Assignment 3

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1 Introduction

Following is the workflow carried out for the given problem statement

- Features extraction - SIFT
- Clustering the features
- BagOfWords representation of features
- Preprocessing - Standardization of features
- Training and Testing
- Confusion Matrix
- Exploratory Analysis

SIFT was used for feature extraction, where features returned have the dimensions as:

$$keypoints \times 128$$

Since features represent the object, some of them might be similar, hence KMeans clustering algorithm was used for clustering similar features. One done with clustering each of the feature points in each cluster together form a visual word. Each image is the represented as a combination of these visual words, rather I should say each image is defined by the these visual words developed after clustering.

Some preprocessing is carried out to ensure that mean of the training features is zero, otherwise large difference in variances can effect the model. Dataset was split into Training and Testing set using the 80-20 rule and confusion matrix was created.

Further exploratory analysis was done by varying the following:

- Dataset Split (80:20, 50:50)
- Number of Clusters - K (100, 80, 50, 20)
- Classifier (Normal Bayesian Classifier, Decision Tree Classifier)

Note : Dataset consists of three classes, namely Airplanes, Motorbikes and Leopard. Code and Dataset.

2 Normal Bayesian Classifier

Following section illustrates the experimentation results obtained by varying the parameters mentioned in earlier section with the Normal Bayesian Classifier. The diagrams and short content mentioned in the subsequent sections should be self explanatory to explain the results obtained. We discuss the accuracy and confusion matrix obtained.

2.1 Split - 80:20, K - 100

Accuracy obtained for individual classes:

- Class 0 - 100%
- Class 1 - 83%
- Class 2 - 81%

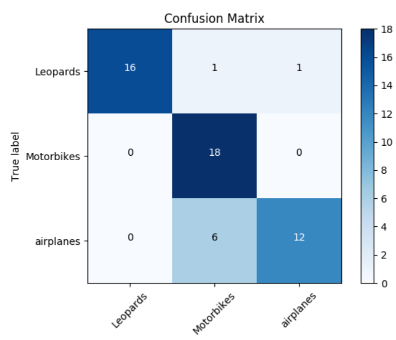

Figure 1: Confusion Matrix

2.2 Split - 80:20, K - 80

Accuracy obtained for individual classes:

- Class 0 - 94%
- Class 1 - 81%
- Class 2 - 81%

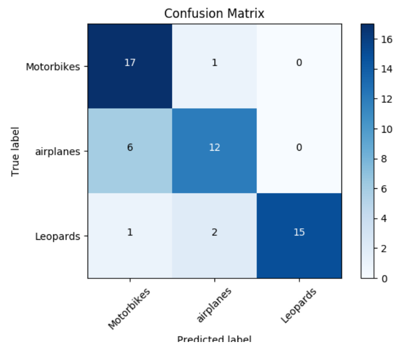

Figure 2: Confusion Matrix

2.3 Split - 80:20, K - 50

Accuracy obtained for individual classes:

- Class 0 - 83%
- Class 1 - 83%
- Class 2 - 78%

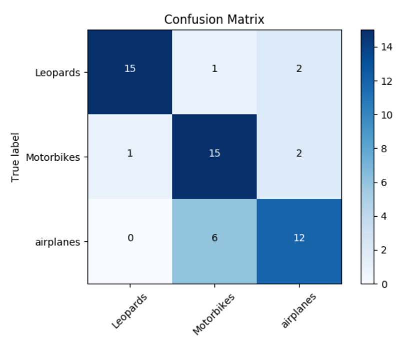

Figure 3: Confusion Matrix

2.4 Split - 80:20, K - 20

Accuracy obtained for individual classes:

- Class 0 - 56%
- Class 1 - 67%
- Class 2 - 57%

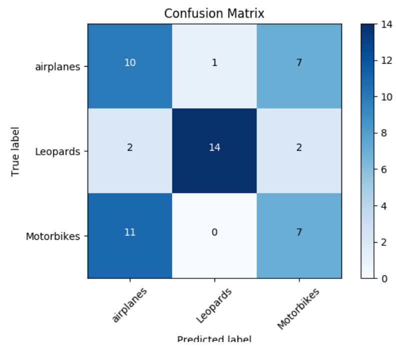

Figure 4: Confusion Matrix

2.5 Split - 50:50, K - 100

Accuracy obtained for individual classes:

- Class 0 - 60%
- Class 1 - 80%
- Class 2 - 84%

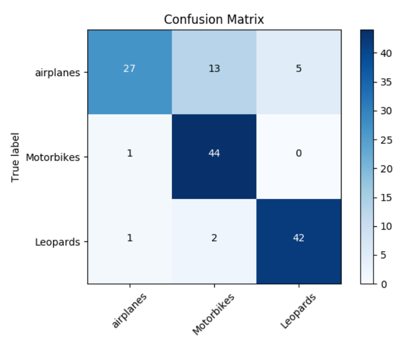

Figure 5: Confusion Matrix

2.6 Split - 50:50, K - 80

Accuracy obtained for individual classes:

- Class 0 - 67%
- Class 1 - 79%
- Class 2 - 84%

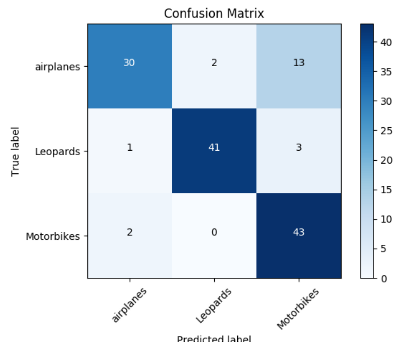

Figure 6: Confusion Matrix

2.7 Split - 50:50, K - 50

Accuracy obtained for individual classes:

- Class 0 - 53%
- Class 1 - 72%
- Class 2 - 79%

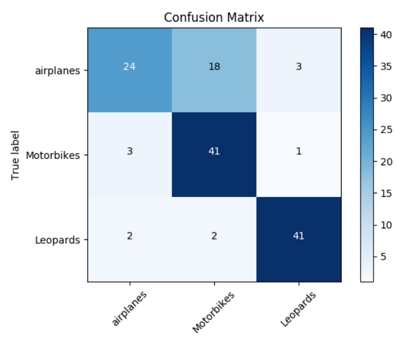

Figure 7: Confusion Matrix

2.8 Split - 50:50, K - 20

Accuracy obtained for individual classes:

- Class 0 - 69%
- Class 1 - 64%
- Class 2 - 69%

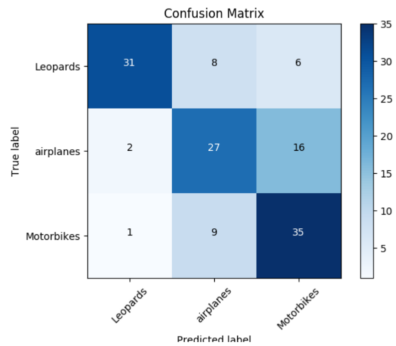

Figure 8: Confusion Matrix

3 Decision Tree Classifier

Following section illustrates the experimentation results obtained by varying the parameters mentioned in earlier section with the Decision Tree Classifier. The diagrams and short content mentioned in the subsequent sections should be self explanatory to explain the results obtained. We discuss the accuracy and confusion matrix obtained.

3.1 Split - 80:20, K - 100

Accuracy obtained for individual classes:

- Class 0 - 100%
- Class 1 - 94%
- Class 2 - 89%

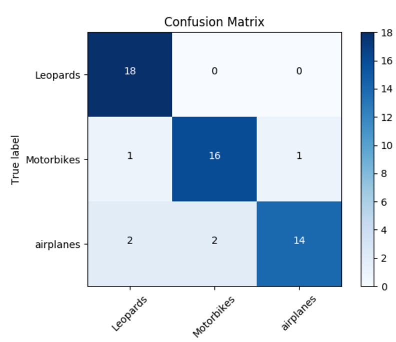

Figure 9: Confusion Matrix

3.2 Split - 50:50, K - 100

Accuracy obtained for individual classes:

- Class 0 - 89%
- Class 1 - 82%
- Class 2 - 82%

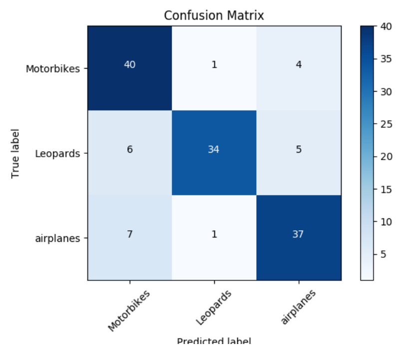

Figure 10: Confusion Matrix

4 Conclusion

Based on exploratory analysis, certainly as expected following observations can be made:

- More the training data, the better the model learns due to large number of features.
- As the number of clusters(K) is reduced, accuracy goes down. This can be attribute to the fact that, many of the features which belong to one class may end up with cluster having features representing other classes resulting in misclassification. Hence, larger the number of clusters, more accurately can each cluster represent a particular object.

Figure 11 and 12 depict some example results of misclassification and classification respectively.

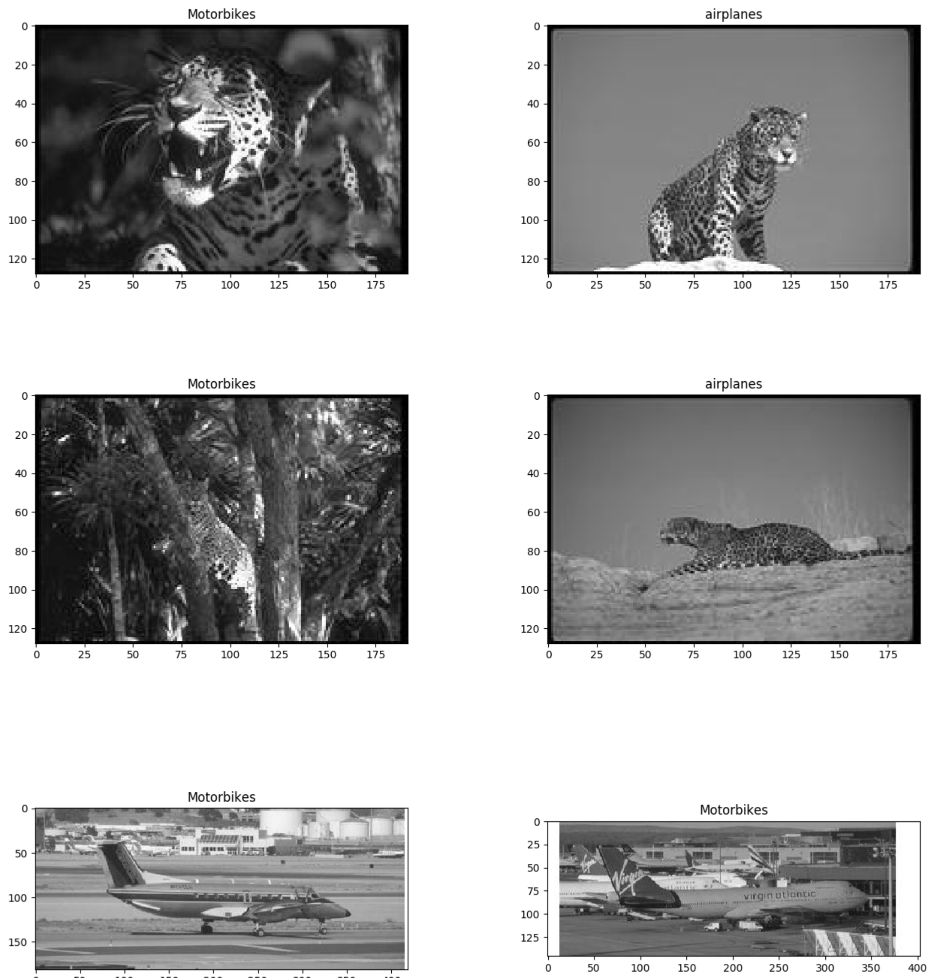

Figure 11: Misclassfication examples

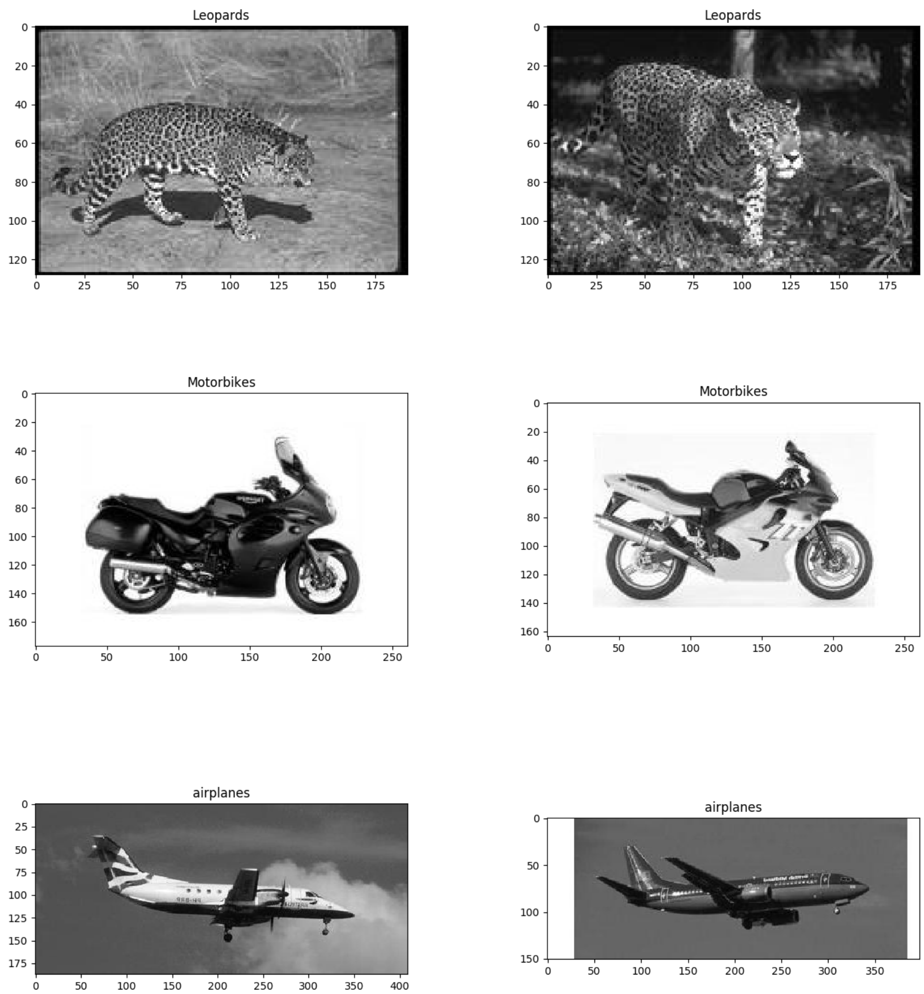

Figure 12: Classfication examples