Table of Contents

1. Required Libraries

In [1]:
```
import os
import cv2
import numpy as np
from sklearn import preprocessing
from sklearn.preprocessing import LabelEncoder
from sklearn.model_selection import train_test_split, cross_validate, StratifiedKFo
from sklearn.neighbors import KNeighborsClassifier
import matplotlib.pyplot as plt
from sklearn.metrics import accuracy_score, confusion_matrix, ConfusionMatrixDispla
from sklearn.neural_network import MLPClassifier
from sklearn.tree import DecisionTreeClassifier
from sklearn.ensemble import RandomForestClassifier
```

2. Data Preprocessing

In [2]:

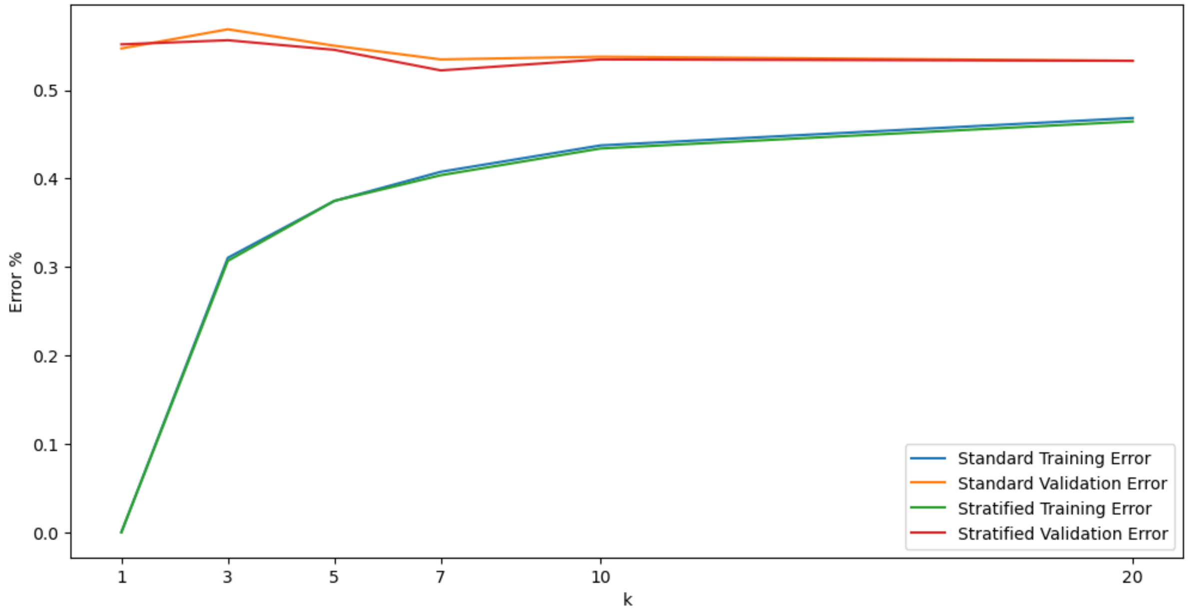
```python
# Converting images to Grayscale and computing their corresponding Pixel Intensity

histograms = []
labels = []

for breed in os.listdir('./images/'):
    breed_path = os.path.join('./images', breed)
    for file in os.listdir(breed_path):
        file_path = os.path.join(breed_path, file)
        image = cv2.imread(file_path, cv2.IMREAD_GRAYSCALE)

        if image is not None:
            histogram = cv2.calcHist([image], [0], None, [256], [0, 256])
            cv2.normalize(histogram, histogram)
            histogram = histogram.flatten()

            histograms.append(histogram)
            labels.append(breed)
        else:
            print(f'Warning: Could not read image file {file_path}')

histograms = np.array(histograms)
labels = np.array(labels)

# print(f'Histograms: {histograms}')
# print(f'Labels: {labels}')

# Standardizing the dataset

scaler = preprocessing.StandardScaler().fit(histograms)
scaled_histograms = scaler.transform(histograms)

# print(f'Scaled Histograms mean: {np.mean(scaled_histograms, axis=0)}')
# print(f'Scaled Histograms variance: {np.std(scaled_histograms, axis=0)}')

# Transforming labels to integers

labelencoder = LabelEncoder()
labels = labelencoder.fit_transform(labels)

# Splitting the dataset into Training/Test (80/20)

x_train, x_test, y_train, y_test = train_test_split(scaled_histograms, labels, test
```

3. Model Selection using KNN

3.1 KNN Process

In [3]:
```python
# Defining k-values for KNN (Number of neighbors)

k_values = [1, 3, 5, 7, 10, 20]

training_errors = []
validation_errors = []
skf_training_errors = []
skf_validation_errors = []

# Defining 5-Fold and Stratified 5-Fold cross-validation methods

kf = KFold(n_splits=5)
skf = StratifiedKFold(n_splits=5)

# Iterating over each k-value to evaluate the KNN classifier

for k in k_values:
    knn = KNeighborsClassifier(n_neighbors=k)

    # Computing training and validation errors for Standard 5-fold cross-validation
    cv_accuracy = cross_validate(knn, x_train, y_train, cv=kf, return_train_score=T
    training_errors.append(1 - cv_accuracy['train_score'].mean())
    validation_errors.append(1 - cv_accuracy['test_score'].mean())

    # Computing training and validation errors for Stratified 5-fold cross-validati
    skf_cv_accuracy = cross_validate(knn, x_train, y_train, cv=skf, return_train_sc
    skf_training_errors.append(1 - skf_cv_accuracy['train_score'].mean())
    skf_validation_errors.append(1 - skf_cv_accuracy['test_score'].mean())


print(f'Standard Training Errors: {training_errors}\n'
      f'Standard Validation Errors: {validation_errors}\n'
      f'Stratified Training Errors: {skf_training_errors}\n'
      f'Stratified Validation Errors: {skf_validation_errors}\n')

# Plotting error curves

plt.figure(figsize=(12, 6))
plt.plot(k_values, training_errors, label='Standard Training Error')
plt.plot(k_values, validation_errors, label='Standard Validation Error')
plt.plot(k_values, skf_training_errors, label='Stratified Training Error')
plt.plot(k_values, skf_validation_errors, label='Stratified Validation Error')
plt.xticks(k_values)
plt.xlabel('k')
plt.ylabel('Error %')
plt.legend()
plt.show()
```

```
Standard Training Errors: [0.0, 0.3104651162790698, 0.3748062015503877, 0.407751937
98449616, 0.43759689922480616, 0.4686046511627906]
Standard Validation Errors: [0.5472868217054263, 0.5689922480620155, 0.550387596899
2248, 0.5348837209302325, 0.537984496124031, 0.5333333333333333]
Stratified Training Errors: [0.0, 0.3069767441860465, 0.3748062015503877, 0.4038759
689922481, 0.43410852713178305, 0.46472868217054264]
Stratified Validation Errors: [0.5519379844961241, 0.5565891472868217, 0.5457364341
085271, 0.5224806201550388, 0.5348837209302325, 0.5333333333333334]
```



3.2 Evaluation and Analysis

Here you will find:

- A summary of the k-values with the lowest errors for training and validation.
- An analysis of the model performance for k=1,3,5,7,10,20.
- An evaluation of the best k-value (based on the lowest mean Stratified validation error obtained in subsection 3.1) on the test Set

```
In [4]: print(f'The k with the lowest mean error for the Standard Training error curve is:
print(f'The k with the lowest mean error for the Standard Validation error curve is
print(f'The k with the lowest mean error for the Stratified Training error curve is
print(f'The k with the lowest mean error for the Stratified Validation error curve

print('For k=1: The training errors are 0, which means it has complete accuracy, bu
      'This indicates that the model is overfitting and has high complexity.')
print('For k=3: Both the training errors and validation errors increase, which mean
      'overfitting, but less so than when k=1.')
print('For k=5: The training errors keep increasing but the validation errors start
      'k is reducing overfitting, though the model is still complex and overfitting
print('For k=7: The training errors increase a bit less than for previous values of
      'stratified cross-validation is at its minimum value, while the validation er
      'significantly. This could mean a balance between bias and variance, indicati
print('For k=10: Both the training and validation errors slightly increase, which m
      'and beginning to underfit.')
print('For k=20: The training errors increase and the validation errors barely decr
      'and less sensitive to the fluctuations in the training data, thus underfitti

### Now, let's evaluate the k with the lowest mean validation error from the Strati

best_k = k_values[np.argmin(skf_validation_errors)]

# Training the KNN Classifier with the best k-value

knn = KNeighborsClassifier(n_neighbors=best_k)
knn.fit(x_train, y_train)

# Predicting on the test set

ypred = knn.predict(x_test)

# Calculating the test error
test_error = 1 - accuracy_score(y_test, ypred)

print(f'The test error using the k with the lowest mean validation error ({best_k})
```

```
The k with the lowest mean error for the Standard Training error curve is: 1
The k with the lowest mean error for the Standard Validation error curve is: 20
The k with the lowest mean error for the Stratified Training error curve is: 1
The k with the lowest mean error for the Stratified Validation error curve is: 7

For k=1: The training errors are 0, which means it has complete accuracy, but the v
alidation errors are very high. This indicates that the model is overfitting and ha
s high complexity.
For k=3: Both the training errors and validation errors increase, which means that
the model is still complex and overfitting, but less so than when k=1.
For k=5: The training errors keep increasing but the validation errors start to dec
rease. This suggests that increasing k is reducing overfitting, though the model is
still complex and overfitting.
For k=7: The training errors increase a bit less than for previous values of k, but
the validation error for the stratified cross-validation is at its minimum value, w
hile the validation error for the standard cross-validation decreases significantly
. This could mean a balance between bias and variance, indicating the model is just
complex enough.
For k=10: Both the training and validation errors slightly increase, which means th
e model is starting to be too simple and beginning to underfit.
For k=20: The training errors increase and the validation errors barely decrease, i
ndicating the model is already too simple and less sensitive to the fluctuations in
the training data, thus underfitting.
The test error using the k with the lowest mean validation error (7) is: 0.52469135
80246914
```

4. Classifiers Comparison

4.1. Comparison Process

This section details the steps involved in training and evaluating the Multi-layer Perceptron(MLP), Decision Tree, and Random Forest Classifiers.

In [5]:

```python
# Initializing Stratified K-Fold cross-validation with 5 splits

skf = StratifiedKFold(n_splits=5)

mlp_acc = []
tree_acc = []
rforr_acc = []

# Defining classifiers

mlp = MLPClassifier(hidden_layer_sizes = (10, 10, 10))
tree = DecisionTreeClassifier(max_depth=10)
rforr = RandomForestClassifier()

my_classifiers = [mlp, tree, rforr]
classi_names = ["MLP", "Decision Tree", "Random Forest"]
accuracies = [mlp_acc, tree_acc, rforr_acc]

# Performing Stratified K-Fold cross-validation for each classifier

for i in range(len(my_classifiers)):
    for train_index, val_index in skf.split(x_train, y_train):
        # Splitting the data into training and validation sets using the generated
        x_train_fold, x_val_fold = x_train[train_index], x_train[val_index]
        y_train_fold, y_val_fold = y_train[train_index], y_train[val_index]

        # Fitting the classifier on the training fold
        my_classifiers[i].fit(x_train_fold, y_train_fold)

        # Predicting on the validation fold
        y_valpred = my_classifiers[i].predict(x_val_fold)
        accuracies[i].append(accuracy_score(y_val_fold, y_valpred))

    # Fitting the classifier on the entire Training set and predict on the Test set

    my_classifiers[i].fit(x_train, y_train)
    ypred = my_classifiers[i].predict(x_test)

    # Converting labels back to the original version ( We need this for plotting)

    breed_orig = labelencoder.inverse_transform(np.unique(y_test))

    # Plotting Confusion Matrix
    cm = confusion_matrix(y_test, ypred)
    cm_disp = ConfusionMatrixDisplay(cm, display_labels=breed_orig).plot()
    plt.title(classi_names[i] + ' Confusion Matrix')
    plt.show()

# Calculating accuracy on the Test set

mlp_acc_test = accuracy_score(y_test, mlp.predict(x_test))
tree_acc_test = accuracy_score(y_test, tree.predict(x_test))
rforr_acc_test = accuracy_score(y_test, rforr.predict(x_test))

# Calculating F1-score on the test set

mlp_f1 = f1_score(y_test, mlp.predict(x_test), average = 'weighted')
tree_f1 = f1_score(y_test, tree.predict(x_test), average = 'weighted')
rforr_f1 = f1_score(y_test, rforr.predict(x_test), average = 'weighted')
```

```
rforr_f1 = f1_score(y_test, rforr.predict(x_test), average = 'weighted')
```

```
C:\Users\aless\anaconda3\Lib\site-packages\sklearn\neural_network\_multilayer_perce
ptron.py:691: ConvergenceWarning: Stochastic Optimizer: Maximum iterations (200) re
ached and the optimization hasn't converged yet.
  warnings.warn(
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ptron.py:691: ConvergenceWarning: Stochastic Optimizer: Maximum iterations (200) re
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  warnings.warn(
```
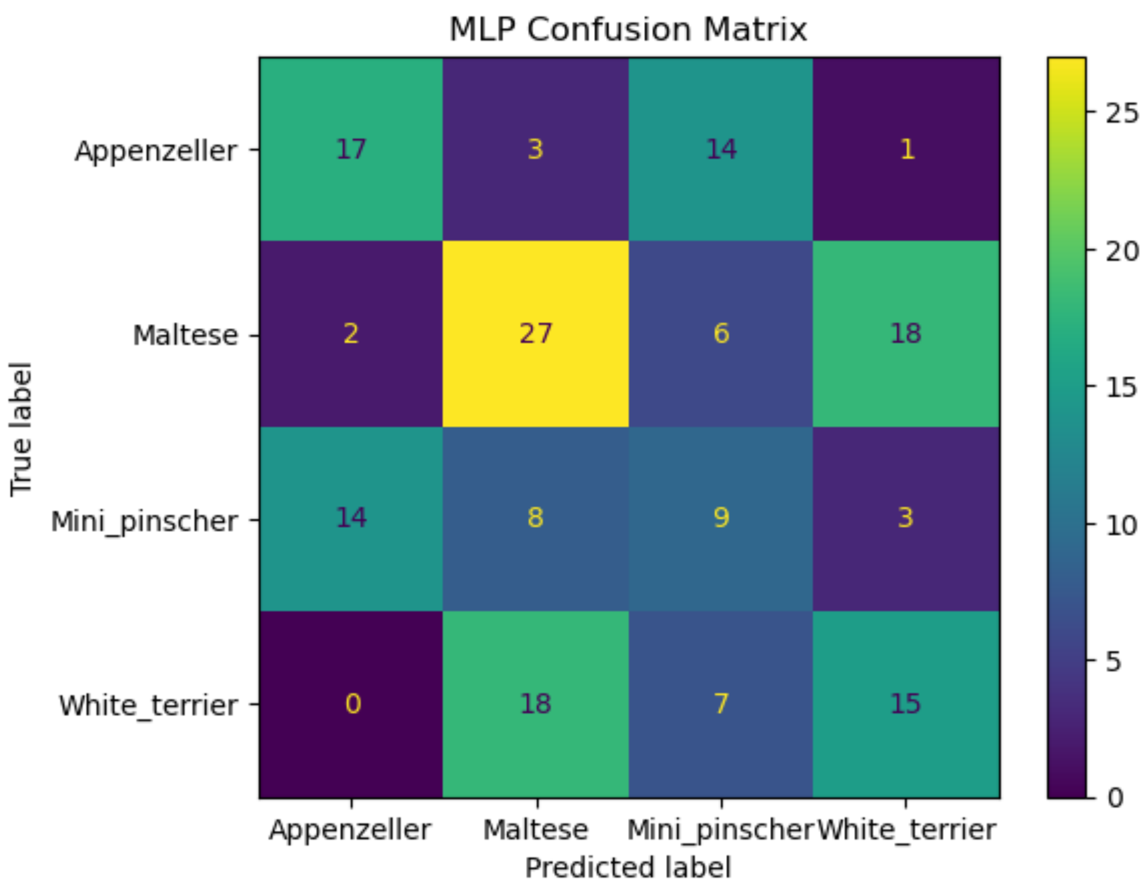
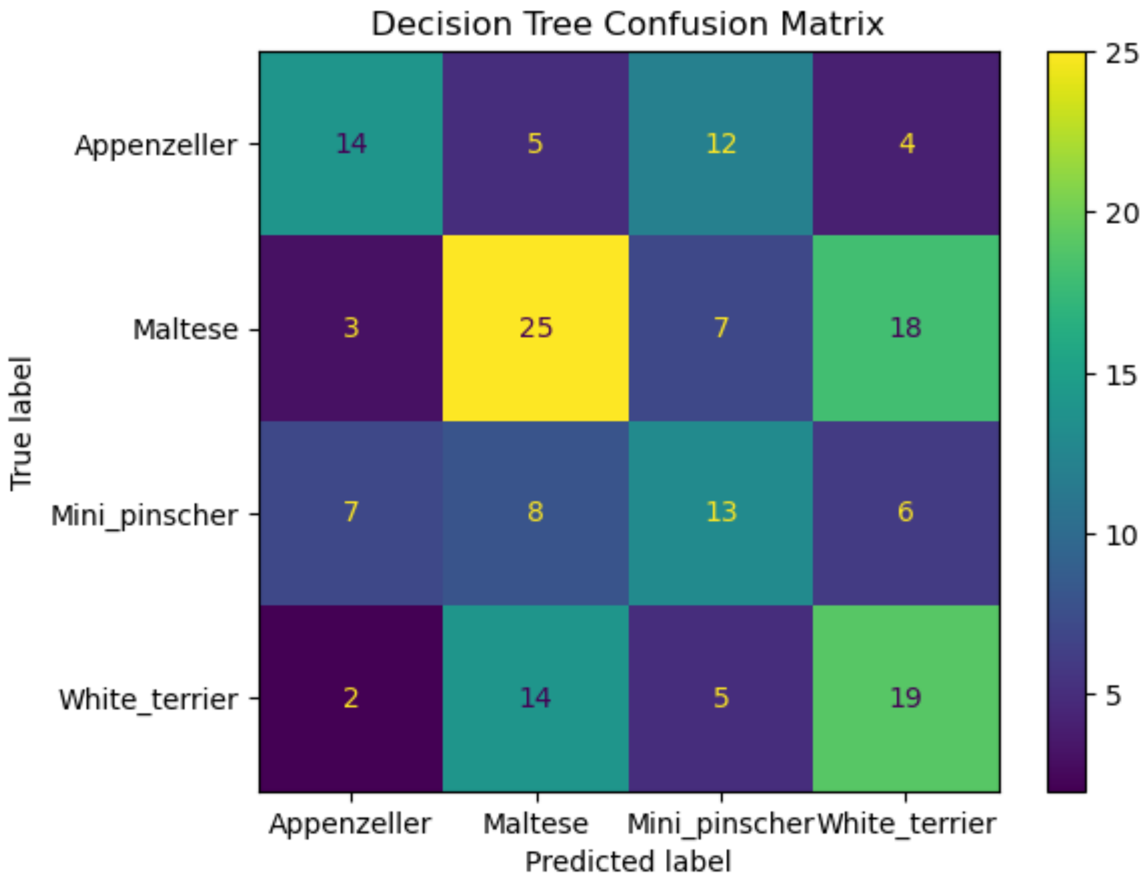
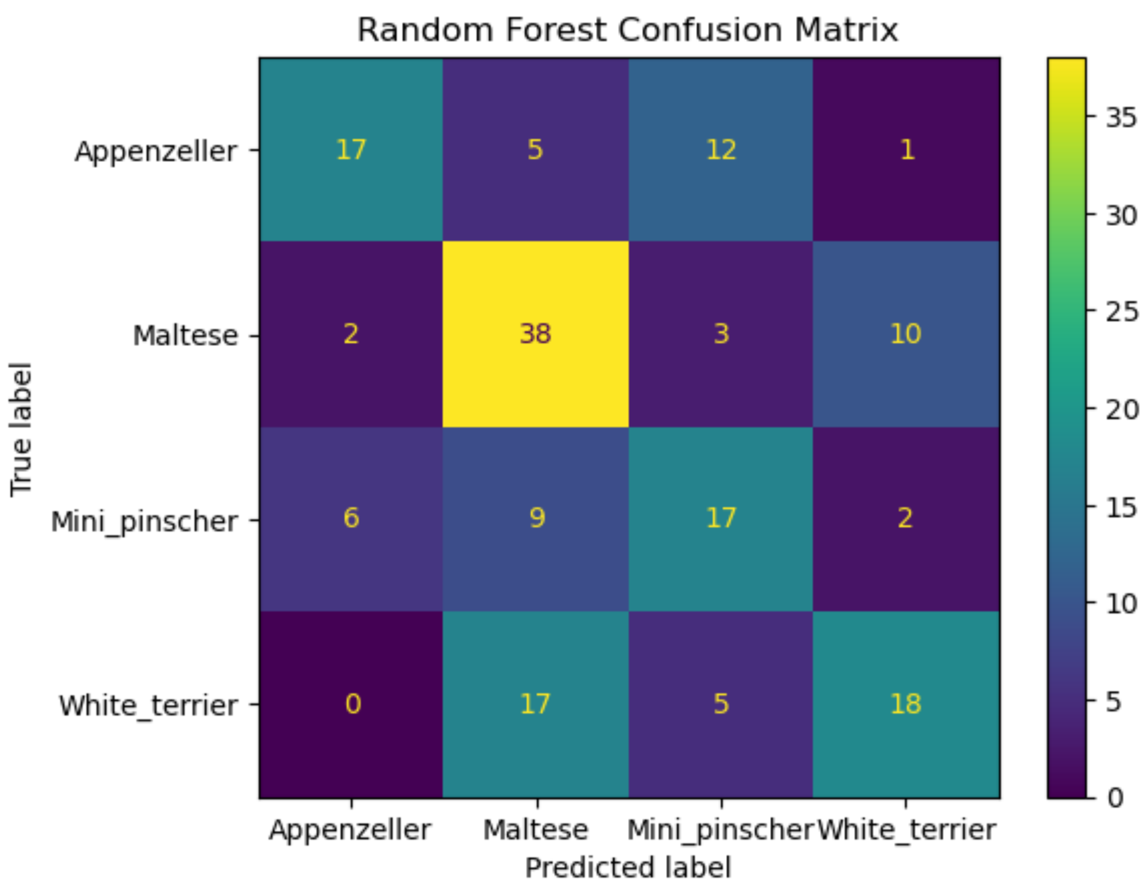




Decision Tree Confusion Matrix
True label
Appenzeller
Maltese
Mini_pinscher
White_terrier
14
5
12
4
3
25
7
18
7
8
13
6
2
14
5
19
Appenzeller
Maltese
Mini_pinscher
White_terrier
Predicted label
25
20
15
10
5


Random Forest Confusion Matrix
True label
Appenzeller
Maltese
Mini_pinscher
White_terrier
17
5
12
1
2
38
3
10
6
9
17
2
0
17
5
18
Appenzeller
Maltese
Mini_pinscher
White_terrier
Predicted label
35
30
25
20
15
10
5
0

4.2. Performance Evaluation

In [6]:
```
# Best Clasifier evaluation

# Best method based on the confusion matrices:
print('Based on the confusion matrices plotted, the one that shows the most True Po

# Best method based on the mean validation accuracies from the 5-fold cross-validat
print('The mean validation accuracies for the classifiers are:')
print(f'MLP Classifier: {np.mean(mlp_acc):.4f}')
print(f'Decision Tree Classifier: {np.mean(tree_acc):.4f}')
print(f'Random Forest Classifier: {np.mean(rforr_acc):.4f}')
print('Based on the mean validation accuracies, the best one is the Random Forest C

# Performance Summary on the test set

# Accuracies:
print('The accuracy on the test set for the classifiers is:')
print(f'MLP Classifier: {mlp_acc_test:.4f}')
print(f'Decision Tree Classifier: {tree_acc_test:.4f}')
print(f'Random Forest Classifier: {rforr_acc_test:.4f}\n')

# F-Measure:
print('The F-measure on the test set for the classifiers is:')
print(f'MLP Classifier: {mlp_f1:.4f}')
print(f'Decision Tree Classifier: {tree_f1:.4f}')
print(f'Random Forest Classifier: {rforr_f1:.4f}')
```

```
Based on the confusion matrices plotted, the one that shows the most True Positives
and the least False Positives/Negatives is the one plotted using the Random Forest
classifier.

The mean validation accuracies for the classifiers are:
MLP Classifier: 0.4589
Decision Tree Classifier: 0.4357
Random Forest Classifier: 0.5271
Based on the mean validation accuracies, the best one is the Random Forest Classifi
er.

The accuracy on the test set for the classifiers is:
MLP Classifier: 0.4198
Decision Tree Classifier: 0.4383
Random Forest Classifier: 0.5556

The F-measure on the test set for the classifiers is:
MLP Classifier: 0.4203
Decision Tree Classifier: 0.4397
Random Forest Classifier: 0.5519
```

5. References

5.1. Dataset

The dataset used for this project was obtained from:

Aditya Khosla, Nityananda Jayadevaprakash, Bangpeng Yao, and Li Fei-Fei, "Stanford Dogs Dataset", 2011, http://vision.stanford.edu/aditya86/StanfordDogs/

5.2. Knowledge Resources

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6. scikit-learn, "ConfusionMatrixDisplay", https://scikit-learn.org/dev/modules/generated/sklearn.metrics.ConfusionMatrixDisplay.html
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8. Towards Data Science (Sarang Narkhede), "Understanding Confusion Matrix", 2018, https://towardsdatascience.com/understanding-confusion-matrix-a9ad42dcfd62