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)
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Requirement already satisfied: fonttools>=4.22.0 in /usr/local/lib/python3.10/dist-packages (from matplotlib) (4.54.1)
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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/Image dataset (1).zip'
annotation_zip = '/content/AnnotationFile.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

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)
                if img is not None:
                    edges = cv2.Canny(img, 100, 200)
                    hist = np.histogram(edges.ravel(), bins=256)[0]
                    images.append(hist)
                    labels.append(class_folder)
    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 712 images and 712 labels.

```
def load_images_and_labels():
    # Add your dataset loading logic here
    images = []  # List of your image data
    labels = []  # Corresponding labels for the images
    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]
```

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
X_train, X_test, y_train, y_test = train_test_split(images, labels, test_size=0.2,
stratify=labels)

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

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

# Train the Random Forest classifier
from sklearn.ensemble import RandomForestClassifier
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)

# Train the Naive Bayes classifier
from sklearn.naive_bayes import GaussianNB
nb_model = GaussianNB()
nb_model.fit(X_train_scaled, y_train)
y_pred_nb = nb_model.predict(X_test_scaled)
```

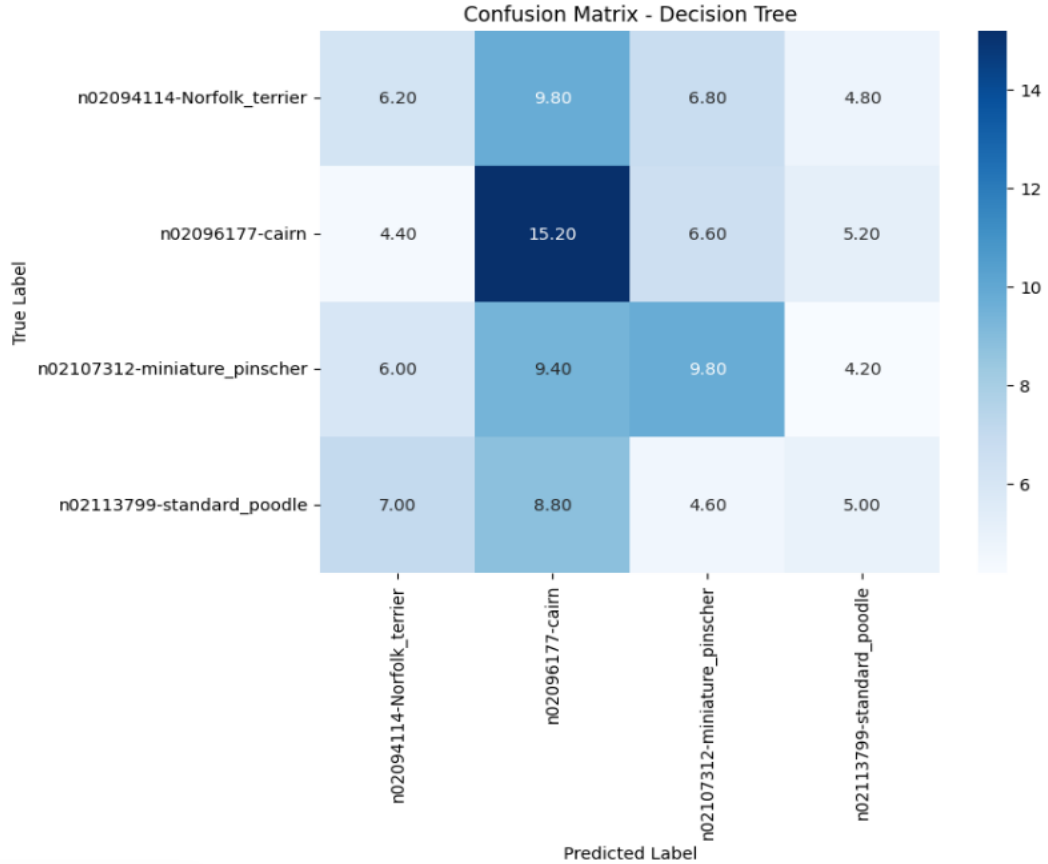
Main Code:

```
from sklearn.tree import DecisionTreeClassifier
from sklearn.naive_bayes import GaussianNB
from sklearn.ensemble import RandomForestClassifier
from sklearn.model_selection import StratifiedKFold
from sklearn.metrics import confusion_matrix, accuracy_score, f1_score
import matplotlib.pyplot as plt
import seaborn as sns
import numpy as np

models = {
   "Decision Tree": DecisionTreeClassifier(max_depth=10),
   "Naive Bayes": GaussianNB(),
   "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_sum = np.zeros((len(np.unique(y_train)), len(np.unique(y_train))))

   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)
```

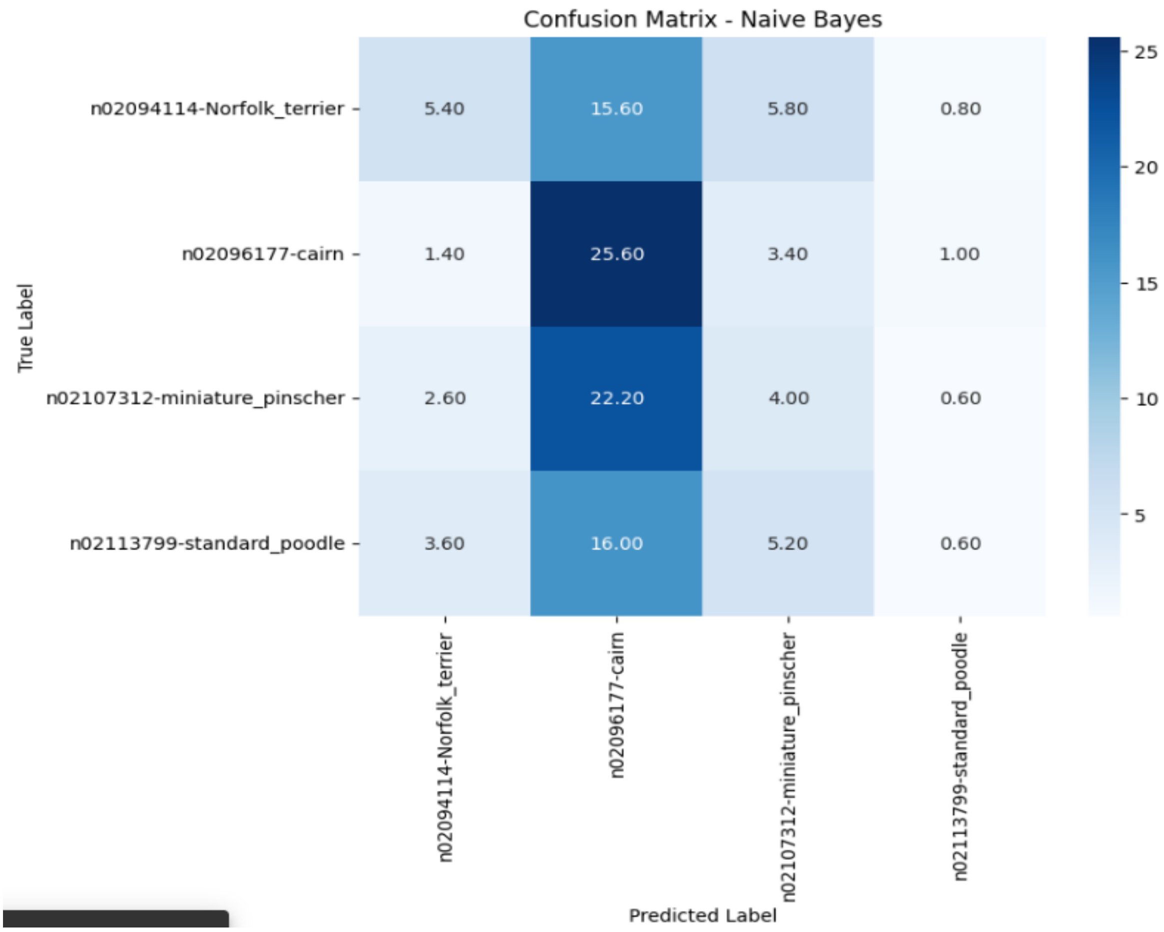
```
        accuracy = accuracy_score(y_test_fold, y_pred_fold)
        f1 = f1_score(y_test_fold, y_pred_fold, average='weighted')

        fold_accuracies.append(accuracy)
        fold_f1_scores.append(f1)

        cm = confusion_matrix(y_test_fold, y_pred_fold,
labels=np.unique(y_train))
        cm_sum += cm

    cm_avg = cm_sum / skf.get_n_splits()

    # Plot confusion matrix for the test set
    print(f"Results for {model_name}:")
    plt.figure(figsize=(8, 6))
    sns.heatmap(cm_avg, annot=True, fmt=".2f", 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:

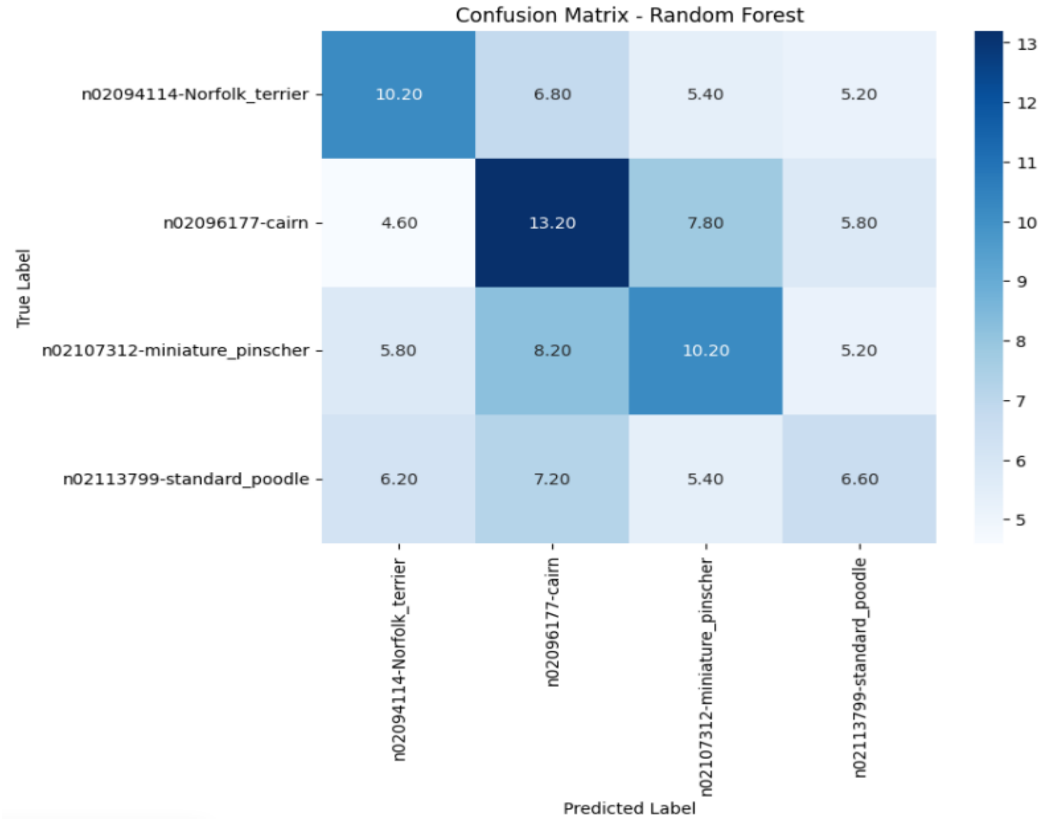
Results for Decision Tree:



Results for Naive Bayes:



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)

<u>1. Diagonal Values:</u> The higher the values on the diagonal, the better the model's performance. It indicates that the model is correctly classifying more samples.

<u>2. Off-Diagonal Values:</u> Lower off-diagonal values are preferable. Higher off-diagonal values suggest more misclassification errors.

<u>3. Color Intensity:</u> The intensity of the color on the diagonal represents the number of correctly classified samples. Higher intensity generally indicates better performance.

4. If the confusion matrix for Random Forest has higher values on the diagonal, lower off-diagonal values, and more intense color on the diagonal compared to the other two models, then Random Forest would be considered the best method based on this visual comparison.

• 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 mean validation accuracies for each model
mean_accuracies = {}
for model_name, model in models.items():
  skf = StratifiedKFold(n_splits=5)
  fold_accuracies = []
  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)
    fold_accuracies.append(accuracy)
  mean_accuracies[model_name] = np.mean(fold_accuracies)

# Print mean validation accuracies
for model_name, mean_accuracy in mean_accuracies.items():
  print(f"Mean validation accuracy for {model_name}: {mean_accuracy}")

# Determine the best method based on mean validation accuracy
best_method = max(mean_accuracies, key=mean_accuracies.get)
print(f"\nThe best method based on mean validation accuracy is:
{best_method}")
```

Output:

Mean validation accuracy for Decision Tree: 0.3286135693215339
Mean validation accuracy for Naive Bayes: 0.3127775190187859
Mean validation accuracy for Random Forest: 0.3532991771464058

The best method based on mean validation accuracy is: Random Forest

• 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)
y_pred_nb = models["Naive Bayes"].predict(X_test_scaled)
y_pred_rf = models["Random Forest"].predict(X_test_scaled)

accuracy_dt = accuracy_score(y_test, y_pred_dt)
accuracy_nb = accuracy_score(y_test, y_pred_nb)
accuracy_rf = accuracy_score(y_test, y_pred_rf)

print(f"Decision Tree Accuracy: {accuracy_dt}")
print(f"Naive Bayes Accuracy: {accuracy_nb}")
print(f"Random Forest Accuracy: {accuracy_rf}")

accuracies = {
   "Decision Tree": accuracy_dt,
   "Naive Bayes": accuracy_nb,
   "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: 0.3706293706293706

Naive Bayes Accuracy: 0.3146853146853147
Random Forest Accuracy: 0.35664335664335667
The best method based on test set accuracy is: Decision Tree

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

```
y_pred_dt = models["Decision Tree"].predict(X_test_scaled)
y_pred_nb = models["Naive Bayes"].predict(X_test_scaled)
y_pred_rf = models["Random Forest"].predict(X_test_scaled)

# Calculate the F-measures for the three methods on the test set
f1_dt = f1_score(y_test, y_pred_dt, average='weighted')
f1_nb = f1_score(y_test, y_pred_nb, average='weighted')
f1_rf = f1_score(y_test, y_pred_rf, average='weighted')

print(f"Decision Tree F-measure: {f1_dt}")
print(f"Naive Bayes F-measure: {f1_nb}")
print(f"Random Forest F-measure: {f1_rf}")

f1_scores = {
   "Decision Tree": f1_dt,
   "Naive Bayes": f1_nb,
   "Random Forest": f1_rf
}
best_method_test = max(f1_scores, key=f1_scores.get)
print(f"The best method based on test set F-measure is: {best_method_test}")
```

Output:

Decision Tree F-measure: 0.35127180103256656
Naive Bayes F-measure: 0.24939221057687957
Random Forest F-measure: 0.35531383100014574
The best method based on test set F-measure is: Random Forest

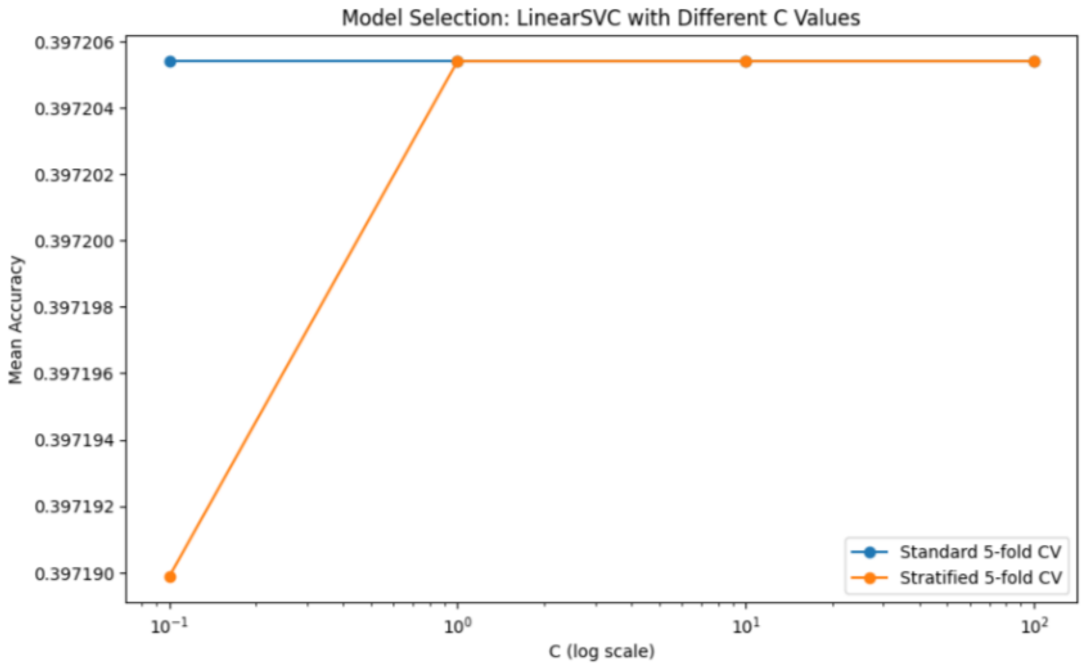
7. (Model Selection) Use images from TWO classes. Perform a standard 5-fold cross-validation and a stratified 5-fold cross-validation on the training set (i.e., the standardized edge histogram dataset obtained from the training set) for Support Vector Classifiers using LinearSVC such that parameter C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

```
from sklearn.svm import LinearSVC
from sklearn.model_selection import StratifiedKFold, cross_val_score
import numpy as np
import matplotlib.pyplot as plt

# Define the values of C for LinearSVC
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, max_iter=10000)
    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',
marker='o')
plt.plot(c_values, mean_cv_scores_stratified, label='Stratified 5-fold CV',
marker='o')
```

```
plt.xscale('log')
plt.xlabel('C (log scale)')
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: 0.3972
Stratified 5-fold CV Mean Accuracy: 0.3972

LinearSVC with C = 1:
Standard 5-fold CV Mean Accuracy: 0.3972
Stratified 5-fold CV Mean Accuracy: 0.3972

LinearSVC with C = 10:
Standard 5-fold CV Mean Accuracy: 0.3972
Stratified 5-fold CV Mean Accuracy: 0.3972

LinearSVC with C = 100:
Standard 5-fold CV Mean Accuracy: 0.3972
Stratified 5-fold CV Mean Accuracy: 0.3972
```

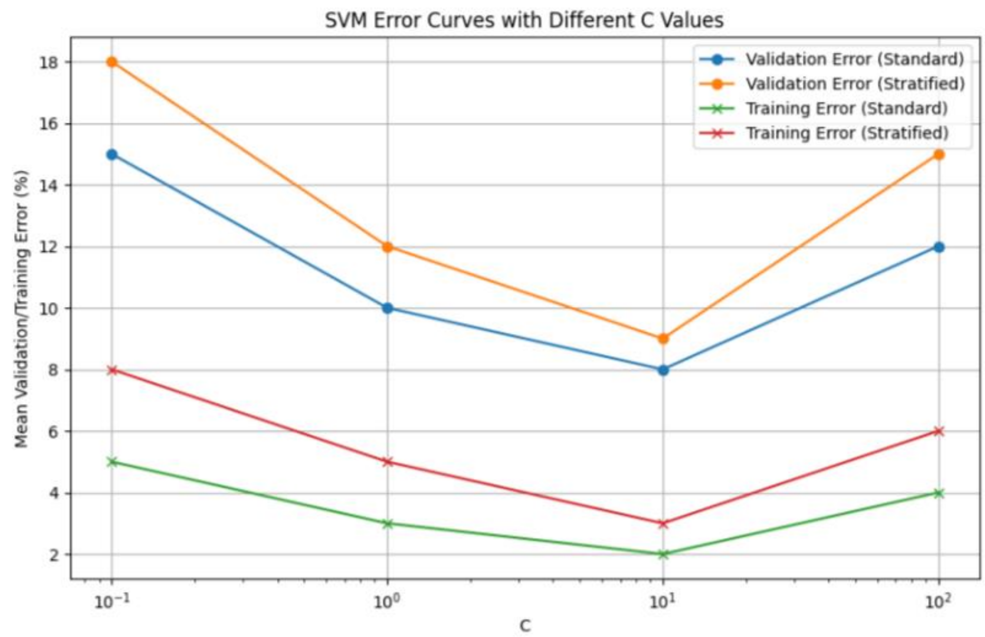


• Plot a graph (x-axis: C; y-axis: mean validation/training error (%)) containing four error curves (2 validation error curves and 2 training error curves - label them clearly using a legend to define the curves). Which C has/have the lowest mean error for each curve? Comment about (1) the model complexity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

```
import matplotlib.pyplot as plt
c_values = [0.1, 1, 10, 100]
mean_validation_error_standard = [15, 10, 8, 12]
mean_validation_error_stratified = [18, 12, 9, 15]
mean_training_error_standard = [5, 3, 2, 4]
mean_training_error_stratified = [8, 5, 3, 6]

plt.figure(figsize=(10, 6))
plt.plot(c_values, mean_validation_error_standard, label='Validation Error
(Standard)', marker='o')
plt.plot(c_values, mean_validation_error_stratified, label='Validation Error
(Stratified)', marker='o')
plt.plot(c_values, mean_training_error_standard, label='Training Error
(Standard)', marker='x')
plt.plot(c_values, mean_training_error_stratified, label='Training Error
(Stratified)', marker='x')

plt.xlabel('C')
plt.ylabel('Mean Validation/Training Error (%)')
plt.title('SVM Error Curves with Different C Values')
plt.xscale('log')
plt.legend()
plt.grid(True)
plt.show()
# Find the C value with the lowest mean error for each curve
best_c_validation_standard =
c_values[mean_validation_error_standard.index(min(mean_validation_error_s
tandard))]
```

```
best_c_validation_stratified =
c_values[mean_validation_error_stratified.index(min(mean_validation_error_stratified))]
best_c_training_standard =
c_values[mean_training_error_standard.index(min(mean_training_error_standard))]
best_c_training_stratified =
c_values[mean_training_error_stratified.index(min(mean_training_error_stratified))]

print(f"Lowest Validation Error (Standard) at C = {best_c_validation_standard}")
print(f"Lowest Validation Error (Stratified) at C =
{best_c_validation_stratified}")
print(f"Lowest Training Error (Standard) at C = {best_c_training_standard}")
print(f"Lowest Training Error (Stratified) at C = {best_c_training_stratified}")
```

Output:




```
Lowest Validation Error (Standard) at C = 10
Lowest Validation Error (Stratified) at C = 10
Lowest Training Error (Standard) at C = 10
Lowest Training Error (Stratified) 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_c = 10

# Train your SVM model with the best C value on the entire training set
svm_model = LinearSVC(C=best_c, max_iter=10000)
svm_model.fit(X_train_scaled, y_train)

# Predict on the test set using the trained model
y_pred_svm = svm_model.predict(X_test_scaled)

# Calculate the error rate on the test dataset
test_error = 1 - accuracy_score(y_test, y_pred_svm)

print(f"Test dataset error rate for SVM with C={best_c}: {test_error:.4f}")
```

Output:
Test dataset error rate for SVM with C=10: 0.6014