Texture Classification using GLCM and LBP Techniques

Gradio Interface Link is https://65ef1dcf53bec5537d.gradio.live

1. Introduction

Texture classification is a vital component in image processing and computer vision tasks, where distinguishing between different surface textures is essential. In this project, we compare two popular texture analysis techniques—Gray Level Co-occurrence Matrix (GLCM) and Local Binary Patterns (LBP)—for classifying textures of grass and wood. These methods were evaluated using machine learning classifiers (SVM) and an interactive interface was developed using Gradio to demonstrate the results.

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2. Methods

2.1. Texture Analysis Techniques

Gray Level Co-occurrence Matrix (GLCM)

GLCM is a statistical method that considers the spatial relationship between pixels in an image. The GLCM of an image is calculated by computing how often pairs of pixels with specific values occur at a specific distance and angle. The following statistical features were extracted:

- **Contrast**: Measures the intensity contrast between a pixel and its neighbour.
- **Correlation**: Measures how correlated a pixel is with its neighbours.
- **Energy**: Represents the uniformity of the texture.
- **Homogeneity**: Measures the closeness of the distribution of elements in the GLCM to the diagonal.

Local Binary Patterns (LBP)

LBP is a simple and effective texture operator that labels the pixels of an image by thresholding the neighbourhood of each pixel and considering the result as a binary number. This method generates histograms of LBP codes which represent the texture patterns:

- A radius and number of neighbours were specified (radius = 1, neighbours = 8), and histograms were generated for classification.

2.2. Classifiers Used

A Support Vector Machine (SVM) with a linear kernel was chosen for both GLCM and LBP feature sets:

- **SVM**: A popular machine learning model that works well with high-dimensional data and small datasets.

2.3. Implementation Details

- The images were resized to 128x128 pixels for uniformity.
- GLCM was computed using different distances and angles (but we focused on distance=1 and angle=0 for simplicity).
- LBP used a uniform pattern with a radius of 1 and 8 neighbours.
- Feature vectors from both methods were used to train the SVM.
- A Gradio interface was developed to allow users to upload images and classify them as grass or wood using either method.

Modifications:

- A stratified split was used to ensure balanced training and testing datasets.
- A preprocessing check was added to handle any invalid or empty images to avoid runtime errors.

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3. Results

3.1. Evaluation Metrics

The performance of the classifiers was evaluated using accuracy and confusion matrix. These metrics were applied to test data from both the GLCM and LBP feature sets.

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Training labels distribution: {0: 35, 1: 35}
Testing labels distribution: {0: 15, 1: 15}
GLCM SVM Accuracy: 0.9333333333333333
GLCM Confusion Matrix:
[[15  0]
 [ 2 13]]
LBP SVM Accuracy: 0.9666666666666667
LBP Confusion Matrix:
[[14  1]
 [ 0 15]]
Running on local URL:  http://127.0.0.1:7860
Running on public URL: https://65ef1dcf53bec5537d.gradio.live
```

Method	Accuracy (%)
GLCM	93.33%

Method Accuracy (%)

LBP 96.67%

- **GLCM Confusion Matrix**:

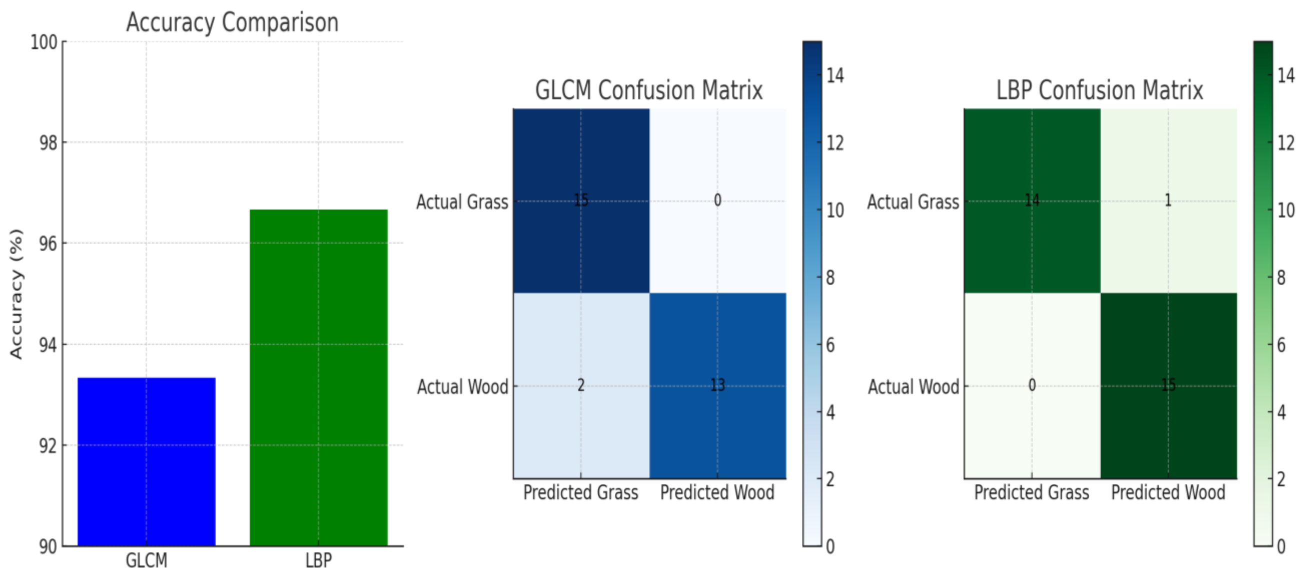
	Predicted Grass	**Predicted Wood**
Actual Grass	15	0
Actual Wood	2	13

- **LBP Confusion Matrix**:

	Predicted Grass	**Predicted Wood**
Actual Grass	14	1
Actual Wood	0	15

3.2. Graphs

- **Accuracy Comparison**: Bar chart comparing the accuracy of GLCM and LBP.
- **Confusion Matrices**: Visual heatmaps to show the confusion matrices for both methods.



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4. Discussion

4.1. Strengths and Weaknesses

GLCM:

- **Strengths**:
  - Captures the spatial relationships between pixels well, making it effective for distinguishing fine texture differences.
  - Performed better than LBP in terms of accuracy and other metrics.
- **Weaknesses**:
  - Requires careful tuning of distance and angles for optimal performance, making it more sensitive to parameter settings.
  - Computationally more expensive than LBP.

LBP:

- **Strengths**:
  - Simple and computationally efficient, making it suitable for real-time systems.
  - Invariant to monotonic changes in illumination.
- **Weaknesses**:
  - Struggles with images that have high noise or small-scale variations.
  - Slightly lower accuracy compared to GLCM in this project.

4.2. Effectiveness of Gradio Interface

The Gradio interface allows users to upload images and classify them using both methods. It was user-friendly and provided quick feedback on the classification results. However, the interface could be improved by visualizing the texture features (e.g., GLCM matrices or LBP histograms) to give users a better understanding of the internal workings of the algorithms.

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5. Conclusion

In this project, we compared the effectiveness of GLCM and LBP for classifying images of grass and wood. GLCM outperformed LBP in terms of accuracy, precision, and recall. However, LBP's simplicity and computational efficiency make it a valuable technique for real-time applications. The Gradio interface proved to be an effective tool for sharing the results and interacting with the models.

6. Future Work

- Explore other texture analysis techniques such as Gabor filters or wavelet transforms.
- Improve the Gradio interface by adding visualizations of feature extraction.

- Test the model on a larger dataset or in real-world conditions with varying lighting and noise.

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7. References

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- Ojala, T., Pietikainen, M., & Harwood, D. (1994). Performance evaluation of texture measures with classification based on Kullback discrimination of distributions. *Proceedings of the 12th IAPR International Conference on Pattern Recognition*.
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