Cross-Validated Handcrafted Feature-Based Object Classification on the COIL-20 Dataset Using PCA/LDA and Support Vector Machines

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***Abstract*—This paper presents a robust handcrafted feature-based object classification pipeline for the COIL-20 dataset. Histogram-of-Oriented-Gradients (HOG) features are extracted from grayscale images and standardized prior to dimensionality reduction. Principal Component Analysis (PCA) and Linear Discriminant Analysis (LDA) are evaluated as feature compression techniques. Classification is performed using both Linear and Radial Basis Function (RBF) Support Vector Machines (SVM). To obtain statistically reliable performance estimates, stratified 5-fold cross-validation is employed. Experimental results demonstrate that LDA combined with RBF SVM achieves the best performance, validating the effectiveness of classical feature-based pipelines for controlled object recognition.**

***Index Terms*—COIL-20, HOG, PCA, LDA, Support Vector Machine, Cross Validation, Confusion Matrix**

I. Introduction

Object classification is a fundamental computer vision task where images are assigned semantic labels. Traditional approaches rely on handcrafted feature extraction methods such as HOG [**?**], dimensionality reduction techniques such as PCA [**?**] and LDA [**?**], followed by classification using SVM [**?**].

The COIL-20 dataset [**?**] contains 20 objects captured from 72 viewpoints, totaling 1440 grayscale images. Due to controlled illumination and background conditions, it serves as a benchmark dataset for evaluating classical classification pipelines.

This work implements a complete end-to-end machine learning pipeline using scikit-learn's modular Pipeline framework to ensure reproducibility and prevent data leakage.

II. Related Work

Dalal and Triggs introduced HOG for human detection, demonstrating robustness to illumination variations [**?**]. PCA has long been used in image recognition for variance-preserving dimensionality reduction [**?**]. Fisher's LDA maximizes class separability in supervised settings [**?**]. Cortes and Vapnik introduced SVM as a maximum-margin classifier [**?**]. The COIL dataset remains widely used for benchmarking classical and deep learning methods [**?**].

III. Methodology

A. Dataset Preprocessing

Images are resized to 128×128 and converted to grayscale:

$$I_{gray} = 0.299R + 0.587G + 0.114B$$

Pixel intensities are normalized to [0,1].

B. HOG Feature Extraction

HOG captures edge orientation distributions.

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

$$M = \sqrt{G_x^2 + G_y^2}, \quad \theta = \arctan 2(G_y, G_x)$$

Each image is divided into 8×8 cells with 9 orientation bins. Overlapping blocks are normalized using L2-Hys. Final feature dimension: 8100.

C. Feature Standardization

Z-score normalization:

$$z = \frac{x - \mu}{\sigma}$$

This is embedded within the cross-validation pipeline.

D. Dimensionality Reduction

1) Principal Component Analysis: PCA computes eigenvectors of covariance matrix:

$$\Sigma = \frac{1}{n} X^T X$$

Top components explaining 95% variance are retained.

2) Linear Discriminant Analysis: LDA solves:

$$S_W^{-1} S_B w = \lambda w$$

reducing features to at most 19 dimensions.

E. Support Vector Machines

Linear and RBF SVM are evaluated.

$$\min_{w,b} \frac{1}{2}||w||^2 + C\sum \xi_i$$

RBF kernel:

$$K(x_i, x_j) = \exp(-\gamma||x_i - x_j||^2)$$

Hyperparameters: Linear SVM ($C = 1$), RBF SVM ($C = 10$, $\gamma = scale$).

F. Stratified 5-Fold Cross-Validation

StratifiedKFold ensures class balance across splits. Performance is measured using:

- Mean accuracy $\pm$ standard deviation
- Cross-validated confusion matrix via cross_val_predict

G. Evaluation Metrics

Accuracy:

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN}$$

Cross-validation ensures robustness.

IV. Results

TABLE I
STRATIFIED 5-FOLD CROSS VALIDATION ACCURACY

Method	Accuracy (%)
PCA + Linear SVM	94.2 $\pm$ 0.8
PCA + RBF SVM	95.5 $\pm$ 0.6
LDA + Linear SVM	96.3 $\pm$ 0.5
LDA + RBF SVM	97.1 $\pm$ 0.4

LDA improves separability due to supervised learning. RBF kernel captures non-linear decision boundaries, leading to best performance.

A. Confusion Matrix Analysis

Cross-validated confusion matrix shows minimal inter-class confusion. Most misclassifications occur between visually similar objects under rotation.

B. Computational Efficiency

Feature extraction requires only seconds. Training per fold is under one second, demonstrating efficiency compared to deep learning models.

V. Limitations

While effective on controlled datasets, handcrafted features may struggle in unconstrained real-world environments involving occlusion or clutter. Deep neural networks may outperform in such scenarios.

VI. Conclusion

A carefully designed handcrafted pipeline with stratified cross-validation achieves approximately 97% accuracy on COIL-20. LDA combined with RBF SVM provides the best performance. The approach is computationally efficient and interpretable, making it suitable for benchmark classification tasks.

References

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Code Availability

The complete implementation of the proposed pipeline, including preprocessing, HOG feature extraction, PCA/LDA dimensionality reduction, SVM classification, and cross-validation evaluation, is publicly available at:

GitHub Repository:
https://github.com/gopi470/COIL20-FeatureBased-Classification