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 KP 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 (seehttps://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,...,0,0)

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)
```

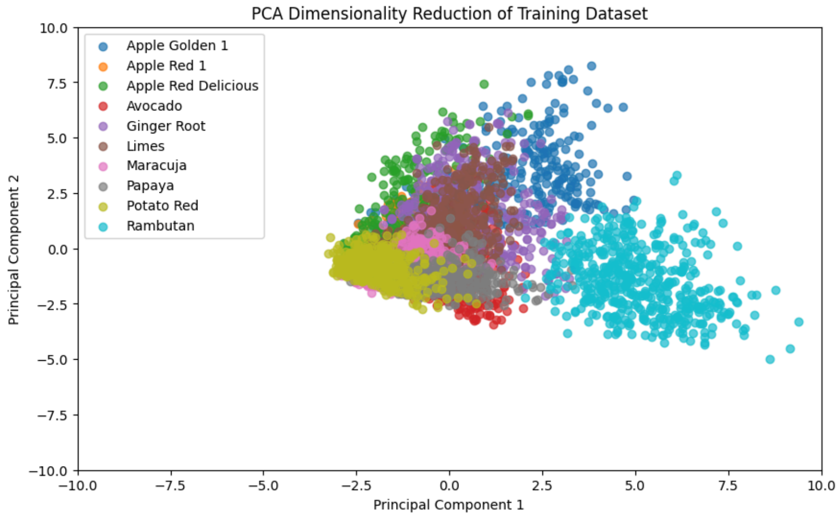
```
/usr/local/lib/python3.10/dist-packages/sklearn/cluster/_kmeans.py:870: FutureWarning: The default value of `n_init` will change from 10 to 'auto' in 1.4. Set the value of `n_init` explicitly to suppress the warning
  warnings.warn(
Example vector representing Image A: [0 0 2 1 1 0 1 1 0 1 1 0 1 0 0 2 1 0 1 1 2 0 0 0 0 0 0 1 0 1 1 1 0 0 1 1 3
 0 0 0 1 3 2 1 0 0 1 2 0 0 0 1 0 0 1 0 1 1 0 0 0 2 0 1 0 1 0 0 1 0 1 1 1 0
 0 1 1 0 3 0 0 0 0 0 0 1 0 0 0 2 2 0 0 4 0 2 0 0 0 0]
Shape of dataset D: (4665, 100)
```

Dimensionality reduction(using Principal Component Analysis,PCA)(seehttps://scikit-learn.
org/stable/modules/generated/sklearn.decomposition.PCA.html for PCA. 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 2 0 0 1 0 0 1 0 0 0 2 0 1 0 1 0 1 0 1 0 0 0 1 3 2 1 0 4 0 1 1 0 1 0 0 0
 0 2 4 0 0 2 0 0 0 0 0 5 0 0 0 0 1 0 0 2 1 0 0 0 2 0 0 0 1 0 0 0 0 1 0 1 0
```

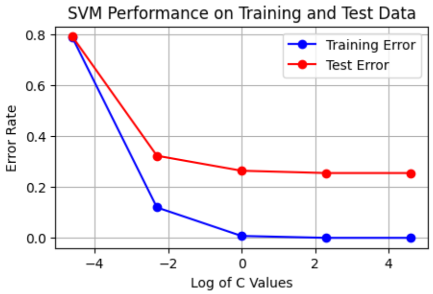
```
  0 0 0 1 1 2 3 0 1 1 1 0 2 0 0 0 0 2 1 0 3 2 0 1 0 0]
 Shape of testing dataset D: (1542, 100)
```

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
    svm_model = SVC(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)

    # 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


import matplotlib.pyplot as plt

# 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')
plt.grid(True)
plt.legend()
plt.show()
```

```
C Value: 0.01
Training Accuracy: 0.2116
Testing Accuracy: 0.2082
Train Error: 0.7884
Test Error: 0.7918

C Value: 0.1
Training Accuracy: 0.8804
Testing Accuracy: 0.6770
Train Error: 0.1196
Test Error: 0.3230

C Value: 1.0
Training Accuracy: 0.9925
Testing Accuracy: 0.7361
Train Error: 0.0075
Test Error: 0.2639

C Value: 10
Training Accuracy: 1.0000
Testing Accuracy: 0.7451
Train Error: 0.0000
Test Error: 0.2549

C Value: 100
Training Accuracy: 1.0000
Testing Accuracy: 0.7451
Train Error: 0.0000
Test Error: 0.2549
```



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).

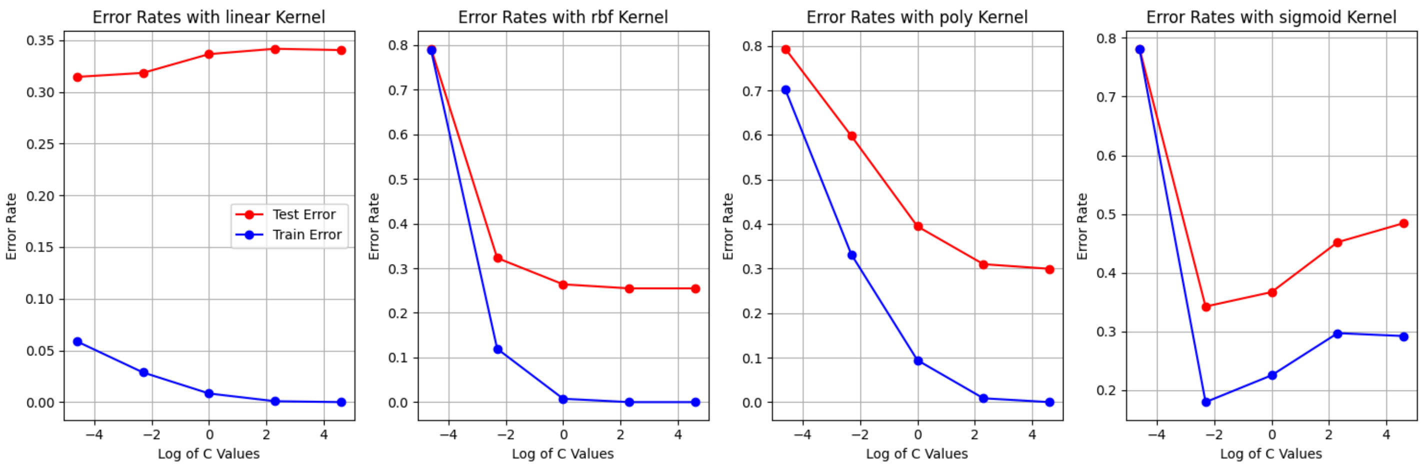
In essence, C values determine the balance between achieving a low training error and generalizing well to unseen data.

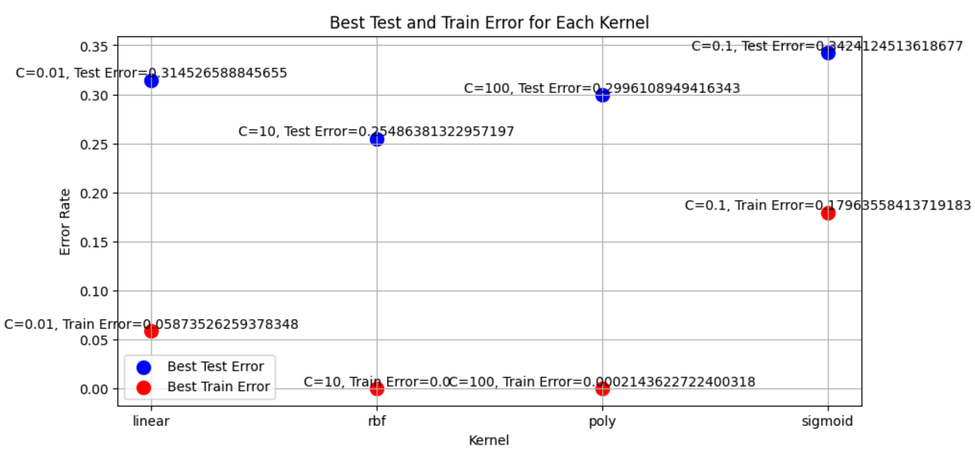
We repeat for kernel = 'linear', 'RBF', 'poly', 'sigmoid'

```
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: 0.9412647374062165, Testing Accuracy: 0.685473411154345, Train Error: 0.05873526259378348, Test Error: 0.314526588845655
C value: 0.1, Training Accuracy: 0.9712754555198285, Testing Accuracy: 0.6815823605706874, Train Error: 0.028724544480171477, Test Error: 0.31841763942931256
C value: 1.0, Training Accuracy: 0.9916398713826367, Testing Accuracy: 0.6634241245136187, Train Error: 0.00836012861736335, Test Error: 0.33657587548638135
C value: 10, Training Accuracy: 0.9991425509110397, Testing Accuracy: 0.6582360570687419, Train Error: 0.0008574490889603492, Test Error: 0.3417639429312581
C value: 100, Training Accuracy: 1.0, Testing Accuracy: 0.6595330739299611, Train Error: 0.0, Test Error: 0.3404669260700389

Kernel: rbf
C value: 0.01, Training Accuracy: 0.21157556270096464, Testing Accuracy: 0.20817120622568094, Train Error: 0.7884244372990353, Test Error: 0.791828793774319
C value: 0.1, Training Accuracy: 0.8803858520900322, Testing Accuracy: 0.6770428015564203, Train Error: 0.11961414790996783, Test Error: 0.32295719844357973
C value: 1.0, Training Accuracy: 0.992497320471597, Testing Accuracy: 0.7360570687418937, Train Error: 0.007502679528403, Test Error: 0.2639429312581063
C value: 10, Training Accuracy: 1.0, Testing Accuracy: 0.745136186770428, Train Error: 0.0, Test Error: 0.25486381322957197
C value: 100, Training Accuracy: 1.0, Testing Accuracy: 0.745136186770428, Train Error: 0.0, Test Error: 0.25486381322957197

Kernel: poly
C value: 0.01, Training Accuracy: 0.2977491961414791, Testing Accuracy: 0.20622568093385213, Train Error: 0.7022508038585209, Test Error: 0.7937743190661479
C value: 0.1, Training Accuracy: 0.6681672025723473, Testing Accuracy: 0.40207522697795073, Train Error: 0.3318327974276527, Test Error: 0.5979247730220493
C value: 1.0, Training Accuracy: 0.9056806002143623, Testing Accuracy: 0.6050583657587548, Train Error: 0.09431939978563775, Test Error: 0.3949416342412452
C value: 10, Training Accuracy: 0.9912111468381565, Testing Accuracy: 0.6900129701686122, Train Error: 0.008788853161843524, Test Error: 0.3099870298313878
C value: 100, Training Accuracy: 0.99978563772776, Testing Accuracy: 0.7003891050583657, Train Error: 0.0002143622722400318, Test Error: 0.2996108949416343

Kernel: sigmoid
C value: 0.01, Training Accuracy: 0.21929260450160773, Testing Accuracy: 0.2185473411154345, Train Error: 0.7807073954983923, Test Error: 0.7814526588845655
C value: 0.1, Training Accuracy: 0.8203644158628082, Testing Accuracy: 0.6575875486381323, Train Error: 0.17963558413719183, Test Error: 0.3424124513618677
C value: 1.0, Training Accuracy: 0.7747052518756699, Testing Accuracy: 0.6329442282749675, Train Error: 0.22529474812433015, Test Error: 0.36705577172503245
C value: 10, Training Accuracy: 0.7028938906752411, Testing Accuracy: 0.5479896238651103, Train Error: 0.2971061093247589, Test Error: 0.4520103761348897
C value: 100, Training Accuracy: 0.7078242229367632, Testing Accuracy: 0.5155642023346303, Train Error: 0.29217577706323683, Test Error: 0.4844357976653697
```





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.