```
from sklearn import datasets
from sklearn.model_selection import train_test_split, cross_val_score, KFold
from sklearn.svm import SVC
from sklearn.metrics import accuracy_score, precision_score, recall_score, f1_score, classification_report, confusion_matrix
from sklearn.preprocessing import StandardScaler
import numpy as np
import matplotlib.pyplot as plt
import pandas as pd
```

```
# Load the Iris dataset
iris = datasets.load_iris()
```

```
iris_df = pd.DataFrame(data= iris.data, columns=iris.feature_names)
iris_df
```

	sepal length (cm)	sepal width (cm)	petal length (cm)	petal width (cm)
0	5.1	3.5	1.4	0.2
1	4.9	3.0	1.4	0.2
2	4.7	3.2	1.3	0.2
3	4.6	3.1	1.5	0.2
4	5.0	3.6	1.4	0.2
...	...	...	...	...
145	6.7	3.0	5.2	2.3
146	6.3	2.5	5.0	1.9
147	6.5	3.0	5.2	2.0
148	6.2	3.4	5.4	2.3
149	5.9	3.0	5.1	1.8

150 rows × 4 columns

Next steps: Generate code with iris_df View recommended plots

```
iris_df['target'] = iris.target
iris_df
```

	sepal length (cm)	sepal width (cm)	petal length (cm)	petal width (cm)	target
0	5.1	3.5	1.4	0.2	0
1	4.9	3.0	1.4	0.2	0
2	4.7	3.2	1.3	0.2	0
3	4.6	3.1	1.5	0.2	0
4	5.0	3.6	1.4	0.2	0
...	...	...	...	...	...
145	6.7	3.0	5.2	2.3	2
146	6.3	2.5	5.0	1.9	2
147	6.5	3.0	5.2	2.0	2
148	6.2	3.4	5.4	2.3	2
149	5.9	3.0	5.1	1.8	2

150 rows × 5 columns

Next steps: Generate code with iris_df View recommended plots

```
#finding null values in dataset
iris_df.isnull()
```

	sepal length (cm)	sepal width (cm)	petal length (cm)	petal width (cm)	target
0	False	False	False	False	False
1	False	False	False	False	False
2	False	False	False	False	False
3	False	False	False	False	False
4	False	False	False	False	False
...	...	...	...	...	...
145	False	False	False	False	False
146	False	False	False	False	False
147	False	False	False	False	False
148	False	False	False	False	False
149	False	False	False	False	False

150 rows × 5 columns

```
# Counting null values
null_values = iris_df.isnull().sum()
print(null_values)
```

```
sepal length (cm)    0
sepal width (cm)     0
petal length (cm)    0
petal width (cm)     0
target               0
dtype: int64
```

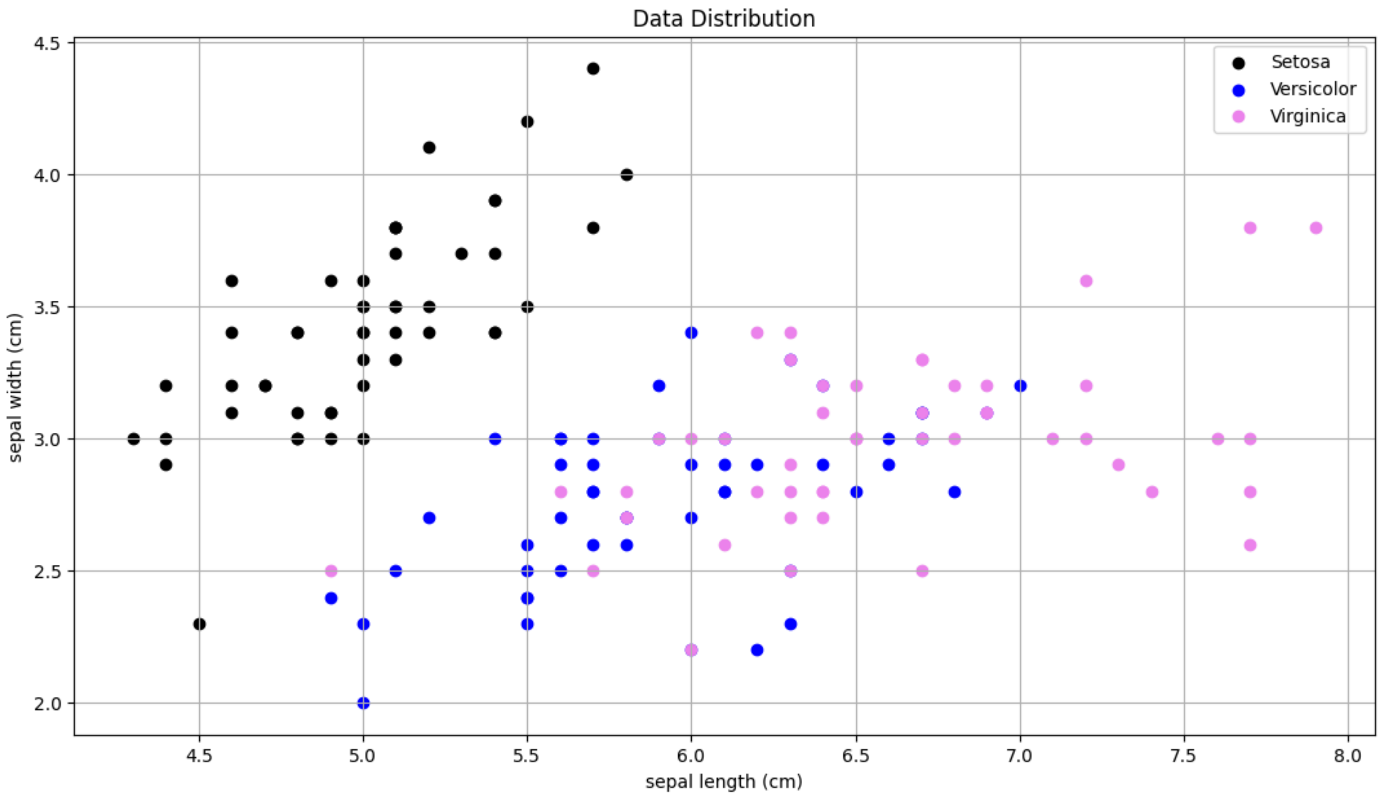
```
# Data Visualization
X = iris.data[:, [0,1]]#Using petal length and petal width for easy visualization
y = iris.target


fig, ax = plt.subplots()
fig.set_size_inches(13, 7) # adjusting the length and width of plot

# lables and scatter points
ax.scatter(X[y == 0,0], X[y == 0,1], label="Setosa", facecolor="black")
ax.scatter(X[y == 1,0], X[y == 1,1], label="Versicolor", facecolor="blue")
ax.scatter(X[y == 2,0], X[y == 2,1], label="Virginica", facecolor="violet")

ax.set_xlabel("sepal length (cm)")
ax.set_ylabel("sepal width (cm)")
ax.grid()
ax.set_title("Data Distribution")
ax.legend()
```

```
<matplotlib.legend.Legend at 0x7a419f6d1f60>
```




```
# Step 1: Data Exploration and Preparation
# Check for missing values (not needed for the Iris dataset)
# Scaling Features
scaler = StandardScaler()
X_scaled = scaler.fit_transform(iris.data)
```

```
X = X_scaled
y = iris.target
```

```
# Split the scaled dataset into training and testing sets
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.3, random_state=42)
```

```
# SVM Implementation, metrics evaluation, cross-validation score

kernels = ['linear', 'poly', 'rbf']#List of kernels

for kernel in kernels:
    # Create an SVM classifier with the given kernel
    svm = SVC(kernel=kernel)

    # Train the classifier
    svm.fit(X_train, y_train)

    # Make predictions on the test set
    y_pred = svm.predict(X_test)

    # Evaluate the performance
    print(f"Kernel: {kernel}")
    print("Confusion Matrix:")
    print(confusion_matrix(y_test, y_pred))
    print("Classification Report:")
    print(classification_report(y_test, y_pred))
    # Apply K-fold cross-validation
    kf = KFold(n_splits=5, shuffle=True, random_state=42)
    cv_scores = cross_val_score(svm, X_train, y_train, cv=kf)
    print(cv_scores)
    print("Mean CV accuracy:", cv_scores.mean())
```

```
Kernel: linear
Confusion Matrix:
[[19  0  0]
 [ 0 12  1]
 [ 0  0 13]]
Classification Report:
              precision    recall  f1-score   support

           0       1.00      1.00      1.00        19
           1       1.00      0.92      0.96        13
           2       0.93      1.00      0.96        13

    accuracy                           0.98        45
   macro avg       0.98      0.97      0.97        45
weighted avg       0.98      0.98      0.98        45

[0.95238095 0.9047619  1.         0.95238095 0.95238095]
Mean CV accuracy: 0.9523809523809523
Kernel: poly
Confusion Matrix:
[[19  0  0]
 [ 0 13  0]
 [ 0  1 12]]
Classification Report:
              precision    recall  f1-score   support

           0       1.00      1.00      1.00        19
           1       0.93      1.00      0.96        13
           2       1.00      0.92      0.96        13

    accuracy                           0.98        45
   macro avg       0.98      0.97      0.97        45
weighted avg       0.98      0.98      0.98        45

[0.95238095 0.95238095 0.9047619  0.80952381 0.9047619 ]
Mean CV accuracy: 0.9047619047619048
Kernel: rbf
Confusion Matrix:
[[19  0  0]
 [ 0 13  0]
 [ 0  0 13]]
Classification Report:
              precision    recall  f1-score   support

           0       1.00      1.00      1.00        19
           1       1.00      1.00      1.00        13
           2       1.00      1.00      1.00        13

    accuracy                           1.00        45
   macro avg       1.00      1.00      1.00        45
weighted avg       1.00      1.00      1.00        45

[0.9047619  0.9047619  1.         0.9047619  0.95238095]
Mean CV accuracy: 0.9333333333333332
```

```
# SVM Classification
X = iris.data[:, :2] # We only take the first two features for visualization
y = iris.target

# Split the scaled dataset into training and testing sets
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.3, random_state=42)
kernels = ['linear', 'poly', 'rbf']

# Create a mesh to plot the decision boundaries
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, 0.02),
                     np.arange(y_min, y_max, 0.02))

# Plot the decision boundaries for each kernel
fig, axes = plt.subplots(3, 1, figsize=(12, 8))
for kernel, ax in zip(kernels, axes.ravel()):
    # Create an SVM classifier with the given kernel
    svm = SVC(kernel=kernel)

    # Fit the classifier to the training data
    svm.fit(X_train, y_train)

    # Plot the decision boundary
    Z = svm.predict(np.c_[xx.ravel(), yy.ravel()])
    Z = Z.reshape(xx.shape)
    ax.contourf(xx, yy, Z, cmap=plt.cm.coolwarm, alpha=0.8)

    # Plot the training data
    ax.scatter(X_train[:, 0], X_train[:, 1], c=y_train, cmap=plt.cm.coolwarm, edgecolors='k')
    ax.set_title(f'Kernel: {kernel}')
    ax.set_xticks(())
    ax.set_yticks(())

plt.show()
```

Kernel: linear