COMP3314 Image Classification Report

Final Accuracy (public board): 79.15%

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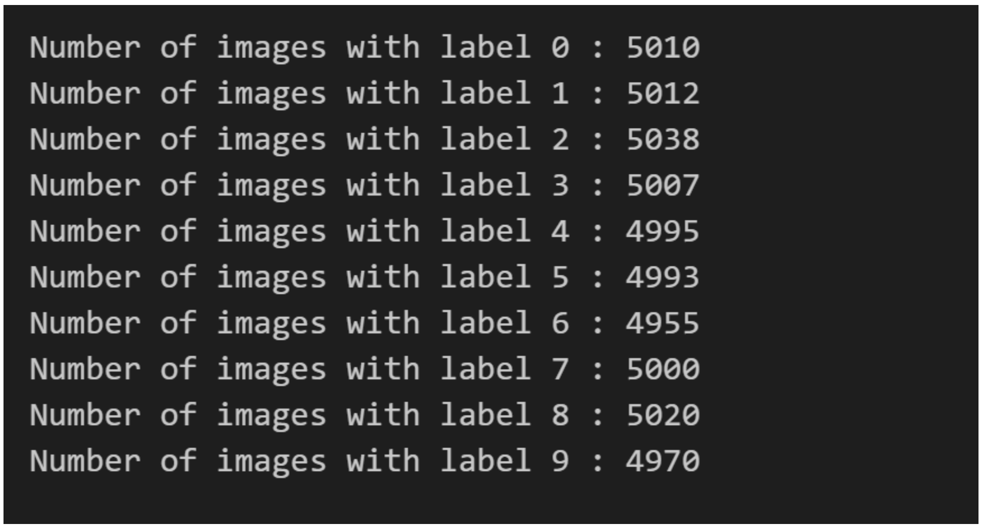
1 Data Analysis

1.1 Dataset Statistics

There are 10 classes of images in total. The number of images for each class are as follows:

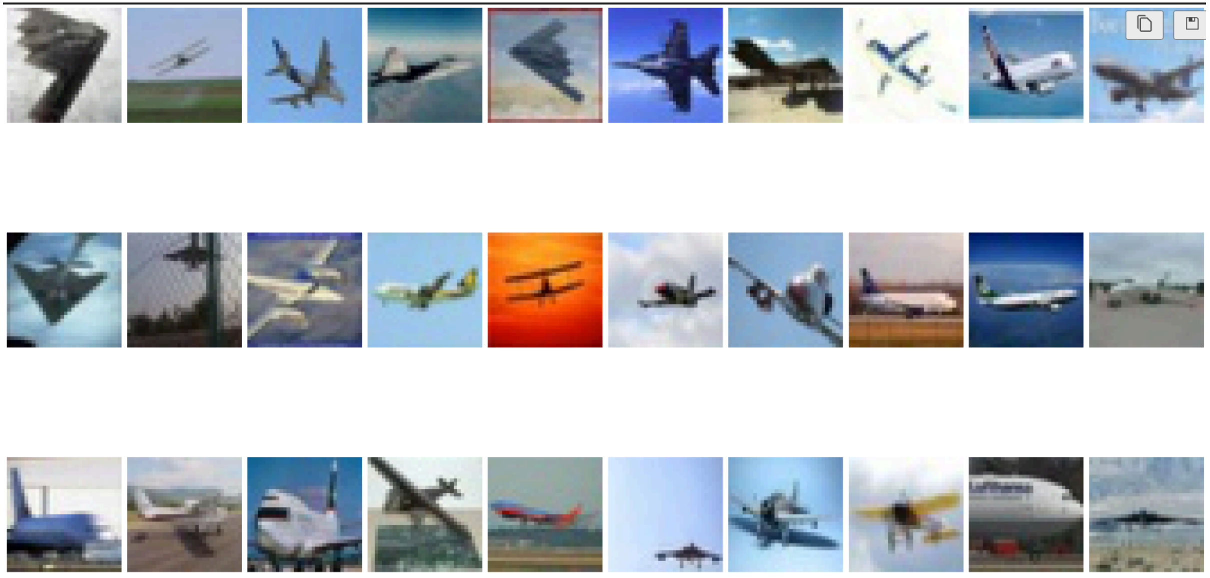


```
Number of images with label 0 : 5010
Number of images with label 1 : 5012
Number of images with label 2 : 5038
Number of images with label 3 : 5007
Number of images with label 4 : 4995
Number of images with label 5 : 4993
Number of images with label 6 : 4955
Number of images with label 7 : 5000
Number of images with label 8 : 5020
Number of images with label 9 : 4970
```

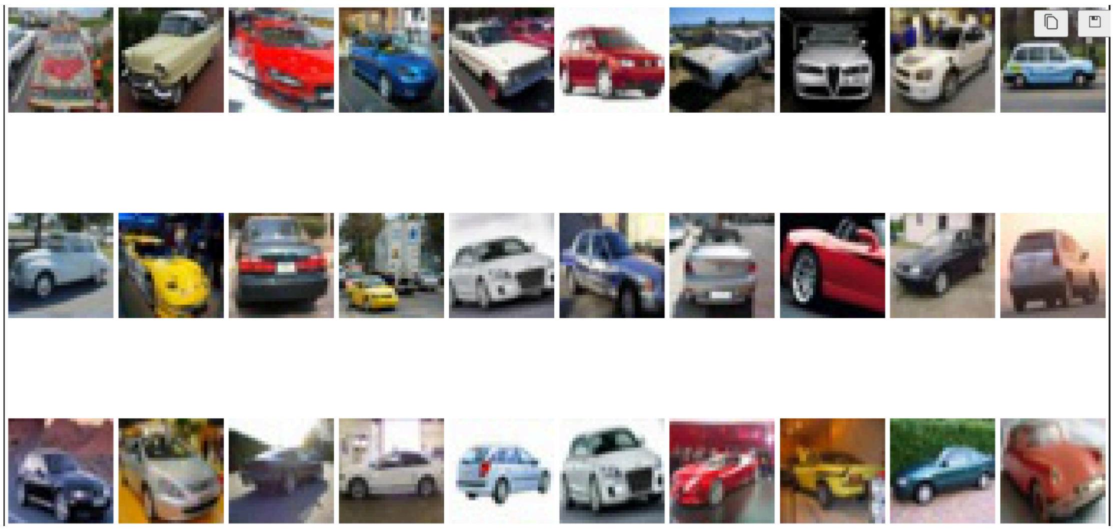
1.2 Data Visualization

For each class of images, the examples are as follows:

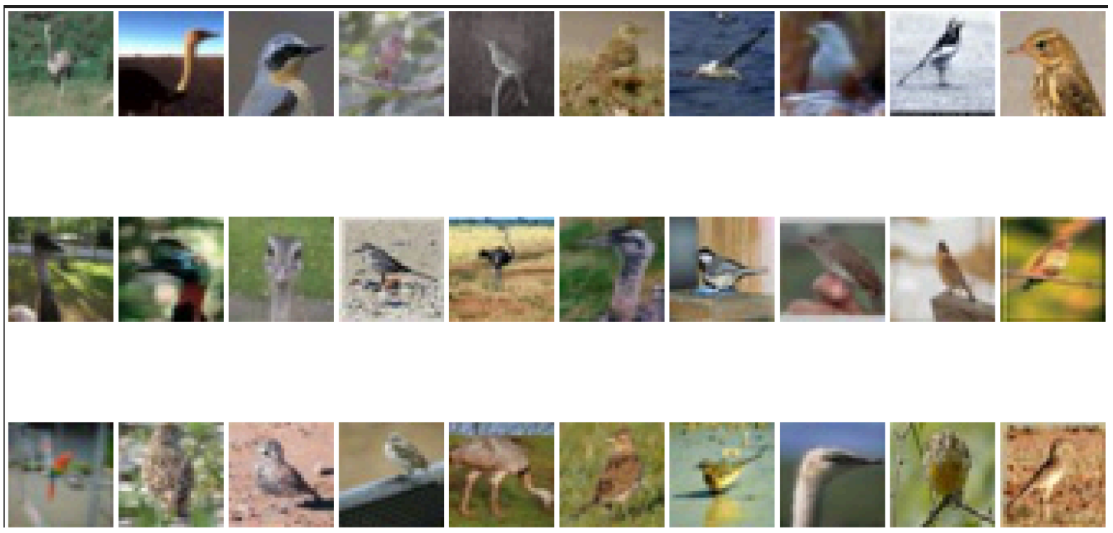
class 0: airplanes



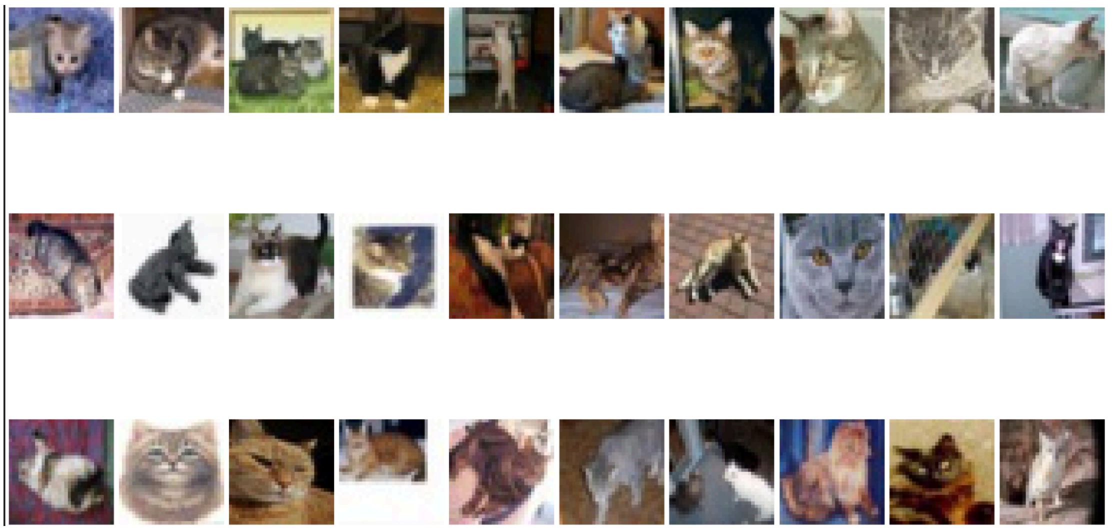
class 1: cars



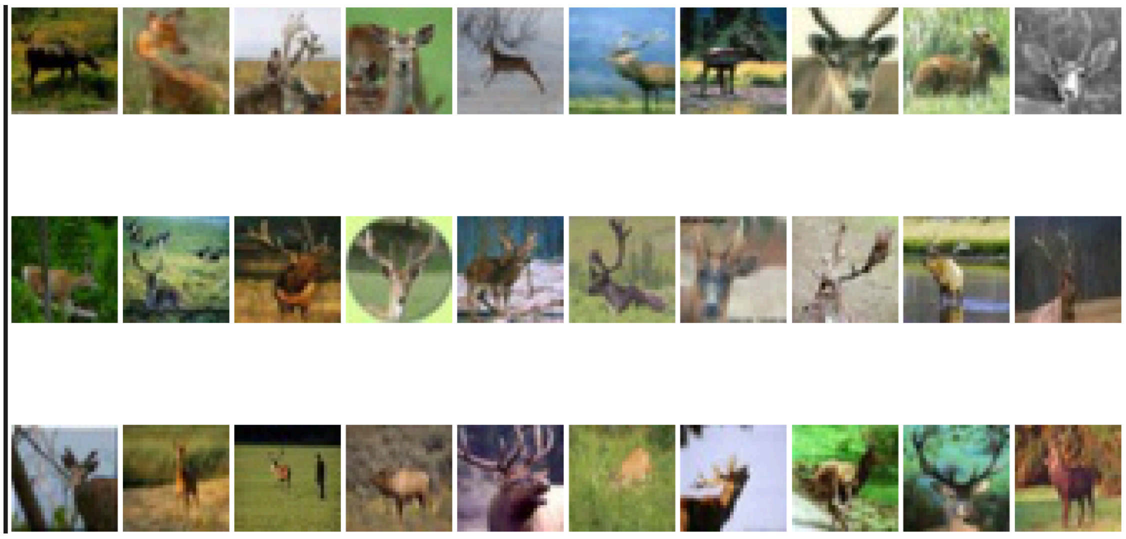
class 2: birds



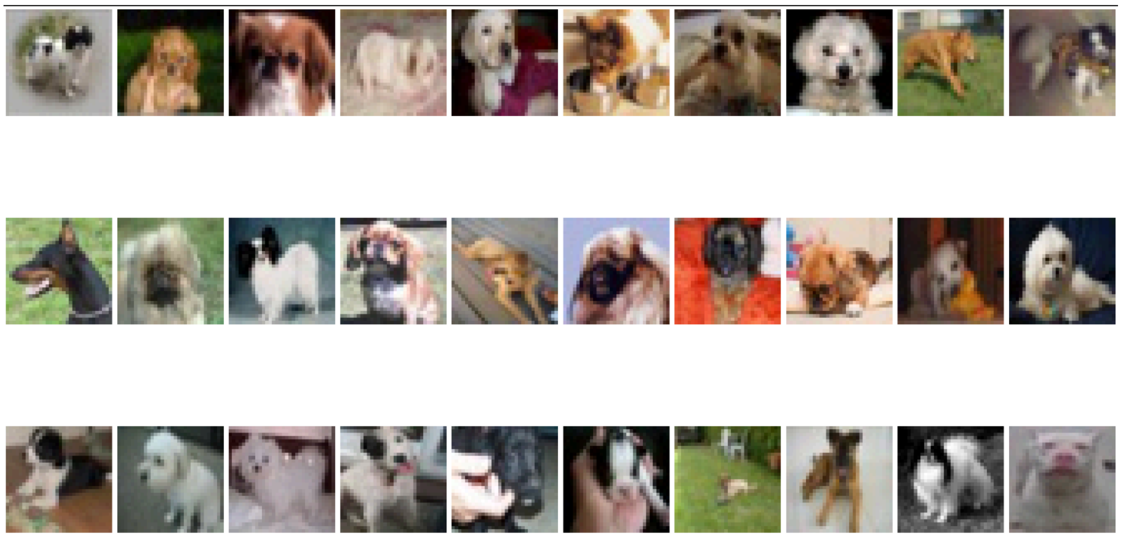
class 3: cats



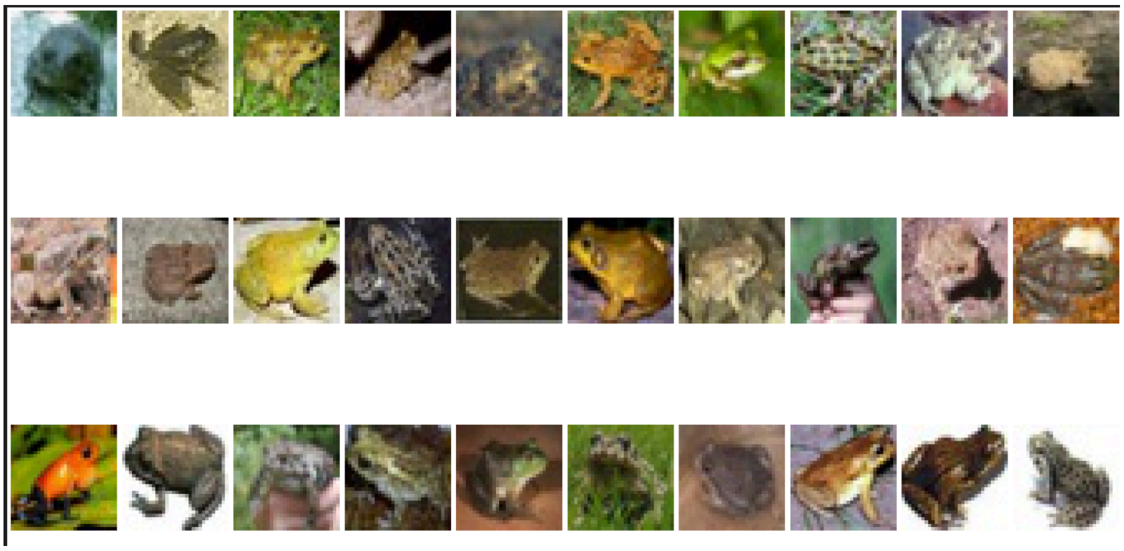
class 4: dears



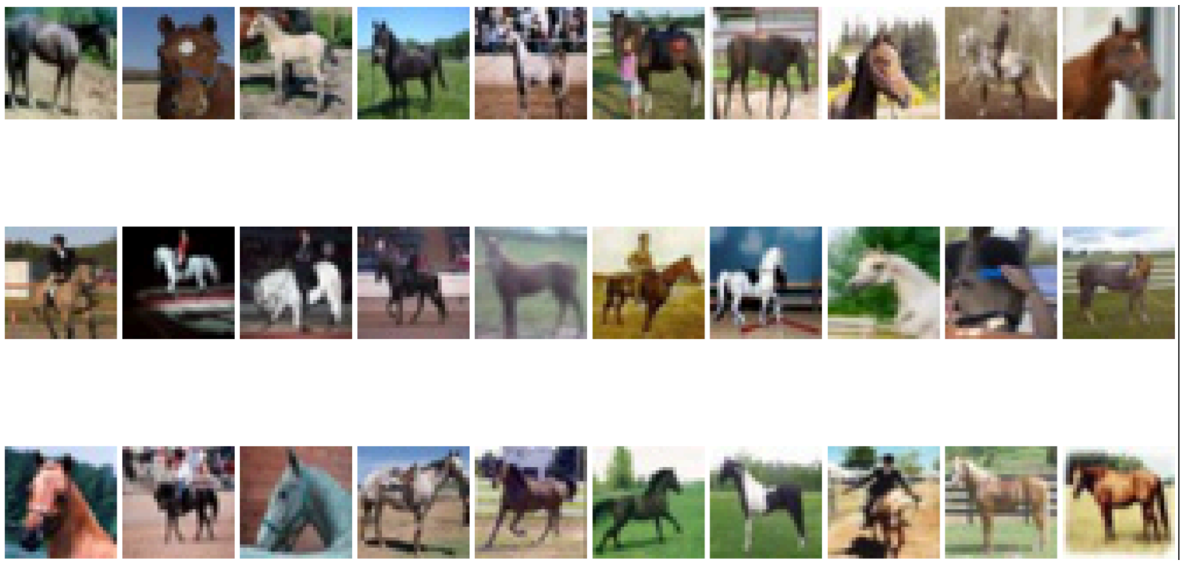
class 5: dogs



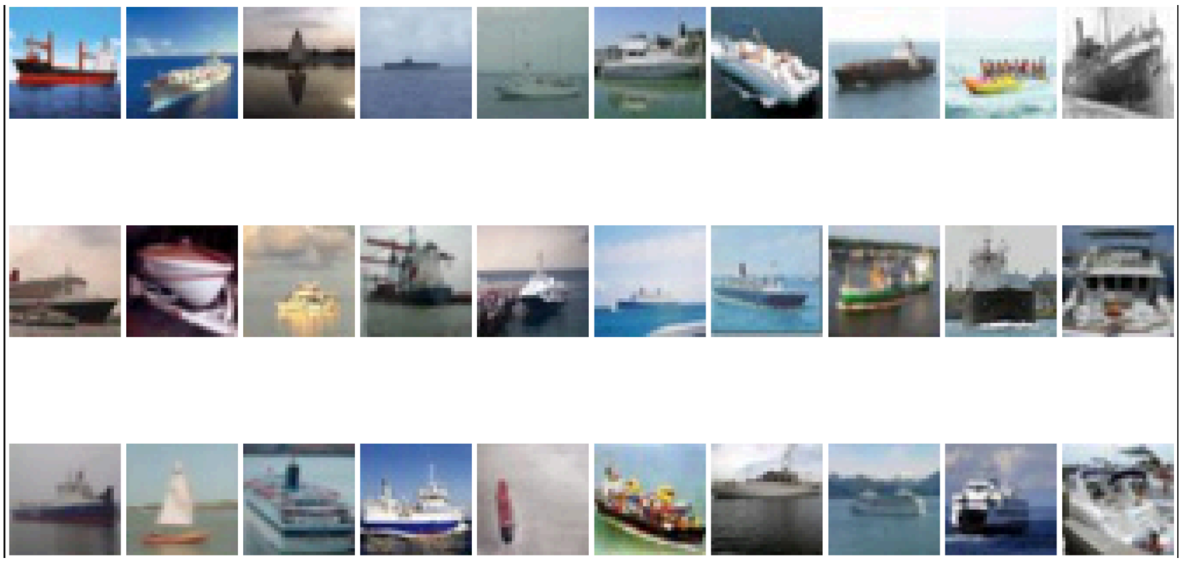
class 6: frogs



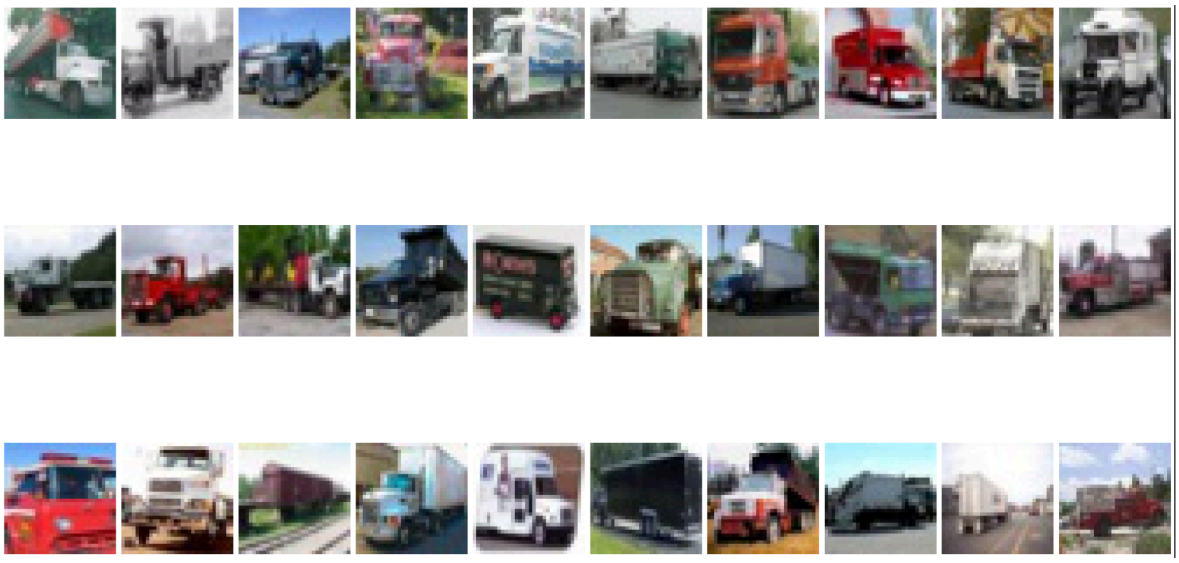
class 7: horses



class 8: ships



class 9: trucks



2 Methods and Experiments

2.1 Data Augmentation

2.1.1 Flip

We use flipping horizontally to augment our dataset. It boosts our model performance in a large extent.
In our sota model:
- without Flip: 0.722
- with Flip: 0.7539

2.1.2 Rotation

It seems that doing rotation will only benefit the local results. The prediction that was uploaded on Kaggle to predict new images has lower accuracy. It may be because repeatedly doing tricks on the same set of pictures may cause the overfit.

2.1.3 Color

Contrast, Saturation, Gray Scale. No time to try it.

2.1.4 Noise

Gaussian noise. Random mask. No time to try it.

2.2 Feature

2.2.1 Global Feature

2.2.1.1 HuMoment

Hu Moments, also known as Hu Invariant Moments or Hu's Seven Moments, are a set of seven statistical moments that are used as shape descriptors in image processing and pattern recognition. They were introduced by M. K. Hu in 1962 as a method to characterize and distinguish between different shapes regardless of their rotation, scale, and translation.

2.2.1.2 Color-based features

We research the train dataset. We find that some classes tend to have some major colors. Like the “airplane” and “ship”, they have blue as their background color. For “dog”, the face of dogs typically is white. For “frog”, the body of them is green. So we have the idea to use the main color of an image as our feature.
We have tried 2 methods:

1. We use KMean to find three of the most significant colors in an image and use their color (r, g, b) as our feature. However, experiment results show that it is not working.
2. We extract the mean value of each RGB value as our feature. It can improve the accuracy by about 1%~2%.

2.2.1.3 Haralick Texture

Texture refers to the visual patterns and structures present in an image that are related to the spatial arrangement of pixel intensities. Haralick texture features capture different aspects of texture, such as smoothness, coarseness, regularity, and complexity.
This feature is useful, which can improve our almost-final model by 0.3%

2.2.2 Local Feature

2.2.2.1 Histogram of Orientated Gradient (HOG)

Histograms of Oriented Gradients can extract local features. The HOG feature descriptor represents the local appearance and shape information of an image by capturing the distribution of gradient orientations. It is based on the observation that object shapes and structures can be characterized by the distribution of intensity gradients or edge directions in an image.
After experiment, only using the HOG feature can get the best accuracy compared with SIFT, Raw image and other features. The possible reasons are:

1. HOG provides feature size of thousands of dimensions. Large dimension is beneficial for SVM classification
2. HOG can extract features using histogram. To some extent, it is more robust to noise like shifting of image or unnormal pixel value.

fine-tuning hyper-parameters of HOG:
model = SVC(kernel='rbf', max_iter=100, gamma=0.09, C=10) +(rgb)HOG_feature(block_size = (16, 16), block_stride = (8, 8), cell_size = (8, 8) num_bins = 9) + TopColor = 0.695

model = SVC(kernel='rbf', max_iter=100, gamma=0.09, C=10)+smooth_raw(16*16)+(grey)HOG_feature(block_size = (16, 16), block_stride = (8, 8), cell_size = (8, 8) num_bins = 9) + TopColor = 0.6718

model = SVC(kernel='rbf', max_iter=100, gamma=0.09, C=10)+(grey)HOG_feature(block_size = (16, 16), block_stride = (8, 8), cell_size = (8, 8) num_bins = 9) + TopColor = 0.6672

model = SVC(kernel='rbf', max_iter=100, gamma=0.09, C=10)+smooth_raw(32*32)+(grey)HOG_feature(block_size = (16, 16), block_stride = (8, 8), cell_size = (8, 8) num_bins = 9) + TopColor = 0.5062

model = SVC(kernel='rbf', max_iter=3000, gamma=0.09, C=10)+smooth_raw(16*16)+(rgb)HOG_feature(block_size = (16, 16), block_stride = (8, 8), cell_size = (8, 8) num_bins = 9) + TopColor = 0.7092

model = SVC(kernel='rbf', max_iter=5000, gamma=0.09, C=10)+smooth_raw(16*16)+(rgb)HOG_feature(block_size = (16, 16), block_stride = (8, 8), cell_size = (8, 8) num_bins = 9) + TopColor = 0.7092

model = SVC(kernel='rbf', max_iter=3000, gamma=0.09, C=10)+smooth_raw(16*16)+(rgb+grey)HOG_feature(block_size = (16, 16), block_stride = (8, 8), cell_size = (8, 8) num_bins = 9) + TopColor = 0.7118

2.2.2.2 SIFT (Scale-Invariant Feature Transform)

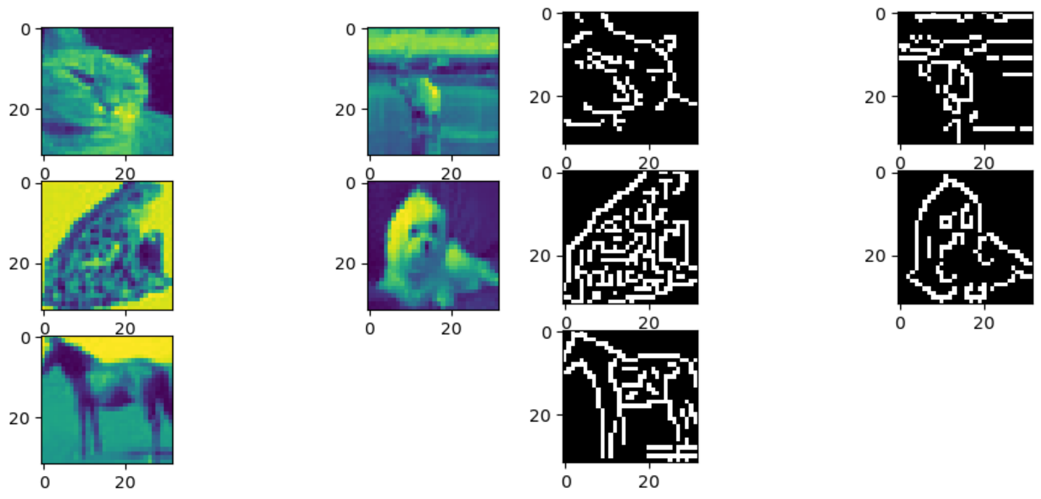
The idea of SIFT is similar to HOG. But it can extract keypoints and their descriptor. At first, we tried to use the “Bags of SIFT” idea. We try to use KMean to abstract the feature and reduce the final feature size, which can also reduce the influence of noise. However the results are not satisfactory. We still only use simple SIFT feature without "Bags".

2.2.2.3 Local Binary Patterns (LBP)

LBP characterizes the local texture patterns by comparing the intensity values of a center pixel with its surrounding neighbors. The basic idea behind LBP is to encode the local structure of an image by quantizing the relationships between neighboring pixels into binary patterns.

2.2.2.4 Edge Orientation Histogram (EOH)

Similar to the mechanism of HOG, by dividing the picture to a certain number of blocks of cells, it first detects the edge of each cell using the Sobel Operator. Then the histograms based on the edge orientation are calculated. In the end the value is normalized to be the features.



Bin represents for dividing the picture into bin*bin number of blocks.
After the experiment, we find bin=8 gets the best result. It is the second-best feature we extracted so far.

model = SVC(kernel='rbf') + (bin=4) = 0.5302
model = SVC(kernel='rbf') + (bin=6) = 0.5684
model = SVC(kernel='rbf') + (bin=7) = 0.5580
model = SVC(kernel='rbf') + (bin=8) = 0.5782
model = SVC(kernel='rbf') + (bin=9) = 0.5422
model = SVC(kernel='rbf') + (bin=10) = 0.5676
model = SVC(kernel='rbf') + (bin=16) = 0.5596

2.2.3 Feature Reduction

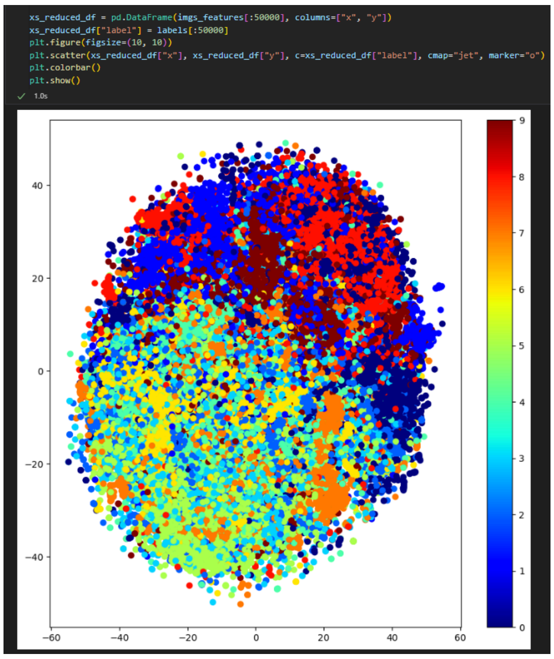
2.2.3.1 Principle Components Analysis

After experiment, we find PCA is a good way to remove redundant or irrelevant feature. Our original feature has a feature size of 5952 and got 0.712 accuracy. However, after putting PCA, the feature size is reduced to 2000, 1000, 500, 200 and the performance even goes up, which justifies that so many

features are redundant. Using PCA can allow us to contract features and allow more memory space for other feature extraction methods.
Experiment result:
HOG from package openCV + raw_feature => noPCA = 0.712 (feature size of 5952)
HOG from package openCV + raw_feature => PCA(2000) = 0.7146 (feature size of 2000)
HOG from package openCV + raw_feature => PCA(1000) = 0.716 (feature size of 1000)
HOG from package openCV + raw_feature => PCA(500) = 0.717 (feature size of 500)
HOG from package openCV + raw_feature => PCA(200) = 0.7222 (feature size of 200)
HOG from package openCV + raw_feature => PCA(150) = 0.7202 (feature size of 150)
HOG from package openCV + raw_feature => PCA(100) = 0.714 (feature size of 100)

2.2.3.2 T-SNE Scale-Invariant Feature Transform

t-SNE (t-distributed Stochastic Neighbor Embedding) is an unsupervised non-linear dimensionality reduction technique for data exploration and visualizing high-dimensional data.
In Assignment 2, t-SNE performs better than PCA to reduce the dimension from 794 to 2. However, in our experiment, the result turns out to be not so good. Using it we only got an accuracy of 41%. Maybe it is because we did not get the preferred parameter. However, running t-SNE is much more time costly than PCA (about 10 times longer for the runtime). So, we finally decided not to replace PCA by t-SNE.
The following is the visualization of t-SNE in our experiment.



```
xs_reduced_df = pd.DataFrame(imgs_features[:50000], columns=["x", "y"])
xs_reduced_df["label"] = labels[:50000]
plt.figure(figsize=(10, 10))
plt.scatter(xs_reduced_df["x"], xs_reduced_df["y"], c=xs_reduced_df["label"], cmap="jet", marker="o")
plt.colorbar()
plt.show()
```

✓ 1.0s

reference: https://distill.pub/2016/misread-tsne/

2.4 Classifiers Analysis

2.4.1 Linear SVM

Linear Support Vector Machine (SVM) is a Support Vector Machine algorithm that uses a linear decision boundary to classify data points into different classes. In this task, it gives a pretty good performance. However, compared to the results given by kernel SVM, which is shown below, Linear SVM is proven to be primarily used for binary classification tasks, but not an image classification task like this. Because the image classification task is highly nonlinear. LinearSVC can be only used for binary classification. In this task, LinearSVC tends to be affected by slight noise. kernel SVM can project the feature into a high dimensional kernel, which can make the new vector more linearly-separable.

Experiment results:

LinearSVC(multi_class='ovr', max_iter=3000, C=1) + HOG_feature + TopColor_feature = 0.5488

SVC(kernel='linear', max_iter=3000) + HOG_feature + TopColor_feature = 0.5034

2.4.2 Kernel SVM

We use the 'rbf' kernel, which is Radial basis function kernel. It projects the original features into an infinite-dimensional space. It is generally good for all kinds of classification tasks.

Experiment results:

SVC(kernel='rbf', max_iter=3000) + HOG_feature + TopColor_feature = 0.6626

Experiment results for tuning gamma and C:

Gamma

model = SVC(kernel='rbf', max_iter=3000, gamma=1) + HOG_feature + TopColor = 0.6004

model = SVC(kernel='rbf', max_iter=3000, gamma=0.3) + HOG_feature + TopColor = 0.6109

model = SVC(kernel='rbf', max_iter=3000, gamma=0.1) + HOG_feature + TopColor = 0.6764

model = SVC(kernel='rbf', max_iter=3000, gamma=0.08) + HOG_feature + TopColor = 0.6755

model = SVC(kernel='rbf', max_iter=3000, gamma=0.01) + HOG_feature + TopColor = 0.596

model = SVC(kernel='rbf', max_iter=3000, gamma=0.001) + HOG_feature + TopColor= 0.5302

model = SVC(kernel='rbf', max_iter=3000, gamma=scale) + HOG_feature + TopColor = 0.6638

C

model = SVC(kernel='rbf', max_iter=3000, gamma=0.1, C=0.1) + HOG_feature = 0.5693

model = SVC(kernel='rbf', max_iter=3000, gamma=0.1, C=1) + HOG_feature = 0.6647

model = SVC(kernel='rbf', max_iter=3000, gamma=0.1, C=10) + HOG_feature = 0.6845

model = SVC(kernel='rbf', max_iter=3000, gamma=0.09, C=10) + HOG_feature = 0.6853

model = SVC(kernel='rbf', max_iter=3000, gamma=0.09, C=10) + HOG_feature + TopColor = 0.6966

model = SVC(kernel='rbf', max_iter=3000, gamma=0.09, C=10) + HOG_feature + ColorEntropy = 0.6778

2.4.3 KNN

2.4.3.1 Mechanism
KNN is short for k-nearest neighbors, which is a quite straightforward algorithm. Firstly, the number of k and a distance metric will be chosen. Then, k-nearest neighbors of the sample will be found. Finally, the class label will be assigned by the majority vote.
The reason for adopting this classifier is that KNN is a memory-based approach. So the runtime will be extremely low. Particularly, when we struggle to run an SVM model for 10 minutes, KNN only takes a few seconds to run. This largely saves us time when deciding the quality of various features at the beginning of our project. However, the memory problem is serious while dealing with samples with high dimensions.
2.4.3.2 Parameter
Impact of p
p is the distance metric to choose while computing the nearest neighbours. p=1 represents for Manhattan distance and p=2 represents for Euclidean distance. In our experiment, the Manhattan distance (p=1) fits better.
Impact of p to KNN:
model = KNeighborsClassifier(n_neighbors=10, p=1, metric='minkowski') + HOG_feature = 0.6311
model = KNeighborsClassifier(n_neighbors=10, p=2, metric='minkowski') + HOG_feature = 0.5637

Impact of n_neighbors
The number of neighbours is also significant. If it is too small, the model may be underfitting, if it is too large, it may be overfitting. In our experiment, n_neighbours = 10 achieved the best balance.
Impact of n to KNN:
model = KNeighborsClassifier(n_neighbors=5, p=2, metric='minkowski') + HOG_feature = 0.5629
model = KNeighborsClassifier(n_neighbors=10, p=2, metric='minkowski') + HOG_feature = 0.5637
model = KNeighborsClassifier(n_neighbors=15, p=2, metric='minkowski') + HOG_feature = 0.5546
model = KNeighborsClassifier(n_neighbors=20, p=2, metric='minkowski') + HOG_feature = 0.5484

2.4.4 Logistic regression
The reason why SVM is better than logistic regression may lie in that logistical regression is vulnerable under occurrence of outliers, which is quite often in this task.

2.4.5 Random forest
Random Forest combines multiple decision trees to make predictions. In this task, its performance is not quite satisfying. This may be because there are noise or irrelevant patterns in the training data, and decision trees are prone to overfitting, especially when the tree becomes too deep and complex, leading to poor generalization and low accuracy on unseen data.

Experiment results:
RandomForestClassifier(entropy,100,42)+ HOG_feature=0.4918

3 Final Model

Our methods to find the best model follows the following procedure:

1. Select a suitable classifier
2. Find the best feature extractors
3. try some resembling learning and data argumentation
4. fine-tuning hyperparameters

3.1 Data Augmentation

We only use flip to double our dataset size. We only flipped our training images horizontally.

```
print("begin data augmentation")
size = len(train_imgs)
for i in range(size):
  img = train_imgs[i]
  # flip
  img = cv2.flip(img, 1)
  train_imgs.append(img)
  train_labels.append(train_labels[i])

print("data augmentation done")
```

3.2 Feature Extraction

After hundreds of experiment, we selected the best 12 features as our final image embeddings. Some have major impacts on performance of our model. Some have less impact but by working together, they can improve our model significantly.
The 12 features are;

1. cvHOG_feature; HOG feature
2. raw_feature; flatten our raw image into one-dimensional 32*32*3 vector
3. Color_feature; take mean value of each color channel
4. EOH_feature; use Canny to extract the local feature
5. HuMoments_feature; use moment to calculate the global moment feature
6. SIFT_feature; find keypoints and descriptors of images as feature
7. LBP_feature; local binary pattern
8. cooccurrence_feature;
9. LPQ_feature;
10. ColorHistogram_feature;
11. Tamura_feature;
12. Daubechies_Wavelets_feature;

```
Daubechies_Wavelets_feature = Daubechies_Wavelets_extractor.featureExtract(imgs)
Tamura_feature = Tamura_extractor.featureExtract(imgs)
```

```
ColorHistogram_feature = ColorHistogram_extractor.featureExtract(imgs)
LPQ_feature = LPQ_extractor.featureExtract(imgs)
cooccurrence_feature = cooccurrence_extractor.featureExtract(imgs)
cvHOG_feature = cvHOG_extractor.featureExtract(imgs)
Color_feature = Color_extractor.featureExtract(imgs)
raw_feature = Raw_extractor.featureExtract(imgs)
EOH_feature = EOH_extractor.featureExtract(imgs)
HuMoments_feature = HuMoments_extractor.featureExtract(imgs)
SIFT_feature = SIFT_extractor.featureExtract(imgs)
LBP_feature = LBP_extractor.featureExtract(imgs)

imgs_features = np.concatenate(
  (cvHOG_feature, raw_feature, Color_feature, EOH_feature, HuMoments_feature, SIFT_feature, LBP_feature,
   cooccurrence_feature, LPQ_feature, ColorHistogram_feature, Tamura_feature,
Daubechies_Wavelets_feature,),
  axis=1)
```

3.3 PCA

We use pca to reduce feature dimension for SVM training. With PCA, we can reduce our original feature vector from 7889 dimensions to less than 400 dimensions but maintain the model performance. PCA also accelerates our SVM training speed. After fine-tuning, we find n_component=0.87 have the best performance.

```
print("begin pca")
pca = PCA(0.87, copy=False)
pca.fit(imgs_features)
imgs_features = pca.fit_transform(imgs_features)
print("pca done")
```

3.4 Classifier

Lastly, we feed our embedding vectors into our SVM model for training. For Classifier, we choose kernel SVM. The kernel is 'rbf', which is a good kernel for most classification jobs. We further fine-tuned hyperparameters like C. We find C=5 > C=10 > C=20 (sorted by prediction accuracy).

```
print("begin training")
model = SVC(kernel='rbf', C=1, random_state=42)
model.fit(train_features, train_labels)
print("training done")
```

4 Appendix

Here are some additional experiment results for reference:
Experiment Results:
Logistic Regression (C=1) + raw_feature = 0.4017
Logistic Regression (C=0.1) + raw_feature = 0.3985

Logistic Regression (C=0.01) + raw_feature = 0.4004
Logistic Regression (C=0.001) + raw_feature = 0.3998

This series of experiment compares *num_bins*
Logistic Regression (C=1) +
HOG_feature (win_size = (32, 32), block_size = (32, 32), block_stride = (8, 8), cell_size = (16, 16), num_bins = 6) = 0.3979

Logistic Regression (C=1) +
HOG_feature (win_size = (32, 32), block_size = (32, 32), block_stride = (8, 8), cell_size = (16, 16), num_bins = 9) = 0.4227

Logistic Regression (C=1) +
HOG_feature (win_size = (32, 32), block_size = (32, 32), block_stride = (8, 8), cell_size = (16, 16), num_bins = 12) = 0.4245

This series of experiment compares *cell_size*

Logistic Regression (C=1) +
HOG_feature (win_size = (32, 32), block_size = (32, 32), block_stride = (8, 8), cell_size = (16, 16), num_bins = 12) = 0.4245

Logistic Regression (C=1) +
HOG_feature (win_size = (32, 32), block_size = (32, 32), block_stride = (8, 8), cell_size = (8, 8), num_bins = 12) = 0.52

Logistic Regression (C=1) +
HOG_feature (win_size = (32, 32), block_size = (32, 32), block_stride = (8, 8), cell_size = (4, 4), num_bins = 12) = 0.5413

This series of experiment compares *block_size*

Logistic Regression (C=1) +
HOG_feature (win_size = (32, 32), block_size = (32, 32), block_stride = (8, 8), cell_size = (4, 4), num_bins = 12) = 0.5413

Logistic Regression (C=1) +
HOG_feature (win_size = (32, 32), block_size = (24, 24), block_stride = (8, 8), cell_size = (4, 4), num_bins = 12) = 0.5589

Logistic Regression (C=1) +
HOG_feature (win_size = (32, 32), block_size = (16, 16), block_stride = (8, 8), cell_size = (4, 4), num_bins = 12) = 0.5624

This series of experiment compares *block_stride*

Logistic Regression (C=1) +
HOG_feature (win_size = (32, 32), block_size = (16, 16), block_stride = (8, 8), cell_size = (4, 4), num_bins = 12) = 0.5624

Logistic Regression (C=1) +
HOG_feature (win_size = (32, 32), block_size = (16, 16), block_stride = (4, 4), cell_size = (4, 4), num_bins = 12) = 0.5639

SVC(kernel='rbf', max_iter=3000) + HOG_feature + TopColor_feature = 0.6626

Logistic Regression (C=1) +
HOG_feature (win_size = (32, 32), block_size = (16, 16), block_stride = (8, 8), cell_size = (4, 4), num_bins = 12) + TopColor_feature= 0.5722

This series of experiment compares *LinearSVM and kernel SVM*

SVC(kernel='rbf', max_iter=3000) + HOG_feature + TopColor_feature = 0.6626

LinearSVC(multi_class='ovr', max_iter=3000, C=1) + HOG_feature + TopColor_feature = 0.5488

SVC(kernel='linear', max_iter=3000) + HOG_feature + TopColor_feature = 0.5034

Gamma

model = SVC(kernel='rbf', max_iter=3000, gamma=1) + HOG_feature + TopColor = 0.6004
model = SVC(kernel='rbf', max_iter=3000, gamma=0.3) + HOG_feature + TopColor = 0.6109
model = SVC(kernel='rbf', max_iter=3000, gamma=0.1) + HOG_feature + TopColor = 0.6764
model = SVC(kernel='rbf', max_iter=3000, gamma=0.08) + HOG_feature + TopColor = 0.6755
model = SVC(kernel='rbf', max_iter=3000, gamma=0.01) + HOG_feature + TopColor = 0.596
model = SVC(kernel='rbf', max_iter=3000, gamma=0.001) + HOG_feature + TopColor= 0.5302
model = SVC(kernel='rbf', max_iter=3000, gamma=scale) + HOG_feature + TopColor = 0.6638

C
0.1 Accuracy: 0.5693
model = SVC(kernel='rbf', max_iter=3000, gamma=0.1, C=0.1) + HOG_feature = 0.5693
model = SVC(kernel='rbf', max_iter=3000, gamma=0.1, C=1) + HOG_feature = 0.6647
model = SVC(kernel='rbf', max_iter=3000, gamma=0.1, C=10) + HOG_feature = 0.6845
model = SVC(kernel='rbf', max_iter=3000, gamma=0.09, C=10) + HOG_feature = 0.6853
model = SVC(kernel='rbf', max_iter=3000, gamma=0.09, C=10) + HOG_feature + TopColor = 0.6966
model = SVC(kernel='rbf', max_iter=3000, gamma=0.09, C=10) + HOG_feature + ColorEntropy = 0.6778

This series of experiment compares the impact of n to KNN
model = KNeighborsClassifier(n_neighbors=5, p=2, metric='minkowski') + HOG_feature = 0.5629
model = KNeighborsClassifier(n_neighbors=10, p=2, metric='minkowski') + HOG_feature = 0.5637
model = KNeighborsClassifier(n_neighbors=15, p=2, metric='minkowski') + HOG_feature = 0.5546
model = KNeighborsClassifier(n_neighbors=20, p=2, metric='minkowski') + HOG_feature = 0.5484

This series of experiment compares the impact of p to KNN
model = KNeighborsClassifier(n_neighbors=10, p=2, metric='minkowski') + HOG_feature = 0.5637
model = KNeighborsClassifier(n_neighbors=10, p=1, metric='minkowski') + HOG_feature = 0.6311
model = KNeighborsClassifier(n_neighbors=10, p=1, metric='minkowski', weight='distance') + HOG_feature = 0.633

This series of experiment compares different features on KNN
model = KNeighborsClassifier(n_neighbors=10, p=2, metric='minkowski', weights='distance') + raw_feature = 0.34
model = KNeighborsClassifier(n_neighbors=10, p=2, metric='minkowski', weights='distance') + Haralick_feature = 0.1685
model = KNeighborsClassifier(n_neighbors=10, p=2, metric='minkowski', weights='distance') + HOG_feature = 0.5636
model = KNeighborsClassifier(n_neighbors=10, p=2, metric='minkowski', weights='distance') + EntropyColor_feature = 0.162
model = KNeighborsClassifier(n_neighbors=10, p=2, metric='minkowski', weights='distance') + LBP_feature = 0.2318
This series of experiment compares the impact of depth to Decision Tree

model = DecisionTreeClassifier(max_depth=5) + HOG_feature = 0.2396
model = DecisionTreeClassifier(max_depth=15) + HOG_feature = 0.264

Random forest
RandomForestClassifier(entropy,100,42)+ HOG_feature=0.4918

Whether TopColor is useful?
model = SVC(kernel='rbf', max_iter=3000, gamma=1, C=1) + HOG_feature= 0.6009

model = SVC(kernel='rbf', max_iter=3000, gamma=1, C=1) + HOG_feature + TopColor = 0.6004

model = KNeighborsClassifier(n_neighbors=10, p=1, metric='minkowski') + HOG_feature = 0.6311

model = KNeighborsClassifier(n_neighbors=10, p=1, metric='minkowski') + HOG_feature + TopColor = 0.6313 确实没用

model = SVC(kernel='rbf', max_iter=3000, gamma=0.09, C=10) + HOG_feature + TopColor = 0.6966 好像又有点用！！！

PCA
model = SVC(kernel='rbf', max_iter=3000, gamma=0.09, C=10)+pca_image(dim=30)+(rgb+grey)HOG_feature(block_size = (16, 16), block_stride = (8, 8), cell_size = (8, 8) num_bins = 9) + TopColor = 0.5204

model = SVC(kernel='rbf', max_iter=3000, gamma=0.09, C=10)+pca_image(dim=200)+(rgb+grey)HOG_feature(block_size = (16, 16), block_stride = (8, 8), cell_size = (8, 8) num_bins = 9) + TopColor = 0.6562

model = SVC(kernel='rbf', max_iter=3000, gamma=0.09, C=10)+pca_image(dim=500)+(rgb+grey)HOG_feature(block_size = (16, 16), block_stride = (8, 8), cell_size = (8, 8) num_bins = 9) + TopColor = 0.6558

model = SVC(kernel='rbf', max_iter=3000, gamma=0.09, C=10)+pca_image(dim=500)+(rgb+grey)HOG_feature(block_size = (16, 16), block_stride = (8, 8), cell_size = (8, 8) num_bins = 9) + TopColor = 0.656

SIFT

We use SIFT feature extractor….
only SIFT
model = SVC(kernel='rbf', max_iter=20000, C=0.01) = 0.2616
model = SVC(kernel='rbf', max_iter=20000, C=0.1) = 0.3109
model = SVC(kernel='rbf', max_iter=20000, C=100) = 0.3076
model = SVC(kernel='rbf', max_iter=20000, C=10) = 0.3244
model = SVC(kernel='rbf', max_iter=20000) = 0.3526
model = SVC(kernel='rbf', max_iter=10000) = 0.3526
model = SVC(kernel='rbf', max_iter=10000, gamma=0.09, C=1) = 0.2266
model = SVC(kernel='rbf', max_iter=3000, gamma=0.09, C=1) = 0.1016
model = SVC(kernel='rbf') = 0.3454

Edge Histogram
model = SVC(kernel='rbf') + (bin=4) = 0.5302
model = SVC(kernel='rbf') + (bin=6) = 0.5684
model = SVC(kernel='rbf') + (bin=7) = 0.5580
model = SVC(kernel='rbf') + (bin=8) = 0.5782
model = SVC(kernel='rbf') + (bin=9) = 0.5422
model = SVC(kernel='rbf') + (bin=10) = 0.5676
model = SVC(kernel='rbf') + (bin=16) = 0.5596

TopColor
model = SVC(kernel='rbf') = 0.3074

HOG
model = SVC(kernel='rbf') = 0.6706

Color
model = SVC(kernel='rbf') = 0.3502

Combination
Increase, Decrease, Equal
TopColor + SIFT = 0.3454
HOG + EOH(bin=4) = 0.6768
HOG + EOH(bin=8) = 0.6776
HOG + Color = 0.6874
HOG + TopColor = 0.6564
Color + EOH(bin=8) = 0.53
Color + EOH(bin=4) = 0.5366
HOG + EOH(bin=4) + Color = 0.6878
HOG + EOH(bin=4) + Color = 0.6878

HOG + Color + EOH + HuM = 0.7564

HOG + EOH + HuM = 0.7588
HOG + EOH = 0.7578
HOG + EOH(bin=4) = 0.7592
HOG + HuM = 0.757
HOG = 0.749
HOG + EOH(bin=4) + HuM = 0.755

HOG and SIFT analysis

HOG from package openCV: 0.6596
HOG from package sklearn: 0.6434
HOG from package openCV + Color_feature = 0.665