

✓ Traditional features construction

Feature extraction from EACH image from the training data using image feature descriptor SIFT (Scale-invariant feature transform) (see https://docs.opencv.org/4.x/da/df5/tutorial_py_sift_intro.html) with 128 dimensions for each keypoint (Note that you should obtain many keypoints from each image). Plot the keypoints on one image from your training dataset (see Fig 1 for one such figure). (0.5 point)

```
import numpy as np
import cv2 as cv
from IPython.display import Image, display

# Read the image
img = cv.imread('/content/drive/MyDrive/TrainingImages/Apple Golden 1/0_100.jpg')

# Convert the image to grayscale
gray = cv.cvtColor(img, cv.COLOR_BGR2GRAY)

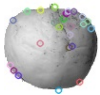
# Initialize the SIFT detector with 180 keypoints
sift = cv.SIFT_create(nfeatures=180)

# Detect keypoints
kp = sift.detect(gray, None)

# Draw keypoints on the original image
img_with_keypoints = cv.drawKeypoints(gray, kp, img)

# Save the image with keypoints
cv.imwrite('sift_keypoints.jpg', img_with_keypoints)

# Display the image
display(Image('sift_keypoints.jpg'))
```



Create a new keypoints dataset K that consists of all the keypoints from all the training images.

Perform K-mean clustering such that $K = 100$ on KP .

Use the learned K-mean clusters (see <https://scikit-learn.org/stable/modules/clustering.html>) to construct a 100-D vector for each image.

Example: For Image A, we have 20 keypoints in Cluster 1 and 10 keypoints in cluster 2, and no keypoints in the other clusters, then the vector representing Image A is (20,10,0,0,...,0,0)

Create a new 100-D dataset D consisting of vectors constructed from the training images.

```

from sklearn.cluster import KMeans
import cv2 as cv
import numpy as np
import os

# Initialize an empty list to store keypoints and labels
KP = []
labels = []

# List of directories containing your training images
dir_paths = ['/content/drive/MyDrive/TrainingImages/Apple Golden 1',
             '/content/drive/MyDrive/TrainingImages/Apple Red 1',
             '/content/drive/MyDrive/TrainingImages/Apple Red Delicious',
             '/content/drive/MyDrive/TrainingImages/Avocado',
             '/content/drive/MyDrive/TrainingImages/Ginger Root',
             '/content/drive/MyDrive/TrainingImages/Limes',
             '/content/drive/MyDrive/TrainingImages/Maracuja',
             '/content/drive/MyDrive/TrainingImages/Papaya',
             '/content/drive/MyDrive/TrainingImages/Potato Red',
             '/content/drive/MyDrive/TrainingImages/Rambutan'
             # Add more directory paths as needed
            ]

# Initialize SIFT detector
sift = cv.SIFT_create()

# Initialize a list to store the image vectors
image_vectors = []

# Initialize KMeans with the desired number of clusters
kmeans = KMeans(n_clusters=100)

# Loop through each directory
for label, dir_path in enumerate(dir_paths):
    # Loop through each image file in the directory
    for filename in os.listdir(dir_path):
        # Read the image
        img = cv.imread(os.path.join(dir_path, filename))
        # Convert the image to grayscale
        gray = cv.cvtColor(img, cv.COLOR_BGR2GRAY)
        # Detect keypoints
        kp = sift.detect(gray, None)
        # Append keypoints to list
        KP.append(kp)
        # Append label to the labels list
        labels.append(label)

# Fit KMeans to keypoints
kmeans.fit(np.concatenate([np.array([kp.pt for kp in kp]) for kp in KP]))

# Loop through each directory again to extract features
for label, dir_path in enumerate(dir_paths):
    # Loop through each image file in the directory
    for filename in os.listdir(dir_path):
        # Read the image
        img = cv.imread(os.path.join(dir_path, filename))
        # Convert the image to grayscale
        gray = cv.cvtColor(img, cv.COLOR_BGR2GRAY)
        # Detect keypoints
        kp = sift.detect(gray, None)
        # Get cluster labels for the keypoints of this image
        image_labels = kmeans.predict(np.array([kp.pt for kp in kp]))
        # Count the occurrences of each cluster label
        cluster_counts = np.bincount(image_labels, minlength=100)
        # Append the cluster counts to the list of image vectors
        image_vectors.append(cluster_counts)

# Convert the list of image vectors to a numpy array
image_vectors_array = np.array(image_vectors)

# Ensure each vector follows the specified structure
for i in range(len(image_vectors_array)):
    # Find the indices where the count is nonzero
    nonzero_indices = np.nonzero(image_vectors_array[i])[0]
    # Create a new vector with counts only at those indices
    new_vector = np.zeros_like(image_vectors_array[i])
    new_vector[nonzero_indices] = image_vectors_array[i][nonzero_indices]
    # Replace the original vector with the new one
    image_vectors_array[i] = new_vector

# Convert the list of labels to a numpy array
labels_array = np.array(labels)

```

```
# Print an example vector
example_vector = image_vectors_array[0]
print("Example vector representing Image A:", example_vector)

# Print the shape of the dataset D
print("Shape of dataset D:", image_vectors_array.shape)
```

```
/usr/local/lib/python3.10/dist-packages/sklearn/cluster/_kmeans.py:870: FutureWarning: The default value of `n_init` will change from 10 to 'auto' in 1.4. Set the value of `n_init` explicitly to suppress the warning
  warnings.warn(
Example vector representing Image A: [0 0 1 1 1 0 1 1 0 0 0 0 1 0 0 3 1 1 1 0 0 0 3 1 0 0 2 0 0 0 1 0 1 0 0 1 0
 0 2 2 1 0 0 2 0 0 0 1 1 2 1 0 0 2 0 1 0 0 0 1 0 1 0 0 1 0 0 0 0 2 0 0 2 3
 1 1 2 1 0 1 2 1 2 0 0 0 0 1 1 0 1 0 1 1 0 1 0 0 0 0]
Shape of dataset D: (4665, 100)
```

Dimensionality reduction(using Principal Component Analysis,PCA)(see<https://scikit-learn.org/stable/modules/generated/sklearn.decomposition.PCA.html> for PCA. [https:// scikit-learn.org/stable/auto_examples/decomposition/plot_pca_iris.html](https://scikit-learn.org/stable/auto_examples/decomposition/plot_pca_iris.html) for code example.)

- i. Perform Principal Component Analysis (PCA) dimensionality reduction Dataset D to 2 dimensions. (Note: You should not use the class labels)
- ii. Plot the 2D points using 10 different colors/symbols for data from the 10 classes (see Figure 2 for an example of the plot without normalization).(1 point)

```

from sklearn.decomposition import PCA
import matplotlib.pyplot as plt
import os

# List of directories containing your training images
train_dir_paths = ['/content/drive/MyDrive/TrainingImages/Apple Golden 1',
                  '/content/drive/MyDrive/TrainingImages/Apple Red 1',
                  '/content/drive/MyDrive/TrainingImages/Apple Red Delicious',
                  '/content/drive/MyDrive/TrainingImages/Avocado',
                  '/content/drive/MyDrive/TrainingImages/Ginger Root',
                  '/content/drive/MyDrive/TrainingImages/Limes',
                  '/content/drive/MyDrive/TrainingImages/Maracuja',
                  '/content/drive/MyDrive/TrainingImages/Papaya',
                  '/content/drive/MyDrive/TrainingImages/Potato Red',
                  '/content/drive/MyDrive/TrainingImages/Rambutan']

# Initialize a list to store the image vectors
train_image_vectors = []
# Initialize a list to store the corresponding class labels
train_labels = []

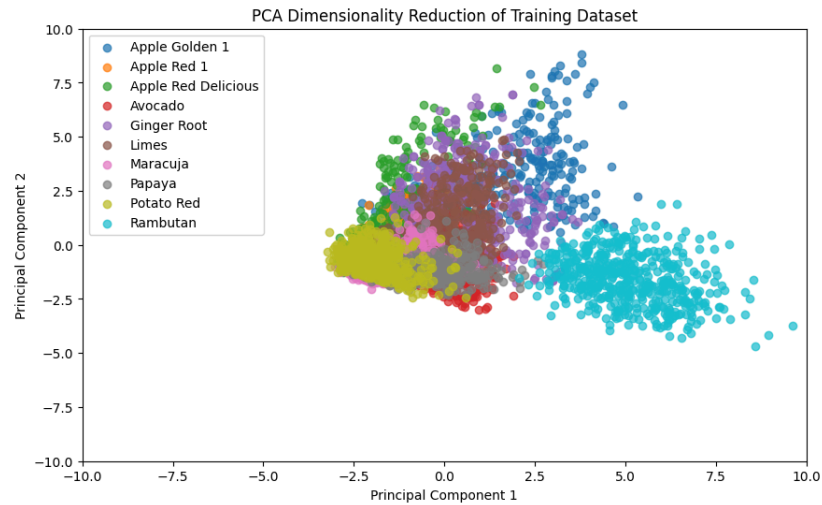
# Loop through each directory
for label, dir_path in enumerate(train_dir_paths):
    # Loop through each image file in the directory
    for filename in os.listdir(dir_path):
        # Read the image
        img = cv.imread(os.path.join(dir_path, filename))
        # Convert the image to grayscale
        gray = cv.cvtColor(img, cv.COLOR_BGR2GRAY)
        # Detect keypoints
        kp = sift.detect(gray, None)
        # Get cluster labels for the keypoints of this image
        image_labels = kmeans.predict(np.array([kp.pt for kp in kp]))
        # Count the occurrences of each cluster label
        cluster_counts = np.bincount(image_labels, minlength=100)
        # Append the cluster counts to the list of image vectors
        train_image_vectors.append(cluster_counts)
        # Assign class label based on folder name
        train_labels.append(os.path.basename(dir_path))

# Convert the lists to numpy arrays
train_image_vectors_array = np.array(train_image_vectors)
train_labels_array = np.array(train_labels)

# Perform PCA dimensionality reduction to 2 dimensions
pca = PCA(n_components=2)
D_pca = pca.fit_transform(train_image_vectors_array)

# Plot the 2D points with different colors/symbols for each class
plt.figure(figsize=(10, 6))
for label in np.unique(train_labels_array):
    class_indices = np.where(train_labels_array == label)[0]
    plt.scatter(D_pca[class_indices, 0], D_pca[class_indices, 1], label=f'{label}', alpha=0.7)
plt.xlabel('Principal Component 1')
plt.ylabel('Principal Component 2')
plt.title('PCA Dimensionality Reduction of Training Dataset')
plt.legend()
plt.xlim(-10, 10)
plt.ylim(-10, 10)
plt.show()

```



✓ “Traditional” Machine Learning Model - Support Vector Machine (SVM)

(a) We perform model selection to learn a linear SVM (see <https://scikit-learn.org/stable/modules/generated/sklearn.svm.SVC.html>) prediction model (i.e., kernel = 'linear').

(b) Train the SVM model using different C parameters. In particular, you will use the following values: 0.01, 0.1, 1.0, 10, 100.

(c) Plot a graph to show the SVM performance on the training data and test data similar to

(d) Repeat Step (b) and (c) for kernel = 'rbf', 'poly', 'sigmoid'. (2 points - include 0.5 for linear kernel.)

(e) Plot a graph to compare the best performance for SVM using the four kernels on the training data and test data similar to Figure 4 (note that you identify the best results for each kernel from results in Step (d))

✓ First, performing the same steps on testing data to create testing dataset

Combine all the keypoints from all the testing images into a single dataset.

Use the 100 cluster centers obtained from the training data to create a 100D vector for each test image.

Process the test images into the test dataset.

This code will create the `test_image_vectors_array` with the features obtained using the cluster centers obtained from the training data.

```

# List of directories containing your testing images
test_dir_paths = ['/content/drive/MyDrive/TestingImages/Apple Golden 1',
                  '/content/drive/MyDrive/TestingImages/Apple Red 1',
                  '/content/drive/MyDrive/TestingImages/Apple Red Delicious',
                  '/content/drive/MyDrive/TestingImages/Avocado',
                  '/content/drive/MyDrive/TestingImages/Ginger Root',
                  '/content/drive/MyDrive/TestingImages/Limes',
                  '/content/drive/MyDrive/TestingImages/Maracuja',
                  '/content/drive/MyDrive/TestingImages/Papaya',
                  '/content/drive/MyDrive/TestingImages/Potato Red',
                  '/content/drive/MyDrive/TestingImages/Rambutan',
                  # Add more directory paths as needed
                  ]

# Initialize an empty list to store keypoints for testing data
test_KP = []

# Initialize a list to store the image vectors for testing data
test_image_vectors = []

# Initialize a list to store the labels for testing data
test_labels = []

# Loop through each directory for testing data
for label, dir_path in enumerate(test_dir_paths):
    # Loop through each image file in the directory
    for filename in os.listdir(dir_path):
        # Read the image
        img = cv.imread(os.path.join(dir_path, filename))

        # Convert the image to grayscale
        gray = cv.cvtColor(img, cv.COLOR_BGR2GRAY)

        # Detect keypoints
        kp = sift.detect(gray, None)

        # Append keypoints to the test_KP dataset
        test_KP.extend(kp)

        # Get cluster labels for the keypoints of this image for testing data
        image_labels = kmeans.predict(np.array([kp.pt for kp in kp]))

        # Count the occurrences of each cluster label
        cluster_counts = np.bincount(image_labels, minlength=100)

        # Append the cluster counts to the list of image vectors for testing data
        test_image_vectors.append(cluster_counts)

        # Append label to the test_labels list
        test_labels.append(label)

# Convert the list of keypoints to an array for testing data
test_KP_array = np.array([kp.pt for kp in test_KP])

# Convert the list of image vectors to a numpy array for testing data
test_image_vectors_array = np.array(test_image_vectors)

# Convert the list of labels to a numpy array for testing data
test_labels_array = np.array(test_labels)

# Ensure each vector follows the specified structure for testing data
for i in range(len(test_image_vectors_array)):
    # Find the indices where the count is nonzero
    nonzero_indices = np.nonzero(test_image_vectors_array[i])[0]
    # Create a new vector with counts only at those indices
    new_vector = np.zeros_like(test_image_vectors_array[i])
    new_vector[nonzero_indices] = test_image_vectors_array[i][nonzero_indices]
    # Replace the original vector with the new one for testing data
    test_image_vectors_array[i] = new_vector

# Print an example vector for testing data
example_vector_test = test_image_vectors_array[0] # Assuming the first image is Image A
print("Example vector representing Image A for testing data:", example_vector_test)

# Print the shape of the testing dataset D
print("Shape of testing dataset D:", test_image_vectors_array.shape)

Example vector representing Image A for testing data: [0 0 0 1 0 4 1 0 0 0 1 0 1 0 5 0 4 1 1 0 0 0 1 1 0 0 0 0 1 0 2 0 2 0 0 2 1
 0 0 0 0 0 0 0 2 0 2 0 0 1 0 0 0 0 0 1 2 0 0 1 1 1 0 0 0 0 0 1 2 0 0 2 0 0
 0 1 0 3 0 0 0 0 0 0 0 2 0 2 0 5 0 0 4 0 0 1 1 0 2 0 1]
Shape of testing dataset D: (1542, 100)

```

✓ Now, we train the model and test it (using classes from the training images as labels)

The below code uses the default kernel function for the Support Vector Classifier (SVC) in scikit-learn, which is the Radial Basis Function (RBF) kernel.

```
from sklearn.svm import SVC
from sklearn.metrics import accuracy_score
import matplotlib.pyplot as plt

# Define C values
C_values = [0.01, 0.1, 1.0, 10, 100]

# Initialize dictionaries to store results
train_scores = {}
test_scores = {}

# Train SVM models for different C values
for C in C_values:
    # Initialize SVM model with linear kernel
    svm_model = SVC(C=C, kernel='linear')

    # Train the model
    svm_model.fit(image_vectors_array, labels_array)

    # Predictions on training data
    train_predictions = svm_model.predict(image_vectors_array)

    # Accuracy on training data
    train_accuracy = accuracy_score(labels_array, train_predictions)
    train_scores[C] = train_accuracy

    # Predictions on testing data
    test_predictions = svm_model.predict(test_image_vectors_array)

    # Accuracy on testing data
    test_accuracy = accuracy_score(test_labels_array, test_predictions)
    test_scores[C] = test_accuracy

# Calculate error rates
train_errors = [1 - train_scores[C] for C in C_values]
test_errors = [1 - test_scores[C] for C in C_values]

# Print the results
for i, C in enumerate(C_values):
    print(f"C Value: {C}")
    print(f"Training Accuracy: {train_scores[C]:.4f}")
    print(f"Testing Accuracy: {test_scores[C]:.4f}")
    print(f"Train Error: {train_errors[i]:.4f}") # Print the corresponding training error
    print(f"Test Error: {test_errors[i]:.4f}") # Print the corresponding testing error
    print()

# Plotting
plt.figure(figsize=(5, 3))
plt.plot(np.log(C_values), train_errors, marker='o', label='Training Error', color='blue')
plt.plot(np.log(C_values), test_errors, marker='o', label='Test Error', color='red')
plt.xlabel('Log of C Values')
plt.ylabel('Error Rate')
plt.title('SVM Performance on Training and Test Data with Linear Kernel')
plt.grid(True)
plt.legend()
plt.show()
```

C Value: 0.01
 Training Accuracy: 0.9353
 Testing Accuracy: 0.6939
 Train Error: 0.0647
 Test Error: 0.3061

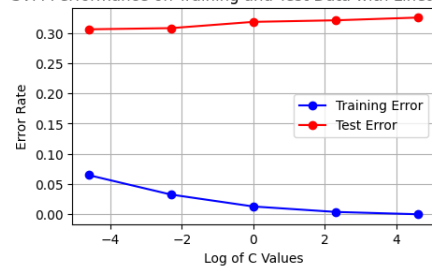
C Value: 0.1
 Training Accuracy: 0.9674
 Testing Accuracy: 0.6920
 Train Error: 0.0326
 Test Error: 0.3080

C Value: 1.0
 Training Accuracy: 0.9871
 Testing Accuracy: 0.6816
 Train Error: 0.0129
 Test Error: 0.3184

C Value: 10
 Training Accuracy: 0.9961
 Testing Accuracy: 0.6790
 Train Error: 0.0039
 Test Error: 0.3210

C Value: 100
 Training Accuracy: 1.0000
 Testing Accuracy: 0.6744
 Train Error: 0.0000
 Test Error: 0.3256

SVM Performance on Training and Test Data with Linear Kernel



In the context of Support Vector Machines (SVM), C values represent the regularization parameter.

Regularization is a technique used to prevent overfitting by adding a penalty term to the loss function. In SVM, the parameter C controls the trade-off between maximizing the margin (decision boundary) and minimizing the classification error.

A small C value allows for a larger margin but may misclassify some points (soft margin). A large C value penalizes misclassifications heavily, potentially resulting in a smaller margin (hard margin).

In essence, C values determine the balance between achieving a low training error and generalizing well to unseen data.

We repeat for kernel = 'linear', 'RBF', 'poly', 'sigmoid'


```

import numpy as np
import matplotlib.pyplot as plt
from sklearn.svm import SVC
from sklearn.metrics import accuracy_score
from sklearn.model_selection import train_test_split

# Define C values
C_values = [0.01, 0.1, 1.0, 10, 100]

# Define kernel functions
kernel_functions = ['linear', 'rbf', 'poly', 'sigmoid']

# Initialize dictionaries to store results
train_errors = {kernel: [] for kernel in kernel_functions}
test_errors = {kernel: [] for kernel in kernel_functions}
train_accuracies = {kernel: [] for kernel in kernel_functions}
test_accuracies = {kernel: [] for kernel in kernel_functions}
best_test_errors = {kernel: float('inf') for kernel in kernel_functions}
best_train_errors = {kernel: float('inf') for kernel in kernel_functions}
best_C_values = {kernel: None for kernel in kernel_functions}

# Train SVM models for different kernel functions and C values
for kernel in kernel_functions:
    for C in C_values:
        # Initialize SVM model
        svm_model = SVC(kernel=kernel, C=C)
        # Train the model
        svm_model.fit(image_vectors_array, labels_array)
        # Predictions on training data
        train_predictions = svm_model.predict(image_vectors_array)
        # Error rate on training data
        train_error = 1.0 - accuracy_score(labels_array, train_predictions)
        # Accuracy on training data
        train_accuracy = accuracy_score(labels_array, train_predictions)
        # Predictions on testing data
        test_predictions = svm_model.predict(test_image_vectors_array)
        # Error rate on testing data
        test_error = 1.0 - accuracy_score(test_labels_array, test_predictions)
        # Accuracy on testing data
        test_accuracy = accuracy_score(test_labels_array, test_predictions)
        # Store errors and accuracies
        train_errors[kernel].append(train_error)
        test_errors[kernel].append(test_error)
        train_accuracies[kernel].append(train_accuracy)
        test_accuracies[kernel].append(test_accuracy)
        # Update best errors and corresponding C value for this kernel
        if test_error < best_test_errors[kernel]:
            best_test_errors[kernel] = test_error
            best_train_errors[kernel] = train_error
            best_C_values[kernel] = C

# Print performance of each kernel with each C value
for kernel in kernel_functions:
    print(f"Kernel: {kernel}")
    for i, C in enumerate(C_values):
        print(f"C value: {C}, Training Accuracy: {train_accuracies[kernel][i]}, Testing Accuracy: {test_accuracies[kernel][i]}, Train Error: {train_errors[kernel][i]}, Test Error: {test_errors[kernel][i]}")
    print()

# Plotting
plt.figure(figsize=(15, 5))

# Plot test error rates corresponding to the best C values for each kernel
for i, kernel in enumerate(kernel_functions, start=1):
    plt.subplot(1, len(kernel_functions), i)
    plt.plot(np.log(C_values), test_errors[kernel], marker='o', label='Test Error', color='red')
    plt.plot(np.log(C_values), train_errors[kernel], marker='o', label='Train Error', color='blue')
    plt.xlabel('Log of C Values')
    plt.ylabel('Error Rate')
    plt.title(f'Error Rates with {kernel} Kernel')
    plt.grid(True)
    if i == 1:
        plt.legend()

plt.tight_layout()
plt.show()

# Plotting best test and train errors corresponding to best C values for each kernel
plt.figure(figsize=(10, 5))
for kernel in kernel_functions:
    plt.scatter([kernel], [best_test_errors[kernel]], color='blue', marker='o', label='Best Test Error' if kernel == 'linear' else None, s=100)
    plt.scatter([kernel], [best_train_errors[kernel]], color='red', marker='o', label='Best Train Error' if kernel == 'linear' else None, s=100)
    plt.text(kernel, best_test_errors[kernel], f'C={best_C_values[kernel]}, Test Error={best_test_errors[kernel]}', ha='center', va='bottom')

```

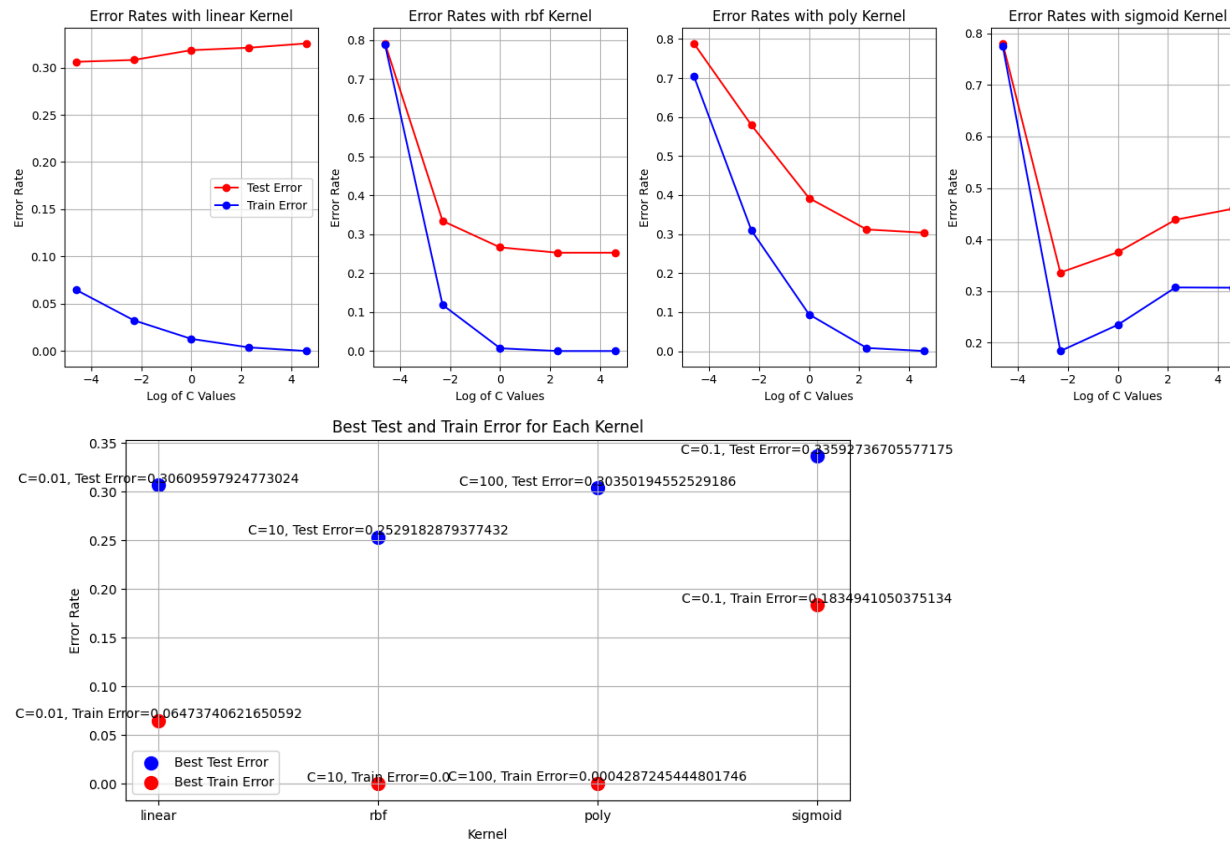
```
plt.text(kernel, best_train_errors[kernel], f'C={best_C_values[kernel]}, Train Error={best_train_errors[kernel]}', ha='center', va='bottom')
plt.xlabel('Kernel')
plt.ylabel('Error Rate')
plt.title('Best Test and Train Error for Each Kernel')
plt.grid(True)
plt.legend()
plt.show()
```

Kernel: linear
 C value: 0.01, Training Accuracy: 0.9352625937834941, Testing Accuracy: 0.6939040207522698, Train Error: 0.06473740621650592, Test Error: 0.30609597924773024
 C value: 0.1, Training Accuracy: 0.967416934619507, Testing Accuracy: 0.691958495460441, Train Error: 0.03258306538049305, Test Error: 0.30804150453955903
 C value: 1.0, Training Accuracy: 0.9871382636655949, Testing Accuracy: 0.6815823605706874, Train Error: 0.012861736334405127, Test Error: 0.31841763942931256
 C value: 10, Training Accuracy: 0.9961414790996784, Testing Accuracy: 0.678983268482491, Train Error: 0.0038585209003215715, Test Error: 0.32101167315175094
 C value: 100, Training Accuracy: 1.0, Testing Accuracy: 0.6744487678339819, Train Error: 0.0, Test Error: 0.3255512321660181

Kernel: rbf
 C value: 0.01, Training Accuracy: 0.21157556270096464, Testing Accuracy: 0.20881971465629054, Train Error: 0.7884244372990353, Test Error: 0.7911802853437094
 C value: 0.1, Training Accuracy: 0.8812433011789925, Testing Accuracy: 0.6653696498054474, Train Error: 0.11875669882100748, Test Error: 0.33463035019455256
 C value: 1.0, Training Accuracy: 0.9929260450160772, Testing Accuracy: 0.7334630350194552, Train Error: 0.0070739549839228255, Test Error: 0.2665369649805448
 C value: 10, Training Accuracy: 1.0, Testing Accuracy: 0.7470817120622568, Train Error: 0.0, Test Error: 0.2529182879377432
 C value: 100, Training Accuracy: 1.0, Testing Accuracy: 0.7470817120622568, Train Error: 0.0, Test Error: 0.2529182879377432

Kernel: poly
 C value: 0.01, Training Accuracy: 0.29517684887459805, Testing Accuracy: 0.21141374837872892, Train Error: 0.704823151125402, Test Error: 0.788586251621271
 C value: 0.1, Training Accuracy: 0.6906752411575563, Testing Accuracy: 0.42088197146562906, Train Error: 0.3093247588424437, Test Error: 0.5791180285343709
 C value: 1.0, Training Accuracy: 0.9056806002143623, Testing Accuracy: 0.6076523994811932, Train Error: 0.09431939978563775, Test Error: 0.3923476005188068
 C value: 10, Training Accuracy: 0.9916398713826367, Testing Accuracy: 0.6880674448767834, Train Error: 0.00836012861736335, Test Error: 0.3119325551232166
 C value: 100, Training Accuracy: 0.9995712754555198, Testing Accuracy: 0.6964980544747081, Train Error: 0.0004287245444801746, Test Error: 0.30350194552529186

Kernel: sigmoid
 C value: 0.01, Training Accuracy: 0.22443729903536977, Testing Accuracy: 0.2191958495460441, Train Error: 0.7755627009646302, Test Error: 0.7808041504539559
 C value: 0.1, Training Accuracy: 0.8165058949624866, Testing Accuracy: 0.6640726329442282, Train Error: 0.1834941050375134, Test Error: 0.33592736705577175
 C value: 1.0, Training Accuracy: 0.7654876741693462, Testing Accuracy: 0.6245136186770428, Train Error: 0.23451232583065384, Test Error: 0.3754863813229572
 C value: 10, Training Accuracy: 0.693032261521972, Testing Accuracy: 0.5616083009079118, Train Error: 0.3069667738478028, Test Error: 0.4383916990920882
 C value: 100, Training Accuracy: 0.6934619506966774, Testing Accuracy: 0.540207522697795, Train Error: 0.3065380493033226, Test Error: 0.45979247730220496



This code plots the best performance (lowest error rate) for each kernel for both the testing and training datasets. It identifies the best performing C value for each kernel based on the lowest error rate achieved on the respective dataset.

✓ Let's test and see what label our trained model will predict for one of our testing images

```
import cv2
import numpy as np
from sklearn.svm import SVC

# Define C value
C = 10

# Initialize SVM model
svm_model = SVC(C=C, kernel='rbf')

# Train the SVM model
svm_model.fit(image_vectors_array, labels_array)

# Define image paths
image_paths = [
    '/content/drive/MyDrive/TestingImages/Apple Red Delicious/13_100.jpg',
    '/content/drive/MyDrive/TestingImages/Rambutan/128_100.jpg',
    '/content/drive/MyDrive/TestingImages/Maracuja/0_100.jpg',
    '/content/drive/MyDrive/TestingImages/Avocado/45_100.jpg',
    '/content/drive/MyDrive/TestingImages/Apple Red 1/321_100.jpg',
    '/content/drive/MyDrive/TestingImages/Apple Golden 1/100_100.jpg',
    '/content/drive/MyDrive/TestingImages/Ginger Root/128_100.jpg',
    '/content/drive/MyDrive/TestingImages/Limes/113_100.jpg',
    '/content/drive/MyDrive/TestingImages/Potato Red/20_100.jpg',
    '/content/drive/MyDrive/TestingImages/Apple Red Delicious/165_100.jpg',
]

# Define the actual class labels for each image
actual_class_labels = ['Apple Red Delicious', 'Rambutan', 'Maracuja', 'Avocado', 'Apple Red 1', 'Apple Golden 1', 'Ginger Root', 'Limes', 'Potato Red', 'Apple Red Delicious']

# Loop through each image path
for i, image_path in enumerate(image_paths):
    # Read the testing image
    testing_image = cv2.imread(image_path)

    # Check if the image is loaded successfully
    if testing_image is not None:
        # Convert the testing image to grayscale
        gray_testing_image = cv2.cvtColor(testing_image, cv2.COLOR_BGR2GRAY)

        # Detect keypoints
        kp = sift.detect(gray_testing_image, None)

        # Get cluster labels for the keypoints of this image
        image_labels = kmeans.predict(np.array([kp.pt for kp in kp]))

        # Count the occurrences of each cluster label
        cluster_counts = np.bincount(image_labels, minlength=100)

        # Reshape the cluster counts to match the shape of the training data
        input_vector = cluster_counts.reshape(1, -1)

        # Use the trained SVM model to predict the label of the testing image
        predicted_label = svm_model.predict(input_vector)

        # Define the class labels
        class_labels = ['Apple Golden 1', 'Apple Red 1', 'Apple Red Delicious', 'Avocado', 'Ginger Root',
                        'Limes', 'Maracuja', 'Papaya', 'Potato Red', 'Rambutan']

        # Map the predicted index to the corresponding class label
        predicted_class_label = class_labels[predicted_label[0]]

        # Print the actual and predicted class labels
        print(f"Actual Class Label: {actual_class_labels[i]}")
        print(f"Predicted Class Label: {predicted_class_label}")

        # Display the testing image
        plt.imshow(cv2.cvtColor(testing_image, cv2.COLOR_BGR2RGB))
        plt.axis('off')
        plt.show()
    else:
        print("Error: Unable to load the image")
```

Actual Class Label: Apple Red Delicious
Predicted Class Label: Apple Red Delicious

