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Pattern recognition and image analysis

Labs Report

2024/2025

Brussels School of Engineering

Introduction

This report summarizes the methodologies, preprocessing techniques, validations, and comparative evaluations conducted during the four laboratory sessions for the course *Pattern Recognition and Image Analysis*. The analysis was carried out using a subset of the CIFAR-10 dataset, consisting of three classes: `airplane`, `bird`, and `horse`. Each image was represented by a 256-dimensional Histogram of Gradient (HoG) feature vector. The aim was to evaluate and compare various supervised learning algorithms.

Lab 0: Introduction to the Dataset and Preprocessing

Dataset Overview

For these report, a modified CIFAR-10 dataset containing only three classes was used:

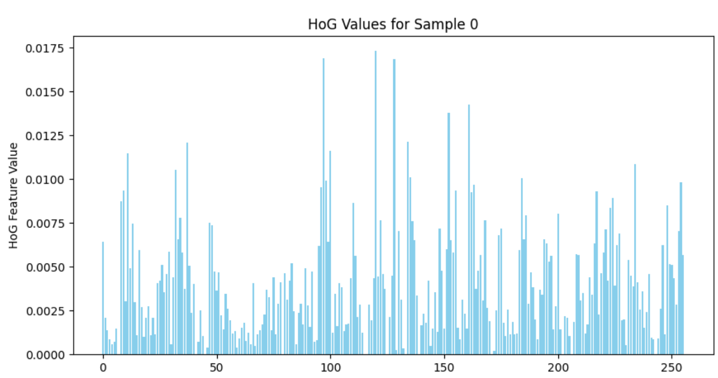
- **Class labels**: `['Airplane', 'Bird', 'Horse']`
- **Dataset structure**:
  - `dataset.train` keys: `['images', 'hog', 'labels']`
  - **Training set**: 15,000 samples (5,000 per class)
  - **Test set**: 3,000 samples (1,000 per class)
  - **HoG features shape**: (15000, 256)

The class distribution is perfectly balanced, which simplifies interpretation and comparison of classification performance.

Descriptive Data Analysis

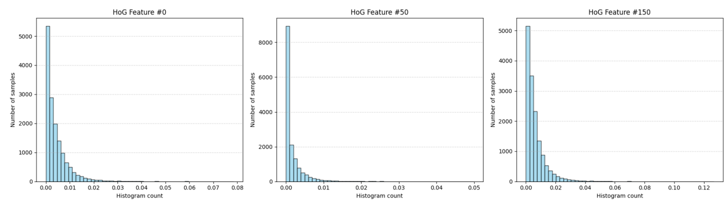
I started with an examination of the raw HoG features. A bar plot of the HoG vector for the first training sample revealed the following:

- All HoG values are **positive and small**.
- The values span a range from near-zero to a maximum of approximately 0.0175.
- The dataset is **not centered around the origin**, which may hinder performance for classifiers that assume zero-mean data (e.g., SVMs, neural networks).



I then visualized the distributions for three sample HoG features: 0, 50, and 150. Across all three, the following characteristics were observed:

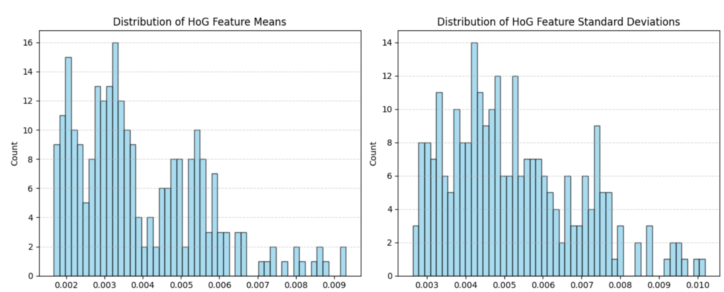
- Strong **skew towards 0**, with most values being very small.
- Long-tailed distribution, indicating sparse activation in gradient space.
- Many HoG features may carry minimal information individually.



To get a sense of variability and bias across features:

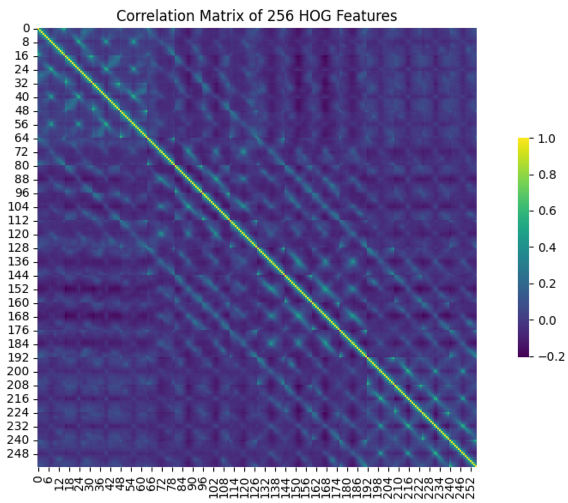
- **Mean distribution** shows most features average between 0.002 and 0.006.
- **Standard deviation distribution** indicates moderate spread, most features below 0.01.

This confirms the need for **standardization** (mean 0, variance 1) prior to applying many ML methods.



A correlation heatmap across the 256 HoG features revealed:

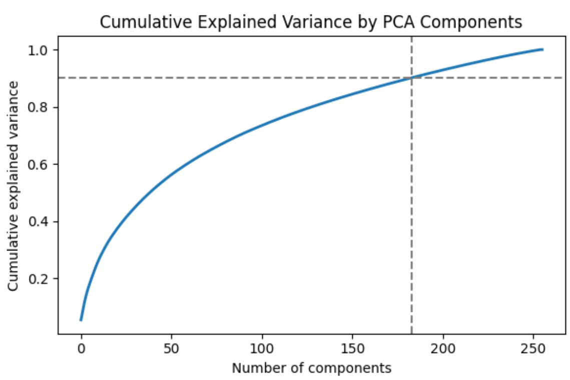
- Some **visible block-structured correlation patterns**, likely due to spatial contiguity in the HoG descriptor.
- Many features remain relatively uncorrelated, which could suggest the use of PCA.



PCA for Dimensionality Reduction

I applied Principal Component Analysis (PCA) to the Standardized HoG data to explore and potentially reduce the feature space:

- PCA helps decorrelate features and reduce noise.
- **183 components** capture **90%** of total variance.
- This represents a **29% dimensionality reduction** (from 256 to 183 dimensions).



While PCA was not always beneficial for classification performance in later labs (especially for SVM with RBF kernel), it remains a useful tool for visual analysis and may assist models that suffer from high-dimensional noise.

Ridge Classifier Baseline Performance

To establish a simple yet effective classification baseline, I trained a Ridge Classifier using the standardized HoG features.

Descriptive Performance

Accuracy: 0.7596

Predictive Performance (5-Fold Cross-Validation)

Fold Accuracies: [0.7403, 0.7387, 0.7413, 0.7547, 0.7473]

Mean CV Accuracy: 0.7445

Why Cross-Validation Matters? Cross-validation provides a more reliable estimate of a classifier's ability to generalize. The data splits used in CV simulate unseen data, and the averaged results approximate the classifier's expected performance on independent and identically distributed (i.i.d.) test data. This is crucial, because:

> A learning algorithm generalizes well if it returns accurate predictions for i.i.d. test data; that is, input/output pairs drawn from the same distribution as the training set but independent of it.

Training accuracy can be overoptimistic, especially in high-dimensional spaces. In contrast, CV accuracy is a better estimator of the true generalization error.

To further improve performance, I used `cross_val_score` from `scikit-learn` to tune the Ridge regularization hyperparameter α:

- **Best** α: 0.1
- **Best mean CV accuracy**: 0.744

Test Set Performance Comparison

RidgeClassifier	Accuracy (%)
Default ($\alpha = 1.0$)	72.90
Tuned ($\alpha = 0.1$)	74.00

While the improvement seems small, I validated it using *McNemar's Test*:

- McNemar's Test: $\chi^2 = 4.995$, $p = 0.025$

Evidence suggest to reject the null hypothesis of equal performance. This result shows that the tuned Ridge Classifier with α=0.1 outperforms the default model in a statistically significant way.

In summary:

- **Standardization** is essential for optimal classifier behavior.
- **PCA** reduces noise and dimensionality with minimal variance loss.
- **Ridge classification** provides a good linear baseline.
- **Cross-validation** and **statistical testing** are key to evaluating model improvements and ensuring generalization.

Lab 1: k-Nearest Neighbors, Decision Trees and Random Forest

All models in this lab have been trained on **standardized HoG features** to ensure proper distance-based behavior and fair feature weighting.

K-Nearest Neighbors (KNN)

The initial results for KNN show:

Descriptive Performance

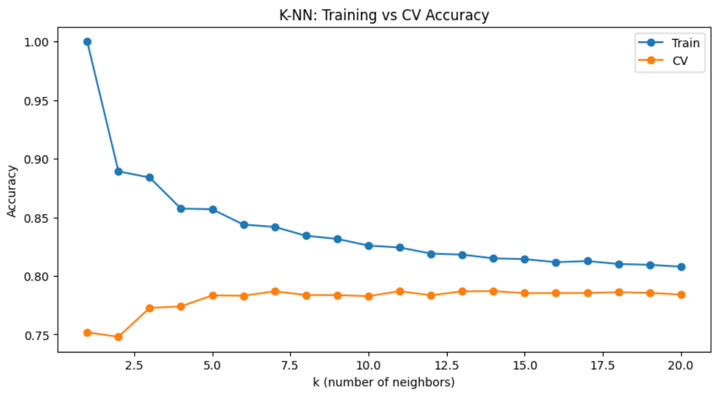
Training Accuracy: 84.75%

Predictive Performance (5-Fold Cross-Validation)

Fold Accuracies: [0.782, 0.7927, 0.792, 0.783, 0.7843]

Mean CV Accuracy: 78.68%

I performed hyperparameter tuning by evaluating accuracy over different `k` values:



Final Test Set Performance:

Accuracy: 78.97%

Class	Precision	Recall	F1-Score	Support
Airplane	0.88	0.78	0.83	1000
Bird	0.70	0.79	0.74	1000
Horse	0.82	0.80	0.81	1000

KNN achieved a **highest test accuracy** compared to Ridge. Performance was stable and errors were well-distributed across classes. Slight overfitting was observed, but it generalizes well overall.

Decision Tree

The initial results for a Decision Tree show:

Descriptive Performance

Training Accuracy: 66.91%

Predictive Performance (5-Fold Cross-Validation)

Fold Accuracies: [0.6087 0.5763 0.5967 0.5937 0.6097]

Mean CV Accuracy: 59.70%

After tuning, I found the best hyper parameters:

```
{'criterion': 'gini', 'max_depth': 10,
'max_features': None}
```

Final Test Set Performance:

Accuracy: 60.17%

Class	Precision	Recall	F1-Score	Support
Airplane	0.74	0.60	0.66	1000
Bird	0.52	0.62	0.57	1000
Horse	0.58	0.58	0.58	1000

The decision tree **underfits the data**, struggling to capture decision boundaries. It performs below all other models and serves only as a basic baseline.

Random Forest

The initial results for Random Forest show:

Descriptive Performance

OOB Score: 0.7401 (Out-of-Bag)

Training Accuracy: 100%

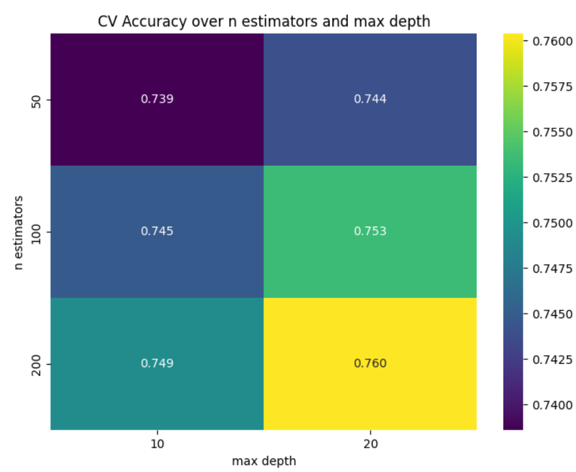
Predictive Performance (5-Fold Cross-Validation)

Fold Accuracies: [0.7593, 0.7463, 0.7593, 0.7617, 0.761]

Mean CV Accuracy: 75.75%

OOB Score Importance: OOB scoring allows performance estimation without needing a separate validation set. It uses bootstrap-resampled data to train each tree and estimates accuracy using samples not included in the training fold.

To improve performance, I tuned the hyperparameters `n_estimators` and `max_depth`.



Final Test Set Performance:

Accuracy: 74.87%

Class	Precision	Recall	F1-Score	Support
Airplane	0.81	0.75	0.78	1000
Bird	0.67	0.71	0.69	1000
Horse	0.78	0.78	0.78	1000

The Random Forest model generalizes better than a single decision tree and is more stable. However, due to its perfect training accuracy, it exhibits **overfitting**, with a ~19% performance gap between training and test accuracy.

Model Comparison Summary

Model	Train Acc	CV Acc	Test Acc
K-Nearest Neighbors	84.75%	78.53%	78.97%
Decision Tree	66.91%	59.39%	60.17%
Random Forest	93.40%	74.24%	74.23%

- **K-Nearest Neighbors**
  - Best generalization (Test Acc ~79%).
  - Low overfitting.
  - Balanced performance across classes.
- **Decision Tree**
  - Underfits the data.
  - Weak baseline classifier.
- **Random Forest**
  - Learns richer patterns than a single tree.
  - Better performance than Decision Tree but overfits more than K-NN.

Among all three models, **K-NN shows the best trade-off between training accuracy, generalization, and test performance**, making it the most effective model so far.

Lab 2: Neural Networks

In this lab, a Multi-Layer Perceptron (MLP) was implemented and evaluated using standardized HoG feature vectors as input.

Initial MLP Evaluation (1 Hidden Layer, 100 Units):

Descriptive Performance

Training Accuracy: 100%

Predictive Performance (5-Fold Cross-Validation)

Fold Accuracies: [0.788, 0.7953, 0.7903, 0.791, 0.7983]

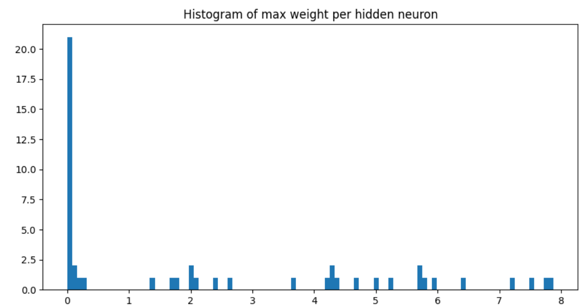
Mean CV Accuracy: 79.26%

While the model fits the training data perfectly, the CV scores reveal realistic generalization performance. This is a typical outcome for flexible models trained on relatively small data.

Neuron Behavior & Weight Analysis

I analyzed the hidden layer neurons to understand internal representation:

- Out of the 50 hidden neurons analyzed, 25 had at least one outgoing weight with magnitude ¿ 1.0.
- This suggests that about half of the neurons are **strongly wired**, meaning they significantly influence the final prediction.
- The distribution of maximum outgoing weights is highly skewed.



The hidden units act as a mix of **activators** and **suppressors**. Some neurons activate for class-relevant patterns (e.g., wing edges for airplanes), while others inhibit incorrect class activation. This reflects a **sparse, specialized internal representation**, where only a few neurons are responsible for decisive contributions. If one feature has a much larger numeric range than another, its weights get updated with much larger steps, which can make training slow or unstable. For this reason normalization may ensures that every dimension contributes roughly equally. By inspecting input hidden weights for the most influential neurons, I observed that the MLP learned distinct orientation-sensitive filters similar to edge detectors.

I explored various MLP architectures and learning settings via grid search:

```
param_grid = {
    'hidden_layer_sizes': [
        (50,), (100,),
        (50, 50), (100, 50),
        (100, 100, 50)
    ],
    'activation': ['relu'],
    'alpha': [1e-4, 1e-3],
    'learning_rate_init': [1e-3, 1e-2]
}
```

Best Configuration Found:

- **Architecture**: (100,)
- **Activation**: ReLU
- **Alpha**: 0.001
- **Initial Learning Rate**: 0.001
- **Best CV Accuracy**: 0.7937

This confirms that the original architecture was already well-suited. Adding more layers or increasing complexity did not yield gains and sometimes led to overfitting or unstable convergence.

Final Test Set Performance:

Accuracy: 80.00%

Class	Precision	Recall	F1-Score	Support
Airplane	0.84	0.82	0.83	1000
Bird	0.75	0.76	0.75	1000
Horse	0.82	0.83	0.82	1000

The MLP achieved the best generalization performance so far, slightly outperforming K-NN. It maintains balanced class-wise precision and recall, showing robust representation learning. The model generalizes well, likely due to the combination of weight regularization and ReLU activation promoting sparsity and stability.

- A simple MLP with 100 hidden units trained on standardized HoG vectors achieved strong classification performance.
- Analysis showed interpretable, sparse activations resembling early vision filters.
- With proper tuning, the MLP model was the best-performing model so far.

Lab 3: Support Vector Machines (SVMs)

This lab focused on training a Support Vector Machine (SVM) classifier using standardized HoG feature vectors.

I started with a default SVM using the RBF kernel:

Descriptive Performance

Training Accuracy: 94.51%

Predictive Performance (5-Fold Cross-Validation)

Fold Accuracies: [0.806, 0.810, 0.8193, 0.825, 0.818]

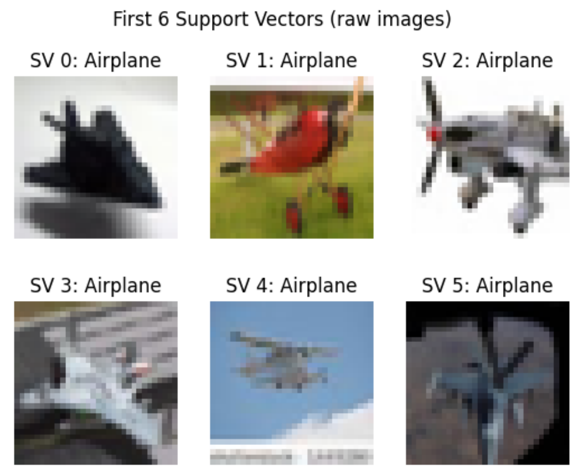
Mean CV Accuracy: 81.57%

These results indicate strong generalization ability out-of-the-box. The gap between training and CV accuracy is acceptable, suggesting moderate overfitting but good generalization.

Support Vector Analysis

SVMs work by finding a maximal-margin decision boundary and using a subset of the data — called **support vectors** — to define it. These are the training samples closest to the decision boundary and are critical in shaping it.

- **Support vectors per class**: [2102, 3155, 2262]
- **Total support vectors**: 7519
- More than 50% of training data were used as support vectors, which is quite high and reflects the non-linearity of the class boundaries in the feature space.



I optimized the following hyperparameters:

- **C**: 10
- **Kernel**: RBF
- **Gamma**: 0.001

Best Model Found:

```
svm = SVC(C=10, kernel='rbf', gamma=0.001,
          random_state=0)
```

Final Test Set Performance:

Accuracy: 82.33%

Class	Precision	Recall	F1-Score	Support
Airplane	0.86	0.85	0.86	1000
Bird	0.76	0.78	0.77	1000
Horse	0.85	0.85	0.85	1000

- The tuned SVM was the best-performing model across all labs, outperforming both the neural network and K-NN on the test set.
- Standardization of input was crucial; unscaled features caused a large drop in performance during initial testing.
- The RBF kernel with a well-tuned gamma allowed the SVM to model non-linear class boundaries, unlike linear models or simpler distance-based classifiers.
- in this model PCA can be counterproductive. The RBF kernel is already a powerful non-linear technique that considers relationships between all features. PCA, by discarding components with low variance, might remove information that the kernel could have used to define a better decision boundary.

The **Support Vector Machine with an RBF kernel** offers the strongest combination of accuracy and robustness on this HoG-based classification task. Its use of support vectors and the flexibility of kernel methods allow it to handle high-dimensional, non-linearly separable data effectively—making it a top choice for this problem.

Comparative Evaluation

Model	Train Acc	CV Acc	Test Acc
Ridge	75.96%	74.63%	74.30%
K-Nearest Neighbors	84.75%	78.53%	78.97%
Decision Tree	66.91%	59.39%	60.17%
Random Forest	93.40%	74.24%	74.23%
Multi-Layer Perceptron	100.00%	79.55%	80.00%
Support Vector Machine	93.77%	81.66%	82.33%

Overall Results:

- **Best Overall**: The Support Vector Machine (SVM) achieved the highest test accuracy at 82.3%.
- **Close Second**: The Multi-Layer Perceptron (MLP) reached 80.0%, showing strong generalization.

Key Observations:

- **Strong Learners (RF, MLP, SVM)**: All models with high expressive power (Random Forest, MLP, SVM) significantly overfit their training data. However, the SVM strikes the best balance between fitting the data and generalizing to new, unseen data. The Kernel Trick is the key. The RBF kernel projects the 256-dimensional HoG features into an infinite-dimensional space. In this new space, the classes likely become much more separable, allowing the SVM to find a clear decision boundary. Models like the MLP approximate this kind of transformation, but the SVM's kernel method is often more effective for "classical" feature vectors like HoG.
- **Competitive Baseline**: K-NN proves to be a simple yet strong non-parametric baseline, reaching 79.0% test accuracy with only moderate overfitting. However, KNN is a non-parametric method that works well when the decision boundary is highly irregular. The HoG features create a space where geometric distance is a meaningful measure of similarity—images with similar gradient patterns (e.g., two different horses) will be "close" to each other. Its strong performance suggests that the classes form relatively distinct clusters in the feature space.
- **Simpler Models**: The linear Ridge model performs reasonably well (74.3%), but it cannot keep up with the more complex models. A single Decision Tree is too weak on its own (60%), highlighting the need for techniques like ensembling (which is what Random Forest does) or pruning to improve its performance.

For classifying the CIFAR-3 (using only 3 classes) dataset using HOG features, a well-tuned SVM is the best choice. The MLP is a very close second, and K-NN stands out as a solid, simpler alternative.

Final Remarks

While classical machine learning methods like SVMs, K-NN, and MLPs trained on hand-crafted HoG features deliver reasonable performance on the simplified CIFAR-10 subset, they inherently struggle to capture the full complexity of natural images.

To further improve classification accuracy, more sophisticated approaches should be considered:

- **Deep neural networks**, eConvolutional Neural Networks (CNNs) implemented in libraries like PyTorch, are better suited for raw image data as they can learn hierarchical and spatially-aware features directly from pixels.
- **Ensemble strategies** such as stacking or voting classifiers that combine multiple models trained on diverse feature representations could also improve robustness and generalization.

Given the rich structure of the CIFAR dataset, such advanced techniques are likely to outperform traditional pipelines based on fixed feature extraction.