PROJECT REPORT

Characterisation of Object Using Geometry and Colour

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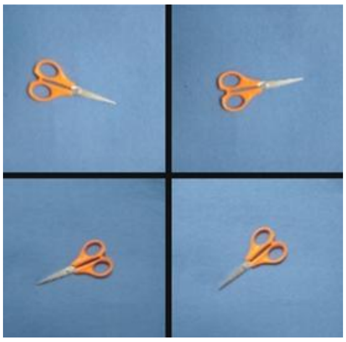
Introduction

Object classification is a core task in computer vision, with applications in manufacturing, robotics, quality inspection, diagnostics, and automated sorting systems. This project develops a robust object-characterization and classification pipeline integrating:

- Background removal using LAB colour distance
- Geometric shape descriptors (boundary sampling, Fourier descriptors, PCA eigen features)
- LAB colour statistics
- Dimensionality reduction via PCA
- Supervised classification (SVM and KNN)

The system is designed to be scale, rotation, and translation-invariant, enabling consistent recognition of object categories under varying orientations and sizes.

Data set:



Class A **Class B** **Class C**

Pipeline Description

1) Pre-processing & Background Removal

• Convert RGB → HSV → enhanced HSV → RGB → LAB. Saturation and brightness are boosted in HSV so that LAB (L, a, b) better separates foreground from background.

• Estimate background colour from the four image corners.
• Compute the Euclidean distance in LAB between each pixel and the background colour. Threshold this distance to create a binary mask isolating the object.

2) Geometric Feature Extraction

(a) Boundary Sampling

• Extract the largest contour will correspond to outer boundary of object.
• Uniformly sample N=30 boundary points and centre them.
• Compute their covariance matrix.

(b) PCA Eigen Description

• Extract two eigenvalues (λ_1, λ_2).
• Use λ_1/λ_2, plus the normalized eigen spectrum, describing aspect ratio, elongation, and object eccentricity.

(c) Fourier Shape Descriptors

• Represent boundary as $z = x + i*y$
• Compute the first n normalized Fourier descriptors, capturing fine shape, scale, and rotation-invariant structure.

(d) Global & Local Shape Characterization

Global Shape (from Canny edges)

• Determine the best-fitting bounding shape (circle/ellipse/rectangle) by comparing hull area vs. bounding shape area.
• The shape with area ratio closest to 1 is selected (will be minimum area)

(e)Local Shapes

• Split object vertically along its principal direction at the mean centre of points.
• For each half, repeat the shape-fitting process to capture internal edge-based local structure.

3) Colour Features

• Convert masked pixels to LAB.
• Compute mean L, mean a, mean b.

4) Final Feature Vector (22 features)

a) PCA eigenvalues: 2
b) Eigenvalue ratio: 1
c) Fourier descriptors: 10
d) Global shape + aspect ratio: 2
e) Local shapes + aspect ratios: 4
f) Colour features (LAB means): 3

6) Classification

Two classifiers are supported:
• Support Vector Machine (SVM)
• K-Nearest Neighbour (KNN)

Results

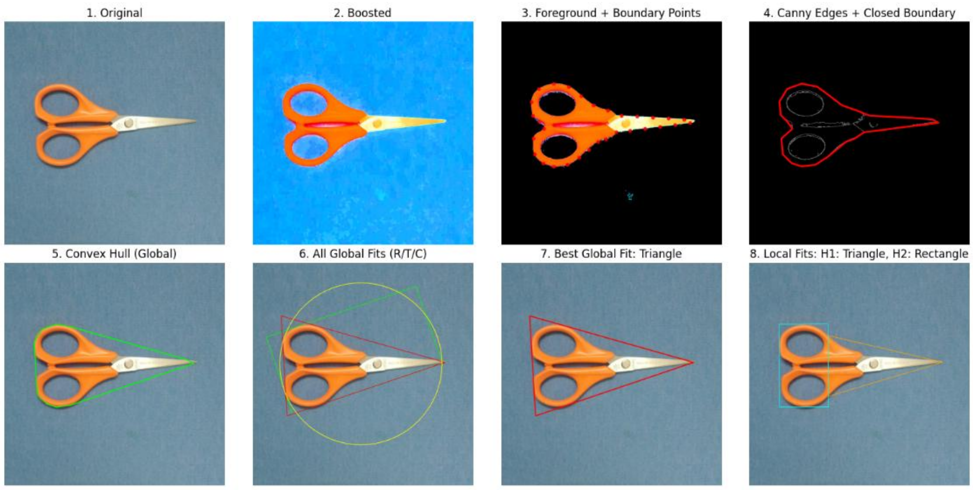


Fig: work flow of obtaining geometry from image for scissor

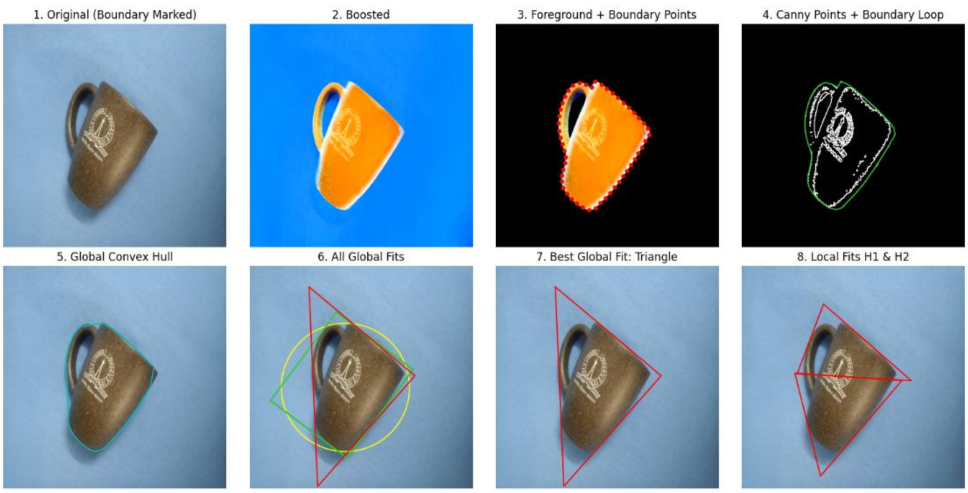


Fig: work flow of obtaining geometry from image for cup

PCA plot:

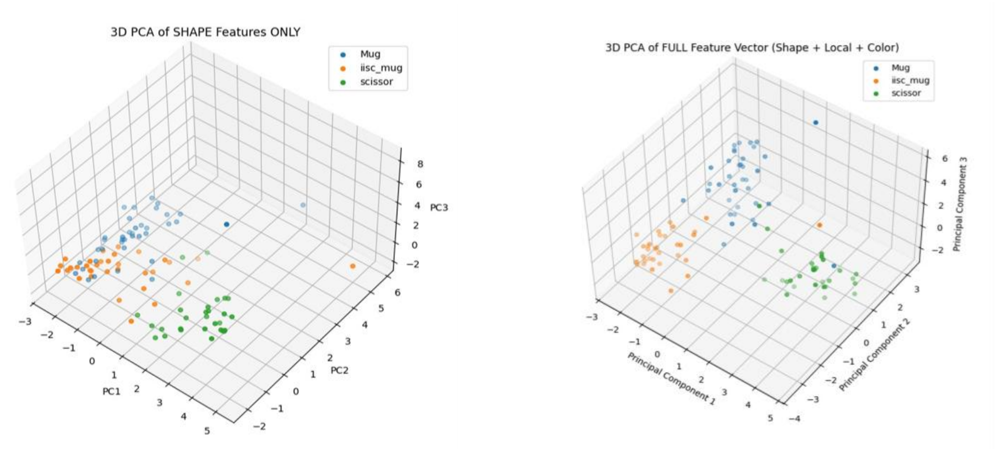


Fig: only using (a) shape feature and (b) all features

Confusion Matrices:

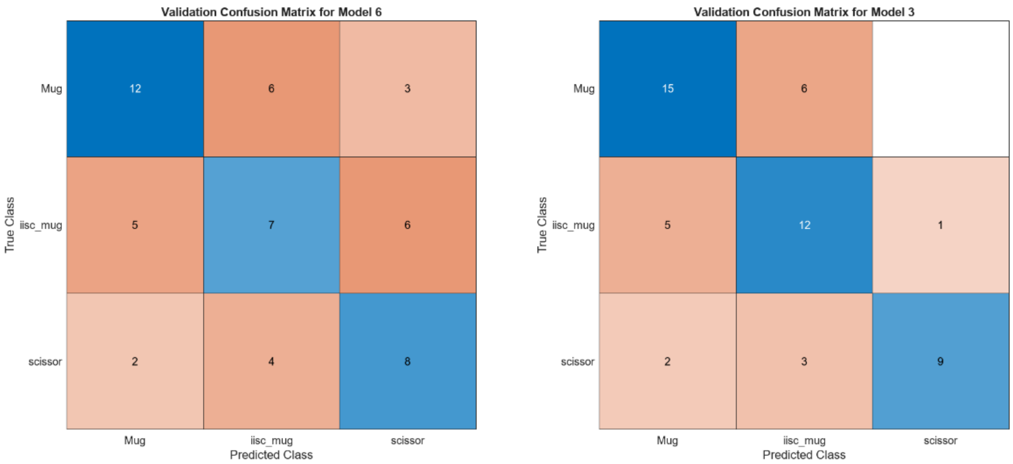


Fig: (a) Using only shape components (a, b, c): Accuracy: 50.9%

(b)Using only global and local shapes (d, e):Accuracy: 67.9%

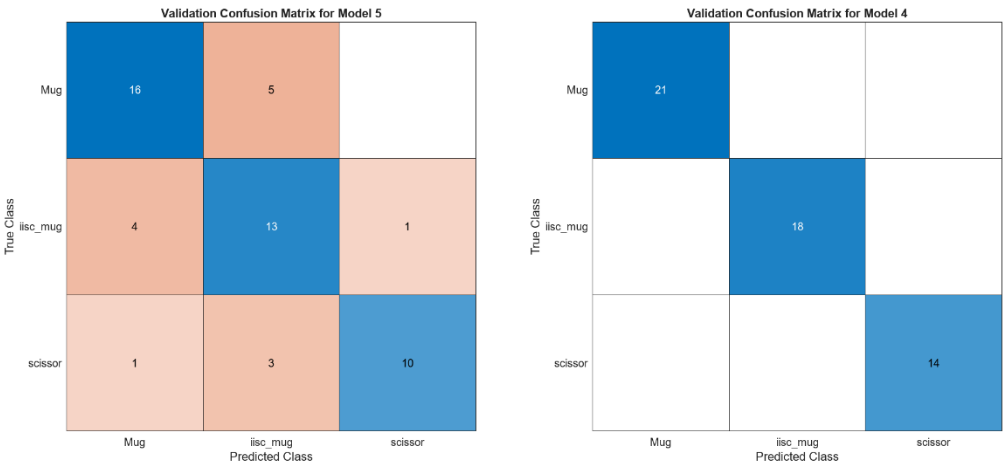


Fig: (a) Using all shape features (a–e):Accuracy: 73.6%

(b) Using all features (shape + colour):Highest overall accuracy

Limitations

- Designed for one object per frame
- Requires uniform background (typical for conveyor systems)
- Works only with colour images
- Performance depends heavily on dataset variability
- PCA feature space changes with training distribution

Conclusion

This project presents a complete, robust pipeline for object characterization using:

- PCA-based geometric shape descriptors
- Fourier boundary analysis
- LAB colour statistics
- Global + local shape analysis

The system achieves strong performance across object classes and maintains invariance to scale, rotation, and position. The combination of shape and colour features significantly improves classification accuracy.

Future scope of work

- Improve concave shape detection and internal structure analysis
- Extend the pipeline to real-time webcam classification
- Reduce colour-dependence by strengthening geometry-driven features
- Generalize the method for arbitrary unseen object shapes
- Explore deep-learning–assisted feature extraction while preserving interpretability