AI and ML task 7

importing libraries

In [1]:
```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
sns.set()
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import LabelEncoder, StandardScaler
from sklearn.svm import SVC
from sklearn.metrics import accuracy_score, classification_report
```

In [2]:
```
data = pd.read_csv("breast-cancer.csv")
```

In [3]:
```
data
```

Out[3]:

	id	diagnosis	radius_mean	texture_mean	perimeter_mean	area_mean	smoothness_mean	compactness_mean	concavity_mean	concave points_mean	...	radius_worst	texture_worst	perimeter_worst	area_worst	smoothness_worst
0	842302	M	17.99	10.38	122.80	1001.0	0.11840	0.27760	0.30010	0.14710	...	25.380	17.33	184.60	2019.0	0.16220
1	842517	M	20.57	17.77	132.90	1326.0	0.08474	0.07864	0.08690	0.07017	...	24.990	23.41	158.80	1956.0	0.12380
2	84300903	M	19.69	21.25	130.00	1203.0	0.10960	0.15990	0.19740	0.12790	...	23.570	25.53	152.50	1709.0	0.14440
3	84348301	M	11.42	20.38	77.58	386.1	0.14250	0.28390	0.24140	0.10520	...	14.910	26.50	98.87	567.7	0.20980
4	84358402	M	20.29	14.34	135.10	1297.0	0.10030	0.13280	0.19800	0.10430	...	22.540	16.67	152.20	1575.0	0.13740
...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...
564	926424	M	21.56	22.39	142.00	1479.0	0.11100	0.11590	0.24390	0.13890	...	25.450	26.40	166.10	2027.0	0.14100
565	926682	M	20.13	28.25	131.20	1261.0	0.09780	0.10340	0.14400	0.09791	...	23.690	38.25	155.00	1731.0	0.11660
566	926954	M	16.60	28.08	108.30	858.1	0.08455	0.10230	0.09251	0.05302	...	18.980	34.12	126.70	1124.0	0.11390
567	927241	M	20.60	29.33	140.10	1265.0	0.11780	0.27700	0.35140	0.15200	...	25.740	39.42	184.60	1821.0	0.16500
568	92751	B	7.76	24.54	47.92	181.0	0.05263	0.04362	0.00000	0.00000	...	9.456	30.37	59.16	268.6	0.08996

569 rows × 32 columns

In [4]:
```
data.shape
```

Out[4]:
```
(569, 32)
```

In [5]:
```
data.head()
```

Out[5]:

	id	diagnosis	radius_mean	texture_mean	perimeter_mean	area_mean	smoothness_mean	compactness_mean	concavity_mean	concave points_mean	...	radius_worst	texture_worst	perimeter_worst	area_worst	smoothness_worst	c
0	842302	M	17.99	10.38	122.80	1001.0	0.11840	0.27760	0.3001	0.14710	...	25.38	17.33	184.60	2019.0	0.1622	
1	842517	M	20.57	17.77	132.90	1326.0	0.08474	0.07864	0.0869	0.07017	...	24.99	23.41	158.80	1956.0	0.1238	
2	84300903	M	19.69	21.25	130.00	1203.0	0.10960	0.15990	0.1974	0.12790	...	23.57	25.53	152.50	1709.0	0.1444	
3	84348301	M	11.42	20.38	77.58	386.1	0.14250	0.28390	0.2414	0.10520	...	14.91	26.50	98.87	567.7	0.2098	
4	84358402	M	20.29	14.34	135.10	1297.0	0.10030	0.13280	0.1980	0.10430	...	22.54	16.67	152.20	1575.0	0.1374	

5 rows × 32 columns

In [6]:
```
data.describe()
```

Out[6]:

	id	radius_mean	texture_mean	perimeter_mean	area_mean	smoothness_mean	compactness_mean	concavity_mean	concave points_mean	symmetry_mean	...	radius_worst	texture_worst	perimeter_worst	area_worst	sm
count	5.690000e+02	569.000000	569.000000	569.000000	569.000000	569.000000	569.000000	569.000000	569.000000	569.000000	...	569.000000	569.000000	569.000000	569.000000	569.000000
mean	3.037183e+07	14.127292	19.289649	91.969033	654.889104	0.096360	0.104341	0.088799	0.048919	0.181162	...	16.269190	25.677223	107.261213	880.583128	
std	1.250206e+08	3.524049	4.301036	24.298981	351.914129	0.014064	0.052813	0.079720	0.038803	0.027414	...	4.833242	6.146258	33.602542	569.356993	
min	8.670000e+03	6.981000	9.710000	43.790000	143.500000	0.052630	0.019300	0.000000	0.000000	0.106000	...	7.930000	12.020000	50.410000	185.200000	
25%	8.692180e+05	11.700000	16.170000	75.170000	420.300000	0.086370	0.064920	0.029560	0.020310	0.161900	...	13.010000	21.080000	84.110000	515.300000	
50%	9.060240e+05	13.370000	18.840000	86.240000	551.100000	0.095870	0.092630	0.061540	0.033500	0.179200	...	14.970000	25.410000	97.660000	686.500000	
75%	8.813129e+06	15.780000	21.800000	104.100000	782.700000	0.105300	0.130400	0.130700	0.074000	0.195700	...	16.790000	29.720000	125.400000	1084.000000	
max	9.113205e+08	28.110000	39.280000	188.500000	2501.000000	0.163400	0.345400	0.426800	0.201200	0.304000	...	36.040000	49.540000	251.200000	4254.000000	

8 rows × 31 columns

In [7]:
```
data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 569 entries, 0 to 568
Data columns (total 32 columns):
 #   Column                   Non-Null Count  Dtype
---  ------                   --------------  -----
 0   id                       569 non-null    int64
 1   diagnosis                569 non-null    object
 2   radius_mean              569 non-null    float64
 3   texture_mean             569 non-null    float64
 4   perimeter_mean           569 non-null    float64
 5   area_mean                569 non-null    float64
 6   smoothness_mean          569 non-null    float64
 7   compactness_mean         569 non-null    float64
 8   concavity_mean           569 non-null    float64
 9   concave points_mean      569 non-null    float64
 10  symmetry_mean            569 non-null    float64
 11  fractal_dimension_mean   569 non-null    float64
 12  radius_se                569 non-null    float64
 13  texture_se               569 non-null    float64
 14  perimeter_se             569 non-null    float64
 15  area_se                  569 non-null    float64
 16  smoothness_se            569 non-null    float64
 17  compactness_se           569 non-null    float64
 18  concavity_se             569 non-null    float64
 19  concave points_se        569 non-null    float64
 20  symmetry_se              569 non-null    float64
 21  fractal_dimension_se     569 non-null    float64
 22  radius_worst             569 non-null    float64
 23  texture_worst            569 non-null    float64
 24  perimeter_worst          569 non-null    float64
 25  area_worst               569 non-null    float64
 26  smoothness_worst         569 non-null    float64
 27  compactness_worst        569 non-null    float64
 28  concavity_worst          569 non-null    float64
 29  concave points_worst     569 non-null    float64
 30  symmetry_worst           569 non-null    float64
 31  fractal_dimension_worst  569 non-null    float64
dtypes: float64(30), int64(1), object(1)
memory usage: 142.4+ KB
```

In [8]:
```
data.isnull().sum()
```

Out[8]:
```
id                         0
diagnosis                  0
radius_mean                0
texture_mean               0
perimeter_mean             0
area_mean                  0
smoothness_mean            0
compactness_mean           0
concavity_mean             0
concave points_mean        0
symmetry_mean              0
fractal_dimension_mean     0
radius_se                  0
texture_se                 0
perimeter_se               0
area_se                    0
smoothness_se              0
compactness_se             0
concavity_se               0
concave points_se          0
symmetry_se                0
fractal_dimension_se       0
radius_worst               0
texture_worst              0
perimeter_worst            0
area_worst                 0
smoothness_worst           0
compactness_worst          0
concavity_worst            0
concave points_worst       0
symmetry_worst             0
fractal_dimension_worst    0
dtype: int64
```

preparing dataset for binary classification

In [9]:
```
le = LabelEncoder()
data['diagnosis'] = le.fit_transform(data['diagnosis'])
```

In [10]:
```
X = data.drop('diagnosis', axis=1)
y = data['diagnosis']
```

In [11]:
```
scaler = StandardScaler()
X_scaled = scaler.fit_transform(X)
```

In [12]:
```
X_train, X_test, y_train, y_test = train_test_split(
    X_scaled, y, test_size=0.2, random_state=42
)
```

train svm with linear and rbf kernel

In [13]:
```
# SVM with linear kernel
svm_linear = SVC(kernel='linear', C=1.0, random_state=42)
svm_linear.fit(X_train, y_train)
y_pred_linear = svm_linear.predict(X_test)

# Train SVM with RBF kernel
svm_rbf = SVC(kernel='rbf', C=1.0, gamma='scale', random_state=42)
svm_rbf.fit(X_train, y_train)
y_pred_rbf = svm_rbf.predict(X_test)
```

In [14]:
```
# Evaluation
print("SVM with Linear Kernel:")
print("Accuracy:", accuracy_score(y_test, y_pred_linear))
print(classification_report(y_test, y_pred_linear))

print("\nSVM with RBF Kernel:")
print("Accuracy:", accuracy_score(y_test, y_pred_rbf))
print(classification_report(y_test, y_pred_rbf))
```

```
SVM with Linear Kernel:
Accuracy: 0.9561403508771931
              precision    recall  f1-score   support

           0       0.97      0.96      0.96        71
           1       0.93      0.95      0.94        43

    accuracy                           0.96       114
   macro avg       0.95      0.96      0.95       114
weighted avg       0.96      0.96      0.96       114


SVM with RBF Kernel:
Accuracy: 0.9824561403508771
              precision    recall  f1-score   support

           0       0.97      1.00      0.99        71
           1       1.00      0.95      0.98        43

    accuracy                           0.98       114
   macro avg       0.99      0.98      0.98       114
weighted avg       0.98      0.98      0.98       114
```

Visualize decision boundary using 2D data.

In [15]:
```
from sklearn.decomposition import PCA
```

In [16]:
```
# Reduce features to 2D using PCA
pca = PCA(n_components=2)
X_train_2D = pca.fit_transform(X_train)
X_test_2D = pca.transform(X_test)
```

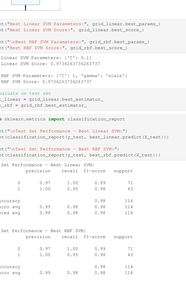
In [17]:
```
# Train new SVMs on 2D data
svm_linear_2D = SVC(kernel='linear', C=1.0).fit(X_train_2D, y_train)
svm_rbf_2D = SVC(kernel='rbf', C=1.0, gamma='scale').fit(X_train_2D, y_train)

def plot_decision_boundary(model, X, y, title):
    h = 0.02  # step size in the mesh
    x_min, x_max = X[:, 0].min() - 1, X[:, 0].max() + 1
    y_min, y_max = X[:, 1].min() - 1, X[:, 1].max() + 1
    xx, yy = np.meshgrid(np.arange(x_min, x_max, h),
                         np.arange(y_min, y_max, h))

    Z = model.predict(np.c_[xx.ravel(), yy.ravel()])
    Z = Z.reshape(xx.shape)

    plt.figure(figsize=(6, 5))
    plt.contourf(xx, yy, Z, alpha=0.3, cmap=plt.cm.coolwarm)
    plt.scatter(X[:, 0], X[:, 1], c=y, edgecolors='k', cmap=plt.cm.coolwarm)
    plt.title(title)
    plt.xlabel("Principal Component 1")
    plt.ylabel("Principal Component 2")
    plt.tight_layout()
    plt.show()
```

In [18]:
```
plot_decision_boundary(svm_linear_2D, X_train_2D, y_train, "SVM Linear Kernel (2D PCA)")
plot_decision_boundary(svm_rbf_2D, X_train_2D, y_train, "SVM RBF Kernel (2D PCA)")
```



Tune hyperparameters like C and gamma.

In [19]:
```
from sklearn.model_selection import GridSearchCV
```

In [20]:
```
# Define parameter grids
param_grid_linear = {
    'C': [0.01, 0.1, 1, 10, 100]
}

param_grid_rbf = {
    'C': [0.1, 1, 10, 100],
    'gamma': [0.01, 0.1, 1, 'scale', 'auto']
}
```

In [21]:
```
# SVM with linear kernel
grid_linear = GridSearchCV(SVC(kernel='linear'), param_grid_linear, cv=5, scoring='accuracy')
grid_linear.fit(X_train, y_train)
```

Out[21]:
```
GridSearchCV
 best_estimator_: SVC
     SVC
```

In [22]:
```
# SVM with RBF kernel
grid_rbf = GridSearchCV(SVC(kernel='rbf'), param_grid_rbf, cv=5, scoring='accuracy')
grid_rbf.fit(X_train, y_train)
```

Out[22]:
```
GridSearchCV
 best_estimator_: SVC
     SVC
```

In [23]:
```
print("Best Linear SVM Parameters:", grid_linear.best_params_)
print("Best Linear SVM Score:", grid_linear.best_score_)

print("\nBest RBF SVM Parameters:", grid_rbf.best_params_)
print("Best RBF SVM Score:", grid_rbf.best_score_)
```

```
Best Linear SVM Parameters: {'C': 0.1}
Best Linear SVM Score: 0.9742637362637363

Best RBF SVM Parameters: {'C': 1, 'gamma': 'scale'}
Best RBF SVM Score: 0.9736263736263737
```

In [24]:
```
# Evaluate on test set
best_linear = grid_linear.best_estimator_
best_rbf = grid_rbf.best_estimator_
```

In [25]:
```
from sklearn.metrics import classification_report

print("\nTest Set Performance - Best Linear SVM:")
print(classification_report(y_test, best_linear.predict(X_test)))

print("\nTest Set Performance - Best RBF SVM:")
print(classification_report(y_test, best_rbf.predict(X_test)))
```

```
Test Set Performance - Best Linear SVM:
              precision    recall  f1-score   support

           0       0.97      1.00      0.99        71
           1       1.00      0.95      0.98        43

    accuracy                           0.98       114
   macro avg       0.99      0.98      0.98       114
weighted avg       0.98      0.98      0.98       114


Test Set Performance - Best RBF SVM:
              precision    recall  f1-score   support

           0       0.97      1.00      0.99        71
           1       1.00      0.95      0.98        43

    accuracy                           0.98       114
   macro avg       0.99      0.98      0.98       114
weighted avg       0.98      0.98      0.98       114
```

```
weighted avg       0.98      0.98      0.98      114

In [ ]:
```