In [ ]:
```
import numpy as np
import matplotlib.pyplot as plt
import cv2
import os
from sklearn.preprocessing import StandardScaler
from sklearn.metrics import accuracy_score, f1_score
```

In [ ]:
```
# mapping labels to 0 to 3 for all the four classes
labmap = {0: "n02089078-black-and-tan_coonhound"
          ,1: "n02091831-Saluki"
          ,2:"n02092002-Scottish_deerhound"
          ,3:"n02095314-wire-haired_fox_terrier"}

# giving the paths of the cropped images
paths = [r'../DataSet/ProcessedDatasets/n02089078-black-and-tan_coonhound/'
         ,r'../DataSet/ProcessedDatasets/n02091831-Saluki/'
         ,r'../DataSet/ProcessedDatasets/n02092002-Scottish_deerhound/'
         ,r'../DataSet/ProcessedDatasets/n02095314-wire-haired_fox_terrier/']


data_set = [] # empty array to save the dataset
labels = [] # empty array to save the labels

# 1. loop to convert the images to gray scale pixel intensity histograms and save the labels and the dataset
for i in paths:
    for dog in os.listdir(i):
        img = cv2.imread(i + dog,cv2.IMREAD_GRAYSCALE)
        hist = cv2.calcHist(img, [0], None, [256], [0, 256])
        data_set.append(hist)
        labels.append(paths.index(i))

# 2. standardize the data set
standard_dset = StandardScaler().fit_transform(np.array(data_set)[:,:,0])

# convert the python list to a numpy array for appending it to the data
labels = np.array(labels)
# final data that consists of the normalized data and labels.
final_data = np.column_stack((standard_dset, labels))
```

In [ ]:
```
from sklearn.model_selection import train_test_split

# referred from https://scikit-learn.org/stable/modules/generated/sklearn.model_selection.train_test_split.html

X_train, X_test, Y_train, Y_test = [], [], [], []

# 3. loop to split training and testing data to 80/20 percent
for i in labmap.keys():
    class_indices = np.where(labels == i)[0]
    X_class = standard_dset[class_indices]
    y_class = labels[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)
    X_train.extend(X_train_class)
    X_test.extend(X_test_class)
    Y_train.extend(Y_train_class)
    Y_test.extend(Y_test_class)

X_train = np.array(X_train)
X_test = np.array(X_test)
Y_train = np.array(Y_train)
Y_test = np.array(Y_test)
```

Standard 5-Fold cross-validation

In [ ]:
```
from sklearn.model_selection import cross_val_score, KFold,StratifiedKFold
from sklearn.neighbors import KNeighborsClassifier
# referred from https://scikit-learn.org/stable/modules/generated/sklearn.model_selection.KFold.html

# list of k values to iterate through
k_values = [1, 3, 5, 7, 10, 20]

# Lists of validation and training errors for standard KFold cross-validation
standard_validation_errors = []
standard_training_errors = []

num_folds = 5

# Initialize a KFold cross-validator
kf = KFold(n_splits=num_folds, shuffle=True, random_state=57)
```

```
for k in k_values:
    # creating a k-NN classifier with the current k value
    knn_standard = KNeighborsClassifier(n_neighbors=k)

    # Initialize error variables for this k value
    validation_errors_k = []
    training_errors_k = []

    for train_index, validation_index in kf.split(X_train):

        # Split the data into training and validation sets
        X_train_fold, X_validation_fold = X_train[train_index], X_train[validation_index]
        Y_train_fold, Y_validation_fold = Y_train[train_index], Y_train[validation_index]

        # Fit the k-NN classifier on the training data
        knn_standard.fit(X_train_fold, Y_train_fold)

        # Predict on the training and validation sets
        Y_pred_train = knn_standard.predict(X_train_fold)
        Y_pred_validation = knn_standard.predict(X_validation_fold)

        # Calculate training and validation errors for this fold
        training_errors_k.append(1 - (Y_pred_train == Y_train_fold).mean())
        validation_errors_k.append(1 - (Y_pred_validation == Y_validation_fold).mean())

    # Calculate the mean errors across all folds for this k value
    mean_training_error = np.mean(training_errors_k)
    mean_validation_error = np.mean(validation_errors_k)

    # Append errors to the respective lists
    standard_training_errors.append(mean_training_error)
    standard_validation_errors.append(mean_validation_error)
```

Stratified 5-Fold cross-validation

In [ ]:

```
import math
# Lists of validation and training errors for stratified 5-fold cross-validation
stratified_validation_errors = []
stratified_training_errors = []
```

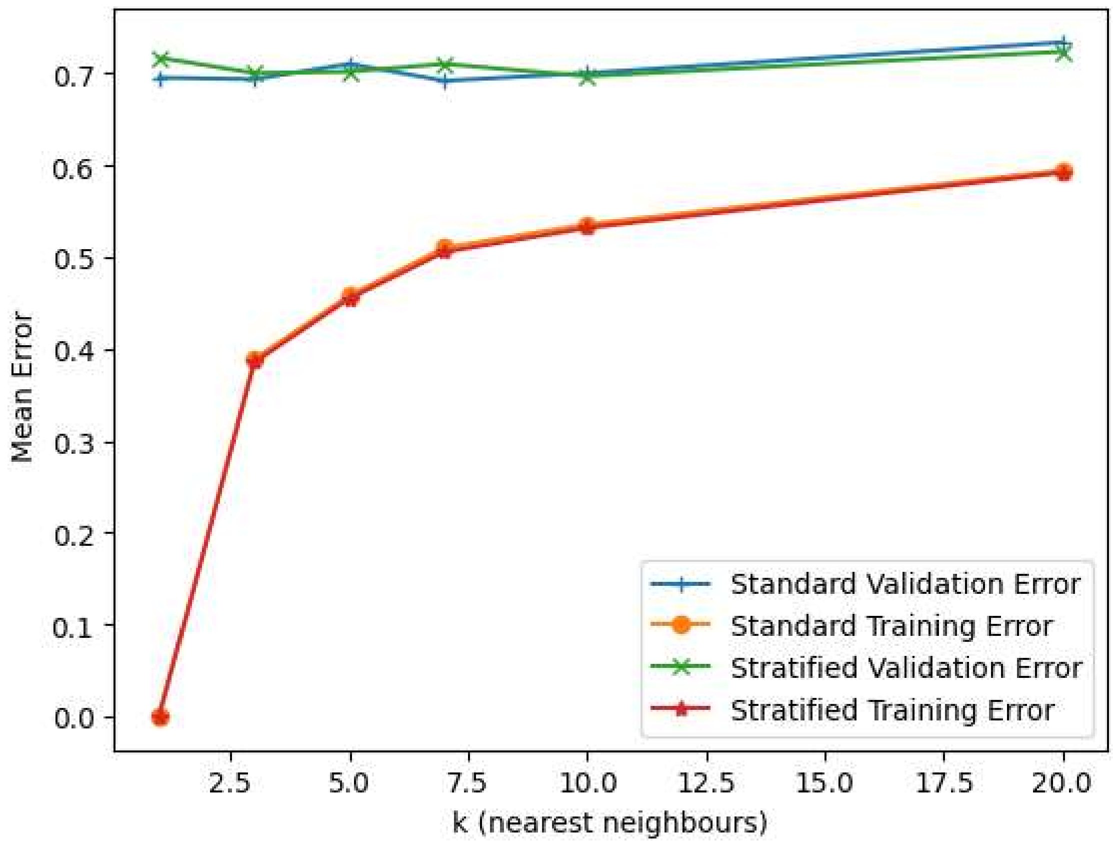
```
best_k_values = []

# reffered from https://scikit-learn.org/stable/modules/generated/sklearn.model_selection.StratifiedKFold.html#sklear

kfs = StratifiedKFold(n_splits=num_folds,shuffle=True,random_state=57)

for k in k_values:
    validation_errors = []
    training_errors = []
    # loop to split the train dataset into stratified 5 fold validation sets
    for train_index, val_index in kfs.split(X_train, Y_train):
        X_train_fold, X_val_fold = X_train[train_index], X_train[val_index] # Getting training data and validation da
        Y_train_fold, Y_val_fold = Y_train[train_index], Y_train[val_index] # Getting training labels and validation

        knn_stratified = KNeighborsClassifier(n_neighbors=k)
        knn_stratified.fit(X_train_fold, Y_train_fold)

        y_pred_train = knn_stratified.predict(X_train_fold)
        y_pred_val = knn_stratified.predict(X_val_fold)


        validation_errors.append(1- (y_pred_val == Y_val_fold).mean())
        training_errors.append(1- (y_pred_train == Y_train_fold).mean())

    mean_validation_error = np.mean(validation_errors)
    mean_training_error = np.mean(training_errors)

    stratified_validation_errors.append(mean_validation_error)
    stratified_training_errors.append(mean_training_error)

    best_k = k_values[np.argmin(stratified_validation_errors)]
    best_k_values.append(best_k)

print(f'validation errors  = {stratified_validation_errors}')
print(f'training errors  = {stratified_training_errors}')
```

```
validation errors  = [0.7170028011204482, 0.7001120448179272, 0.7017787114845939, 0.7102100840336135, 0.6967787114845
938, 0.7235714285714285]
training errors  = [0.0, 0.38526266852626684, 0.45476873415611874, 0.5054559967720149, 0.5318316184661807, 0.59213354
03454295]
```

Plotting the validation and training errors for both the cross-validations

In [ ]:
```
import matplotlib.pyplot as plt



# Plot the validation and training error curves for standard 5-fold cross-validation
plt.plot(k_values, standard_validation_errors, label='Standard Validation Error', marker='+')
plt.plot(k_values, standard_training_errors, label='Standard Training Error', marker='o')

# Plot the validation and training error curves for stratified 5-fold cross-validation
plt.plot(k_values, stratified_validation_errors, label='Stratified Validation Error', marker='x')
plt.plot(k_values, stratified_training_errors, label='Stratified Training Error', marker='*')

# Label the axes and add a legend
plt.xlabel('k (nearest neighbours)')
plt.ylabel('Mean Error ')
plt.legend()

# Find the best k for each curve
best_k_standard_validation = k_values[standard_validation_errors.index(min(standard_validation_errors))]
best_k_standard_training = k_values[standard_training_errors.index(min(standard_training_errors))]
best_k_stratified_validation = k_values[stratified_validation_errors.index(min(stratified_validation_errors))]
best_k_stratified_training = k_values[stratified_training_errors.index(min(stratified_training_errors))]

# Print the best k values for each curves
print(f'K with the least Standard Validation Error: {best_k_standard_validation} with {min(standard_validation_errors
print(f'K with the least Standard Training Error: {best_k_standard_training}' )
print(f'K with the least Stratified Validation Error: {best_k_stratified_validation} wit h with {min(stratified_valid
print(f'K with the least Stratified Training Error: {best_k_stratified_training}')

# Show the plot
plt.show()
```

```
K with the least Standard Validation Error: 7 with 0.6917366946778711 validation error
K with the least Standard Training Error: 1
K with the least Stratified Validation Error: 10 wit h with 0.6967787114845938 validation error
K with the least Stratified Training Error: 1
```



Comments

5 nearest neighbours has the least mean validation error for stratified cross fold validations 7 nearest neighbours has the least mean validation error for standard cross fold validations 1 nearest neighbours has the least mean training error for both standard and stratified cross fold validations 1 nearest neighbours has the least mean training error for both standard and stratified cross fold validations From the above curves The training error increases gradually as the number of neighbours increases. The model complexity depends on the number of number of zones or clusters that the model can make. If the number of nearest neighbours is 1 then for each datapoint the model tries to draw a boundary to it. Hence for a less k value the model is much complex and over fit. If the k value is more the model has big clustering zones and the model is very simple and the is under fit as it a lot of data points from other class may also fit into the current class. The best spot is somewhere between to have a less complex model but

with better fit.
From the give nK values the table can say whether the model is complex or simple and overfit or under fit.

K neighbours	complexity	overfit/underfit
1	more complexity	overfit
3	less complexity	close to best fit
5	less complexity	best fit
7	less complexity	close to best fit
10	simple	underfit
20	simple	underfit

In [ ]:
```
knn_s = KNeighborsClassifier(n_neighbors=best_k_stratified_validation)

# Train the k-NN classifier on the entire training dataset
knn_s.fit(X_train, Y_train)

# Evaluate the model on the test dataset and calculate the test error
Y_pred_test = knn_s.predict(X_test)
test_error = 1 - (Y_pred_test == Y_test).mean()  # Test error in terms of misclassification rate

print(f'Test Error with k={best_k_stratified_validation}: {test_error * 100:.2f}% ')
```

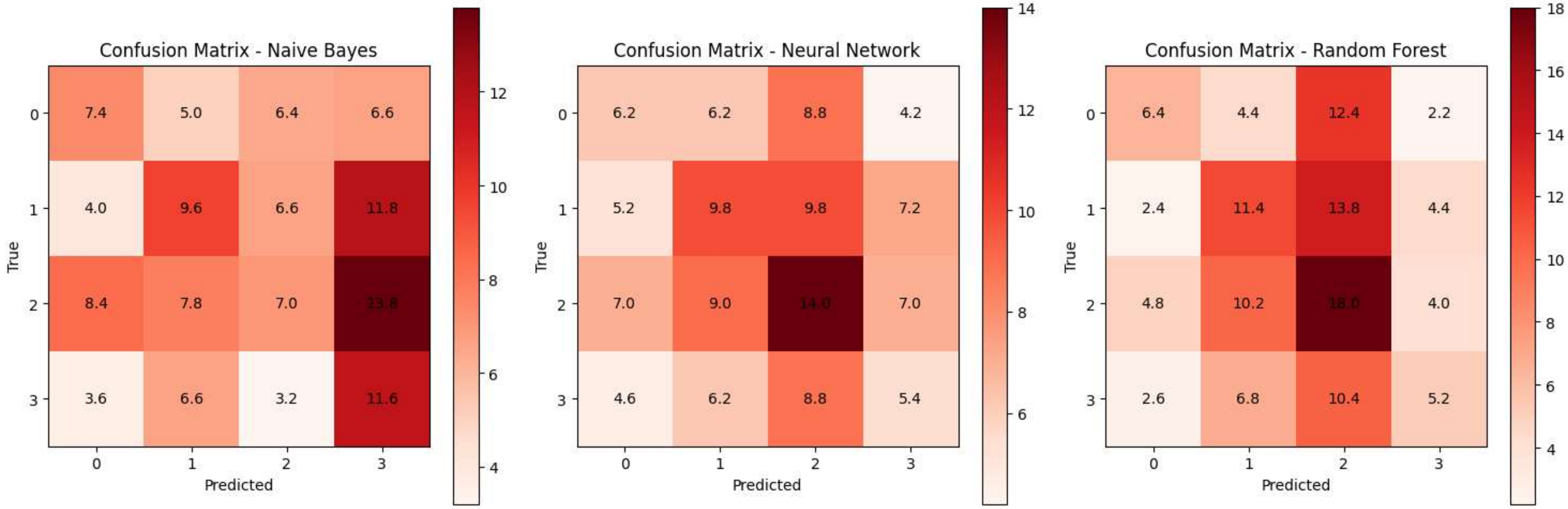
```
Test Error with k=10: 68.87%
```

In [ ]:
```
import numpy as np
import matplotlib.pyplot as plt
from sklearn.model_selection import StratifiedKFold
from sklearn.metrics import confusion_matrix
from sklearn.naive_bayes import GaussianNB
from sklearn.neural_network import MLPClassifier
from sklearn.ensemble import RandomForestClassifier
# reffered from https://scikit-learn.org/stable/modules/generated/sklearn.metrics.confusion_matrix.html


class_labels = np.unique(Y_train)

naive_bayes = GaussianNB()
```

```
neural_network = MLPClassifier(hidden_layer_sizes=(10, 10, 10))
random_forest = RandomForestClassifier()

models = [naive_bayes, neural_network, random_forest]
model_names = ['Naive Bayes', 'Neural Network', 'Random Forest']

skf = StratifiedKFold(n_splits=5, shuffle=True,random_state=57)

confusion_matrices = []
confusion_matrices_test = []
validation_accuracies = []

for model, model_name in zip(models, model_names):
    fold_matrices = []
    validation_accuracy_model = []
    for train_index, tv_index in skf.split(X_train, Y_train):
        X_train_fold, X_tv_fold = X_train[train_index], X_train[tv_index]
        Y_train_fold, y_tv_fold = Y_train[train_index], Y_train[tv_index]

        model.fit(X_train_fold, Y_train_fold)

        Y_val_pred = model.predict(X_tv_fold)   # predictions based on validation set
        fold_matrix = confusion_matrix(y_tv_fold, Y_val_pred, labels=class_labels) # confusion matrix based on test s
        validation_accuracy_model.append(accuracy_score(y_tv_fold , Y_val_pred)) # to find validation accuracy
        fold_matrices.append(fold_matrix)
    validation_accuracies.append(np.array(validation_accuracy_model).mean())
    confusion_matrices.append(fold_matrices)

best_model = ""
best_accuracy = 0
plt.figure(figsize=(15, 5))
for i, model_name in enumerate(model_names):
    plt.subplot(1, 3, i + 1)
    average_matrix = np.mean(confusion_matrices[i], axis=0)
    plt.imshow(average_matrix, cmap=plt.cm.Reds)
    plt.title(f'Confusion Matrix - {model_name}')
    plt.colorbar()
    tick_marks = np.arange(len(class_labels))
    plt.xticks(tick_marks, class_labels)
    plt.yticks(tick_marks, class_labels)
    plt.xlabel('Predicted')
    plt.ylabel('True')
```

```
    for i in range(len(class_labels)):
        for j in range(len(class_labels)):
            plt.text(j, i, f'{average_matrix[i, j]}', ha='center', va='center', color='black')

    print(f'Confusion Matrix - {model_name}')
    print(average_matrix)
    sum = 0
    for i in range(len(average_matrix)):
        for j in range(len(average_matrix[0])):
            if i==j:
                sum+=average_matrix[i,j]
    print(f'{sum} Average correct prediction for {model_name} on stratified 5 fold on test dataset.')
    if(sum>best_accuracy):
        best_accuracy = sum
        best_model = model_name


plt.tight_layout()
plt.show()

print(f"Best model according to confusion matrices is {best_model} with average correct prediction  of {best_accurac

print(f"Best model according to validation accuracy is {model_names[validation_accuracies.index(max(validation_accura
```

```
c:\Users\kaasa\AppData\Local\Programs\Python\Python310\lib\site-packages\sklearn\neural_network\_multilayer_perceptro
n.py:691: ConvergenceWarning: Stochastic Optimizer: Maximum iterations (200) reached and the optimization hasn't conv
erged yet.
  warnings.warn(
c:\Users\kaasa\AppData\Local\Programs\Python\Python310\lib\site-packages\sklearn\neural_network\_multilayer_perceptro
n.py:691: ConvergenceWarning: Stochastic Optimizer: Maximum iterations (200) reached and the optimization hasn't conv
erged yet.
  warnings.warn(
c:\Users\kaasa\AppData\Local\Programs\Python\Python310\lib\site-packages\sklearn\neural_network\_multilayer_perceptro
n.py:691: ConvergenceWarning: Stochastic Optimizer: Maximum iterations (200) reached and the optimization hasn't conv
erged yet.
  warnings.warn(
c:\Users\kaasa\AppData\Local\Programs\Python\Python310\lib\site-packages\sklearn\neural_network\_multilayer_perceptro
n.py:691: ConvergenceWarning: Stochastic Optimizer: Maximum iterations (200) reached and the optimization hasn't conv
erged yet.
  warnings.warn(
c:\Users\kaasa\AppData\Local\Programs\Python\Python310\lib\site-packages\sklearn\neural_network\_multilayer_perceptro
n.py:691: ConvergenceWarning: Stochastic Optimizer: Maximum iterations (200) reached and the optimization hasn't conv
erged yet.
  warnings.warn(
Confusion Matrix - Naive Bayes
[[ 7.4  5.   6.4  6.6]
 [ 4.   9.6  6.6 11.8]
 [ 8.4  7.8  7.  13.8]
 [ 3.6  6.6  3.2 11.6]]
35.6 Average correct prediction for Naive Bayes on stratified 5 fold on test dataset.
Confusion Matrix - Neural Network
[[ 6.2  6.2  8.8  4.2]
 [ 5.2  9.8  9.8  7.2]
 [ 7.   9.  14.   7. ]
 [ 4.6  6.2  8.8  5.4]]
35.4 Average correct prediction for Neural Network on stratified 5 fold on test dataset.
Confusion Matrix - Random Forest
[[ 6.4  4.4 12.4  2.2]
 [ 2.4 11.4 13.8  4.4]
 [ 4.8 10.2 18.   4. ]
 [ 2.6  6.8 10.4  5.2]]
41.0 Average correct prediction for Random Forest on stratified 5 fold on test dataset.
```




```
Best model according to confusion matrices is Random Forest with average correct prediction  of 41.0
Best model according to validation accuracy is Random Forest with average validation accuracy of 0.34347338935574 23
```

In [ ]:
```
y_true = Y_test

models[0].fit(X_train,Y_train)
models[1].fit(X_train,Y_train)
models[2].fit(X_train,Y_train)

y_pred_naive_bayes = models[0].predict(X_test)
y_pred_neural_network = models[1].predict(X_test)
y_pred_random_forest = models[2].predict(X_test)

accuracy_naive_bayes = accuracy_score(y_true, y_pred_naive_bayes)
accuracy_neural_network = accuracy_score(y_true, y_pred_neural_network)
accuracy_random_forest = accuracy_score(y_true, y_pred_random_forest)

f1_naive_bayes = f1_score(y_true, y_pred_naive_bayes, average='weighted')
f1_neural_network = f1_score(y_true, y_pred_neural_network, average='weighted')
f1_random_forest = f1_score(y_true, y_pred_random_forest, average='weighted')

print(f"Test Accuracy - Naive Bayes: {accuracy_naive_bayes * 100:.2f}%")
print(f"Test Accuracy - Neural Network: {accuracy_neural_network * 100:.2f}%")
print(f"Test Accuracy - Random Forest: {accuracy_random_forest * 100:.2f}%")
```

```
print(f"F-Measure - Naive Bayes: {f1_naive_bayes:.4f}")
print(f"F-Measure - Neural Network: {f1_neural_network:.4f}")
print(f"F-Measure - Random Forest: {f1_random_forest:.4f}")
```

```
c:\Users\kaasa\AppData\Local\Programs\Python\Python310\lib\site-packages\sklearn\neural_network\_multilayer_perceptro
n.py:691: ConvergenceWarning: Stochastic Optimizer: Maximum iterations (200) reached and the optimization hasn't conv
erged yet.
  warnings.warn(
Test Accuracy - Naive Bayes: 27.81%
Test Accuracy - Neural Network: 24.50%
Test Accuracy - Random Forest: 32.45%
F-Measure - Naive Bayes: 0.2650
F-Measure - Neural Network: 0.2437
F-Measure - Random Forest: 0.3100
```

Random forest is the best classification according to test Accuracy. Random forest is the best classification according to F-measure

References:

1. https://scikit-learn.org/stable/modules/generated/sklearn.metrics.confusion_matrix.html
2. https://scikit-learn.org/stable/modules/generated/sklearn.model_selection.StratifiedKFold.html#sklearn.model_selection.StratifiedKFold.split
3. https://scikit-learn.org/stable/modules/generated/sklearn.model_selection.train_test_split.html
4. https://scikit-learn.org/stable/modules/generated/sklearn.model_selection.KFold.html