Rico Mossinkoff - 12805157 *Hannah Lim - 10588973*
Ewoud Vermeij - 11348860 *Yke Rusticus - 11306386*

Bag of words based image classification

Introduction

For this project our goal is build a proper SVM classifier able to classify and distinguish between 5 different images: images containing an airplane, images containing a bird, images containing a ship, images containing a horse and images containing a car. The idea is to create 5 binary SVM classifiers for this. Each being able to tell whether an image for example is the image of a car or not. As the title indicates, we used the bag of words implementation to train and test our SVM classifiers. In this report we will evaluate differently trained classifiers with different configurations to see how our SVM classifiers perform under different circumstances. In the end we do expect a classifier trained on RGB or opponent images, using a broad vocabulary with a size of 4000 and dense SIFT for feature extraction to show the best performance. Dense sift gives a constant amount of descriptors of a predefined set of patches, a broad vocabulary can make the classifier more precise and RGB or opponent give more information about an image since they contain 3 channels.

Demo.m trains all configurations and shows the results afterwards.

Training and testing settings

In this section we will elaborate our training configurations to get our SVM classifiers. First of all, we used two different sift operations: keypoint SIFT and dense SIFT. Keypoint SIFT looks for keypoints in a given image and then takes the descriptors of the found keypoints. This will result in a different amount of descriptors per image. Dense SIFT takes descriptors from a predefined set of image patches, which results in a constant amount of descriptors per image. For dense SIFT, we used 2 different configurations: size 8 with step 4 and size 16 with step 8. Further we also used different image types to train our classifiers with: RGB, opponent and grayscale.

To train our SVM classifiers we first need to cluster all image descriptors from a predefined image set, to create a vocabulary. We used K-means to cluster the image descriptors with 3 different hyperparameters: 400, 1000 and 4000 different cluster. This means that we have 3 x 3 x 2 + 9 different models which we will evaluate all (+9 for the 9 extra for different dense SIFT configurations). Our training set consists of 2500 images and our testing set contains 4000 images. Due to limited computational resources, we were not able to create a K-means cluster with more than 600 images (it took around 30GB of ram at some moments). However we were able to use half of the 2500 images to perform bag of words and all of the 4000 images for testing.

For testing we will evaluate the precision, recall and accuracy of each of the 27 different configurations.

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Testing results and evaluations

Keypoint SIFT - Precision

color\cluster size	**400**	**1000**	**4000**
RGB	0.41431	0.45392	0.54006
OPPONENT	0.40145	0.43005	0.48031
GRAYSCALE	0.4025	0.39214	0.45582

Keypoint SIFT - Recall

color\cluster size	**400**	**1000**	**4000**
RGB	0.47925	0.46175	0.423
OPPONENT	0.45825	0.4465	0.4055
GRAYSCALE	0.435	0.41175	0.35725

Keypoint SIFT - Accuracy

color\cluster size	**400**	**1000**	**4000**
RGB	0.76035	0.78125	0.81255
OPPONENT	0.755	0.77095	0.79335
GRAYSCALE	0.75785	0.7547	0.78615

Dense SIFT (size: 8, step: 4) - Precision

color\cluster size	**400**	**1000**	**4000**
RGB	0.69212	0.76795	0.8482
OPPONENT	0.62228	0.72797	0.81316
GRAYSCALE	0.64505	0.75972	0.82777

Dense SIFT (size: 8, step: 4) - Recall

color\cluster size	**400**	**1000**	**4000**
RGB	0.72725	0.74875	0.7655
OPPONENT	0.69275	0.7165	0.7355
GRAYSCALE	0.68875	0.7525	0.74274

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Dense SIFT (size: 8, step: 4) - Accuracy

color\cluster size	**400**	**1000**	**4000**
RGB	0.88075	0.9045	0.9257
OPPONENT	0.85445	0.88975	0.9133
GRAYSCALE	0.86195	0.9029	0.9178

Dense SIFT (size: 16, step: 8) - Precision

color\cluster size	**400**	**1000**	**4000**
RGB	0.60522	0.6761	0.76543
OPPONENT	0.58443	0.65858	0.74262
GRAYSCALE	0.62735	0.64879	0.74372

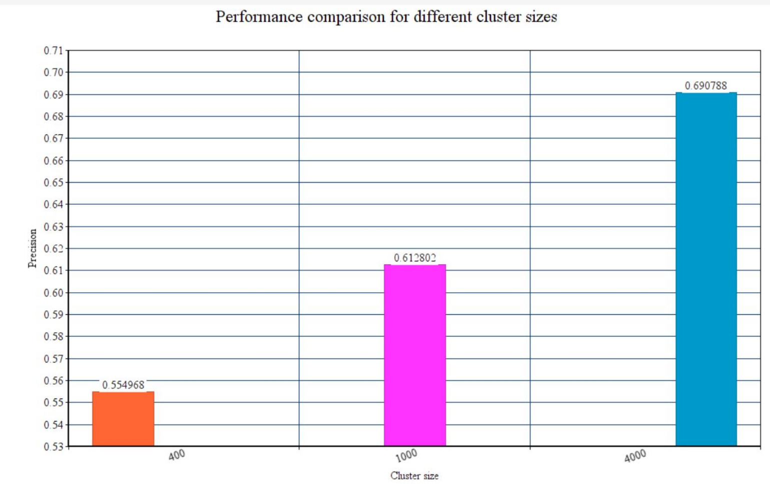
Dense SIFT (size: 16, step: 8) - Recall

color\cluster size	**400**	**1000**	**4000**
RGB	0.678	0.6925	0.70075
OPPONENT	0.66325	0.6785	0.6665
GRAYSCALE	0.6755	0.6715	0.68125

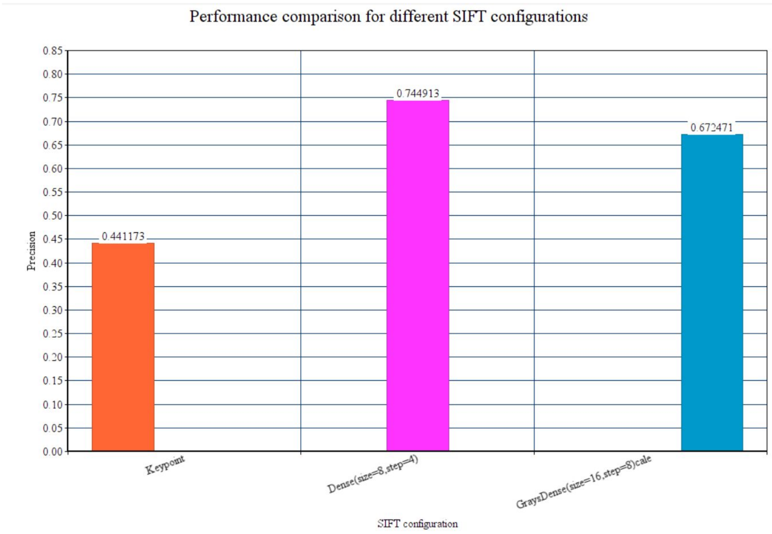
Dense SIFT (size: 16, step: 8) - Accuracy

color\cluster size	**400**	**1000**	**4000**
RGB	0.84715	0.87215	0.8972
OPPONENT	0.83775	0.86535	0.8871
GRAYSCALE	0.85485	0.8616	0.8893

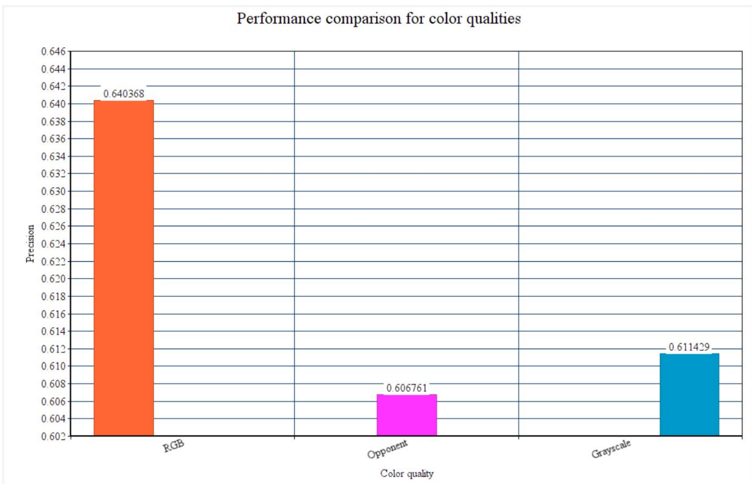
When we look at the performance of different cluster sizes, we can see that generally a higher amount of clusters correlates with a higher precision. When there are more clusters to categorize features to, more detail can be classified. This might be the reason why more clusters can classify an image better, because there are more distinct points that characterize an object. However, while the correlation seems linear in the graph, the amount of clusters are not linear.



For the different SIFT configurations there are quite some differences in performance. Dense SIFT with a size of 8 and a step of 4 performs the best of our 3 configurations. A smaller size and step lead to more details, which can help in categorizing an object. Overall, dense SIFT seems to outperform keypoint SIFT. This might be because dense SIFT looks more to local features then keypoint SIFT. This again gives more detail about the objects which can help in categorizing it.



Our models perform better with RGB images than with grayscale or opponent images. Grayscale performs slightly better than opponent, but this difference is neglectable. RGB can give more information about an object by showing its colors. This might be useful in some situations, where colors are distinct for a certain object. This might explain our results. RGB does not perform much better than the others, as there is a difference of only 3-4%.



The values in the charts are based on the average of our data. This generalizes the data to make it more reliable.

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mAP of all classes of all configurations

conf\class	airplane	bird	ship	horse	car
400_dense_rgb	0.42294	0.51306	0.50284	0.54366	0.52036
400_dense_opponent	0.33536	0.48115	0.46674	0.4986	0.38787
400_dense_gray	0.37853	0.4614	0.4651	0.48281	0.42996
400_key points_rgb	0.17711	0.17243	0.24369	0.23129	0.20905
400_key points_opponent	0.17754	0.15981	0.19342	0.21499	0.19787
400_key points_gray	0.15684	0.14219	0.19921	0.20707	0.18617
1000_dense_rgb	0.45013	0.53957	0.67166	0.63075	0.57039
1000_dense_opponent	0.40909	0.53834	0.58502	0.62612	0.46453
1000_dense_gray	0.45344	0.53015	0.62308	0.64953	0.57721
1000_key points_rgb	0.18603	0.20477	0.24455	0.2235	0.20878
1000_key points_opponent	0.16166	0.17401	0.18212	0.22663	0.20976
1000_key points_gray	0.14379	0.12879	0.18322	0.18119	0.16591
4000_dense_rgb	0.57787	0.60989	0.69897	0.70209	0.6454
4000_dense_opponent	0.49944	0.59983	0.67344	0.70545	0.53
4000_dense_gray	0.53615	0.57043	0.65454	0.68034	0.60553
4000_key points_rgb	0.26837	0.17796	0.26051	0.24321	0.25203
4000_key points_opponent	0.19759	0.19331	0.19376	0.2545	0.16814
4000_key points_gray	0.15561	0.1094	0.20417	0.175	0.1804
Average per class	0.315972	0.350361	0.402558	0.415374	0.361631

In the table above we can see mAP values for each class for all configurations. As the tables with the precision of the classifiers combined, the sift method has great influence on the performance of the models. Again, this is most likely caused by the fact that dense sift gives much more information about the images compared to keypoint SIFT. We can also see performance differences per class classifier. In the averages per class we can see that the classifier for horses performs better compared to the airplanes. This could be caused by the fact that the images of horses are usually in very similar situations like standing in a field. While an airplane can be in the air, on the ground, on the water (water airplane) which makes it more difficult to distinguish and classify.

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Conclusion

From the results of our testing we can conclude that the sift method has great influence on the performance of our models. We expect this being caused by the fact that finding keypoints in an image can be quite difficult and result in relatively few descriptors. Dense SIFT gives a constant number of descriptors from an image, such that descriptors from less interesting areas are also retrieved. Therefor dense SIFT also gives a tremendous amount of information about each image. We also noticed this during the creation of our vocabulary, where close to 30GB of RAM was used at some moments, and with the creation of the bag of words.

It was also interesting to notice that having three channels and therefore more information per image, does not always lead to better performance. Grayscale outperforms opponent in many occasions. However, RGB seems to be the best representation of the image in terms of information to create a good classifier with. Image type also has some influence on the performance of a classifier, as shown by the mAP. It is shown that a horse is easier classified than a plane. mAP also shows again that dense SIFT, 4000 cluster size and RGB images make the SVM models perform at their best.

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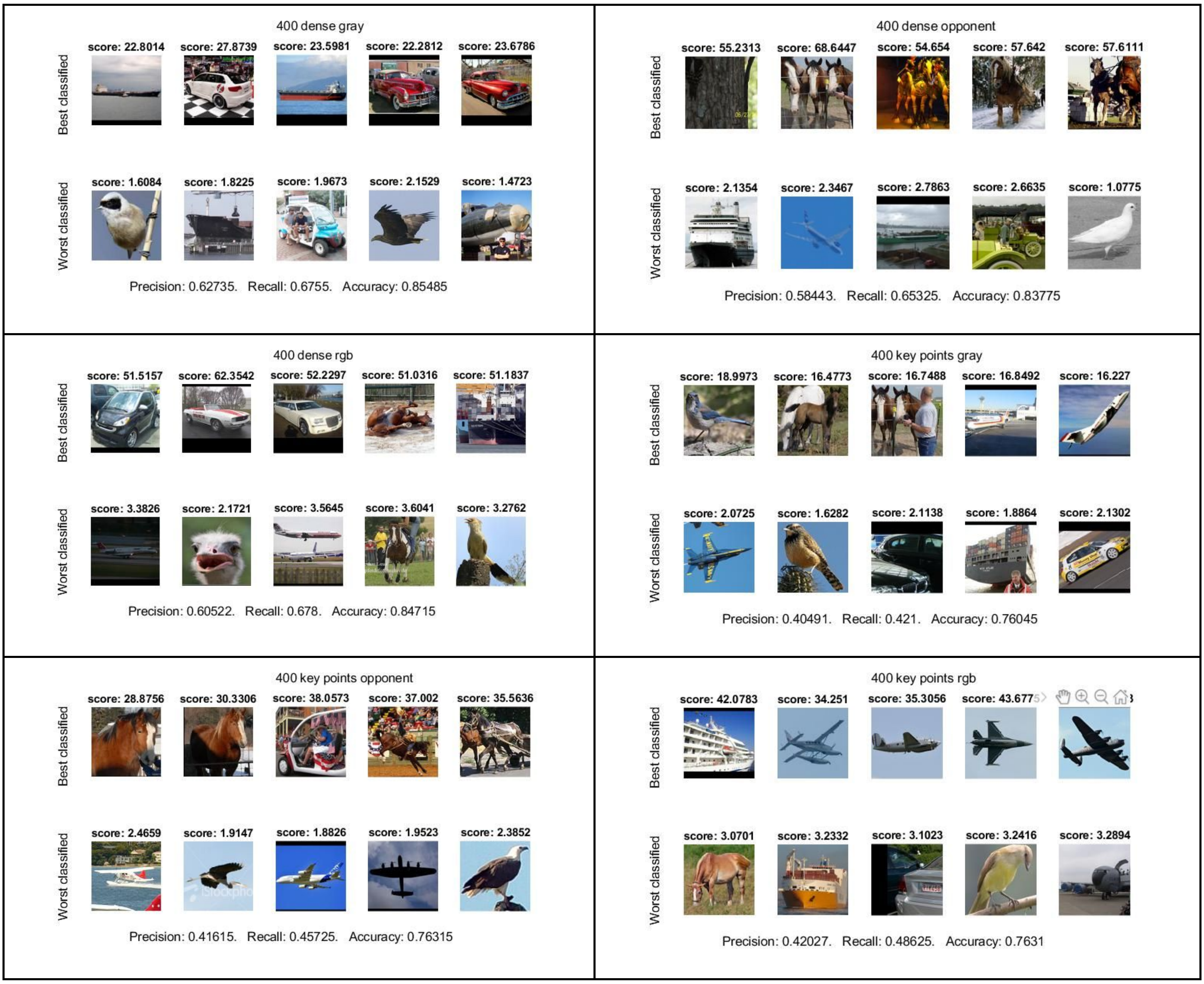
Dense configuration:

- **Size = 16**
- **Step = 8**



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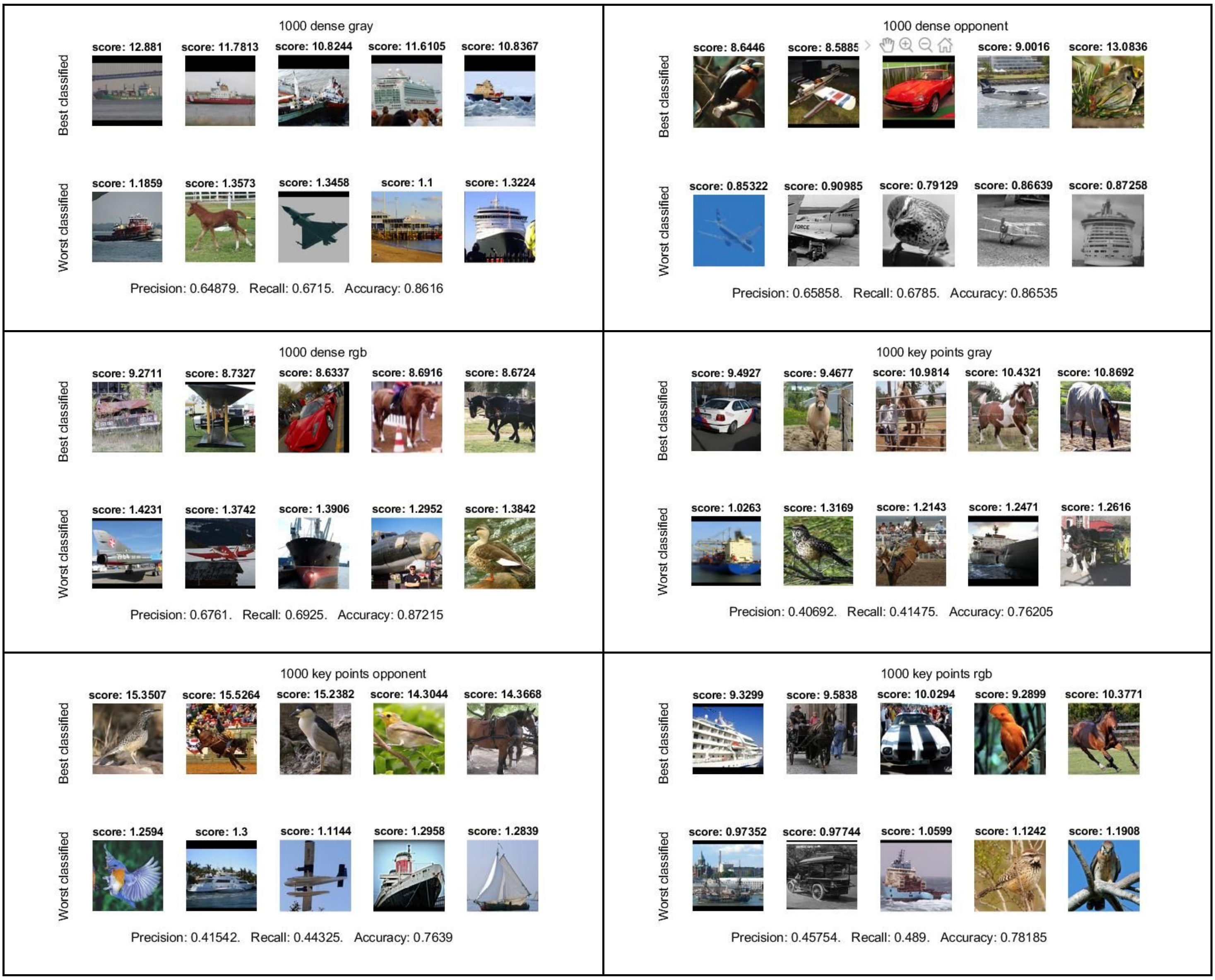

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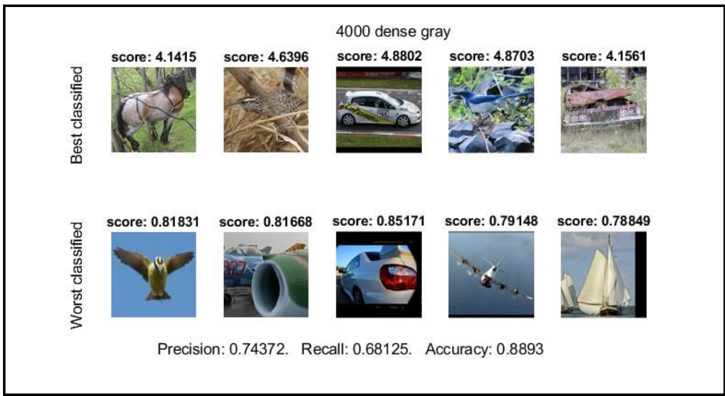

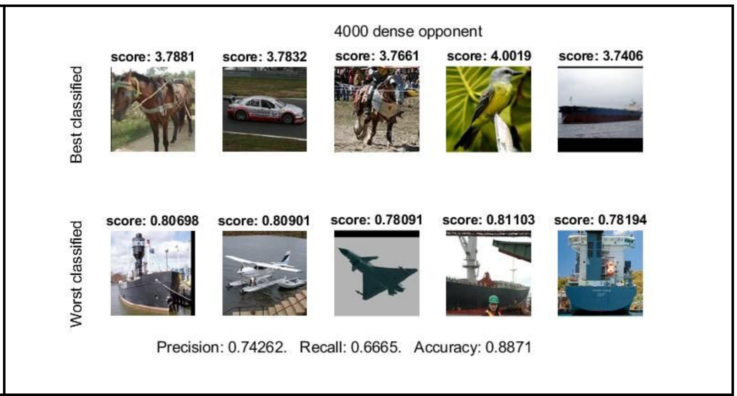

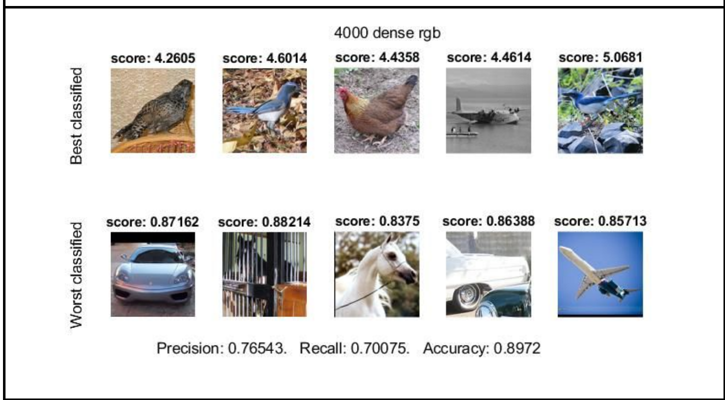

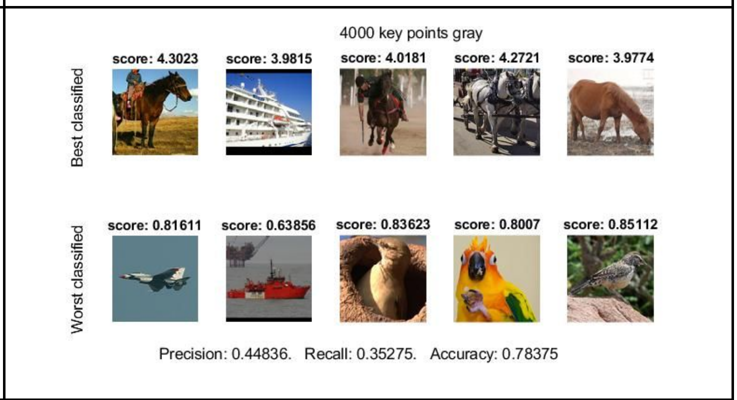

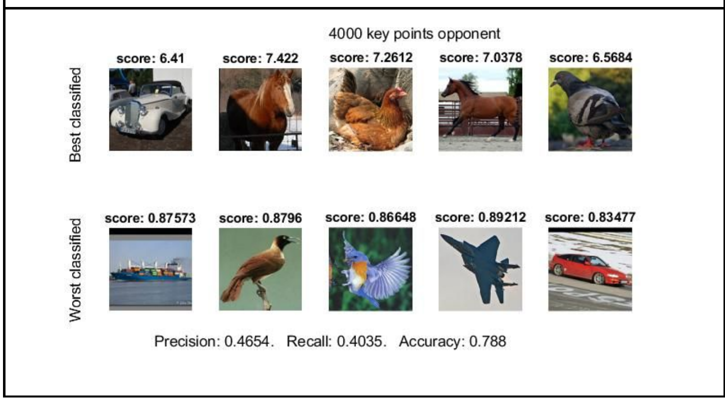

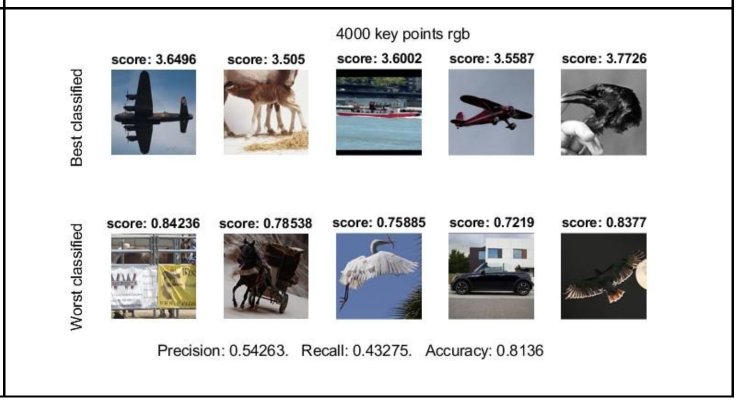

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Dense configuration:

- **Size = 8**
- **Step = 4.**