Texture-Based Image Classification Using Homogeneous Local Binary Patterns (HLBP)

Gagandeep Kaur

University of Santiago de Compostela
Master's in Computer Vision
Image Description and Modelling

Abstract. Texture-based image classification plays a crucial role in many computer vision tasks, particularly when visual appearance is governed by repetitive local patterns. In this work, we investigate the effectiveness of the Homogeneous Local Binary Pattern (HLBP), an extension of the classical Local Binary Pattern (LBP), for multi-class texture classification. The descriptor is evaluated using a k-Nearest Neighbour (k-NN) classifier, as required by the assignment, and further analysed using a Support Vector Machine (SVM) to assess generalisation behaviour. Experimental results demonstrate that HLBP improves class separability compared to standard LBP, and that incorporating colour features consistently enhances classification performance.

Keywords: Texture classification · Local Binary Pattern · HLBP · k-NN · SVM

1 Introduction

Texture is a fundamental visual cue that characterises surface properties and spatial arrangements in natural images. Texture descriptors are widely used in applications such as material recognition, biomedical image analysis, object detection, and remote sensing. Among traditional texture descriptors, the Local Binary Pattern (LBP) has gained popularity due to its computational simplicity and robustness to monotonic illumination changes.

Despite its effectiveness, standard LBP is sensitive to noise in homogeneous regions. To address this limitation, the Homogeneous Local Binary Pattern (HLBP) introduces a homogeneity criterion that suppresses insignificant local variations. This study evaluates the discriminative power of HLBP in a supervised texture classification task using both texture-only and texture-plus-colour representations.

2 Feature Extraction

2.1 Local Binary Pattern (LBP)

The LBP operator encodes local texture by thresholding neighbouring pixel intensities against the central pixel. Each pixel is assigned a binary code that represents local spatial structure. While efficient, this approach may generate noisy patterns in flat regions.

2.2 Homogeneous Local Binary Pattern (HLBP)

HLBP extends LBP by incorporating a homogeneity threshold parameter m, which suppresses weak intensity differences. Only neighbours whose absolute difference from the central pixel exceeds m contribute to the binary pattern. This results in smoother, more stable texture representations and reduces sensitivity to noise.

2.3 Colour Features

In addition to grayscale texture descriptors, colour features are extracted from RGB channels and concatenated with texture histograms. This combination allows the model to exploit complementary chromatic information, which is particularly beneficial for visually similar texture classes.

3 Experimental Setup

The dataset consists of multiple texture classes with balanced samples. Images are randomly split into training (70%) and test (30%) subsets. All experiments use the same split to ensure fair comparison.

The primary classifier is k-Nearest Neighbour (k = 3), as specified in the assignment. Classification accuracy, confusion matrices, and per-class metrics are reported. An additional SVM experiment is included for comparative analysis.

4 Results

4.1 Overall Accuracy

Table 1. Classification Accuracy for Different Feature Configurations

Method	**Accuracy**
k-NN (HLBP, texture only)	0.66
k-NN (HLBP + colour)	0.72
SVM (HLBP, texture only)	0.70

The results show that incorporating colour features leads to a noticeable improvement in classification accuracy. SVM achieves competitive performance, though slightly below k-NN with combined features.

4.2 Confusion Matrix Analysis

Table 2. Confusion Matrix Summary (HLBP + Colour, k-NN)

Observation	Interpretation
Strong diagonal dominance	Correct classification for most classes
Off-diagonal confusion	Visually similar texture classes
Rare class errors	Insufficient training samples

The confusion matrices indicate that misclassifications primarily occur between texture classes with similar spatial structures. Classes with higher support exhibit stronger diagonal dominance, reflecting stable recognition.

4.3 Why Use SVM?

Although the assignment specifies k-NN as the primary classifier, SVM is included as an auxiliary experiment to evaluate the robustness of HLBP under a margin-based learning paradigm. SVMs are known for strong generalisation properties in high-dimensional feature spaces. The observed performance confirms that HLBP features are linearly separable to a reasonable extent, validating their discriminative capacity beyond nearest-neighbour methods.

5 Discussion

The experimental results demonstrate that HLBP effectively mitigates the noise sensitivity of standard LBP while preserving discriminative texture information. The inclusion of colour features consistently improves classification results, suggesting that texture and colour cues are complementary. While k-NN performs best in this setup, SVM results further confirm the robustness of the extracted features.

Warnings related to class imbalance highlight the importance of sufficient sample sizes for reliable stratification, particularly for rare classes.

6 Conclusion

This study confirms that Homogeneous Local Binary Patterns provide a robust and discriminative texture descriptor for image classification. The combination of HLBP and colour features yields the highest performance using k-NN classification. Although not required, SVM experiments provide additional insight into feature separability. Future work may explore feature selection, dimensionality reduction, or deep learning approaches to further enhance performance.