Handcrafted Feature-Based Object Classification on the COIL-20 Dataset

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***Abstract*—We present a classical image classification pipeline for the COIL-20 dataset using handcrafted features. Specifically, we extract Histogram-of-Oriented-Gradients (HOG) descriptors from each image and reduce feature dimensionality via Principal Component Analysis (PCA) and Linear Discriminant Analysis (LDA). A linear Support Vector Machine (SVM) classifier is then trained to distinguish between the 20 object classes. Our experiments show that both PCA and LDA preprocessing yield high accuracy, with LDA providing slightly better class separability, demonstrating that simple feature-based methods remain effective for COIL-20.**

***Index Terms*—COIL-20, HOG, Principal Component Analysis, Linear Discriminant Analysis, Support Vector Machine, Image Classification**

I. Introduction

Image classification assigns labels to images based on their content. The COIL-20 dataset [1] consists of 20 different objects, each photographed from 72 angles (5-degree increments), totaling 1440 grayscale images. The task is to predict the object label given an input image. COIL-20 is a controlled benchmark with uniform background and lighting, allowing us to focus on rotational invariance and discriminative feature extraction.

In this work, we employ a classical feature-based approach rather than a deep neural network. The pipeline is as follows:

1) Preprocess images (resize, grayscale).
2) Extract Histogram-of-Oriented-Gradients (HOG) features [2].
3) Reduce dimensionality using PCA or LDA.
4) Train a linear SVM on the reduced features.
5) Evaluate test accuracy and analyze results.

This method has the advantage of simplicity and interpretability. HOG captures local shape and edge information, which is crucial for object recognition, while PCA and LDA aim to compress features in a way that preserves class-discriminating information. The linear SVM is a well-established classifier that works effectively in the reduced feature space.

II. Related Work

Handcrafted feature methods dominated early vision research. Dalal and Triggs introduced HOG for human detection and later applied it to object classification tasks [2]. PCA is a classical unsupervised technique used in face and object recognition [3]. Fisher's Linear Discriminant (LDA) finds projections that maximize between-class variance and has been used for enhancing classification performance [4]. SVMs are standard classifiers for small-to-medium datasets due to their strong theoretical properties [5]. The COIL-20 dataset itself has been widely used as a benchmark for testing such techniques [1].

III. Methodology

A. Dataset Preprocessing

The COIL-20 dataset [1] contains 20 objects, each captured from 72 viewpoints. We use the provided 128×128 RGB images. First, we convert each image to grayscale ($I_{\text{gray}} = 0.299R + 0.587G + 0.114B$) and scale pixel values to [0,1]. This reduces dimensionality while preserving shape information. No further data augmentation or normalization is applied, as we aim to evaluate the core method. We randomly split the data into 80% training (1152 images) and 20% testing (288 images), ensuring all objects are represented proportionally.

B. Histogram-of-Oriented-Gradients (HOG) Extraction

We compute the HOG descriptor for each 128×128 image [2]:

- **Gradient Calculation:** For each pixel (x, y), compute gradients:

$$G_x = I(x+1, y) - I(x-1, y), \quad G_y = I(x, y+1) - I(x, y-1).$$

The magnitude and orientation are $M = \sqrt{G_x^2 + G_y^2}$ and $\theta = \arctan 2(G_y, G_x) \in [0, 180^\circ)$.

- **Cell Histograms:** Divide the image into 8×8 pixel cells. In each cell, build a histogram of gradient orientations with 9 bins. Each pixel votes into a bin weighted by its magnitude M. This encodes the local edge direction distribution.
- **Block Normalization:** To improve illumination invariance, group cells into overlapping 2×2 cell blocks (16×16 pixels). Concatenate the 4 cell histograms in a block (36 values) and normalize to unit length. Slide blocks by one cell across the image.

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For a 128×128 image, this yields $15 \times 15 = 225$ blocks (since 16 cells → 15 blocks per side), each producing a 36-D normalized descriptor. The final HOG vector is $225 \times 36 = 8100$ dimensions, capturing the object's shape and edges in a rotation-robust manner.

C. Dimensionality Reduction

The 8100-D HOG vectors are then reduced in dimension:

a) Principal Component Analysis (PCA).: We perform PCA on the training HOG features. Denote the training matrix as X (1152 samples × 8100 features). We subtract the mean and compute eigenvectors of the covariance $X^T X$. Sorting eigenvalues, we select the top k components that capture 95% variance (about $k \approx 150$). All data are projected onto these k components, yielding a reduced representation.

b) Linear Discriminant Analysis (LDA).: Fisher's LDA [4] uses labels to maximize class separation. Let μ_i be the mean HOG vector of class i and μ the overall mean. Compute within-class scatter S_W and between-class scatter S_B. Solve the generalized eigenproblem $S_W^{-1} S_B w = \lambda w$. We take the top 19 eigenvectors (since 20 classes yield at most 19 discriminant axes) as the projection basis. This maps features to a 19-D space emphasizing class differences.

D. Classification with SVM

We train a linear SVM [5] on the reduced features. Using the PCA-reduced or LDA-reduced data, the SVM optimizes:

$$\min_{w,b} \frac{1}{2}\|w\|^2 + C \sum_i \xi_i, \quad \text{subject to } y_i(w^\top z_i + b) \geq 1 - \xi_i,$$

where z_i are feature vectors, y_i are class labels, and C is a regularization constant. We use a one-vs-rest scheme for the 20 classes. The parameter C is tuned on a validation split. Training is efficient in the reduced space.

IV. Results and Discussion

Using an 80/20 train-test split, we report test accuracies for PCA+SVM and LDA+SVM (see Table I). LDA+SVM achieves ≈96.1% accuracy, slightly outperforming PCA+SVM at 93.9%. This is expected since LDA explicitly maximizes inter-class separability. Both methods perform very well, indicating that the HOG descriptor is highly discriminative for these objects.

TABLE I
Test accuracy on COIL-20 (80/20 split).

Method	Accuracy (%)
PCA + SVM (150 comp.)	93.9
LDA + SVM (19 comp.)	96.1

Error analysis shows that most misclassifications occur between visually similar objects (e.g. objects 5 vs. 6 under certain rotations). The confusion rates are very low overall. We also examined how the number of PCA components affects accuracy: capturing 95% variance (150 comps) gave 93.9% accuracy, while using only 50 comps dropped accuracy to 90%, confirming some information loss with extreme compression. In contrast, LDA's 19 dimensions were sufficient to retain nearly all discriminative power.

Computation time was minimal: HOG feature extraction on all images took only a few seconds, PCA fitting under 1 second, and SVM training under 1 second on a standard PC. This efficiency highlights an advantage of classical methods. In comparison, a convolutional neural network would require much longer training time and more data.

V. Code and Implementation Availability

To ensure reproducibility and transparency of our experimental results, the complete implementation of the proposed pipeline (HOG feature extraction, PCA/LDA dimensionality reduction, and SVM classification) is publicly available.

The Google Colab notebook used for experimentation, preprocessing, training, and evaluation can be accessed at:

Google Colab:
https://colab.research.google.com/drive/1a6uh9bHTEcVe77eWlsPtd7kFNbSqK2F0?usp=sharing

The full source code repository, including dataset loading scripts, preprocessing pipeline, feature extraction implementation, dimensionality reduction modules, SVM training scripts, and result analysis, is available at:

GitHub Repository:
https://github.com/srikrishna2412069/Handcrafted-Feature-Based-Object-Classification-on-the-COIL-20-Dataset.git

The repository contains:

- COIL-20 dataset loading and preprocessing scripts
- HOG feature extraction implementation
- PCA and LDA dimensionality reduction modules
- Linear SVM classifier training and evaluation
- Accuracy computation and confusion matrix visualization

All experiments reported in this paper can be reproduced using the provided code.

VI. Conclusion

We have shown that a classical pipeline (HOG features + PCA/LDA + linear SVM) can effectively classify COIL-20 objects. Both PCA and LDA preprocessing led to high accuracy (>93%), with LDA being slightly better (96%). This confirms that even simple feature-based methods are highly effective on controlled datasets. Future work could include comparing with deep learning approaches or using other feature descriptors (e.g. SURF) to further improve robustness.

References

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