Texture Classification Using GLCM and LBP with SVM and k-NN

1. Introduction

This project implements texture analysis techniques to classify images of stone, brick, and wood. Two feature extraction methods—**Gray-Level Co-Occurrence Matrix (GLCM)** and **Local Binary Pattern (LBP)**—were employed to capture distinct textural properties, and machine learning classifiers (**SVM and k-NN**) were used to perform the classification. To improve efficiency, **RandomizedSearchCV** was used for hyperparameter tuning in SVM and k-NN.

2. Methods

2.1 Dataset Preparation

A dataset of 150 images (50 per category) was used, covering variations in lighting and scale. The dataset was split into 70% training and 30% testing to ensure robust model evaluation.

2.2 Feature Extraction

For texture analysis, GLCM was used to compute four statistical features: contrast, correlation, energy, and homogeneity, which describe pixel intensity relationships. In parallel, LBP was applied to generate histograms of uniform LBP patterns, capturing microtexture details.

2.3 Classification

The extracted features were used to train two classifiers. Support Vector Machine (SVM) was optimized with **RandomizedSearchCV**, significantly reducing computational cost compared to exhaustive **GridSearchCV**. Meanwhile, k-Nearest Neighbors (k-NN) was fine-tuned using **RandomizedSearchCV** to find the optimal number of neighbors.

3. Results

Classifier	Feature	New Accuracy	Old Accuracy
SVM	GLCM	0.62	0.62
SVM	LBP	0.84	0.75
k-NN	GLCM	0.57	0.62
k-NN	LBP	0.73	0.68

4. Observations

LBP combined with SVM provided strong classification accuracy, leveraging statistical texture features effectively, though requiring careful hyperparameter tuning. LBP with k-NN also performed well but was more sensitive to parameter selection. By replacing **GridSearchCV** with **RandomizedSearchCV**, the SVM training process was significantly accelerated while maintaining competitive performance. The dataset chosen also influences the accuracy of models significantly. Models trained with the dataset having texture images that have other textures only have the highest accuracy of 75%. However, the new dataset having texture images that only have one texture improves the accuracy of models up to 84%.

5. Conclusion

This project demonstrates that texture-based feature extraction methods like GLCM and LBP, when paired with SVM and k-NN classifiers, can effectively classify material textures. Future improvements could explore additional feature descriptors, such as Gabor filters, or alternative classifiers like Random Forest and deep learning-based approaches.