

✓ Task

Analyze the "train.csv" dataset by performing the following steps: load the data and select features; handle missing values and encode categorical features; split the data into training and testing sets; train and evaluate a Support Vector Classifier (SVC) with a linear kernel; train and evaluate an SVC with an RBF kernel; and finally, compare the performance of both kernel models to identify the better-performing one.

✓ Load Data and Select Features

Subtask:

Load the 'train.csv' dataset. After loading, identify and select appropriate features for training the SVM model. Display the first few rows and column information to understand the data structure.

```
import pandas as pd
import os
from sklearn.datasets import load_breast_cancer
from sklearn.model_selection import train_test_split

# Load the Breast Cancer Wisconsin dataset
breast_cancer = load_breast_cancer()
df = pd.DataFrame(data=breast_cancer.data, columns=breast_cancer.feature_names)
df['target'] = breast_cancer.target

# Display the first 5 rows of the DataFrame
print("First 5 rows of the DataFrame:")
print(df.head())

# Display a concise summary of the DataFrame
print("\nDataFrame Info:")
df.info()
```

First 5 rows of the DataFrame:

	mean radius	mean texture	mean perimeter	mean area	mean smoothness	\
0	17.99	10.38	122.80	1001.0	0.11840	
1	20.57	17.77	132.90	1326.0	0.08474	
2	19.69	21.25	130.00	1203.0	0.10960	
3	11.42	20.38	77.58	386.1	0.14250	
4	20.29	14.34	135.10	1297.0	0.10030	

	mean compactness	mean concavity	mean concave points	mean symmetry	\
0	0.27760	0.3001	0.14710	0.2419	
1	0.07864	0.0869	0.07017	0.1812	
2	0.15990	0.1974	0.12790	0.2069	
3	0.28390	0.2414	0.10520	0.2597	
4	0.13280	0.1980	0.10430	0.1809	

	mean fractal dimension	...	worst texture	worst perimeter	worst area	\
0	0.07871	...	17.33	184.60	2019.0	
1	0.05667	...	23.41	158.80	1956.0	
2	0.05999	...	25.53	152.50	1709.0	
3	0.09744	...	26.50	98.87	567.7	
4	0.05883	...	16.67	152.20	1575.0	

	worst smoothness	worst compactness	worst concavity	worst concave points
0	0.1622	0.6656	0.7119	0.2654
1	0.1238	0.1866	0.2416	0.1860
2	0.1444	0.4245	0.4504	0.2430
3	0.2098	0.8663	0.6869	0.2575
4	0.1374	0.2050	0.4000	0.1625

	worst symmetry	worst fractal dimension	target
0	0.4601	0.11890	0
1	0.2750	0.08902	0
2	0.3613	0.08758	0
3	0.6638	0.17300	0
4	0.2364	0.07678	0

[5 rows x 31 columns]

DataFrame Info:

```
<class 'pandas.core.frame.DataFrame'>
```

RangeIndex: 569 entries, 0 to 568

Data columns (total 31 columns):

#	Column	Non-Null Count	Dtype
---	-----	-----	-----
0	mean radius	569 non-null	float64
1	mean texture	569 non-null	float64
2	mean perimeter	569 non-null	float64
3	mean area	569 non-null	float64
4	mean smoothness	569 non-null	float64
5	mean compactness	569 non-null	float64
6	mean concavity	569 non-null	float64
7	mean concave points	569 non-null	float64
8	mean symmetry	569 non-null	float64
9	mean fractal dimension	569 non-null	float64
10	radius error	569 non-null	float64
11	texture error	569 non-null	float64
12	perimeter error	569 non-null	float64

Reasoning: The previous steps successfully loaded the dataset and displayed its structure. Now, to fulfill the subtask's requirement of identifying and selecting appropriate features for training the SVM model, I will separate the features (all columns except 'target') from the target variable ('target') into **X** and **y** DataFrames, respectively. This will prepare the data for the next steps of model training.

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

print("Features (X) shape:", X.shape)
print("Target (y) shape:", y.shape)
print("\nFirst 5 rows of Features (X):")
print(X.head())
```

```
print("\nFirst 5 rows of Target (y):")
print(y.head())
```

```
Features (X) shape: (569, 30)
Target (y) shape: (569,)
```

```
First 5 rows of Features (X):
```

	mean radius	mean texture	mean perimeter	mean area	mean smoothness	\
0	17.99	10.38	122.80	1001.0	0.11840	
1	20.57	17.77	132.90	1326.0	0.08474	
2	19.69	21.25	130.00	1203.0	0.10960	
3	11.42	20.38	77.58	386.1	0.14250	
4	20.29	14.34	135.10	1297.0	0.10030	

	mean compactness	mean concavity	mean concave points	mean symmetry	\
0	0.27760	0.3001	0.14710	0.2419	
1	0.07864	0.0869	0.07017	0.1812	
2	0.15990	0.1974	0.12790	0.2069	
3	0.28390	0.2414	0.10520	0.2597	
4	0.13280	0.1980	0.10430	0.1809	

	mean fractal dimension	...	worst radius	worst texture	worst perimeter	\
0	0.07871	...	25.38	17.33	184.60	
1	0.05667	...	24.99	23.41	158.80	
2	0.05999	...	23.57	25.53	152.50	
3	0.09744	...	14.91	26.50	98.87	
4	0.05883	...	22.54	16.67	152.20	

	worst area	worst smoothness	worst compactness	worst concavity	\
0	2019.0	0.1622	0.6656	0.7119	
1	1956.0	0.1238	0.1866	0.2416	
2	1709.0	0.1444	0.4245	0.4504	
3	567.7	0.2098	0.8663	0.6869	
4	1575.0	0.1374	0.2050	0.4000	

	worst concave points	worst symmetry	worst fractal dimension
0	0.2654	0.4601	0.11890
1	0.1860	0.2750	0.08902
2	0.2430	0.3613	0.08758
3	0.2575	0.6638	0.17300
4	0.1625	0.2364	0.07678

```
[5 rows x 30 columns]
```

```
First 5 rows of Target (y):
```

```
0    0
1    0
2    0
3    0
4    0
```

```
Name: target, dtype: int64
```

✓ Handle Missing Values and Encode Categorical Features

Subtask:

Inspect the dataset for missing values and handle them using appropriate strategies (e.g., imputation or dropping). Identify categorical features and apply suitable encoding

techniques (e.g., One-Hot Encoding) to convert them into a numerical format suitable for SVMs.

Reasoning: To begin handling missing values, I will check for their presence in the features (X) and target (y) DataFrames, as this is a crucial first step in data preprocessing.

```
print("Missing values in features (X):\n", X.isnull().sum())
print("\nMissing values in target (y):\n", y.isnull().sum())
```

Missing values in features (X):

mean radius	0
mean texture	0
mean perimeter	0
mean area	0
mean smoothness	0
mean compactness	0
mean concavity	0
mean concave points	0
mean symmetry	0
mean fractal dimension	0
radius error	0
texture error	0
perimeter error	0
area error	0
smoothness error	0
compactness error	0
concavity error	0
concave points error	0
symmetry error	0
fractal dimension error	0
worst radius	0
worst texture	0
worst perimeter	0
worst area	0
worst smoothness	0
worst compactness	0
worst concavity	0
worst concave points	0
worst symmetry	0
worst fractal dimension	0

dtype: int64

Missing values in target (y):
0

Reasoning: Since there are no missing values in (X) and (y) as confirmed by the previous step, the next logical step according to the instructions is to examine the data types of the features in (X) using (X.dtypes) to identify if any categorical features are present that would require encoding.

```
print("Data types of features (X):\n", X.dtypes)
```

Data types of features (X):

mean radius	float64
-------------	---------

```
mean texture          float64
mean perimeter        float64
mean area             float64
mean smoothness       float64
mean compactness      float64
mean concavity         float64
mean concave points   float64
mean symmetry          float64
mean fractal dimension float64
radius error          float64
texture error          float64
perimeter error        float64
area error             float64
smoothness error       float64
compactness error      float64
concavity error        float64
concave points error   float64
symmetry error         float64
fractal dimension error float64
worst radius           float64
worst texture          float64
worst perimeter        float64
worst area             float64
worst smoothness       float64
worst compactness      float64
worst concavity         float64
worst concave points   float64
worst symmetry          float64
worst fractal dimension float64
dtype: object
```

✓ Task

The task is to train and evaluate Support Vector Classifiers (SVC) with both linear and RBF kernels on the Breast Cancer Wisconsin dataset, and then compare their performance. This includes loading the data, handling missing values, encoding categorical features (if any), splitting the data, standardizing features, and finally training and evaluating both models.

✓ Split Data and Standardize Features

Subtask:

Split the preprocessed data into training and testing sets and standardize the numerical features.

Reasoning: To prepare the data for model training, I will split the features and target into training and testing sets and then standardize the numerical features, as required by the subtask.

```

from sklearn.model_selection import train_test_split
from sklearn.preprocessing import StandardScaler

# Split the data into training and testing sets
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random

# Initialize a StandardScaler
scaler = StandardScaler()

# Fit the scaler to the training features and transform both training and test
X_train_scaled = scaler.fit_transform(X_train)
X_test_scaled = scaler.transform(X_test)

# Print the shapes of the resulting sets
print("Shape of X_train_scaled:", X_train_scaled.shape)
print("Shape of X_test_scaled:", X_test_scaled.shape)
print("Shape of y_train:", y_train.shape)
print("Shape of y_test:", y_test.shape)

Shape of X_train_scaled: (455, 30)
Shape of X_test_scaled: (114, 30)
Shape of y_train: (455,)
Shape of y_test: (114,)

```

✓ Train and Evaluate SVC with Linear Kernel

Subtask:

Initialize and train a Support Vector Classifier (SVC) using a linear kernel on the scaled training data. Evaluate its performance on the test set using accuracy, a confusion matrix, and a classification report. Display these metrics.

Reasoning: To address the subtask, I will import the necessary SVC and metrics classes, then initialize and train a Support Vector Classifier with a linear kernel, make predictions on the test set, and finally, evaluate its performance by calculating and displaying the accuracy score, confusion matrix, and classification report.

```

from sklearn.svm import SVC
from sklearn.metrics import accuracy_score, confusion_matrix, classification_re

# Initialize SVC with a linear kernel
svc_linear = SVC(kernel='linear', random_state=42)

# Train the model
svc_linear.fit(X_train_scaled, y_train)

# Make predictions on the test set
y_pred_linear = svc_linear.predict(X_test_scaled)

# Evaluate the model
accuracy_linear = accuracy_score(y_test, y_pred_linear)

```

```

conf_matrix_linear = confusion_matrix(y_test, y_pred_linear)
class_report_linear = classification_report(y_test, y_pred_linear)

print(f"SVC with Linear Kernel - Accuracy: {accuracy_linear:.4f}")
print("\nSVC with Linear Kernel - Confusion Matrix:\n", conf_matrix_linear)
print("\nSVC with Linear Kernel - Classification Report:\n", class_report_linear)

```

SVC with Linear Kernel - Accuracy: 0.9561

SVC with Linear Kernel - Confusion Matrix:

```

[[41  2]
 [ 3 68]]

```

SVC with Linear Kernel - Classification Report:

	precision	recall	f1-score	support
0	0.93	0.95	0.94	43
1	0.97	0.96	0.96	71
accuracy			0.96	114
macro avg	0.95	0.96	0.95	114
weighted avg	0.96	0.96	0.96	114

✓ Train and Evaluate SVC with RBF Kernel

Subtask:

Initialize and train another Support Vector Classifier (SVC) using a Radial Basis Function (RBF) kernel on the scaled training data. Evaluate its performance on the test set using accuracy, a confusion matrix, and a classification report. Display these metrics.

Reasoning: To train and evaluate an SVC with an RBF kernel, I will initialize the model with the specified kernel, train it on the scaled training data, make predictions on the test set, and then compute and display the accuracy, confusion matrix, and classification report, as requested by the subtask.

```

from sklearn.svm import SVC
from sklearn.metrics import accuracy_score, confusion_matrix, classification_re

# Initialize SVC with an RBF kernel
svc_rbf = SVC(kernel='rbf', random_state=42)

# Train the model
svc_rbf.fit(X_train_scaled, y_train)

# Make predictions on the test set
y_pred_rbf = svc_rbf.predict(X_test_scaled)

# Evaluate the model
accuracy_rbf = accuracy_score(y_test, y_pred_rbf)
conf_matrix_rbf = confusion_matrix(y_test, y_pred_rbf)
class_report_rbf = classification_report(y_test, y_pred_rbf)

```

```
print(f"SVC with RBF Kernel - Accuracy: {accuracy_rbf:.4f}")
print("\nSVC with RBF Kernel - Confusion Matrix:\n", conf_matrix_rbf)
print("\nSVC with RBF Kernel - Classification Report:\n", class_report_rbf)
```

SVC with RBF Kernel - Accuracy: 0.9825

SVC with RBF Kernel - Confusion Matrix:

```
[[41  2]
 [ 0 71]]
```

SVC with RBF Kernel - Classification Report:

	precision	recall	f1-score	support
0	1.00	0.95	0.98	43
1	0.97	1.00	0.99	71
accuracy			0.98	114
macro avg	0.99	0.98	0.98	114
weighted avg	0.98	0.98	0.98	114

Compare Performance of Both Kernel Models

Subtask:

Compare the performance of the SVC models with linear and RBF kernels based on their accuracy, confusion matrices, and classification reports to identify which kernel performed better for this dataset.

Comparison:

Based on the evaluation results:

SVC with Linear Kernel:

- Accuracy: 0.9561
- Confusion Matrix:

```
[[41  2]
 [ 3 68]]
```

- Classification Report:

	precision	recall	f1-score	support
0	0.93	0.95	0.94	43
1	0.97	0.96	0.96	71
accuracy			0.96	114
macro avg	0.95	0.96	0.95	114

weighted avg 0.96 0.96 0.96 114

```
**SVC with RBF Kernel:**  
- Accuracy: 0.9825  
- Confusion Matrix:
```

[[41 2] [0 71]]

- Classification Report:

	precision	recall	f1-score	support
0	1.00	0.95	0.98	43
1	0.97	1.00	0.99	71
accuracy			0.98	114
macro avg	0.99	0.98	0.98	114

weighted avg 0.98 0.98 0.98 114

```
### Conclusion:  
The **SVC with RBF kernel** achieved a higher accuracy of **0.9825** compared to th
```

Final Task

Subtask:

Summarize the findings, including the performance of each kernel and the identification of the better-performing kernel with a brief explanation of why it performed better for this dataset.

Summary:

Q&A

- **Which kernel performed better for this dataset?** The Radial Basis Function (RBF) kernel performed better, achieving a higher accuracy of 0.9825 compared to the linear kernel's accuracy of 0.9561.
- **Why did the better-performing kernel perform better?** The RBF kernel model demonstrated superior performance primarily due to its ability to correctly identify all positive cases (malignant) with a perfect recall of 1.00 for class 1 and fewer false

negatives (0) compared to the linear kernel (3 false negatives). This suggests that the RBF kernel was better at capturing the non-linear relationships within the data, which is typical for datasets where a linear boundary is insufficient.

Data Analysis Key Findings

- The dataset was successfully split into training (455 samples, 30 features) and testing (114 samples, 30 features) sets, and features were standardized.
- The Support Vector Classifier (SVC) with a linear kernel achieved an accuracy of 0.9561. Its confusion matrix was $\begin{bmatrix} 41 & 2 \\ 3 & 68 \end{bmatrix}$, indicating 3 false negatives.
- The SVC with an RBF kernel achieved a higher accuracy of 0.9825. Its confusion matrix was $\begin{bmatrix} 41 & 2 \\ 0 & 71 \end{bmatrix}$, indicating 0 false negatives and a perfect recall of 1.00 for class 1.
- The RBF kernel model showed better performance, particularly in identifying all positive cases, demonstrating its effectiveness for this dataset.

Insights or Next Steps

- Given the strong performance of the RBF kernel, consider hyperparameter tuning (e.g., C, gamma) for the RBF SVC to potentially achieve even higher accuracy and robustness.
- Explore other non-linear classification models (e.g., Random Forest, Gradient Boosting) to see if they can match or exceed the RBF kernel's performance for this specific dataset.