[
        ('num', StandardScaler(), numeric_cols),
        ('cat', OneHotEncoder(handle_unknown='ignore'), categorical_cols)
    ]
)

X.head(20)
```

	age	sex	cp	trestbps	chol	fbs	restecg	thalach	exang	oldpeak	slope	ca	thal
0	63.0	1.0	1.0	145.0	233.0	1.0	2.0	150.0	0.0	2.3	3.0	0.0	6.0
1	67.0	1.0	4.0	160.0	286.0	0.0	2.0	108.0	1.0	1.5	2.0	3.0	3.0
2	67.0	1.0	4.0	120.0	229.0	0.0	2.0	129.0	1.0	2.6	2.0	2.0	7.0
3	37.0	1.0	3.0	130.0	250.0	0.0	0.0	187.0	0.0	3.5	3.0	0.0	3.0
4	41.0	0.0	2.0	130.0	204.0	0.0	2.0	172.0	0.0	1.4	1.0	0.0	3.0
5	56.0	1.0	2.0	120.0	236.0	0.0	0.0	178.0	0.0	0.8	1.0	0.0	3.0
6	62.0	0.0	4.0	140.0	268.0	0.0	2.0	160.0	0.0	3.6	3.0	2.0	3.0
7	57.0	0.0	4.0	120.0	354.0	0.0	0.0	163.0	1.0	0.6	1.0	0.0	3.0
8	63.0	1.0	4.0	130.0	254.0	0.0	2.0	147.0	0.0	1.4	2.0	1.0	7.0
9	53.0	1.0	4.0	140.0	203.0	1.0	2.0	155.0	1.0	3.1	3.0	0.0	7.0
10	57.0	1.0	4.0	140.0	192.0	0.0	0.0	148.0	0.0	0.4	2.0	0.0	6.0
11	56.0	0.0	2.0	140.0	294.0	0.0	2.0	153.0	0.0	1.3	2.0	0.0	3.0
12	56.0	1.0	3.0	130.0	256.0	1.0	2.0	142.0	1.0	0.6	2.0	1.0	6.0
13	44.0	1.0	2.0	120.0	263.0	0.0	0.0	173.0	0.0	0.0	1.0	0.0	7.0
14	52.0	1.0	3.0	172.0	199.0	1.0	0.0	162.0	0.0	0.5	1.0	0.0	7.0
15	57.0	1.0	3.0	150.0	168.0	0.0	0.0	174.0	0.0	1.6	1.0	0.0	3.0
16	48.0	1.0	2.0	110.0	229.0	0.0	0.0	168.0	0.0	1.0	3.0	0.0	7.0
17	54.0	1.0	4.0	140.0	239.0	0.0	0.0	160.0	0.0	1.2	1.0	0.0	3.0
18	48.0	0.0	3.0	130.0	275.0	0.0	0.0	139.0	0.0	0.2	1.0	0.0	3.0
19	49.0	1.0	2.0	130.0	266.0	0.0	0.0	171.0	0.0	0.6	1.0	0.0	3.0

Next steps: Generate code with X | View recommended plots | New interactive sheet

4 Train-test split (80 / 20)

```
X_train, X_test, y_train, y_test = train_test_split(
    X, y, test_size=0.2, random_state=RANDOM_STATE, stratify=y
)
print(f'Train: {X_train.shape}, Test: {X_test.shape}')
```

```
Train: (242, 13), Test: (61, 13)
```

5 Feature Extraction 🔧 — **PCA**

We'll keep enough components to explain **95 % variance** (you can tweak).

```
pca = PCA(n_components=0.95, random_state=RANDOM_STATE)

pca_pipe = Pipeline(steps=[
    ('pre', preprocess),
    ('pca', pca)
])

X_train_pca = pca_pipe.fit_transform(X_train)
X_test_pca  = pca_pipe.transform(X_test)

print(f'PCA components chosen: {pca.n_components_}')
```

```
PCA components chosen: 12
```

6 Classification on PCA features

```
models = {
    'LogReg':  LogisticRegression(max_iter=1000, random_state=RANDOM_STATE),
    'RF':      RandomForestClassifier(n_estimators=300, random_state=RANDOM_STATE)
}

def evaluate(name, clf, X_tr, X_te):
```

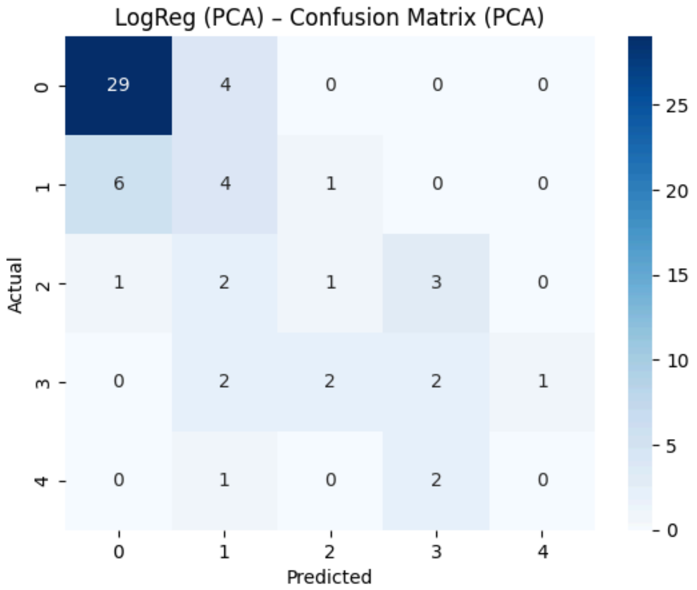
```
        clf.fit(X_tr, y_train)
        y_pred = clf.predict(X_te)
        print(f'\n=== {name} ===')
        print(f'Accuracy : {accuracy_score(y_test, y_pred):.4f}')



        cm = confusion_matrix(y_test, y_pred)
        sns.heatmap(cm, annot=True, fmt='d', cmap='Blues')
        plt.title(f'{name} – Confusion Matrix (PCA)')
        plt.xlabel('Predicted'); plt.ylabel('Actual')
        plt.show()

    for name, clf in models.items():
        evaluate(f'{name} (PCA)', clf, X_train_pca, X_test_pca)
```

```
=== LogReg (PCA) ===
Accuracy : 0.5902
```




```
=== RF (PCA) ===
Accuracy : 0.5902
```