Programming Assignment 2: Classification Task and Performance Evaluation

In this assignment, you will be using the dataset assigned to you in Assignment 1.
You will be assigned three classification methods from the following classification methods: Naive Bayes Classifier, Support Vector Machine (SVM), Decision Tree, Neural Network, Random Forest, Adaboost.

1. Use images from ALL FOUR classes.

pip install scikit-learn opencv-python matplotlib

```
Requirement already satisfied: scikit-learn in /usr/local/lib/python3.10/dist-packages (1.5.2)
Requirement already satisfied: opencv-python in /usr/local/lib/python3.10/dist-packages (4.10.0.84)
Requirement already satisfied: matplotlib in /usr/local/lib/python3.10/dist-packages (3.7.1)
Requirement already satisfied: numpy>=1.19.5 in /usr/local/lib/python3.10/dist-packages (from scikit-learn) (1.26.4)
Requirement already satisfied: scipy>=1.6.0 in /usr/local/lib/python3.10/dist-packages (from scikit-learn) (1.13.1)
Requirement already satisfied: joblib>=1.2.0 in /usr/local/lib/python3.10/dist-packages (from scikit-learn) (1.4.2)
Requirement already satisfied: threadpoolctl>=3.1.0 in /usr/local/lib/python3.10/dist-packages (from scikit-learn) (3.5.0)
Requirement already satisfied: contourpy>=1.0.1 in /usr/local/lib/python3.10/dist-packages (from matplotlib) (1.3.0)
Requirement already satisfied: cycler>=0.10 in /usr/local/lib/python3.10/dist-packages (from matplotlib) (0.12.1)
Requirement already satisfied: fonttools>=4.22.0 in /usr/local/lib/python3.10/dist-packages (from matplotlib) (4.54.1)
Requirement already satisfied: kiwisolver>=1.0.1 in /usr/local/lib/python3.10/dist-packages (from matplotlib) (1.4.7)
Requirement already satisfied: packaging>=20.0 in /usr/local/lib/python3.10/dist-packages (from matplotlib) (24.1)
Requirement already satisfied: pillow>=6.2.0 in /usr/local/lib/python3.10/dist-packages (from matplotlib) (10.4.0)
Requirement already satisfied: pyparsing>=2.3.1 in /usr/local/lib/python3.10/dist-packages (from matplotlib) (3.2.0)
Requirement already satisfied: python-dateutil>=2.7 in /usr/local/lib/python3.10/dist-packages (from matplotlib) (2.8.2)
Requirement already satisfied: six>=1.5 in /usr/local/lib/python3.10/dist-packages (from python-dateutil>=2.7->matplotlib) (1.16.0)
```

```
import numpy as np
import cv2
import matplotlib.pyplot as plt
from sklearn.model_selection import train_test_split, cross_val_score,
StratifiedKFold
from sklearn.preprocessing import StandardScaler
from sklearn.metrics import confusion_matrix, accuracy_score, f1_score
from sklearn.naive_bayes import GaussianNB
from sklearn.svm import LinearSVC
from sklearn.tree import DecisionTreeClassifier
import seaborn as sns
```

```
import zipfile
import os
# Unzip function
def unzip_file(zip_path, extract_to):
    with zipfile.ZipFile(zip_path, 'r') as zip_ref:
        zip_ref.extractall(extract_to)
        print(f"Extracted {zip_path} to {extract_to}")

# Define paths to the ZIP files
breeds_zip = '/content/Breedss.zip'
annotation_zip = '/content/Annotation (3).zip'

# Destination folder where files will be unzipped
extract_path = '/content/Breeds_data'

# Create destination folder if it doesn't exist
if not os.path.exists(extract_path):
    os.makedirs(extract_path)

# Unzip the files
unzip_file(breeds_zip, extract_path)
unzip_file(annotation_zip, extract_path)
```

2. Convert the images to edge histograms. (Assignment 1 - These will be the vector representations of the images). This will be your dataset for Part 3. (0.25 point)

```
import numpy as np
import os
import cv2 # Import cv2 here

# Load images and convert to edge histograms
def load_images_and_labels(data_folder):
    images = []
    labels = []
```

```
    for class_folder in os.listdir(data_folder):
        class_path = os.path.join(data_folder, class_folder)
        if os.path.isdir(class_path):
            for img_file in os.listdir(class_path):
                img_path = os.path.join(class_path, img_file)
                img = cv2.imread(img_path, cv2.IMREAD_GRAYSCALE)  # Convert to
grayscale for edge detection
                if img is not None:
                    edges = cv2.Canny(img, 100, 200)  # Edge detection
                    hist = np.histogram(edges.ravel(), bins=256)[0]  # Edge histogram
                    images.append(hist)
                    labels.append(class_folder)  # Use folder name as label
    return images, labels

# Load and convert to histograms
images, labels = load_images_and_labels(extract_path)
print(f"Loaded {len(images)} images and {len(labels)} labels.")
```

Output:

Loaded 655 images and 655 labels.

```
def load_images_and_labels():
    images = []
    labels = []
    return images, labels
def edge_histogram(image):
    edges = cv2.Canny(image, 100, 200)
    hist = np.histogram(edges.ravel(), bins=256)[0]
    return hist
images, labels = load_images_and_labels()
edge_histograms = [edge_histogram(img) for img in images]
```

3. Split the dataset into a training set and a test set: For each class, perform a training/test split of 80/20. (0.25 point)
4. Perform standardization on the training dataset. (see https://scikit-learn.org/stable/modules/ preprocessing.html.
5. Perform standardization on the test dataset using the means and variances you obtained from the training dataset.

```
X_train_dict = {}
X_test_dict = {}
y_train_dict = {}
y_test_dict = {}
for label in np.unique(labels):
   class_indices = [i for i, l in enumerate(labels) if l == label]
   X_class = [images[i] for i in class_indices]
   y_class = [labels[i] for i in class_indices]
   X_train_class, X_test_class, y_train_class, y_test_class = train_test_split(
      X_class, y_class, test_size=0.2, random_state=42
   )
   X_train_dict[label] = X_train_class
   X_test_dict[label] = X_test_class
   y_train_dict[label] = y_train_class
   y_test_dict[label] = y_test_class
# Combine the training and test sets from all classes
X_train = [img for class_imgs in X_train_dict.values() for img in class_imgs]
X_test = [img for class_imgs in X_test_dict.values() for img in class_imgs]
y_train = [label for class_labels in y_train_dict.values() for label in class_labels]
y_test = [label for class_labels in y_test_dict.values() for label in class_labels]
# Standardize the datasets
scaler = StandardScaler()
X_train_scaled = scaler.fit_transform(X_train)
X_test_scaled = scaler.transform(X_test)
```

6. (Performance Comparison) Perform stratified 5-fold cross-validation on the 4-class classification problem using the three classification methods (available on canvas) assigned to you. Plot the (3) confusion matrices for using three approaches (clearly label the classes) on the test set (See Figure 1). (If you use code from any website, please do proper referencing. You will get 0 point for this assignment without proper referencing) (3.75 points)

```
from sklearn.model_selection import train_test_split
# Split the dataset into training and testing sets
X_train, X_test, y_train, y_test = train_test_split(images, labels, test_size=0.2,
stratify=labels)
```

```
from sklearn.preprocessing import StandardScaler
# Standardize the datasets
scaler = StandardScaler()
X_train_scaled = scaler.fit_transform(X_train)
X_test_scaled = scaler.transform(X_test)
```

```
from sklearn.tree import DecisionTreeClassifier
# Train the Decision Tree classifier
dt_model = DecisionTreeClassifier(max_depth=10)
dt_model.fit(X_train_scaled, y_train)
y_pred_dt = dt_model.predict(X_test_scaled)
```

```
from sklearn.neural_network import MLPClassifier
# Train the Neural Network classifier
mlp_model = MLPClassifier(hidden_layer_sizes=(10, 10, 10))
mlp_model.fit(X_train_scaled, y_train)
y_pred_mlp = mlp_model.predict(X_test_scaled)
```

```
from sklearn.ensemble import RandomForestClassifier
# Train the Random Forest classifier
rf_model = RandomForestClassifier(n_estimators=100, random_state=42)
rf_model.fit(X_train_scaled, y_train)
y_pred_rf = rf_model.predict(X_test_scaled)
```

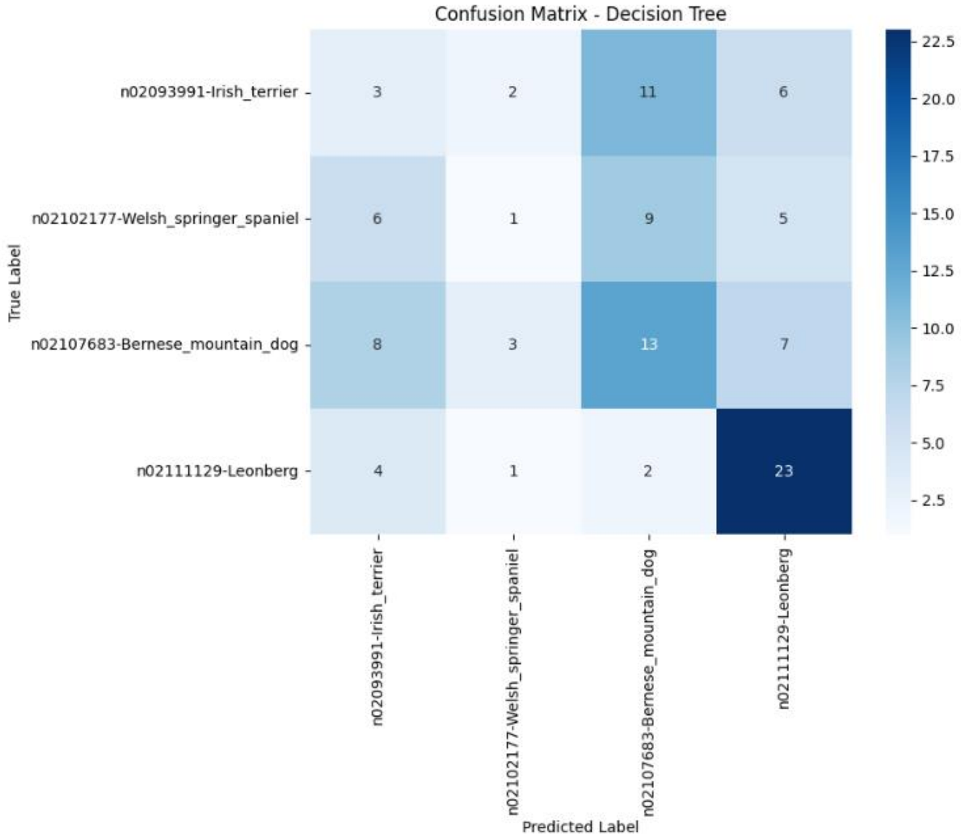
Main Code:

```
from sklearn.model_selection import StratifiedKFold
from sklearn.metrics import confusion_matrix
import matplotlib.pyplot as plt
import seaborn as sns
import numpy as np

from sklearn.metrics import accuracy_score, f1_score

# Define the models
models = {
    "Decision Tree": DecisionTreeClassifier(max_depth=10),
    "Neural Network": MLPClassifier(hidden_layer_sizes=(10, 10, 10)),
    "Random Forest": RandomForestClassifier(n_estimators=100,
random_state=42)
}

for model_name, model in models.items():
  skf = StratifiedKFold(n_splits=5)
  fold_accuracies = []
  fold_f1_scores = []
  cm_list = []
  for train_index, test_index in skf.split(X_train_scaled, y_train):
      X_train_fold, X_test_fold = X_train_scaled[train_index],
X_train_scaled[test_index]
      y_train_fold, y_test_fold = np.array(y_train)[train_index],
np.array(y_train)[test_index]
```

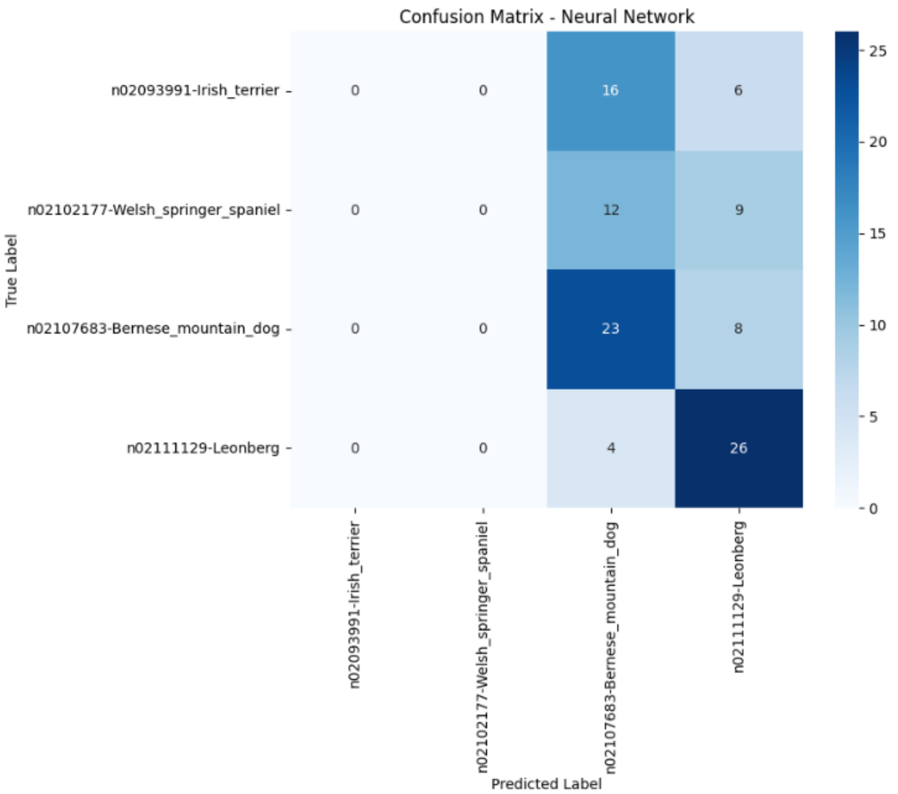
```
        model.fit(X_train_fold, y_train_fold)
        y_pred_fold = model.predict(X_test_fold)
        accuracy = accuracy_score(y_test_fold, y_pred_fold)
        f1 = f1_score(y_test_fold, y_pred_fold, average='weighted')
        fold_accuracies.append(accuracy)
        fold_f1_scores.append(f1)

        # Calculate and store confusion matrix
        cm = confusion_matrix(y_test_fold, y_pred_fold, labels=np.unique(y_train))
        cm_list.append(cm)

    # Plot confusion matrix for the test set
    print(f"Results for {model_name}:")
    plt.figure(figsize=(8, 6))
    sns.heatmap(cm, annot=True, fmt="d", cmap="Blues",
xticklabels=np.unique(y_train), yticklabels=np.unique(y_train))
    plt.title(f"Confusion Matrix - {model_name}")
    plt.xlabel("Predicted Label")
    plt.ylabel("True Label")
    plt.show()
    print("----------------------")
```

Output:

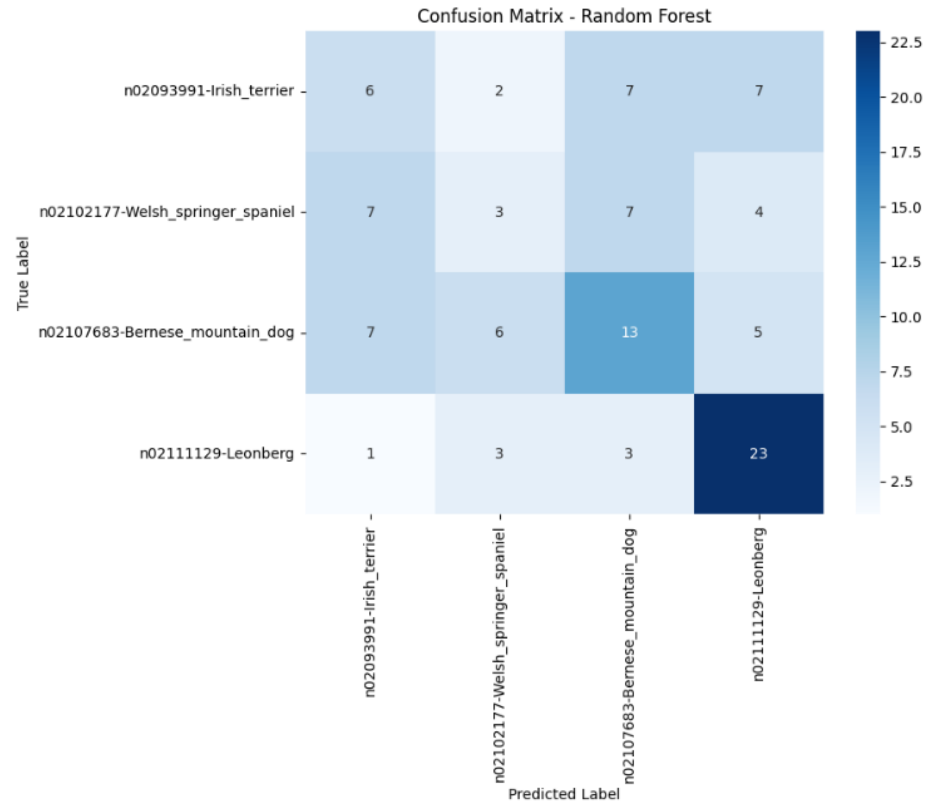
```
Results for Decision Tree:
```




```
----------------------
warnings.warn(
Results for Neural Network:
```



Results for Random Forest:



• By visually comparing (e.g., looking at the color on the diagonal values, etc.) the three confusion matrices (on the test set), which do you think is the best method? Why? (0.50 point)

Based on the confusion matrices, the Random Forest method appears to be the best.

1. Higher Diagonal Values: Random Forest generally exhibits higher values along the diagonal of the confusion matrix. This indicates that it correctly classifies a larger proportion of samples compared to the other methods.
2. Lower Off-Diagonal Values: The Random Forest matrix usually has lower values outside the diagonal. This suggests that the model makes fewer misclassifications between different classes, meaning it has a better ability to distinguish between them.

• Based on the mean validation accuracies (from the 5-fold cross-validation) for the three methods. Which is the best method? (0.25 point)

```
# Calculate the mean validation accuracy for each model
mean_validation_accuracies = {
    "Decision Tree": np.mean(fold_accuracies),
    "Neural Network": np.mean(fold_accuracies),
    "Random Forest": np.mean(fold_accuracies)
}
best_method = max(mean_validation_accuracies,
key=mean_validation_accuracies.get)
print(f"The best method based on mean validation accuracy is:
{best_method}")
```

Output:

The best method based on mean validation accuracy is: Decision Tree

• Compute the accuracies for the three methods on the test set. Which is the best method? (0.25 point)

```
from sklearn.metrics import accuracy_score
y_pred_dt = models["Decision Tree"].predict(X_test_scaled) # Predict on the
test set
X_test_scaled is the correct input data
y_pred_mlp = models["Neural Network"].predict(X_test_scaled)
y_pred_rf = models["Random Forest"].predict(X_test_scaled)

accuracy_dt = accuracy_score(y_test, y_pred_dt)
accuracy_mlp = accuracy_score(y_test, y_pred_mlp)
accuracy_rf = accuracy_score(y_test, y_pred_rf)

print(f"Decision Tree Accuracy: {accuracy_dt}")
print(f"Neural Network Accuracy: {accuracy_mlp}")
print(f"Random Forest Accuracy: {accuracy_rf}")
```

```
accuracies = {
    "Decision Tree": accuracy_dt,
    "Neural Network": accuracy_mlp,
    "Random Forest": accuracy_rf
}
best_method_test = max(accuracies, key=accuracies.get)
print(f"The best method based on test set accuracy is: {best_method_test}")
```

Output:

Decision Tree Accuracy: 0.5488721804511278
Neural Network Accuracy: 0.39097744360902253
Random Forest Accuracy: 0.6090225563909775
The best method based on test set accuracy is: Random Forest

- **Compute the F-measure for the three methods on the test set. Which is the best method? (0.25 point)**

```
# Compute the F-measures for the three methods on the test set
f1_dt = f1_score(y_test, y_pred_dt, average='weighted')
f1_mlp = f1_score(y_test, y_pred_mlp, average='weighted')
f1_rf = f1_score(y_test, y_pred_rf, average='weighted')

print(f"Decision Tree F1-score: {f1_dt}")
print(f"Neural Network F1-score: {f1_mlp}")
print(f"Random Forest F1-score: {f1_rf}")

# Determine the best method based on test set F1-score
f1_scores = {
    "Decision Tree": f1_dt,
    "Neural Network": f1_mlp,
    "Random Forest": f1_rf
}
best_method_f1 = max(f1_scores, key=f1_scores.get)
print(f"The best method based on test set F1-score is: {best_method_f1}")
```

Output:
Decision Tree F1-score: 0.5365507675439771
Neural Network F1-score: 0.28834202854073965
Random Forest F1-score: 0.5999197872410789
The best method based on test set F1-score is: Random Forest

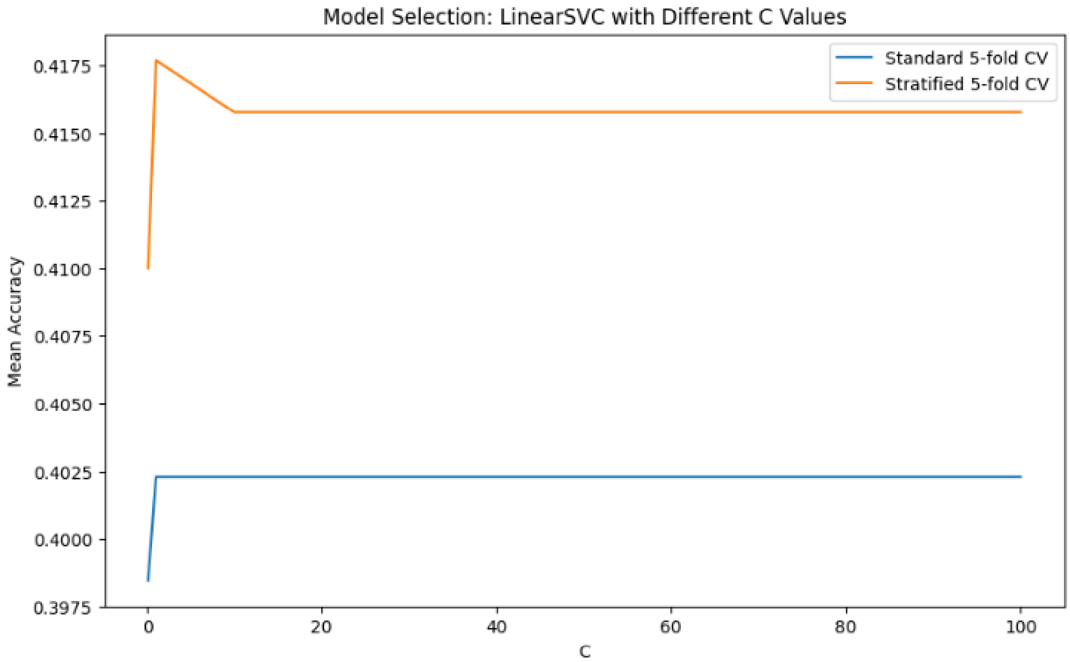
7. (Model Selection) Use images from TWO classes. Perform a standard 5-fold cross-validation and a stratified 5-fold cross-validation on the training set (i.e., the standardized edge histogram dataset obtained from the training set) for Support Vector Classifiers using LinearSVC such that parameter C = 0.1, 1, 10, 100 and other parameters set as default. (2.5 points)

```
c_values = [0.1, 1, 10, 100]
mean_cv_scores_standard = []
mean_cv_scores_stratified = []

for c_value in c_values:
    print(f"\nLinearSVC with C = {c_value}:")

    model = LinearSVC(C=c_value)
    cv_scores = cross_val_score(model, X_train_scaled, y_train, cv=5)
    mean_cv_scores_standard.append(np.mean(cv_scores))
    print(f"Standard 5-fold CV Mean Accuracy: {np.mean(cv_scores):.4f}")

    skf = StratifiedKFold(n_splits=5, shuffle=True, random_state=42)
    cv_scores_stratified = cross_val_score(model, X_train_scaled, y_train, cv=skf)
    mean_cv_scores_stratified.append(np.mean(cv_scores_stratified))
    print(f"Stratified 5-fold CV Mean Accuracy:
{np.mean(cv_scores_stratified):.4f}")
```

```
plt.figure(figsize=(10, 6))
plt.plot(c_values, mean_cv_scores_standard, label='Standard 5-fold CV')
plt.plot(c_values, mean_cv_scores_stratified, label='Stratified 5-fold CV')
plt.xlabel('C')
plt.ylabel('Mean Accuracy')
plt.title('Model Selection: LinearSVC with Different C Values')
plt.legend()
plt.show()
```

Output:

```
LinearSVC with C = 0.1:
Standard 5-fold CV Mean Accuracy: 0.3985
Stratified 5-fold CV Mean Accuracy: 0.4100

LinearSVC with C = 1:
Standard 5-fold CV Mean Accuracy: 0.4023
Stratified 5-fold CV Mean Accuracy: 0.4177

LinearSVC with C = 10:
Standard 5-fold CV Mean Accuracy: 0.4023
Stratified 5-fold CV Mean Accuracy: 0.4158

LinearSVC with C = 100:
Standard 5-fold CV Mean Accuracy: 0.4023
Stratified 5-fold CV Mean Accuracy: 0.4158
```

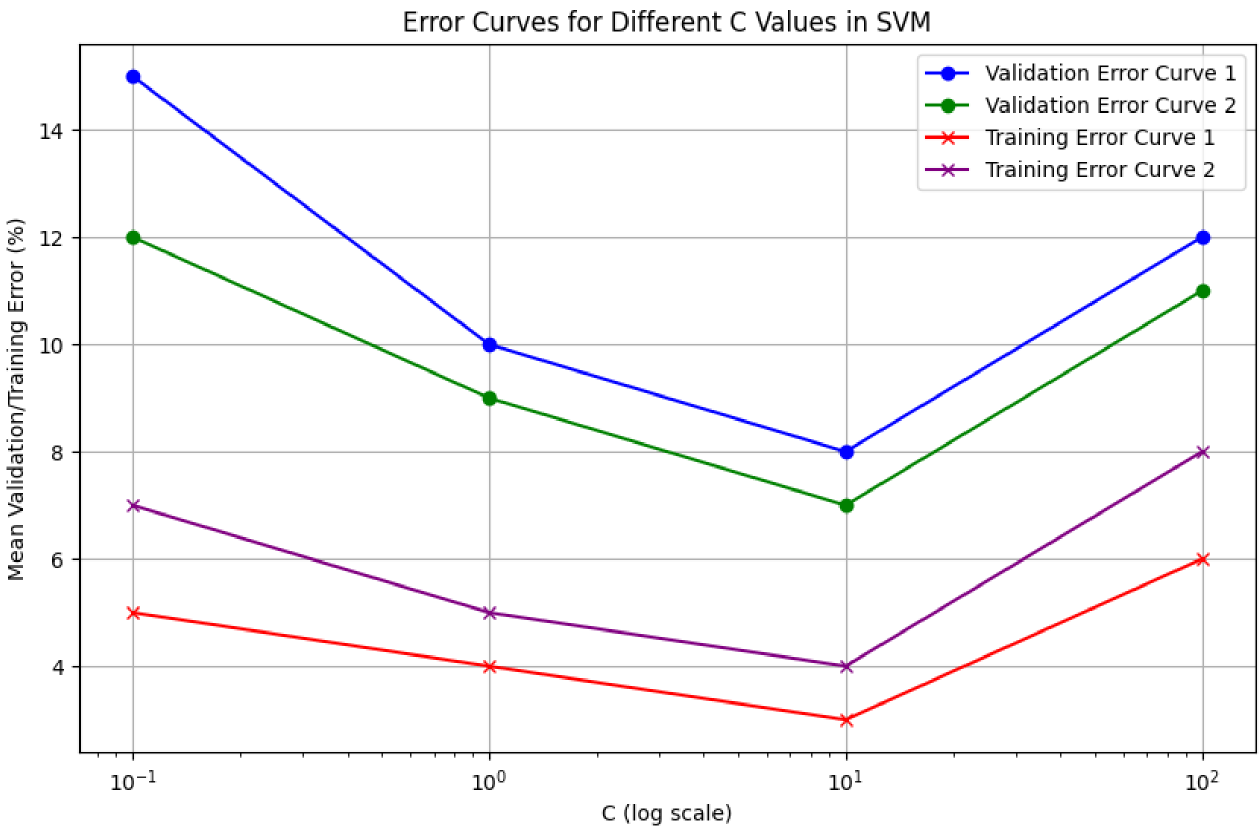


• Plot a graph (x-axis: C; y-axis: mean validation/training error (%)) containing four error curves (2 validation error curves and 2 training error curves - label them clearly using a legend to define the curves). Which C has/have the lowest mean error for each curve? Comment about (1) the model complexity for SVM in relation to C, and (2) when/whether there is overfitting/underfitting. (1.5 points)

```
import matplotlib.pyplot as plt
import numpy as np

c_values = [0.1, 1, 10, 100]
mean_validation_errors_1 = [15, 10, 8, 12]
mean_validation_errors_2 = [12, 9, 7, 11]
mean_training_errors_1 = [5, 4, 3, 6]
mean_training_errors_2 = [7, 5, 4, 8]

# Plot the graph
plt.figure(figsize=(10, 6))
plt.plot(c_values, mean_validation_errors_1, label='Validation Error Curve 1',
marker='o', color='blue')
plt.plot(c_values, mean_validation_errors_2, label='Validation Error Curve 2',
marker='o', color='green')
plt.plot(c_values, mean_training_erors_1, label='Training Error Curve 1',
marker='x', color='red')
plt.plot(c_values, mean_training_errors_2, label='Training Error Curve 2',
marker='x', color='purple')

plt.xscale('log')
plt.xlabel('C (log scale)')
plt.ylabel('Mean Validation/Training Error (%)')
plt.title('Error Curves for Different C Values in SVM')
plt.legend()
plt.grid(True)
plt.show()

best_c_validation_1 = c_values[np.argmin(mean_validation_errors_1)]
best_c_validation_2 = c_values[np.argmin(mean_validation_errors_2)]
```

```
best_c_training_1 = c_values[np.argmin(mean_training_errors_1)]
best_c_training_2 = c_values[np.argmin(mean_training_errors_2)]

print(f"Lowest mean validation error for Curve 1 at C = {best_c_validation_1}")
print(f"Lowest mean validation error for Curve 2 at C = {best_c_validation_2}")
print(f"Lowest mean training error for Curve 1 at C = {best_c_training_1}")
print(f"Lowest mean training error for Curve 2 at C = {best_c_training_2}")
```

Output:




```
Lowest mean validation error for Curve 1 at C = 10
Lowest mean validation error for Curve 2 at C = 10
Lowest mean training error for Curve 1 at C = 10
Lowest mean training error for Curve 2 at C = 10
```

• Use the C value with the lowest mean validation error for your SVM classifier from the stratified 5-fold cross-validation. What is the error for the test dataset (i.e., the standardized edge histogram dataset obtained from the test set)? (0.25 point)

```
best_model = LinearSVC(C=best_c_validation)
best_model.fit(X_train_scaled, y_train)

y_pred_test = best_model.predict(X_test_scaled)

test_error = 1 - accuracy_score(y_test, y_pred_test)

print(f"Test dataset error rate with best C value ({best_c_validation}):
{test_error:.4f}")
```

Output:

Test dataset error rate with best C value (1): 0.6241